ONLINE PARAMETER ESTIMATION APPLIED TO MIXED CONDUCTION/RADIATION

A Thesis

by

TEJAS JAGDISH SHAH

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2005

Major Subject: Mechanical Engineering

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Approved as to style and content by:

Ali Beskok (Chair of Committee)	Alexander. G. Parlos (Member)
David. R. Boyle (Member)	Dennis O'Neal (Head of Department)

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ABSTRACT

Online Parameter Estimation Applied to
Mixed Conduction/Radiation. (May 2005)
Tejas Jagdish Shah, B.E., Andhra University, India
Chair of Advisory Committee: Dr Ali Beskok

The conventional method of thermal modeling of space payloads is expensive and cumbersome. Radiation plays an important part in the thermal modeling of space payloads because of the presence of vacuum and deep space viewing. This induces strong nonlinearities into the thermal modeling process. There is a need for extensive correlation between the model and test data. This thesis presents Online Parameter Estimation as an approach to automate the thermal modeling process. The extended Kalman filter (EKF) is the most widely used parameter estimation algorithm for nonlinear models. The unscented Kalman filter (UKF) is a new and more accurate technique for parameter estimation. These parameter estimation techniques have been evaluated with respect to data from ground tests conducted on an experimental space payload

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I would like to thank Dr. Rudolph Van der Merwe for providing the ReBEL tool kit, which is a collection of scripts in matlab for estimation purposes and has been used in this thesis.

Finally, I would like to thank Olivier Godard. His constructive criticism has helped alot in improving my writing and presentation skills.

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CHAPTER I

INTRODUCTION

Because of vacuum, conduction and radiation are the primary means of thermal management of payloads and spacecrafts in space. Since temperature regulation of these payloads is essentially enabled by the final heat sink of deep space viewing, radiation is playing an important part in the thermal design of payloads. As such, thermal modeling has to deal with the strong nonlinearities induced by radiation heat transfer. Thermal vacuum testing of payloads that are designed for space use is a process needed to evaluate their safety margins and design parameters. Even for small payloads, the process of performing thermal vacuum testing can be cumbersome. A thermal model needs to be first built. The thermal model is then subjected to the expected environmental heat loads of the space mission. Finally the model is then expected to correlate with the test data obtained from the thermal vacuum testing. In many cases, payloads are tested individually and are then integrated in larger platforms. Thermal vacuum testing is also needed for these larger platforms. At every step of the process, the thermal modeling has to produce coarser description of every component in order to keep the complexity of the overall model at a moderate size. Specifically, at the initial level, there is usually some amount of model reduction in order to go from a Finite Element Model (FEM) to a lumped parameter approach (see Fig 1). While this work is usually left as an exercise to the thermal engineer, it may need a certain degree of automation in the future. The iterative nature of this overall process as well as the need to perform elemental tests makes it a cumbersome and expensive process. For instance, with very large satellites, the qualification process

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can take years. Furthermore, conservative assumptions used in the thermal vacuum testing procedure may be unnecessary and yield an overly conservative design.

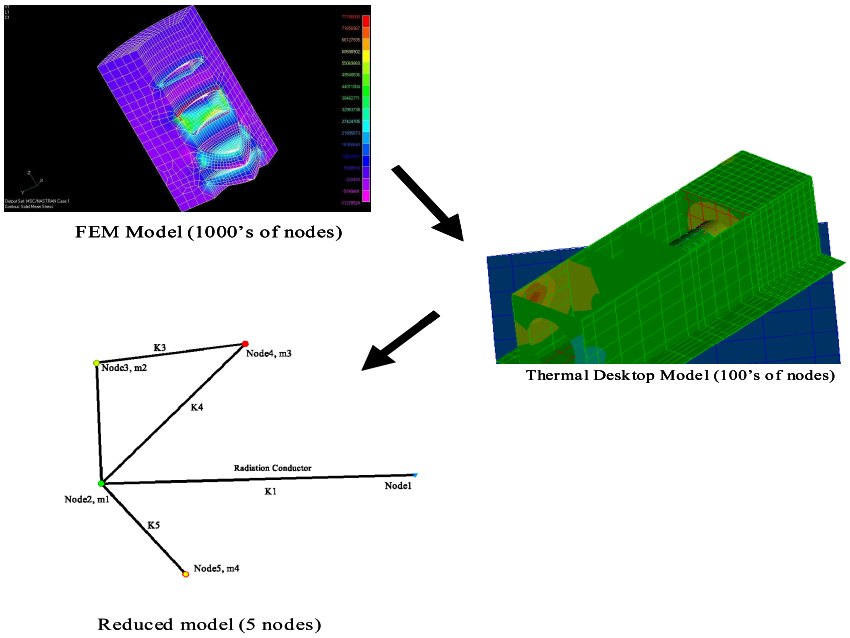

Fig. 1. Initial Model Reduction Needed

The goal of this thesis is to provide a path to accelerate the design and testing processes while increasing the accuracy of the modeling and the design (see Fig 2). We therefore address the issue of online parameter estimation as applied to a mixed conduction/radiation heat transfer environment which is the case encountered in payloads evolving in the vacuum of space. This online estimation is expected to be used while the testing is being performed in the ground thermal vacuum testings. There is an expectation that the testing itself will eventually be driven by an automated system that will integrate the results of the online parameter estimation. The estimation process uses all the measured data and observations up to the current times in order to obtain an approximation of the current state.

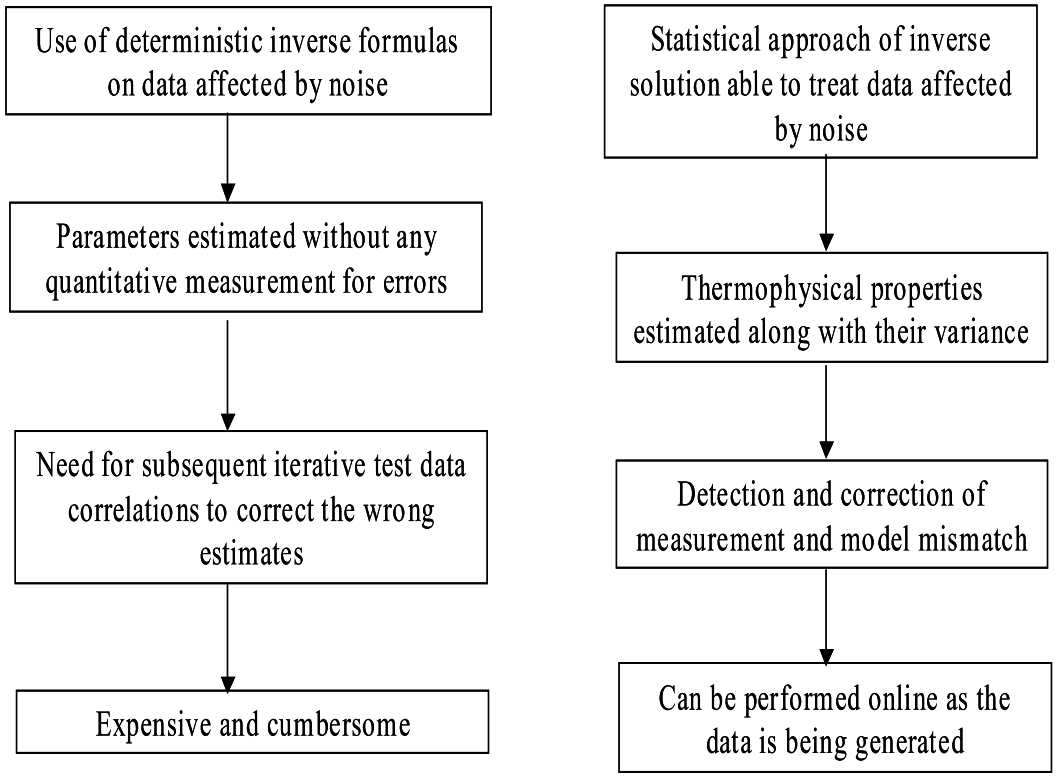

Fig. 2. Comparison of a) Conventional Approach and b) Parameter Estimation Approach to Thermal Modeling

Traditionally, most estimation work has been geared toward evaluating state models only. Most techniques rely on Kalman filtering and its associated nonlinear schemes such as the extended Kalman filter (EKF.) In order to both estimate the state and parameters of the thermal model from the data, two approaches can be used. One is iterative (see Fig 3) in nature while the other one is sequential (see Fig 4). In the iterative approach the model and all the data are used to estimate the signal, then the estimated signal and all available data are used to estimate the model parameters. Since all the data is required at each step of this process, it can only be used for offline estimation or batch processing.

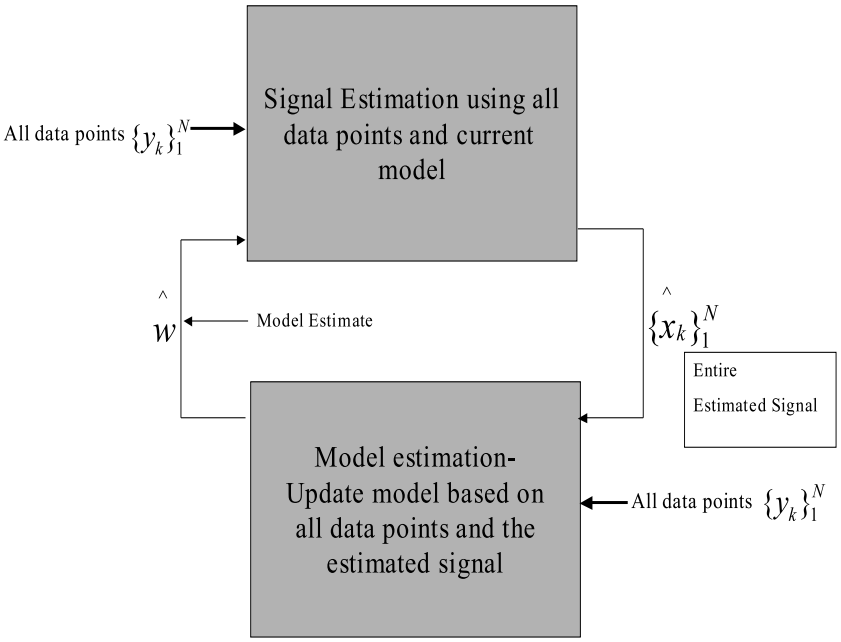

Fig. 3. Iterative Estimation

The sequential estimation is, on the other hand, recursive in nature. The state and parameters of the model are estimated simultaneously from the data. This type of approach can be used for online estimation purposes and can be applied as the data become available.

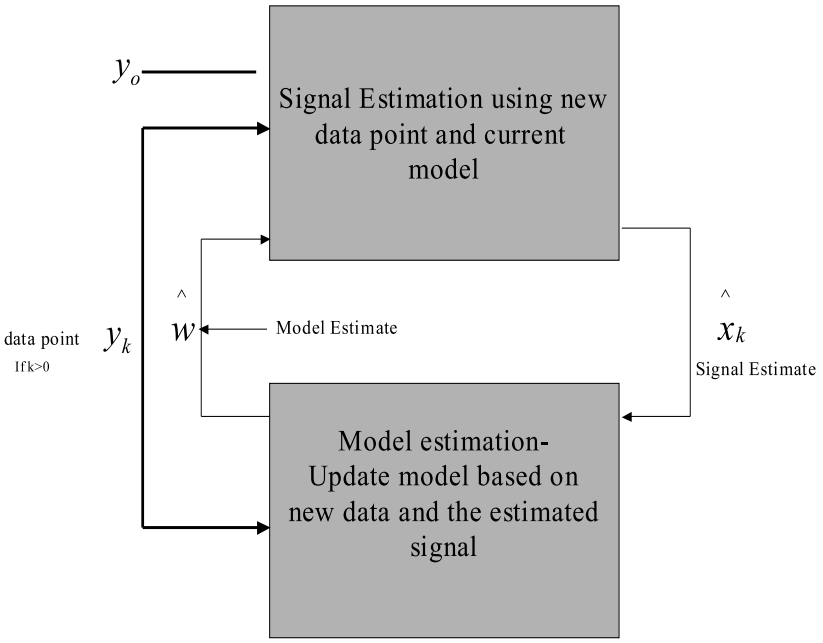

Fig. 4. Sequential Estimation

The Kalman filter is the oldest standard recursive solution for linear filtering problems. The focus of this thesis is on evaluating nonlinear extension of the Kalman Filter specifically the well known extended Kalman filter(EKF) and the new unscented Kalman filter(UKF) for the purpose of parameter and state estimation. EKF is the standard approach used for nonlinear estimation, where as UKF is a fairly new technique, when used as a parameter estimation technique. Both these filters are part of the family of sequential estimation algorithms which are required for online estimation.

This thesis presents online parameter estimation applied to temperature data obtained from different environmental tests on an experimental payload (StarNav I), that eventually flew on STS-107 the space shuttle Columbia. A reduced five node simplified model is built to understand the thermal system and to reduce the number of model parameters. A state space model is then built from the nodal equations of this model. The parameters like conductance or thermal masses are estimated from four thermal tests, using initial guesses obtained from the CAD model using the Thermal Desktop software.

Chapter II is a literature review summarizing the current research going on in the field of parameter estimation and its application in heat transfer.

Chapter III describes the theory of the Kalman filters and their non linear derivatives. It also describes the equations associated with them.

Chapter IV explains the StarNav I payload and the various ground test conducted on it. It also describes the simplified model of StarNav I.

Chapter V describes the noise associated with the estimation process. It explains the significance of the process and observation noise.

Chapter VI has the results of the estimation process. Results are shown for both EKF and UKF estimators.

Chapter VII describes the work that can be done to extend the possibilities of this work.

Chapter VIII is the conclusion.

The appendix has all the data collected from the ground tests. It also describes the location of the internal and external thermistors on StarNav I.

CHAPTER II

LITERATURE REVIEW

Parameter estimation is a discipline that provides tools for the efficient use of data for aiding in mathematical modeling of the phenomena, and estimating the constants appearing in these models. A good overview of parameter estimation techniques has been done by Nelson [1]. These include the Standard Kalman Filter, The Extended Kalman Filter and their application in Dual Estimation

The Kalman filter was developed by Kalman [2] where he described a new approach to linear filtering and prediction problems. Kalman Filter is a recursive solution to the discrete data linear filtering problem. Kalman described the dynamic system with the concept of state - some quantitative information, which is the least amount of data one has to know about the past behavior in order to predict its future behavior. The dynamics is then described in terms of state transitions, i.e how one state is transformed into another as time passes. A key property of the Kalman filter is that it is the minimum mean-square (variance) estimator of the state of a linear dynamical system.

For nonlinear state models, Kalman filtering may be extended through a linearization procedure. The resulting filter is referred to as the Extended Kalman Filter (EKF) [3] - [5]. The EKF linearizes the state space model at each time instant around the most recent time estimate. Once a linear model is obtained the standard Kalman filter equations are applied. The EKF gives accuracy to the first order (Taylor series approximation) of any nonlinearities.

The Extended Kalman Filter is the most widely used estimation algorithm for nonlinear systems. However years of experience in the estimation community has shown that it is difficult to implement, difficult to tune and only reliable for

systems that are almost linear on the time scale of the updates. The Unscented Kalman Filter is proposed as an alternative to Extended Kalman Filter by Julier and Uhlmann [6] - [8] and further developed by Wan and van der Merwe [9] - [12]. The UKF is provably superior to the EKF as it does not need to explicitly calculate the Jacobians or Hessians. The UKF not only outperforms the EKF in accuracy (Second order approximation versus first order approximation) but is also computationally efficient. A small number of carefully chosen sample points when propagated in each estimation step provide a compact parametrization of the underlying distribution. Several examples of parameter estimation are now listed.

Chatterjee and Litt [13] have studied/analyzed online parameter estimation using Kalman filters. They apply parameter estimation to the degradation effects of jet engine components over their life time of use. The Kalman estimator provided accurate real time estimates of the engine health parameters with rapid convergence to the degraded engine state variables and outputs. The estimated health parameters helped in correcting the thrust response of a severely degraded engine to that of a nominal engine. Desired engine performance/thrust levels were attained in an engine subjected to severe degradation.

Jain [14] performs parameter estimation of ground thermal properties (soil and ground thermal conductivity.) He describes methods for both online and offline parameter estimation. For online parameter estimation he used two approaches namely the nonlinear recursive estimator and the application of the nonlinear optimization method. The nonlinear recursive estimator is basically a form of the Extended Kalman Filter. Results show that the non linear recursive estimator fails to converge to a minimum under highly nonlinear conditions.

Arulampalam et al. [15] reviews optimal and suboptimal Bayesian algorithms for non-linear/non-Gaussian tracking problems with a focus on particle filters. Par-

ticle filters can be applied to any state space model and generalize the traditional Kalman filtering methods. Several particle filter variants are discussed and compared with the standard Extended Kalman Filter. If the true density is non-Gaussian then Particle filters yield an improvement in performance compared to the EKF. Particle methods require the computations of integrals of many variables. This type of computation is generally only attempted with Monte-carlo techniques that are slow to converge.

With regard to parameter estimation in the area of thermal engineering, few researchers have done relevant work. Milano et al. [16] describes the parameter estimation theory as the best way to estimate thermophysical properties from dynamic experiments. Experience gained in implementation of inverse algorithms based on parameter estimation theory and kalman filtering is summarized and presented. Several examples of estimation of thermophysical properties are presented and compared with data obtained with consolidated techniques.

Biering and Hagelschuer [17] present a Kalman filtering algorithm based approach to estimate parameters for heat transfer from transient measured target temperature. Accurate estimates of parameters are obtained by the Kalman Filtering algorithm. These parameters are found to be in close tandem with those calculated using theoretical methods.

Cullimore [18] describes how SINDA/FLUINT an advanced heat transfer and fluid flow analyzer is used to estimate the parameters from test data. The technique used is offline estimation and requires many iterations over the test data to estimate the parameters. The minimization function used in SINDA/FLUINT is akin to the least square method.

Sorenson [19] in his paper describes the origin of the least - squares estimation theory from its inception by Gauss, to its modern form developed by Kalman. He

mentions the Kalman Filter as an efficient computational solution to the least squared method. His discussion mentions the least-square method as introduction to more advanced techniques.

Papalexandris and Milman [20] describe parameter updating techniques for thermal models. They place emphasis on applications where radiation plays a dominant role, such as the thermal modeling of spacecrafts. The problem is formulated as a nonlinear, least-square optimization problem. The efficacy of the method is examined through tests on large-scale spacecraft models that have been used in ongoing NASA projects like the SEAWINDS scatterometer, a radar used to measure near surface wind speed and direction. The test on the SEAWINDS scatterometer specifies the temperature profile and then tries to estimate the emissivities that correspond to that profile. In all the tests the parameters were estimated with very good accuracy. In this thesis too, radiation plays an important role in incorporating non linearity into the observation vector. However the state and model parameters are estimated simultaneously using non linear forms of the Kalman filter like the extended Kalman filter and the unscented Kalman filter.

ARSIE, PIANESE, and RIZZO [21] compare two methods of parameter estimation, the least square method and the Kalman filtering approach. This study was performed on a set of 35 air-fuel ratio dynamic transients generated on a dynamic test bench for a spark ignition Alfa Romeo 1.4 litres with 4 cylinders, equipped with a IAW multi-point ECS. The least square method required offline identifications for estimating the model parameters. It relies on a global optimum criteria with respect to each transient without accounting for local specific fuel dynamic behavior. The Kalman filtering technique on the other was performed online to identify both the state and model parameters. It allows to estimate the local optimum value of each parameter along the transient, through a comparison between model estimation and

a direct measurement on the system. The least square method was found more suitable for generating look up table without accounting for engine wear and tear. The Kalman filtering approach was found more suitable for design of model based control system.

The software ReBEL [22](Recursive Bayesian Estimation Library) is a work in progress by Rudolph van der Merwe and Eric A Wan. It consolidates research on new methods like the UKF. The code has functional units which can be adapted to use for state or joint estimation. It also has functional units to implement standard approaches to nonlinear estimation like the Extended Kalman Filter. Haykin [23] has chapters devoted to dual estimation using extended Kalman filter and the novel unscented Kalman filter. It is also an unofficial guide on the usage of the ReBEL toolbox and has the theory of the functional units implemented in it.

Mortari, Junkins, and Samaan [24] have developed the lost in space algorithm which runs the Starnav I payload. The parameters of this payload have been estimated in this thesis using ReBEL described above.

From the above literature survey it can be concluded that the current research in the field of parameter estimation is not geared toward thermal engineering. This thesis addresses the problem of automating the parameter estimation process in mixed conduction/heat transfer environment as would be the case for a payload in space. Earlier attempts have either estimated state or model parameters using filters which are not specifically designed for non linear data. In this thesis the state and model parameters are estimated simultaneously. This would significantly decrease the amount of time spent after data collection from qualification tests to estimate the thermal model.

CHAPTER III

THEORY

The first approach to any physical system, is to develop a mathematical model that adequately represents some aspects of the behavior of that system.

To observe the actual behavior, measurement devices are constructed to output data signals proportional to certain variables of interest. There are disturbances/noise which go into the readings obtained from these measurements. Therefore the objective would be to extract valuable information from noisy data and optimally estimate the quantities of interest.

A. Kalman Filter

The Kalman filter [23] is the oldest standard recursive solution for linear filtering problems. The word recursive means that the Kalman filter does not require all the past data to be kept in memory and processed for each new state. It processes previous observations/ measurements to obtain the current state, each updated estimate of state is computed from previous estimate and new input data.

Kalman filter tries to produce an estimate of the desired quantity in such a manner that the error is minimized statistically. The filter can only be applied to linear models. The Kalman filter is adaptive and the adaptation is automatic.The Kalman Filter is briefly summarized below.

Assume the following State space model:

Process equation :

$$x_{k+1} \;=\; F_{k+1,k}x_k \;+\; w_k \tag{3.1}$$

Measurement equation :

$$y_k = H_k x_k + v_k \tag{3.2}$$

where w_k and v_k are independent, zero mean white, Gaussian noise processes with covariance matrix Q_k and R_k.

Initial values for $k = 0$

Initial estimate of state :

$$\hat{x_0} = E[x_0] \tag{3.3}$$

Initial estimate of a posteriori covariance :

$$P_0 = E[(x_0 - E[x_0])(x_0 - E[x_0])^T] \tag{3.4}$$

Time update equations

The time update equations are responsible for projecting forward the current state and error covariance estimates to obtain the a priori estimates for the next time step.

State estimate propagation

$$\hat{x_k}^- = F_{k,k-1} \hat{x_{k-1}}^- \tag{3.5}$$

Error covariance propagation

$$P_k^- = F_{k,k-1} P_{k-1} F_{k,k-1}^T + Q_{k-1} \tag{3.6}$$

Measurement update equations

The measurement update equations are responsible for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate.

The first step during the measurement update is to calculate the Kalman gain. The kalman gain is chosen such that it minimizes the a posteriori error covariance.

Kalman gain matrix

$$G_k = P_k^- H_k^T [H_k P_k H_k^T + R_k]^{-1} \tag{3.7}$$

State estimation update

$$\hat{x_k} = \hat{x_k}^- + G_k(y_k - H_k \hat{x_k}^-) \tag{3.8}$$

Error covariance update

$$P_k = (I - G_k H_k) P_k^- \tag{3.9}$$

B. Extended Kalman Filter

The Kalman filtering problem considered above has addressed the estimation of a state vector in a linear model of a dynamical system. The Extended Kalman filter (EKF) is the first approach widely used for non linear systems. The EKF linearizes the state space model at each time instant around the most recent time estimate.

Consider a nonlinear dynamical system described by the following state-space model [23]:

$$x_{k+1} \ = \ f(k, x_k) \ + \ w_k \tag{3.10}$$

$$y_k \ = \ h(k, x_k) \ + \ v_k \tag{3.11}$$

w_k and v_k are independent zero-mean white Gaussian noise processes with covariance matrices R_k and Q_k

The Extended Kalman Filter [18] is an approximate method applied to non-

linear models, that approximate the non linear model as time varying linear model during certain steps in the estimation process. This approximation allows the use of linear Kalman Filter equations described so far.

The approximation follows in the following two steps:

Stage 1:

$$F_{k+1,k} = \frac{\partial f(k,x)}{\partial x}_{x=x_k} \tag{3.12}$$

$$H_k = \frac{\partial h(k,x_k)}{\partial x}_{x=x_k^-} \tag{3.13}$$

The ijth entry of $F_{k+1,k}$ is equal to the partial derivative of the ith component of $F(k,x)$ with respect to the jth component of x. The ijth component of H_k is equal to the partial derivative of the ith component of $H(k,x)$ with respect to the jth component of x.

Stage 2:

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

$$F(k,x_k) \approx \ F(x,x_k) + F_{k+1,k}(x,x_k) \tag{3.14}$$

$$H(k,x_k) \approx \ H(x,x_k) + H_{k+1,k}(x,x_k^-) \tag{3.15}$$

hence the non linear state equations are given as

$$x_{k+1} \approx \ F_{k+1,k}x_k + w_k + d_k \tag{3.16}$$

$$\overline{y}_k \approx \ H_k x_k + v_k \tag{3.17}$$

where

$$\overline{y}_k = y_k - h(x,x_k^-) - H_k x_k^- \tag{3.18}$$

$$d_k = f(x, x_k) - F_{k+1,k}x_k \tag{3.19}$$

Extended Kalman Filter Equations

Initialize:

For k = 0,

Initial estimate of state :

$$\hat{x_0} = E[x_0] \tag{3.20}$$

Initial estimate of a posteriori covariance :

$$P_0 = E[(x_0 - E[x_0])(x_0 - E[x_0])^T] \tag{3.21}$$

Time update equations

State estimate propagation

$$\hat{x_k}^- = f(k, \hat{x_{k-1}}) \tag{3.22}$$

Error covariance propagation

$$P_k^- = F_{k,k-1}P_{k-1}F_{k,k-1}^T + Q_{k-1} \tag{3.23}$$

Measurement update equations

Kalman gain matrix

$$G_k = P_k^- H_k^T [H_k P_k H_k^T + R_k]^{-1} \tag{3.24}$$

State estimation update

$$\hat{x_k} = \hat{x_k}^- + G_k y_k - h(k, \hat{x_k}^-) \tag{3.25}$$

Error covariance update

$$P_k = (I - G_k H_k) P_k^- \tag{3.26}$$

C. Unscented Kalman Filter

The Extended Kalman Filter is the most widely used estimation algorithm for non linear systems [8]. However years of experience in the estimation community has shown that it is difficult to implement, difficult to tune and only reliable for systems that are almost linear on the time scale of the updates. This filter approximates the non linear model as time varying linear model, where the state distribution is propagated through the first - order linearization of the non linear system. This provides only an approximation to non linear estimation and also could introduce large errors in the posterior mean and covariance and could lead to divergence of the filter.

The Unscented Kalman Filter is proposed as an alternative to Extended Kalman Filter. The UKF is provably superior to the EKF. It does not need to explicitly calculate the Jacobians or Hessians. The UKF not only outperforms the EKF in accuracy (Second order approximation vs first order approximation) but is also computationally efficient. A small number of carefully chosen sample points when propagated in each estimation step provide a compact parametrization of the underlying distribution (see Fig. 5) [9].

Unscented Transformation

The Unscented Transformation [23] (UT) is a method for calculating the statistics of a random variable which undergoes a nonlinear transformation. When propagating a random variable x through a nonlinear function, $y = f(x)$. x has mean

$\overline{x}$ and covariance P_x. To calculate the statistics of y, we form a matrix x of $2L + 1$ sigma vectors Xi according to the following:

$$X_o = \overline{x} \tag{3.27}$$

$$X_i = \overline{x} + (\sqrt{(L+\lambda)P_x})_i \tag{3.28}$$

$$X_i = \overline{x} - (\sqrt{(L+\lambda)P_x})_{i-L} \tag{3.29}$$

where $\lambda = \alpha^2(L + \kappa) - L$ is a scaling parameter. The constant α determines the spread of the sigma points around $\overline{x}$, and is usually a small positive value. The constant κ is a secondary scaling parameter, = 3 - L. β is used to determine distribution of x. The sigma points are propagated through the non linear function. These sigma points are propagated through the non linear function and the mean and covariance are approximated using a weighted sample mean and covariance of the posterior sigma points.

$$\overline{y} \approx \sum_{0}^{2L} W_i^{(m)} Y_i \tag{3.30}$$

$$P_y \approx \sum_{0}^{2L} W_i^{(c)} (Y_i - \overline{y})(Y_i - \overline{y})^T \tag{3.31}$$

The Weights are calculated as follows.

$$\begin{aligned} W_o^{(m)} &= \frac{\lambda}{L+\lambda} \\ W_o^{(c)} &= \frac{\lambda}{L+\lambda} + 1 - \alpha^2 + \beta \\ W_i^{(m)} &= W_i^{(c)} = \frac{1}{2(L+\lambda)} \end{aligned} \tag{3.32}$$

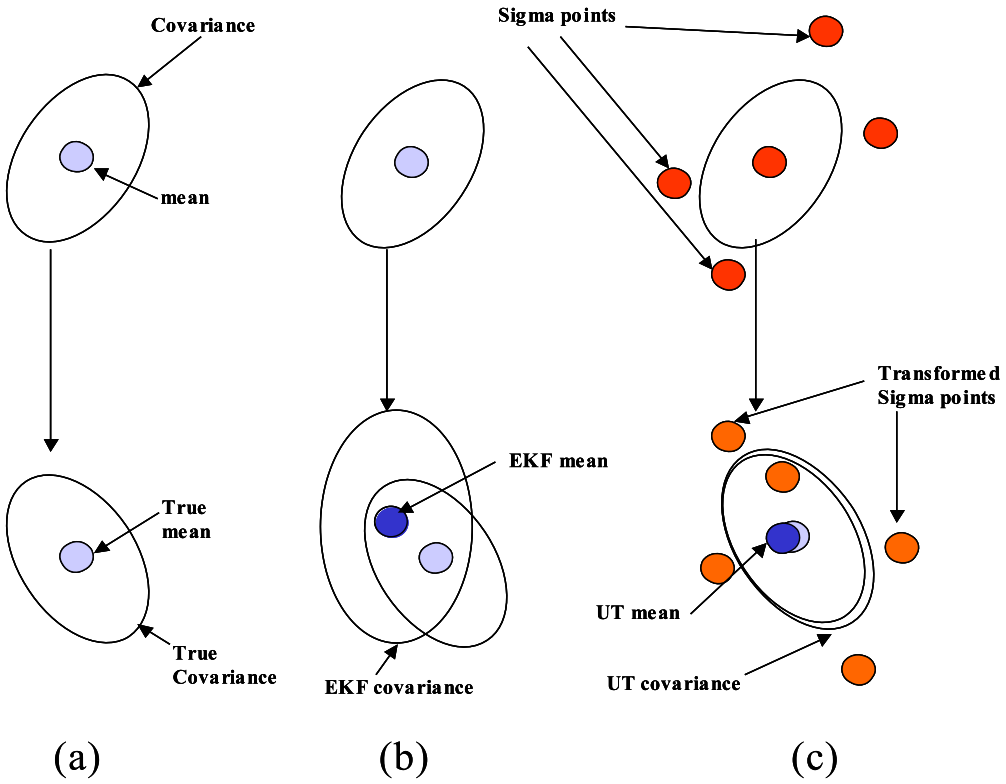

Fig. 5. A Graphical Depiction of the Superiority of the Unscented Transformation. (a) Actual Propagation (b) First Order EKF Linearization (c) Unscented Transformation

Notice how the UT performs much better with fewer sigma points

The **Unscented Kalman Filter** is an extension of the Unscented transformation. The random variable is redefined as the concatenation of the original state and noise variables: $x_k^a = [x_k^T v_k^T n_k^T]^T$. The UKF equations are given below.

Initialization :

$$\hat{x} = E[x_0] \tag{3.33}$$

$$P_0 = E[(x_0 - \hat{x_0})(x_0 - \hat{x_0})^T], \tag{3.34}$$

$$\hat{x_0} = E[x^a] = [\hat{x}^T 00]^T \tag{3.35}$$

$$P_0^a = E[(x_0^a - \hat{x_0}^a)(x_0^a - \hat{x_0^a})^T = \begin{bmatrix} P_0 & 0 & 0 \\ 0 & R^v & 0 \\ 0 & 0 & R^n \end{bmatrix} \tag{3.36}$$

Calculate sigma points :

$$X_{k-1}^a = \begin{bmatrix} x_{\hat{k-1}}^a & x_{\hat{k-1}}^a + \gamma\sqrt{P_{k-1}^a} & x_{\hat{k-1}}^a - \gamma\sqrt{P_{k-1}^a} \end{bmatrix} \tag{3.37}$$

Time update equations

$$X_{k|k-1}^x = F(X_{k|k-1}^x, u_{k-1}, X_{k-1}^v) \tag{3.38}$$

$$\hat{x_k}^- = \sum_{i=0}^{2L} W_i^{(m)} X_{i,k|k-1}^x \tag{3.39}$$

$$P_k^- = \sum_{i=0}^{2L} W_i^{(c)} (X_{i,k|k-1}^x - \hat{x_k}^-)(X_{i,k|k-1}^x - \hat{x_k}^-)^T \tag{3.40}$$

$$Y_{k|k-1} = H(X_{k|k-1}^x, X_{k-1}^n) \tag{3.41}$$

$$\hat{y_k}^- = \sum_{i=0}^{2L} W_i^{(m)} Y_{i,k|k-1} \tag{3.42}$$

Measurement update equations

$$P_{\tilde{y_k}\tilde{y_k}} = \sum_{i=0}^{2L} W_i^{(c)} (Y_{i,k|k-1} - \hat{y_k}^-)(Y_{i,k|k-1} - \hat{y_k}^-)^T \tag{3.43}$$

$$P_{x_k y_k} = \sum_{i=0}^{2L} W_i^{(c)} (X_{i,k|k-1} - \hat{x_k}^-)(Y_{i,k|k-1} - \hat{y_k}^-)^T \tag{3.44}$$

$$K_k = P_{x_k y_k} P_{\tilde{y_k}\tilde{y_k}}^{-1} \tag{3.45}$$

$$\hat{x_k} = \hat{x_k}^- + K_k(y_k - \hat{y_k}^-) \tag{3.46}$$

$$P_k = P_k^- K_k P_{\tilde{y_k}\tilde{y_k}} K_k^T \tag{3.47}$$

where

$x^a = [x^T v^T n^T]^T, X^a = [(X^x)^T (X^v)^T (X^n)^T]^T, \gamma = \sqrt{L + \lambda}$

λ is the composite scaling parameter, L is the dimension of the augmented state, R^v is the process noise covariance, R^n is the measurement noise covariance.

We have presented the theory and equations of the kalman filter. The non linear derivatives of the Kalman Filter, the extended Kalman filter and the unscented Kalman filter are described. The derivation of these filters is also presented.

CHAPTER IV

STARNAV I

The StarNav1 design was based on a star-tracker technology development program with the Aerospace Engineering Department at Texas A&M University and the Spacecraft Technology Center (formerly known as Commercial Space Center for Engineering) also 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. John Junkins in the Aerospace Engineering Department at Texas A & M University for determining precise spacecraft attitude without prior knowledge of position [24].

The StarNav flight experiment hardware is based on successful ground demonstration units that have been used to test attitude determination algorithms with night sky images. All components were packaged in a custom configuration for mating to the single SpaceHab Inc. QuEST (Q9) platform. The Quest location was provided by Spacehab Inc (see Fig. 6) on top of the Spacehab module.

The payload structure is comprised of two major components, the flight enclosure and the mounting plate, each fabricated with aluminum. These are mated in such a way that there are no exposed fasteners other than the six bolts required to connect the mounting plate directly to the Q9. The electronics, optical assembly and baffles are all contained within the flight enclosure. Fig. 7 illustrates the components within the enclosure.

The components used to construct StarNav were primarily commercial off the shelf (COTS) configured to support the unique algorithm development. The CCD array is housed in a small vacuum vessel and actively cooled by a thermoelectric cooler. The optical assembly for the StarNav flight hardware was created using a set

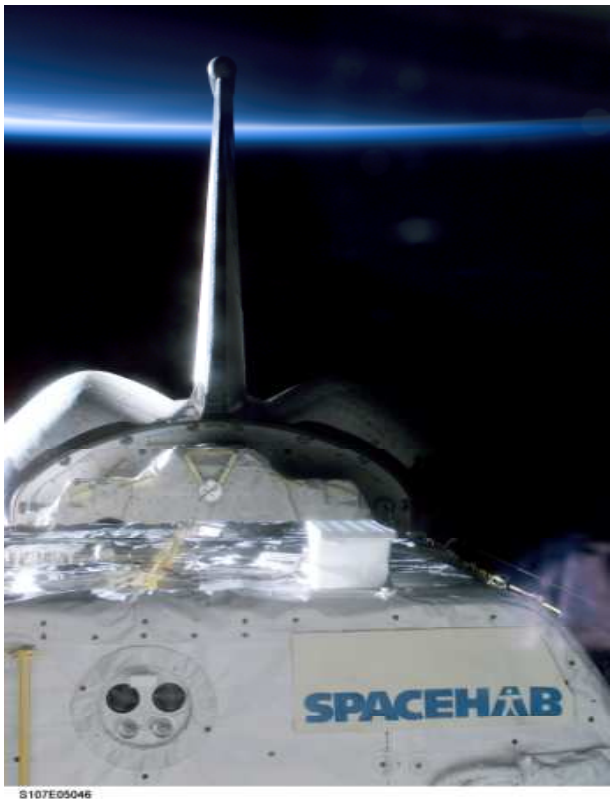

Fig. 6. Photograph of the SpaceHab Module Taken During the STS-107 Flight. Starnav is Located Right Behind the Square Box

of optics from a commercial 35mm lens (Canon). The baffle assembly consists of 2 plates with varying hole diameters that create a conical light path to the CCD array of 7 degrees. The minimum distance between StarNav and the payload bay envelope is estimated to be no less than 4 feet.

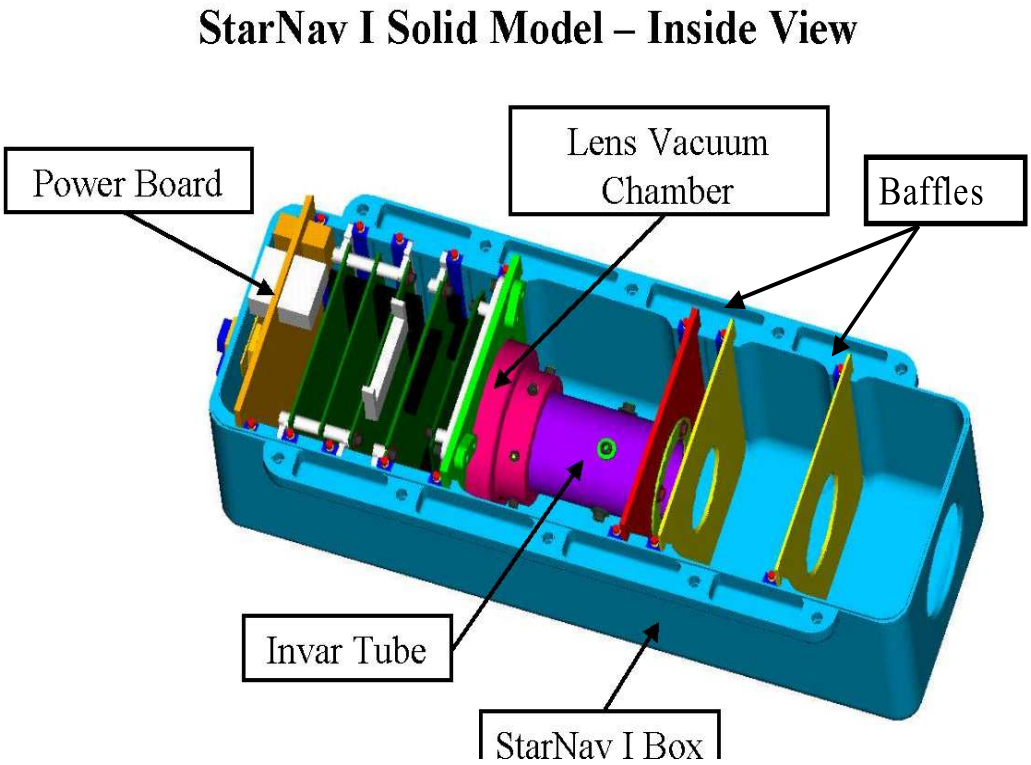

Fig. 7. StarNav Components

A. Ground Tests on StarNav I

In order to successfully pass safety reviews requested by NASA, the StarNav I payload underwent different thermal vacuum tests. The thermal model was estimated through the course of the various thermal tests (see Fig. 8).

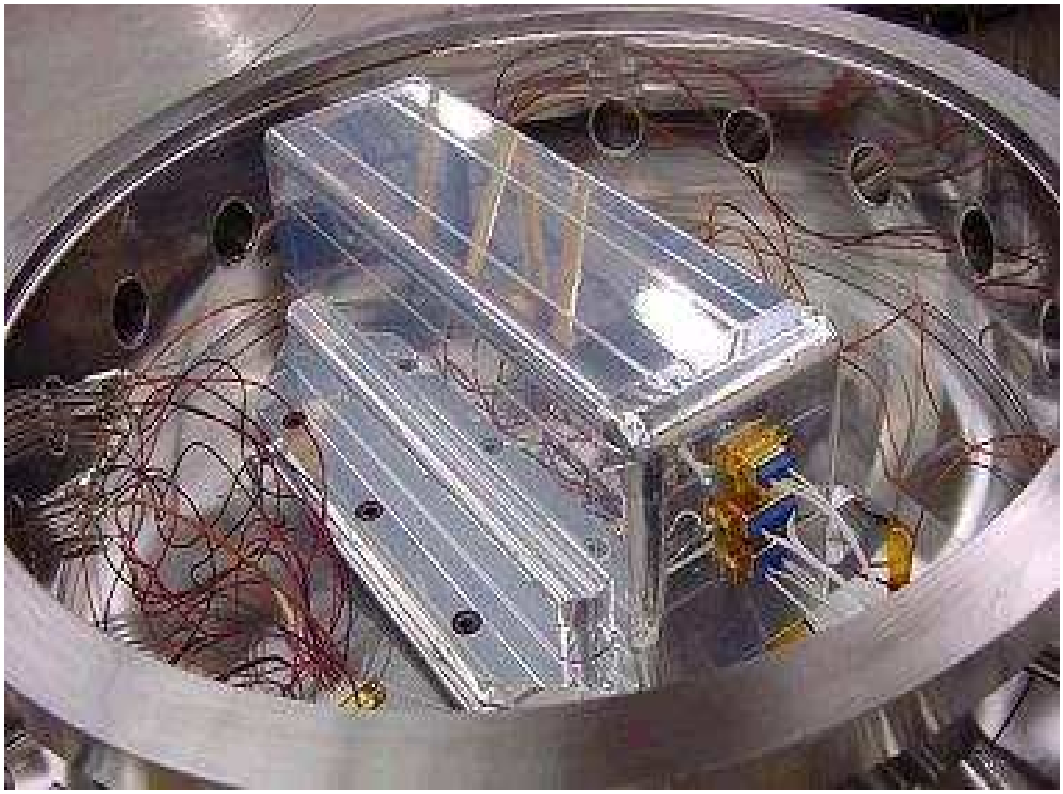

Fig. 8. StarNav Being Tested in a Vacuum Chamber

There were four tests conducted on StarNav I. Each test underwent different cycles.

1. Test 1 Conducted May 2001

This test was performed at the Air Force Research Laboratory in Albuquerque, NM. Jackson and Tull Inc. performed the test to prove that the star tracker could survive extreme temperatures and heat fluxes. The environmental temperature in this test was cycled between -50C and +40C. This test comprised five cycles with each cycle performing a hot soak or a cold soak for about one hour.

2. Test 2 Conducted Dec 2001

This test was performed at the Space System Integration laboratory of the Spacecraft Technology Center. Only one continuous cycle was performed. This test was conducted at 290K in vacuum.

3. Test 3 Conducted Jan 2002

The primary purpose of this test was to validate the effect of copper plate/heat sink of a component that had overheated during Test 2. The success criteria of this test was that all temperature measurement devices stay below 70C. This test was conducted at 290K in vacuum.

4. Test 4 Conducted March 2002

This test was conducted to estimate the contact conductance between the star tracker and the Spacehab module located in the shuttle bay at the Kennedy Space Center. It was conducted at 290K in a convective environment.

B. StarNav I Simplified Model

The Thermal Desktop© /SINDA conductance model of StarNav I must be reduced in order to reduce the total number of parameters in the thermal model (see Fig. 9). A simplified thermal model of five nodes was devised. Each node represents different interconnected parts of the instrument.

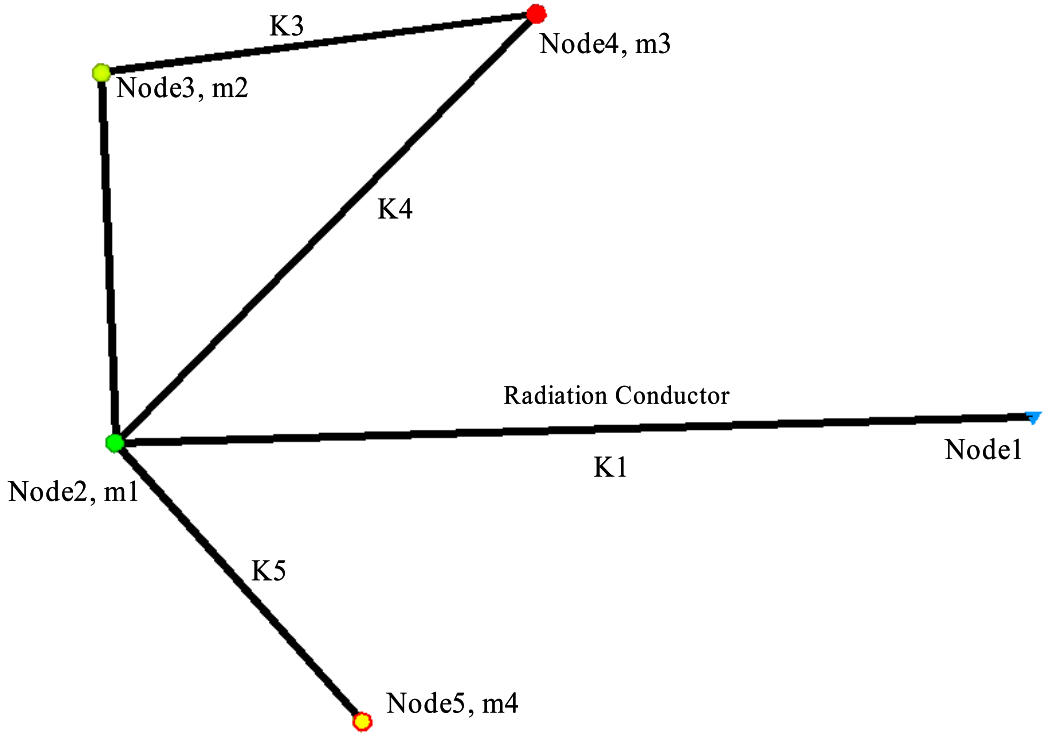

Fig. 9. StarNav Simplified Model

Node1: Environmental temperature

Node2: StarNav I Box

Node3: Invar Tube

Node4: Vacuum Chamber

Node5: Powerboard

m1 = Thermal mass of Node2 (J/C)

m2 = Thermal mass of Node3 (J/C)

m3 = Thermal mass of Node4 (J/C)

m4 = Thermal mass of Node5 (J/C)

k1 = conductance between Node2 and Node1 (W/C)

k2 = conductance between Node2 and Node3 (W/C)

k3 = conductance between Node3 and Node4 (W/C)

k4 = conductance between Node2 and Node4 (W/C)

k5 = conductance between Node2 and Node5 (W/C)

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

Node 1: Environmental Temperature

Node 2: Starnav I box

$$m_1 \frac{d}{dt} T_2 = k_2(T_3 - T_2) + k_4(T_4 - T_2) + k_5(T_5 - T_2) - K_1(T_2 - T_1) - \sigma A(T_2^4 - T_1^4) \quad (4.1)$$

Node 3: Invar Tube (contains optics)

$$m_2 \frac{d}{dt} T_3 = k_3(T_4 - T_3) - k_2(T_3 - T_2) \quad (4.2)$$

Node 4: Lens Vacuum Chamber

$$m_3 \frac{d}{dt} T_4 = q_3 - k_3(T_4 - T_3) - k_4(T_4 - T_2) \tag{4.3}$$

Node 5: Power Board

$$m_4 \frac{d}{dt} T_5 = q_4 - k_5(T_5 - T_2) \tag{4.4}$$

C. Joint Estimation and Dual Estimation

The Dual estimation approach represents a decoupled type of approach where a separate state space representation is used to estimate the state and parameter values. In the Joint Estimation approach the state vector is augmented with the parameters to create a state space representation with concatenated state. The process noise covariance matrix is changed accordingly.

CHAPTER V

NOISE

A. Process Noise

The random noise associated with the dynamics of the system is called process noise. The process noise is modeled as white, gaussian with zero mean. The process noise covariance affects the convergence rate of the parameters. The larger the covariance of the process noise, the quicker old data is forgotten. A process noise adaptation technique has been used. This has already been implemented in ReBEL [22]. The idea is to start out initially with a high process noise level which allows for aggressive/fast searching of the model parameter space. The covariance of this noise must be adapted/annealed over time in order to allow for eventual convergence(if a local minima in the error surface exists). This kind of process annealing is important in the context of the estimation performed in this thesis, because most of the tests have few measurements.

The figures shown below demonstrate the effect of process noise on parameter estimation.

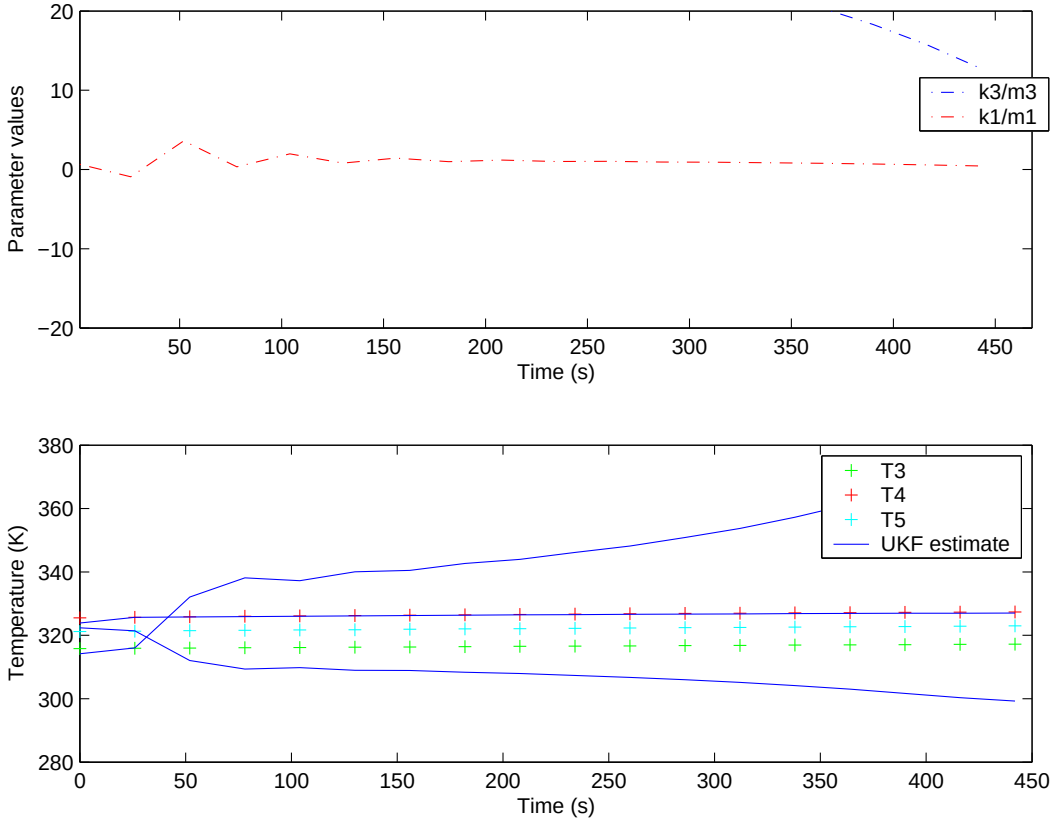

Fig. 10. Test 4 Very Low Process Noise

The estimation in Fig. 10 was performed with a very low process noise. Neither the state parameters, not the model parameters have converged.

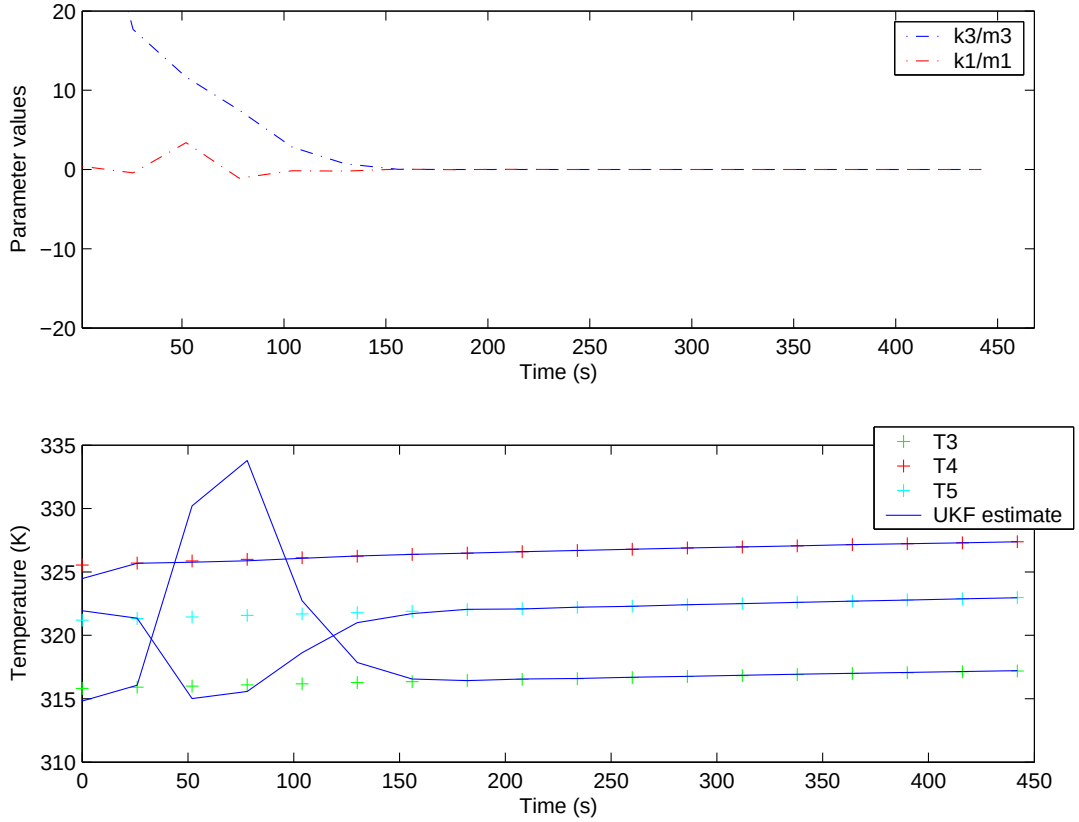

Fig. 11. Test 4 Process Noise Annealing

The estimation in Fig. 11 was performed incorporating process noise annealing. The parameter space has been identified and the state and the model parameters have converged pretty well. The initial process noise covariance has been modeled as $.1I_p$, where I_p represents the identity matrix of process noise dimension four. This Process noise has been annealed with time using a multiplicative factor of .95

B. Observation Noise

The noise related with the measurements being taken is called the observation noise. For parameter estimation purposes, the absolute value of the observation noise is not critical. Only the relative values determine the relative weighing of output errors. The observation noise can be calculated from thermistor specifications. The observation noise covariance used is $.01I_n$, where I_n represents the identity matrix of observation noise dimension three.

CHAPTER VI

RESULTS

A. ReBEL - Recursive Bayesian Estimation Library

ReBEL [22] is a Matlab©toolbox designed to facilitate the sequential estimation in general state space models. It consolidates research on new methods like the UKF. It has scripts to perform estimation using more widely used estimation algorithms like the EKF. ReBEL is developed and maintained by Rudolph van der Merwe [22]. These scripts have been used in the estimation performed in this thesis.

B. Estimation Results

Fig. 12 shows the estimation of the parameters $k5/m4$ and $1/m3$ using Extended Kalman Filter. The parameter $1/m3$ is the coefficient to $q3$, which is a parameter of the exogenous input. The state parameters converges rapidly. The parameters model fluctuates initially when the algorithm searches for a parameter space and then converges to a final asymptotic value. The estimated values of the parameters are $k5/m4 = 0.0059$ and $1/m3 = 0.0067$. Fig. 13 shows the state estimation performed with the model parameters obtained above.

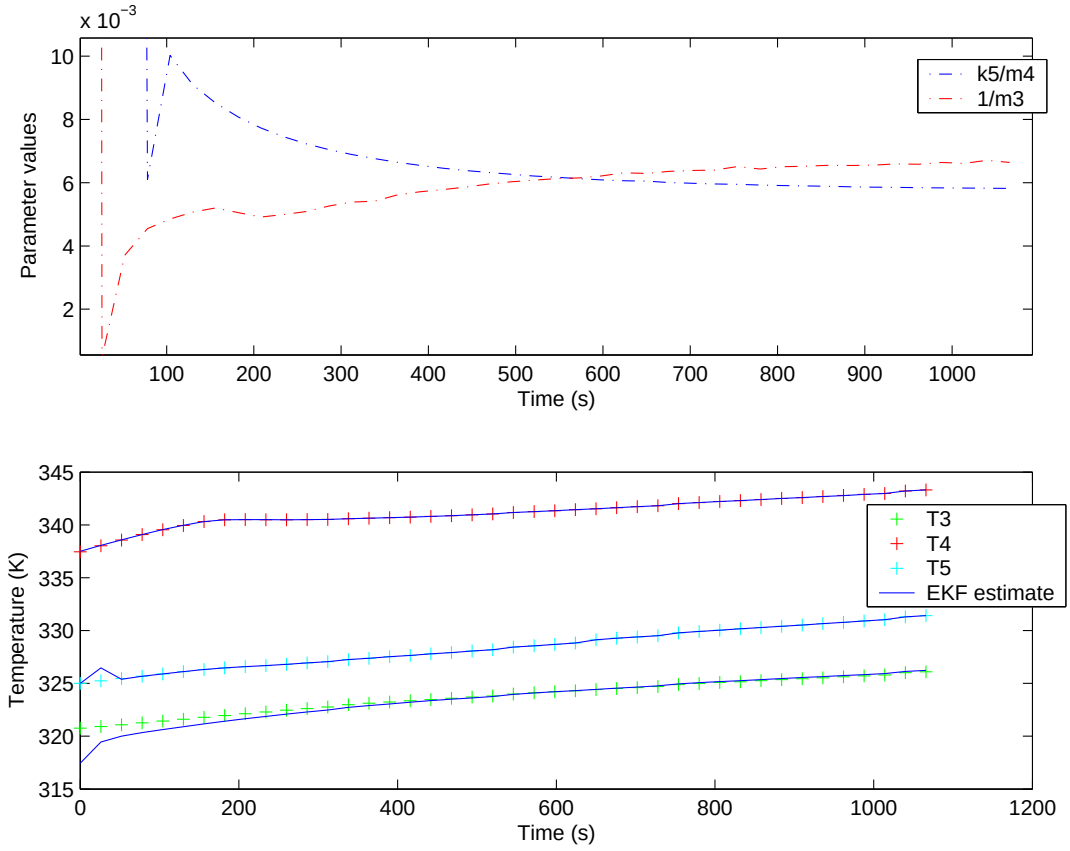

Fig. 12. Data Set 8 EKF Joint Estimation

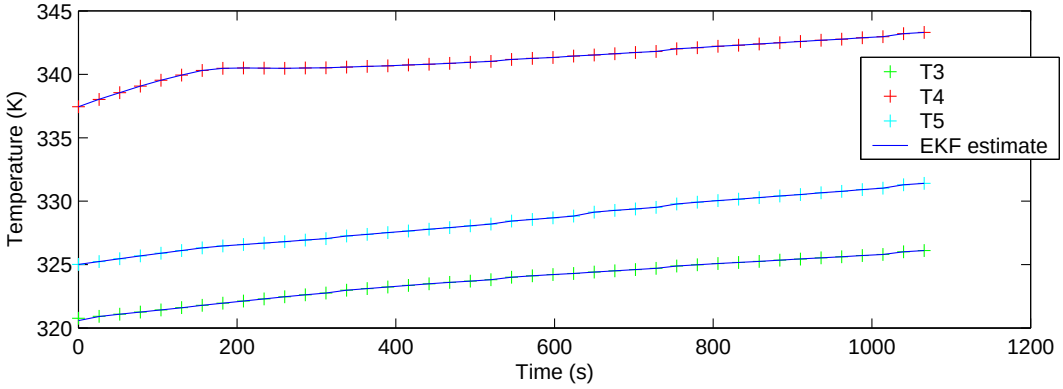

Fig. 13. Data Set 8 EKF State Estimation

Fig. 14 shows the estimation of the parameters $k5/m4$ and $1/m3$ using Square root Unscented Kalman filter. The results obtained are similar to the ones obtained by the Extended Kalman Filter. The estimated values of the parameters are $k5/m4 = 0.0058$ and $1/m3 = 0.0067$. Fig. 15 shows the state estimation performed with the model parameters obtained above.

The estimation using Extended Kalman Filter of the parameters $k3/m3$ and $k1/m1$ failed. A significant disadvantage of the Extended Kalman Filter is that it makes a locally linear approximation to the relationship between the state and observation. Because of this the Extended kalman Filter can fail to converge or lack robustness.

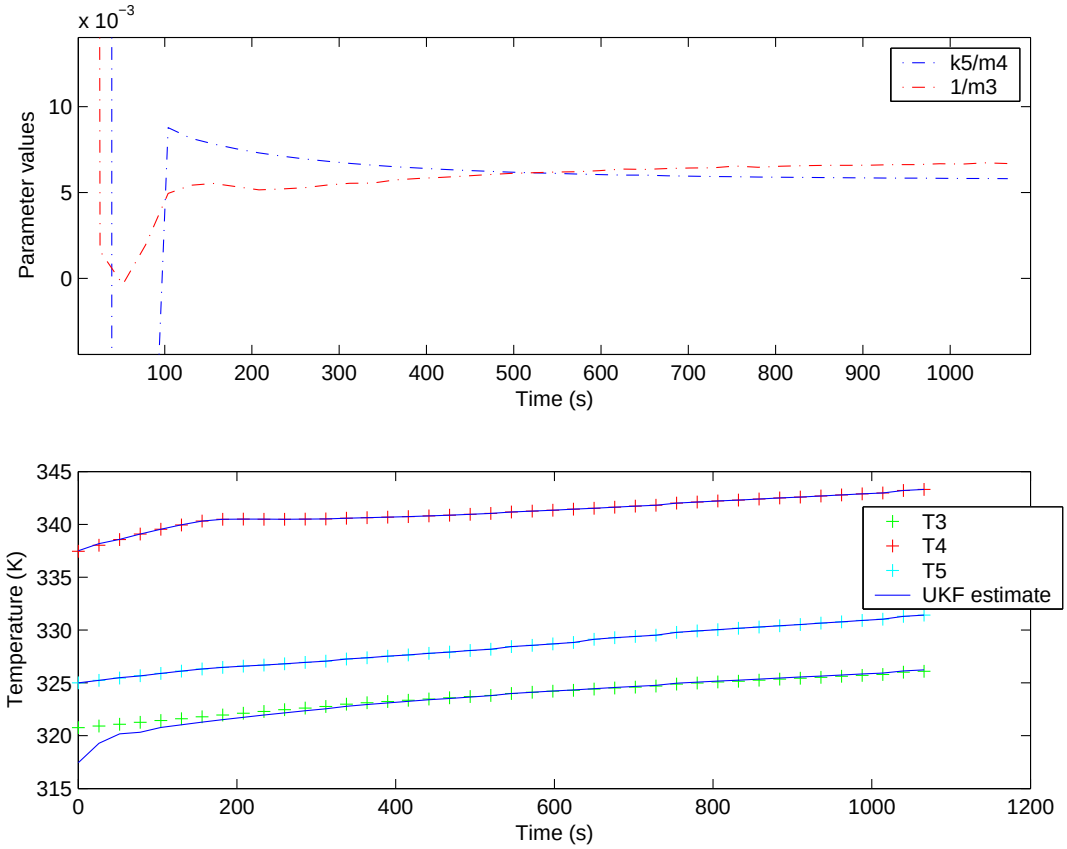

Fig. 14. Data Set 8 UKF Joint Estimation

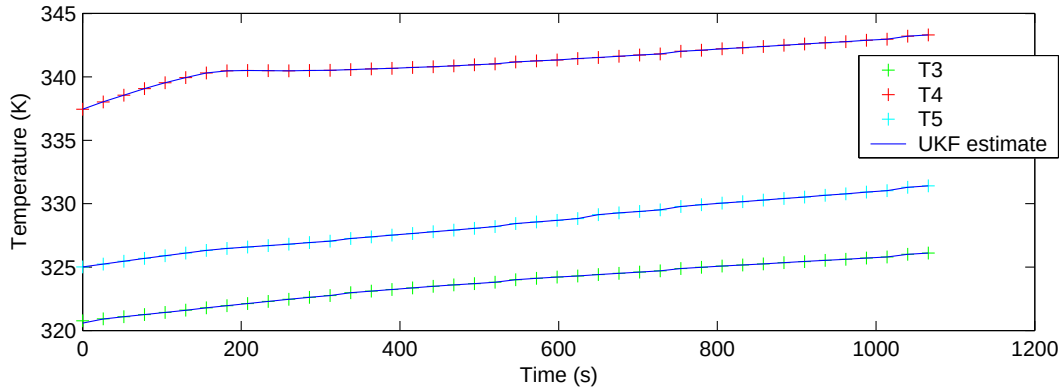

Fig. 15. Data Set 8 UKF State Estimation

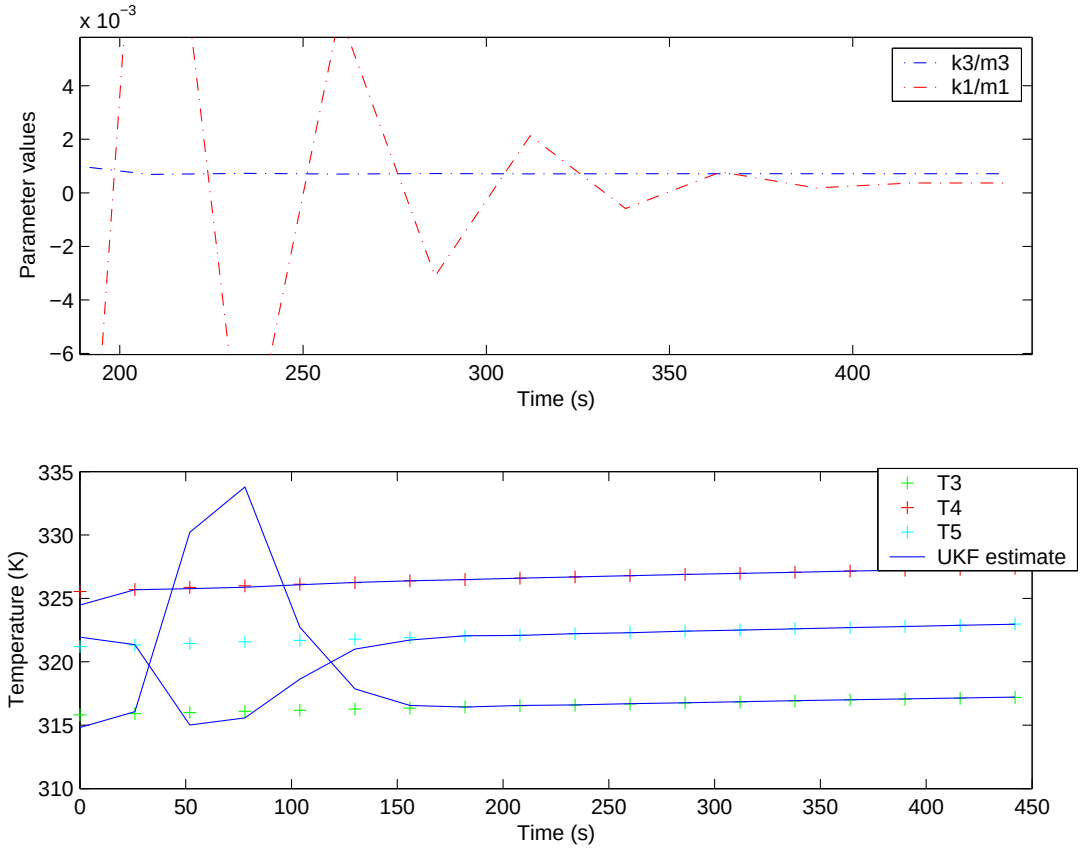

Fig. 16. Data Set 10 UKF Joint Estimation

Fig. 16 shows the estimation of the parameters $k3/m3$ and $k1/m1$. The test at Kennedy space center (Test 4) was conducted to measure k_1, the contact conductance from the startracker to the SpaceHab module in the shuttle bay. After initial fluctuation of both the state and model parameters a good convergence is obtained. The estimated values of the parameters are $k3/m3 = 0.0007$ and $k1/m1 = 0.0004$. Fig. 17 shows the state estimation performed with the model parameters obtained above.

Fig. 18 shows the estimation of the parameter $k2/m2$ using Extended Kalman filter. The model parameters fluctuate initially when the algorithm searches for a

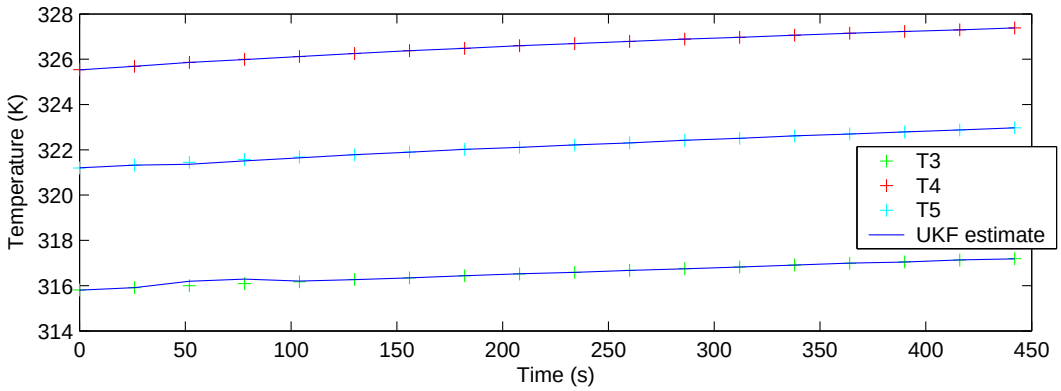

Fig. 17. Data Set 10 UKF State Estimation

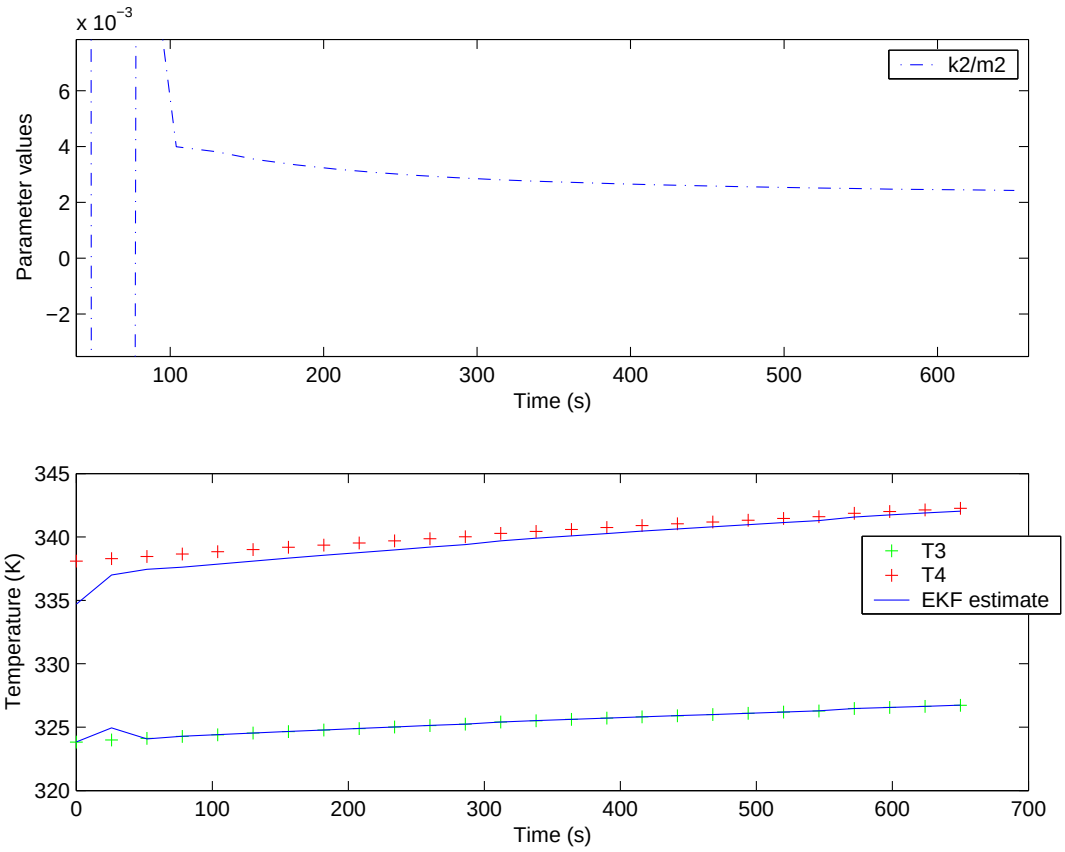

Fig. 18. Data Set 9 EKF Joint Estimation

parameter space and then converge to a final asymptotic value.The estimated value of the parameter is $k2/m2 = 0.0024$. Fig. 19 shows the state estimation performed with the model parameters obtained above.

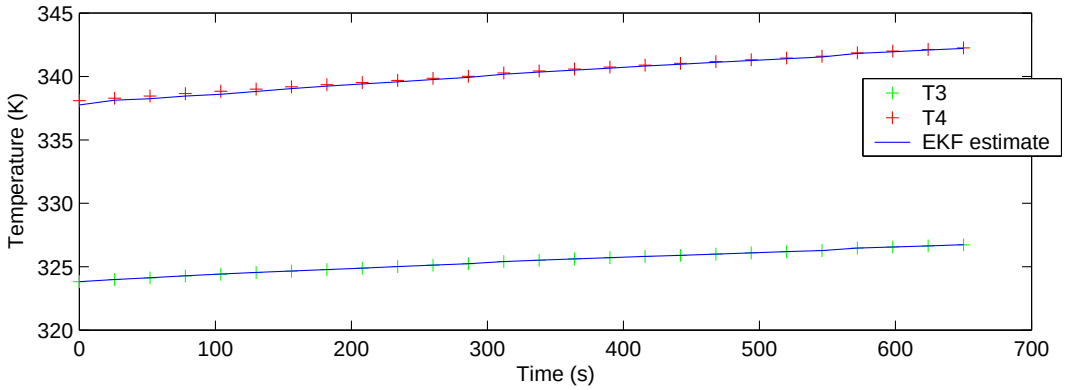

Fig. 19. Data Set 9 EKF State Estimation

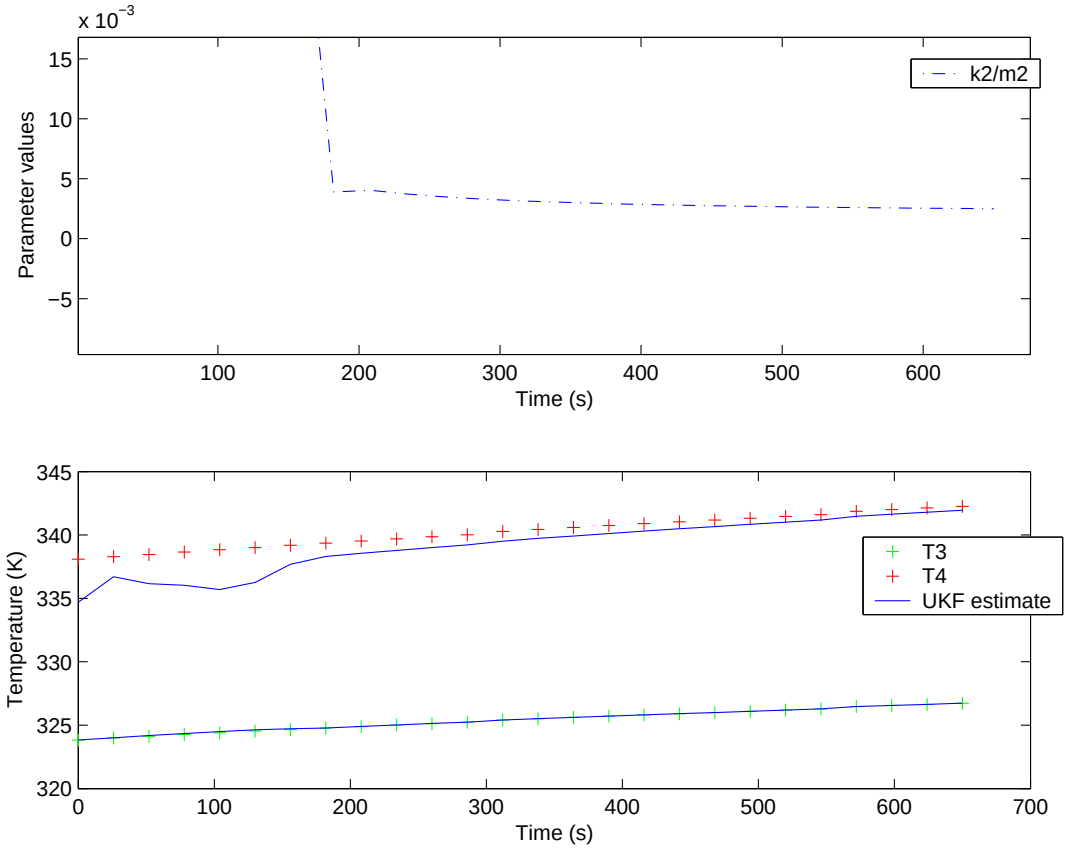

Fig. 20. Data Set 9 UKF Joint Estimation

Fig. 20 shows the estimation of the parameter $k2/m2$ using Square root Unscented Kalman filter. The results obtained are similar to the ones obtained by Extended Kalman Filter. The estimated value of the parameter is $k2/m2 = 0.0025$. Fig. 21 shows the state estimation performed with the model parameters obtained above.

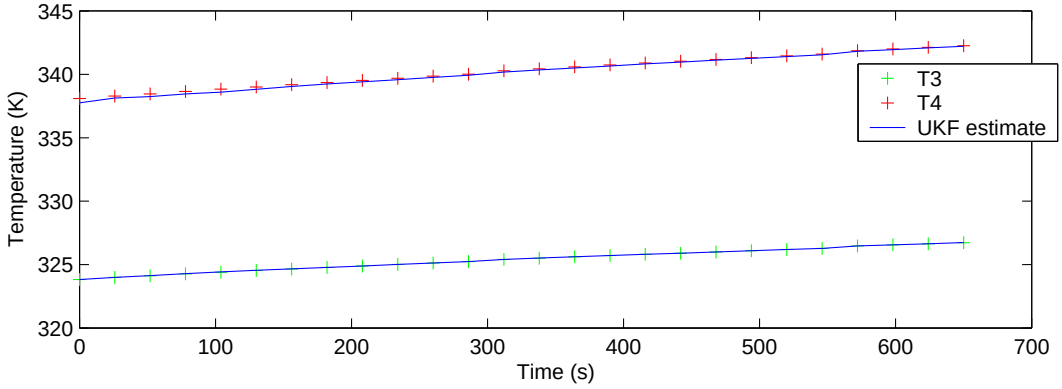

Fig. 21. Data Set 9 UKF State Estimation

Fig. 22 shows the estimation of the parameters $k4/m3$ and $1/m4$ using Extended Kalman filter. The parameter $1/m4$ is the coefficient to $q4$, which is a parameter of the exogenous input. The state parameters have converged rapidly. The model parameters fluctuate initially when the algorithm searches for a parameter space and then converge to a final asymptotic value. The estimated values of the parameters are $k4/m3 = 0.0018$ and $1/m4 = 0.0071$. Fig. 23 shows the state estimation performed with the model parameters obtained above.

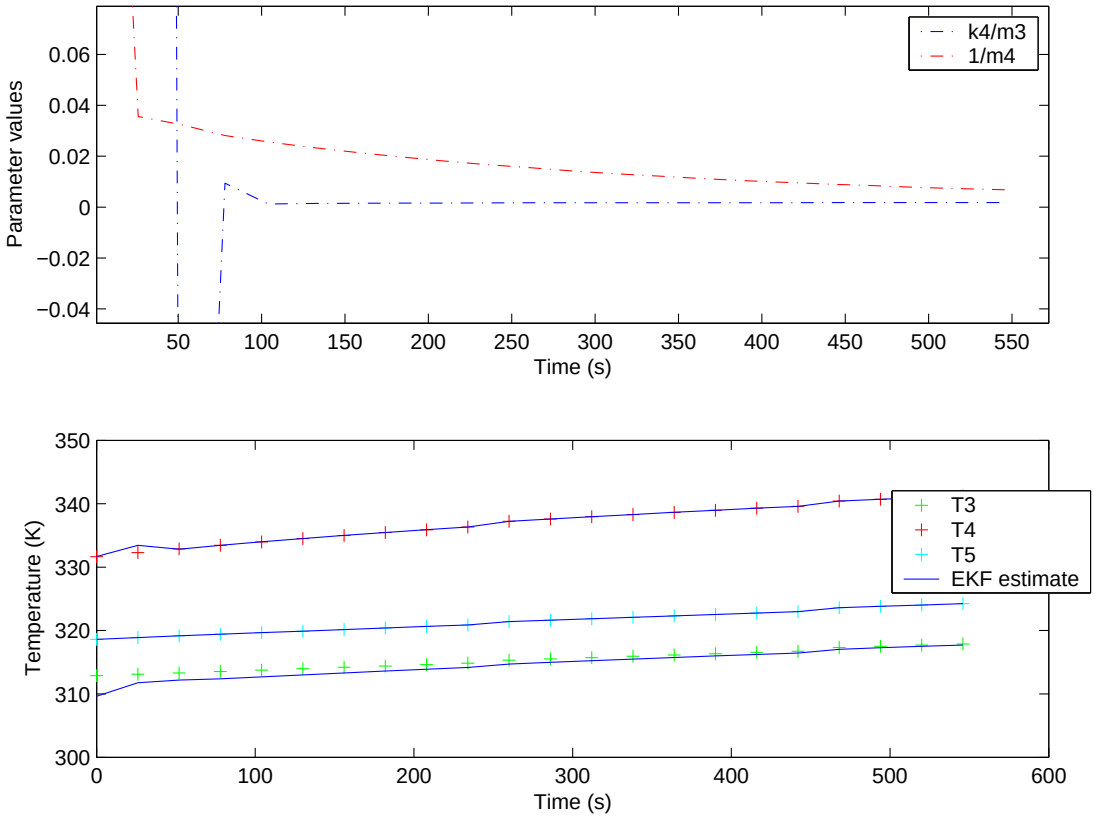

Fig. 22. Data Set 7 EKF Joint Estimation

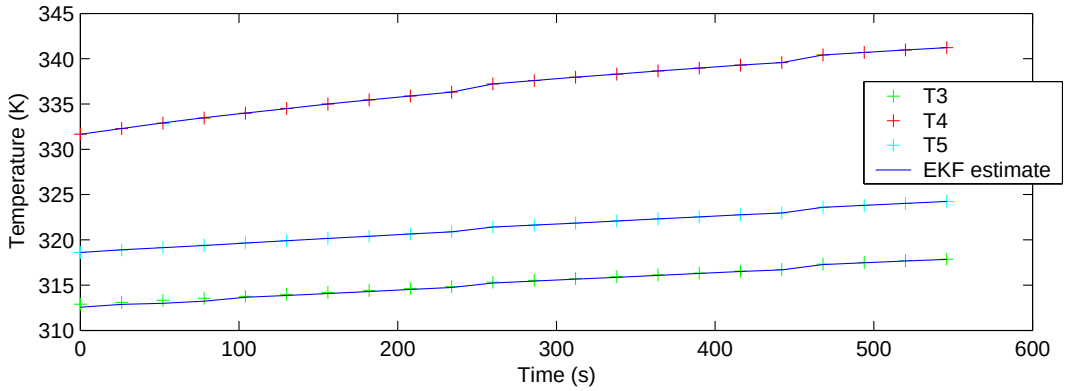

Fig. 23. Data Set 7 EKF State Estimation

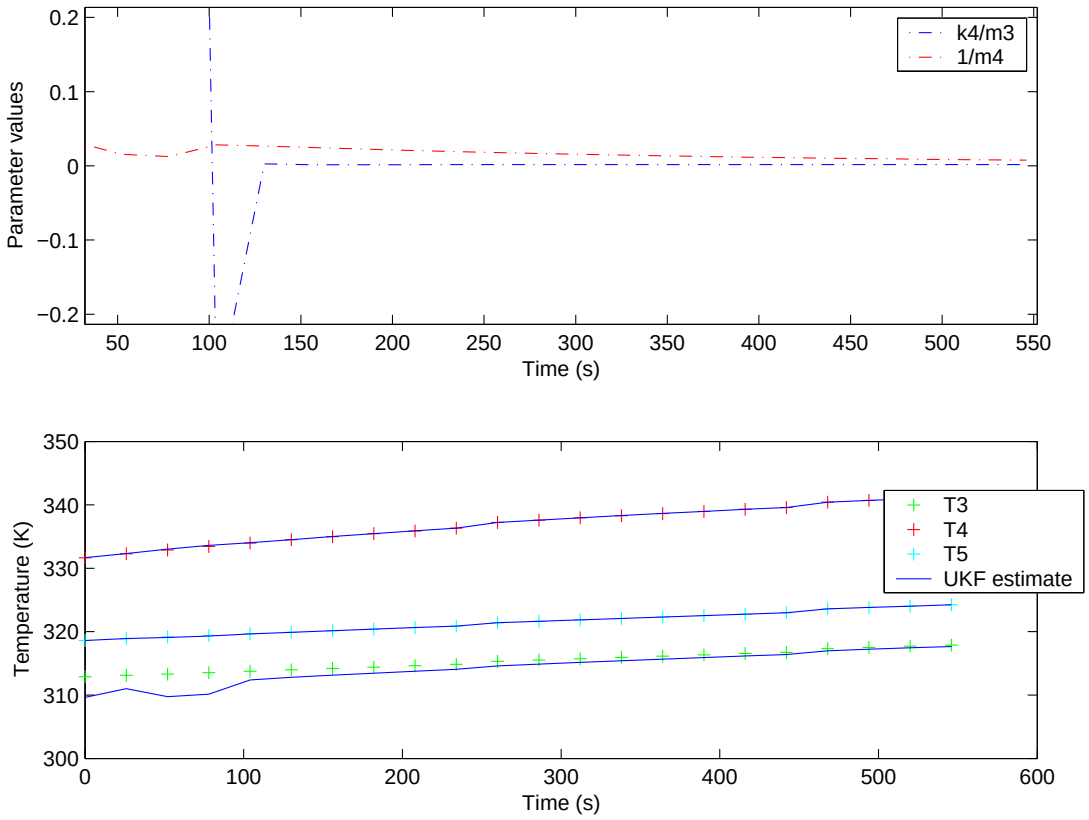

Fig. 24. Data Set 7 UKF Joint Estimation

Fig. 24 shows the estimation of the parameters $k4/m3$ and $1/m4$ using Square root Unscented Kalman filter. The results obtained are similar to the ones obtained by Extended Kalman Filter. The estimated values of the parameters are $k4/m3 = 0.0018$ and $1/m4 = 0.0081$. Fig. 25 shows the state estimation performed with the model parameters obtained above.

The estimation using Extended Kalman Filter of the parameters $k3/m2$ and $k2/m1$ failed. This test was conducted in a vacuum chamber with the environment temperature cycling between -60C and +40C. This fluctuation of environment temperatures induced strong radiative non linearities into the observation vector. We

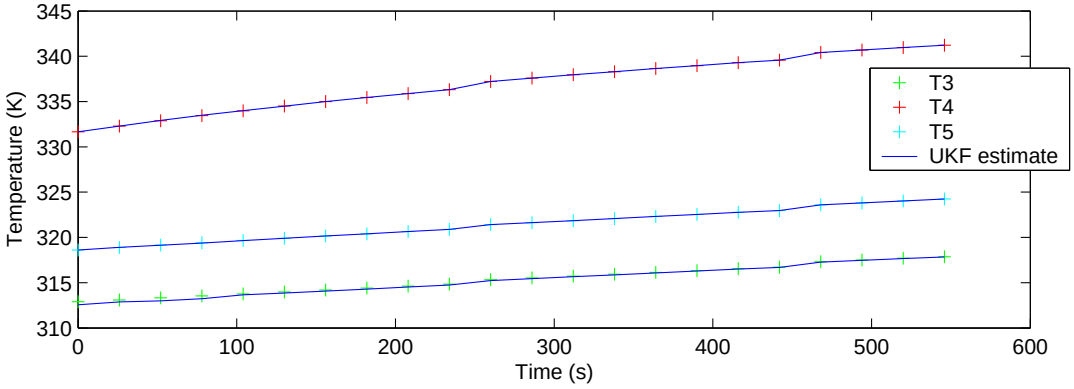

Fig. 25. Data Set 7 UKF State Estimation

believe that the EKF failed due to these non linearities in the observation vector.

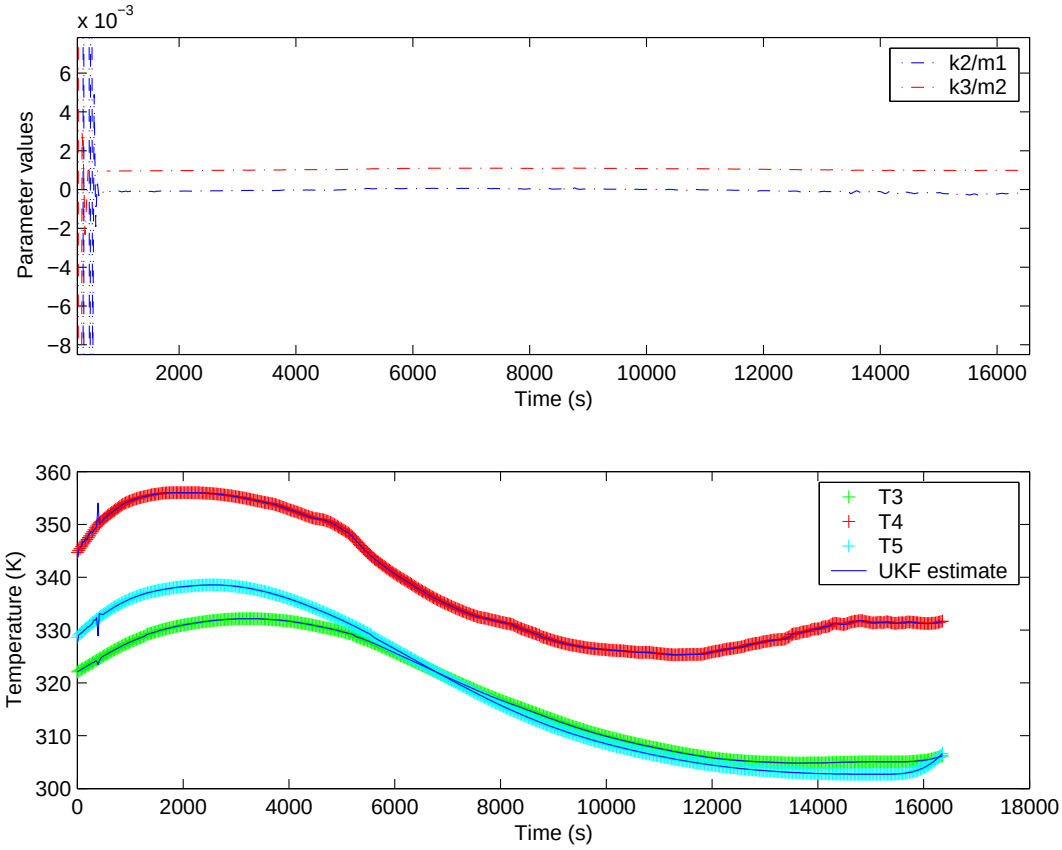

Fig. 26. Data Set 2 UKF Joint Estimation

Fig. 26 shows the estimation of the parameter $k3/m2$ and $k2/m1$ using Square root Unscented Kalman filter. The state parameters have converged rapidly. The model parameters fluctuate initially when the algorithm searches for a parameter space. The parameter $k3/m2$ converged to a final asymptotic value of 0.0010. The parameter $k2/m1$ does not converge and fluctuates between +0.0001 and -0.0001. Since a negative value of $k2/m1$ would have no meaning the value used is 0.0001. Fig. 27 shows the state estimation performed with the model parameters obtained above.

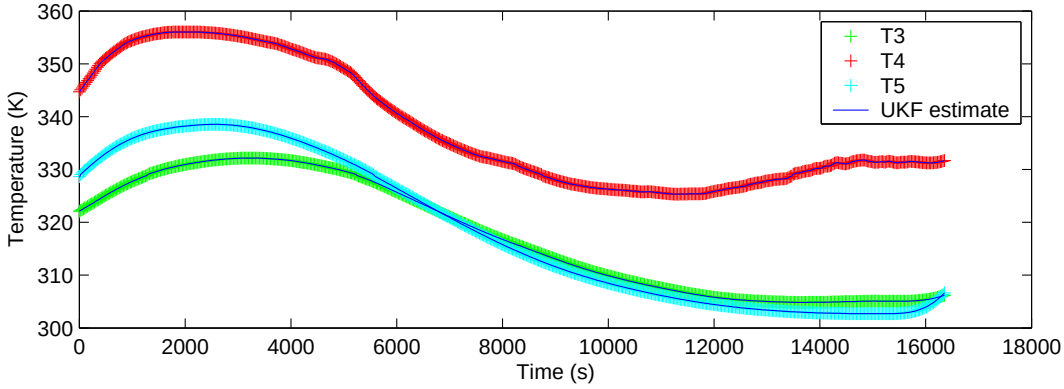

Fig. 27. Data Set 2 UKF State Estimation

Table. I compares the results obtained by SRUKF and EKF. Table. II gives the estimated value of each parameter.

Table I. Comparison of Values Obtained by SRUKF and EKF

Parameters Estimated	SRUKF Results	EKF Results
$k5/m4$ and $1/m3$	0.0058, 0.0067	0.0059, 0.0067
$k3/m3$ and $k1/m1$	0.0007, 0.0004	FAILED
$k2/m2$	0.0025	0.0024
$k4/m3$ and $1/m4$	0.0018, 0.0081	0.0020,0.0071
$k2/m1$ and $k3/m2$	0.0001, 0.0010	FAILED

Table II. Final Estimated Values of the Parameters

Parameter	Final Estimated Value
$k1$	0.5W/C
$k2$	0.25W/C
$k3$	0.10W/C
$k4$	0.27W/C
$k5$	0.71W/C
$m1$	2500J/C
$m2$	100J/C
$m3$	149.25J/C
$m4$	123.45J/C

CHAPTER VII

FUTURE WORK

A. Time Lag Between Observation and Estimation

It has been observed that the time required to estimate is approximately ten times less compared to the time required to perform the experiment. This implies that slower computers on embedded systems could be used to perform online fault detection and correction in an autonomous capacity in space. Furthermore more models can be estimated at each time step on the ground using faster computers.

B. Rationalize the Selection of Parameter with Test Data

There are 18 data sets and 9 parameters to identify. As already mentioned, one of the most important goals of this thesis is to automate the identification of the thermal model online while the data is being generated. The selection of right tests for each parameter is critical to get a good estimate of the parameter. Right now there is no system to correlate a particular test with a parameter to estimate. The test and the corresponding parameters have been selected at random.

CHAPTER VIII

CONCLUSION

The concept of online parameter estimation as a tool to automate the thermal modeling process has been presented. Two methods have been used to perform the parameter estimation. The first is the extended Kalman filter which is the most widely used approach to non linear estimation, and the second is the unscented Kalman filter which is a new and more accurate approach. These techniques have been successfully applied to test data obtained from ground testing on a space payload (StarNav I). Furthermore it is intended to use these techniques to identify unknown parameters like the environmental heat load from the shuttle data while in orbit. It has been observed that the extended Kalman filter lacks robustness, and it is unable to converge when significant non linearities are present. This confirms that the extended Kalman filter is only reliable for systems that are almost linear on the time scale of the updates. The unscented Kalman filter on the other hand performs well with all test data.

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APPENDIX A

There were four tests conducted on the StarNav I payload. This section contains a description of the tests as well as the plots of the data from the tests. The data from these tests have been used for benchmarking purposes and to pass the safety review specifications.

The following tests have been described in this section.

(1) Vacuum Testing by Jackson and Tull Albuquerque Team at Air Force Research Lab, NM May 2001

(2) Vacuum Test Conducted at CSCE- Dec 2001

(3) Vacuum Test Conducted at CSCE- Jan 2002

(4) Test Conducted at Kennedy Space Center - March 2002

- Data Set Nomenclature -

As mentioned 4 tests were conducted on StarNav I. Each test comprised of several cycles. The naming convention used while plotting and estimating purposes is to name the 1^{st} cycle of the first test as Data set 1, the 2^{nd} cycle as Data set 2, ..., the 7^{th} cycle of the fourth set as Data set 16.

A. Test 1 Vacuum Testing by Jackson and Tull Team at Air Force Research Lab Albuquerque, NM -May 2002

The StarNav I payload was located on the QUEST platform on top of the Spacehab module in the shuttle bay. The estimation of the surrounding environment was that it would be colder than other locations having a full view of the shuttle bay. Hence this test focussed on temperature ranges in the colder regions and restarts in adverse

conditions. This test was intended to prove that the camera could survive extreme temperatures and heat fluxes in the IR range. This test was also testing the assumption of a large conduction coupling between the aluminum shell of the payload and the inner camera board.

Two sets of thermistors were used for this test. The first consisted of the inner bank and would be working when the camera was turned on. The other set of thermistors were the outer thermistors and were powered at all times. Collection of data was synchronized between the inner bank of thermistors and the outer bank of thermistors whenever the inner bank of thermistors were turned on. Temperature bounds for the data gathered during this test were limited between -70^oC and $+100^oC$.

The test was conducted in vacuum with the environment temperature cycling between -50^oC and $+40^oC$ (see Fig. 28). There were five cycles (Fig. 29 - Fig. 38) having both external and internal thermistor readings. The fourth and fifth cycles differed from the first three cycles. They involved a cold start of Starnav 1 after it had been turned off after completion of the hot soak.

The following information gives the relation between the the column number in the data file $\Rightarrow$ its correspondence with the node number in the simplified model $\Rightarrow$ and to what thermistor reading it corresponds.

For internal thermistor data file:

Column 1 = Array number

Column 2 = Time

Column 3 = Node 3 in simplified model = Thermistor 5

Column 4 = Node 4 in simplified model = Thermistor 4

Column 5 = Node 5 in simplified model = Thermistor 1

For external thermistor data file:

For external thermistor data file:

Column 1 = Array number

Column 2 = Time

Column 3 = Node 1 in simplified model(boundary node)

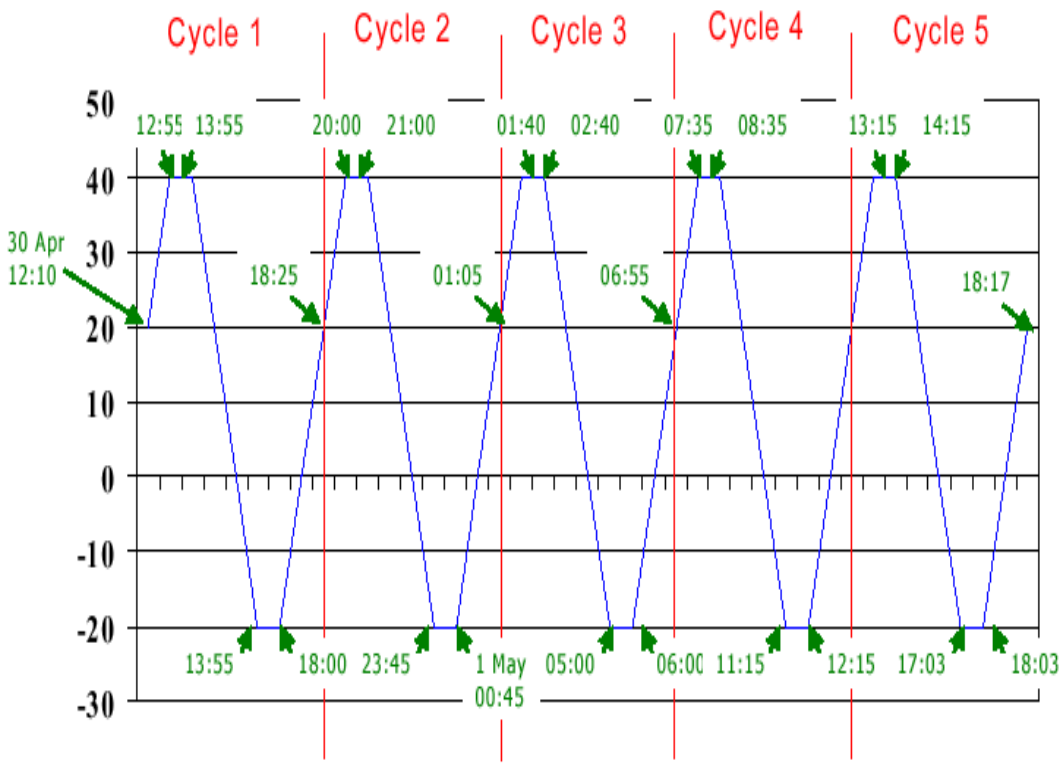


Fig. 28. Thermal Profile for Test 1

B. Test 2 Vacuum Test Conducted at SSIL/STC - Dec2001

This test was conducted in vacuum at 290k. It comprised of only one continuous cycle (Fig. 39) with periodic transfer of temperatures from StarNav I to the desktop for monitoring.

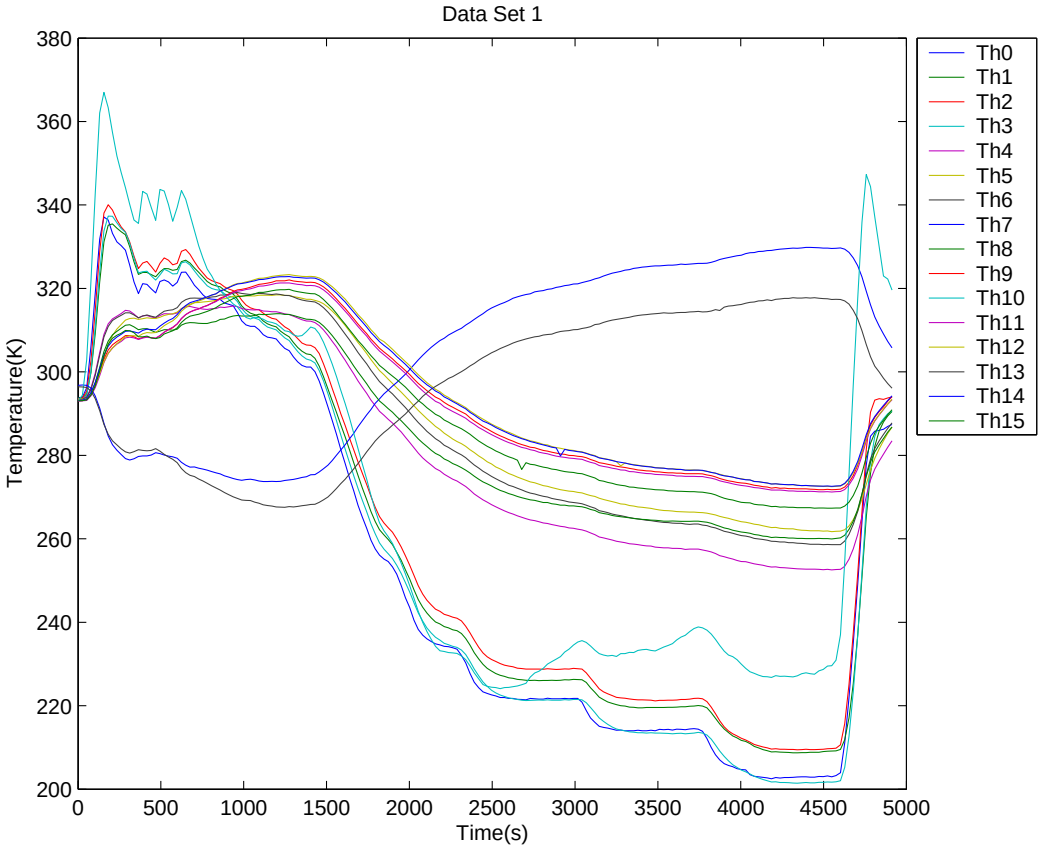


Fig. 29. Data Set 1 External Thermistor Readings

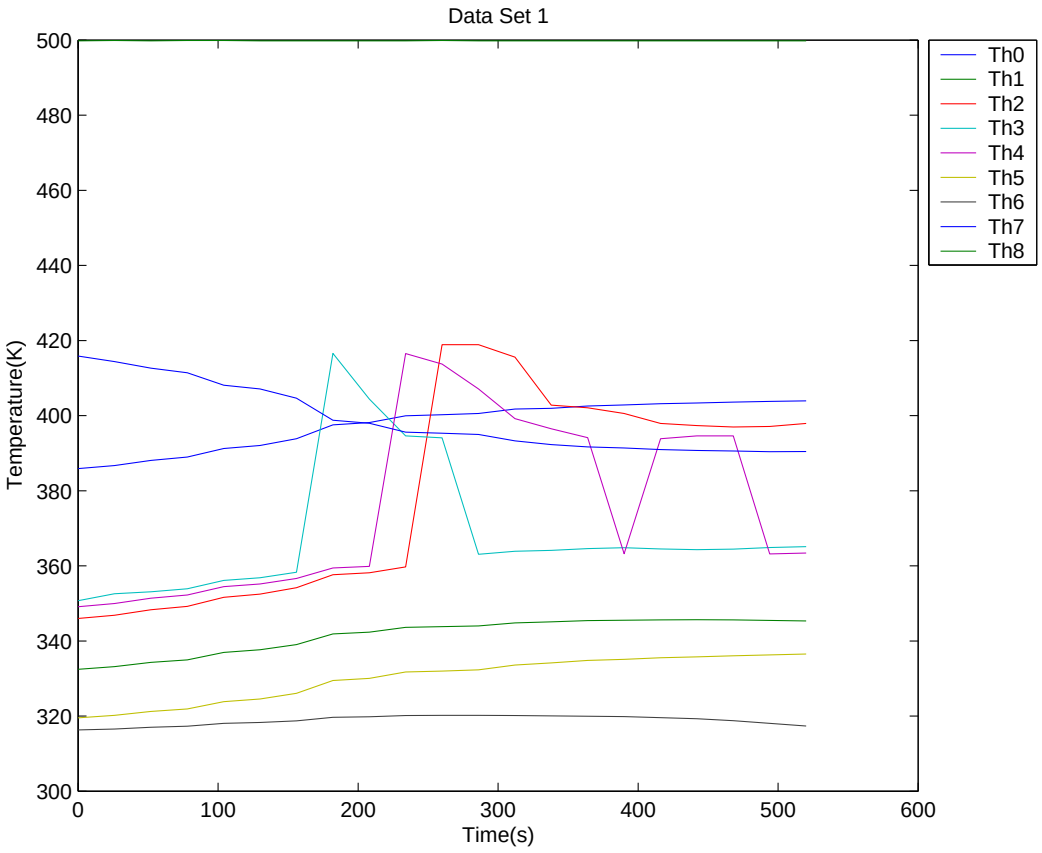


Fig. 30. Data Set 1 Internal Thermistor Readings

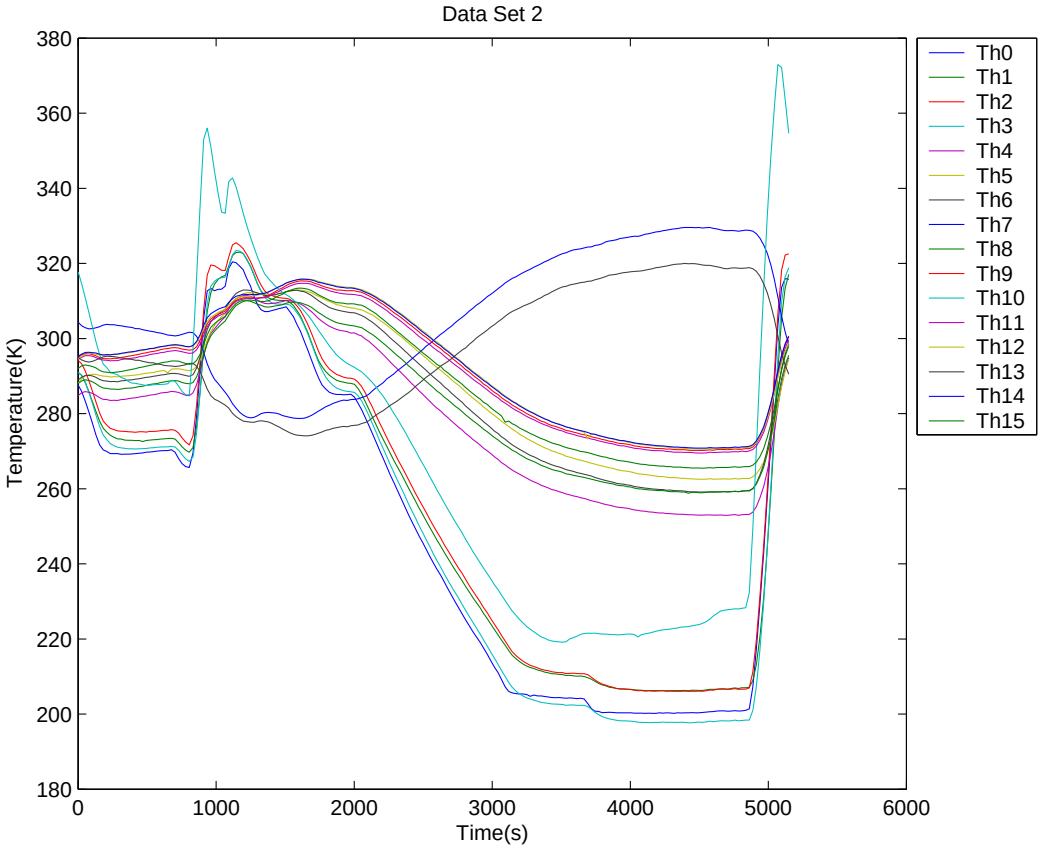


Fig. 31. Data Set 2 External Thermistor Readings

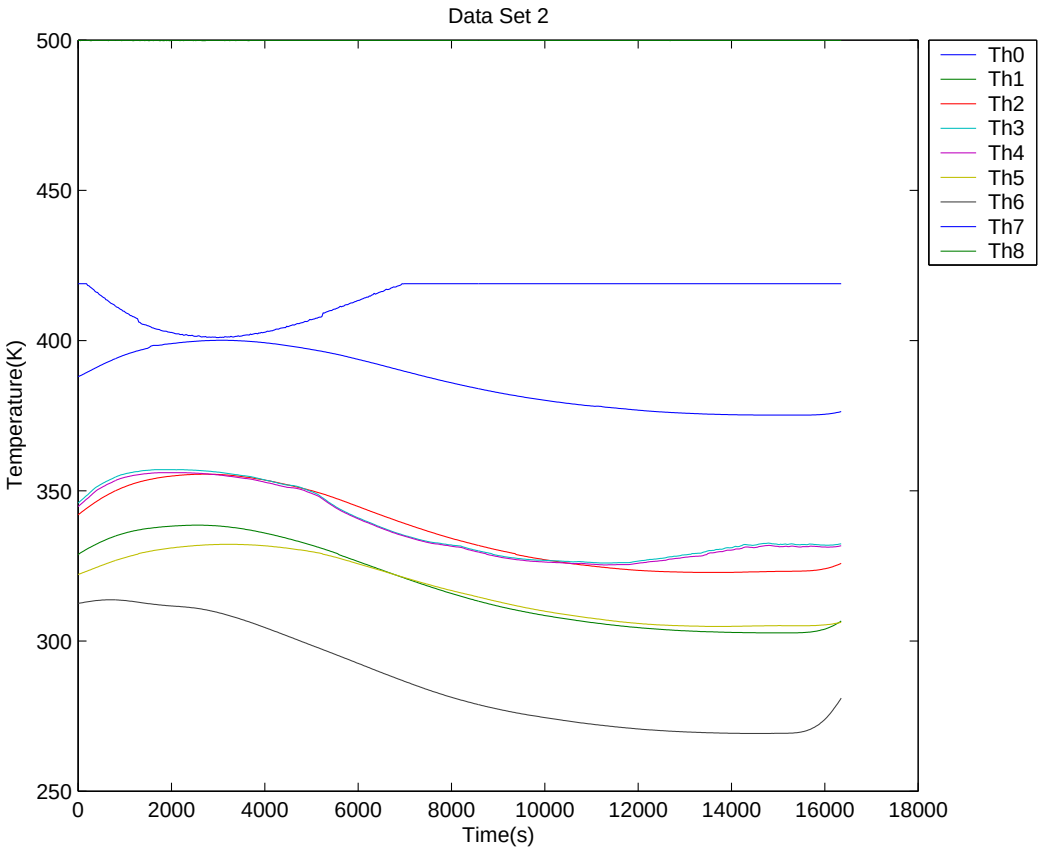


Fig. 32. Data Set 2 Internal Thermistor Readings

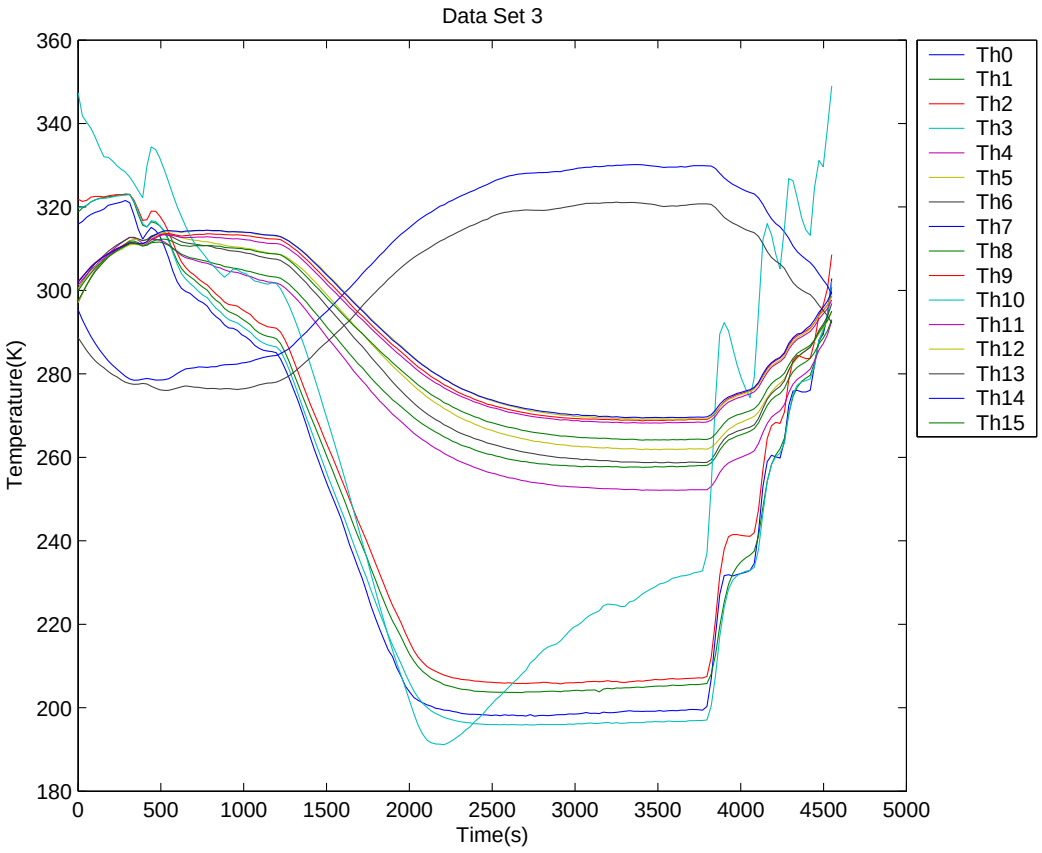


Fig. 33. Data Set 3 External Thermistor Readings

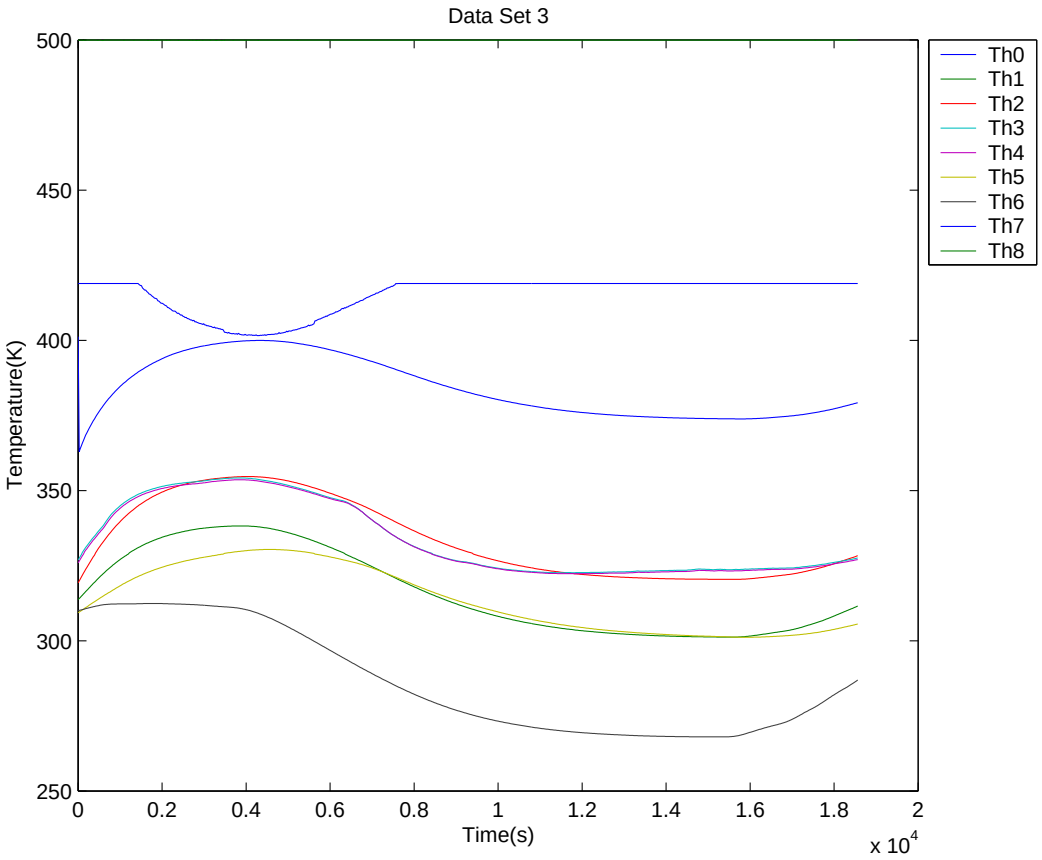


Fig. 34. Data Set 3 Internal Thermistor Readings

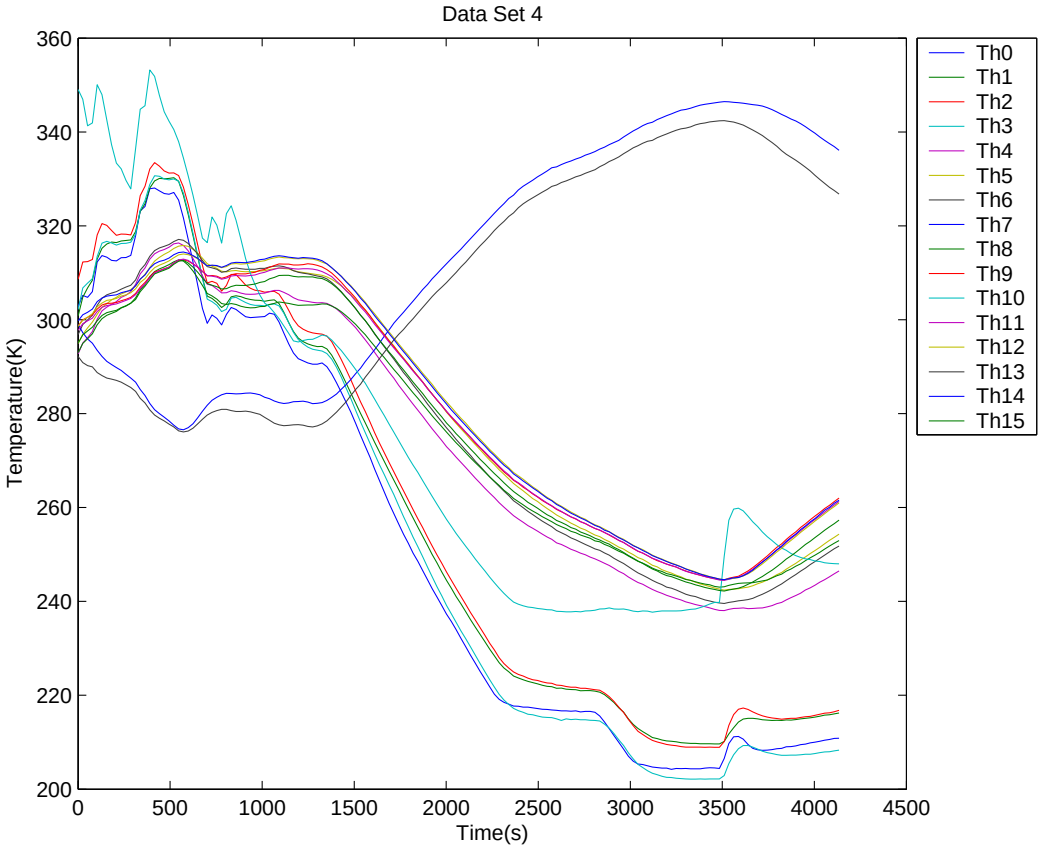


Fig. 35. Data Set 4 External Thermistor Readings

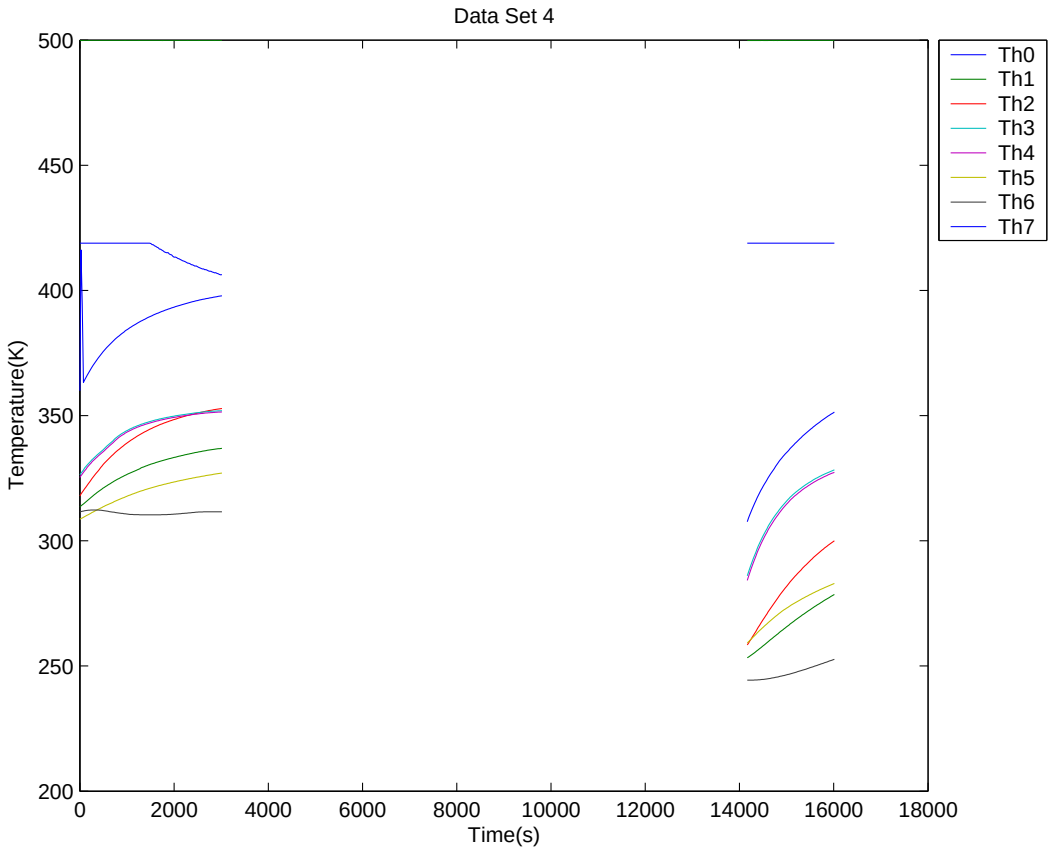


Fig. 36. Data Set 4 Internal Thermistor Readings

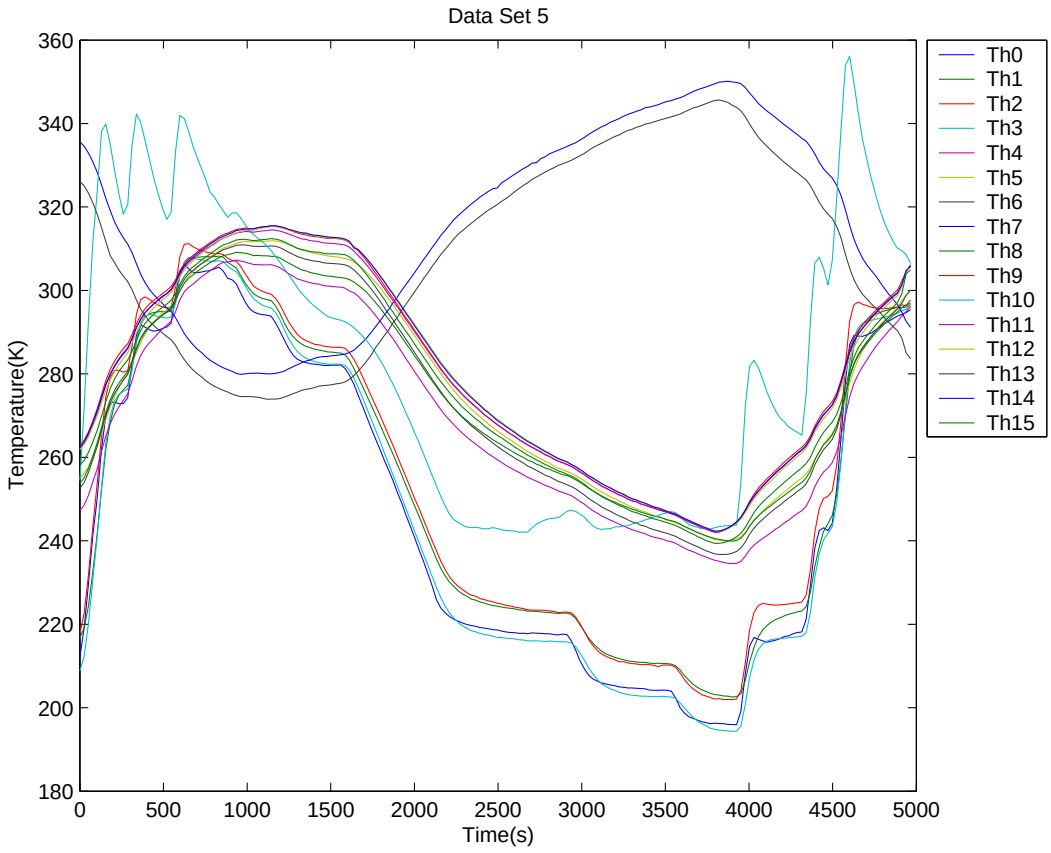


Fig. 37. Data Set 5 External Thermistor Readings

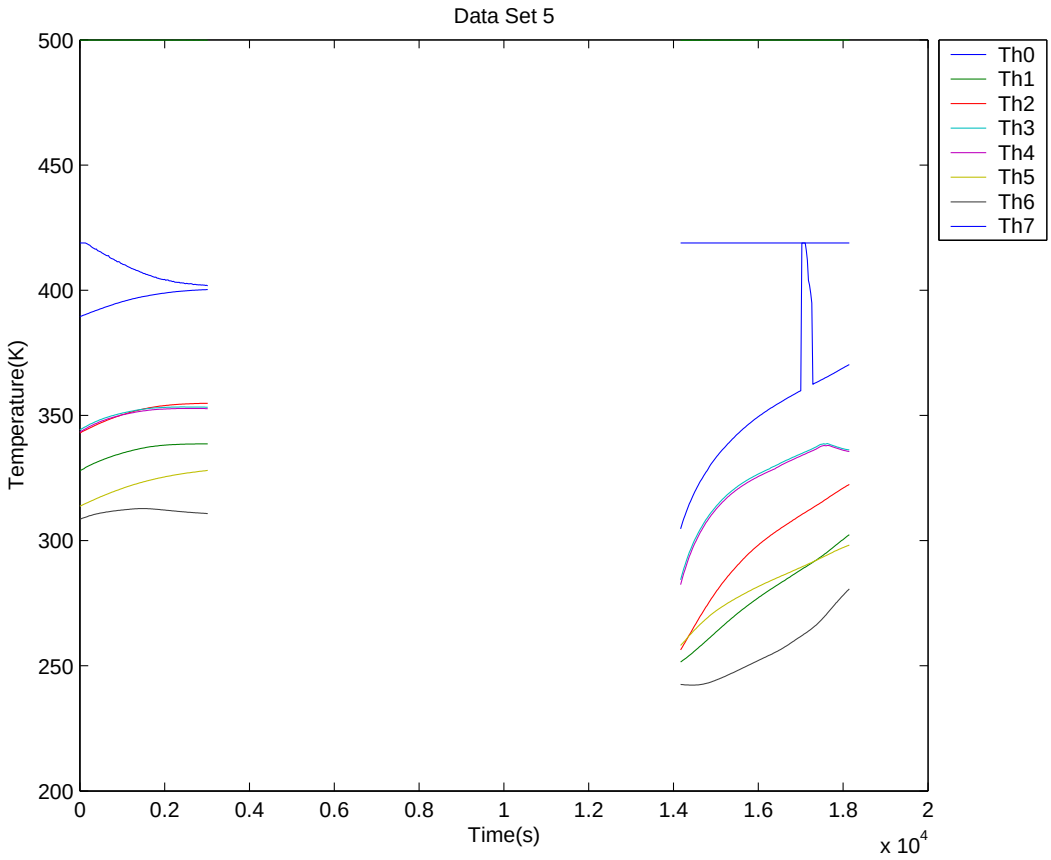


Fig. 38. Data Set 5 Internal Thermistor Readings

The following information gives the relation between the the column number in the data file ⇒ its correspondence with the node number in the simplified model ⇒ and to what thermistor reading it corresponds.

For internal thermistor data file:

Column 1 = Array number

Column 2 = Time

Column 3 = Node 3 in simplified model = Thermistor 5

Column 4 = Node 4 in simplified model = Thermistor 4

Column 5 = Node 5 in simplified model = Thermistor 1

No external thermistors

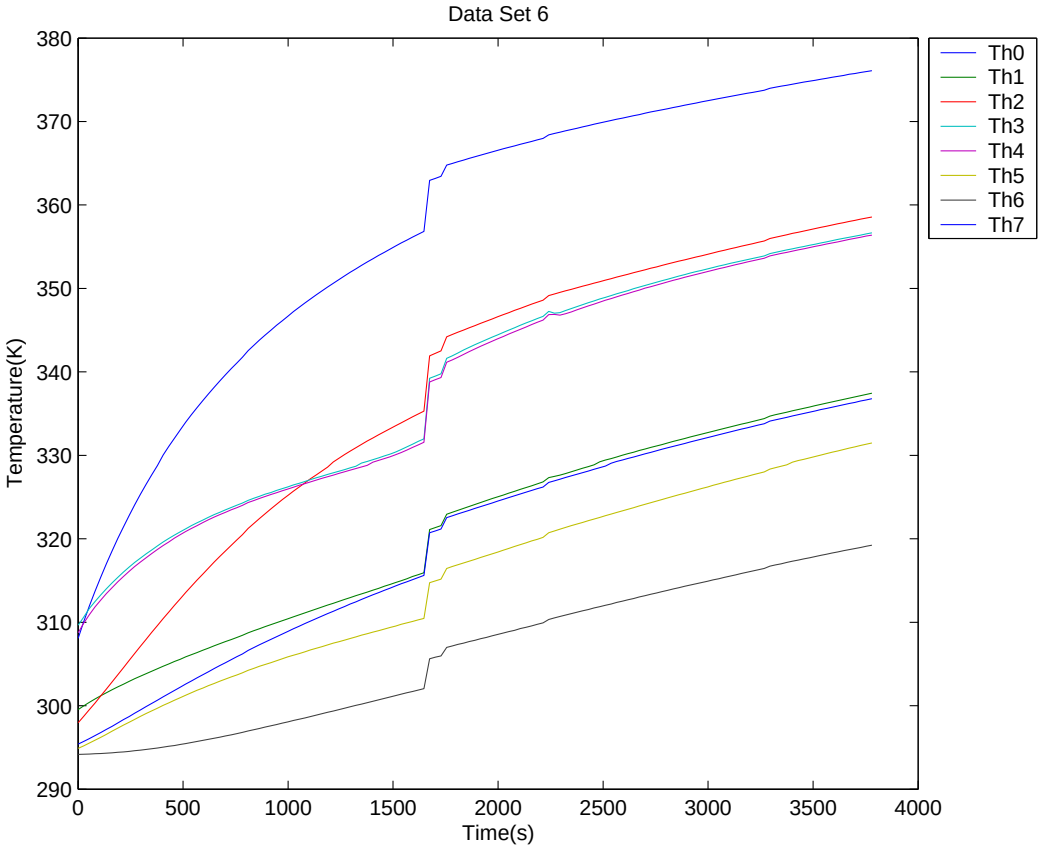


Fig. 39. Data Set 6 Internal Thermistor Readings

C. Test 3 Vacuum Test Conducted at SSIL/STC- Jan 2002

This test was conducted in vacuum at 290k. Its objective was to benchmark the thermal analysis conducted by the thermal group and to validate the effect of the copper plate/heat sink solution for previously over heated components. The success criterion for this test required temperatures from all temperature measurement devices to stay below 70^oC for the duration of the test cycles. This test comprised of three cycles (Fig. 40 - Fig. 42) with the Starnav Camera turned on for 14 minutes during each cycle before being turned off.

The following information gives the relation between the the column number in the data file $\Rightarrow$ its correspondence with the node number in the simplified model $\Rightarrow$ and to what thermistor reading it corresponds.

For internal thermistor data file:

Column 1 = Array number

Column 2 = Time

Column 3 = Node 3 in simplified model = Thermistor 5

Column 4 = Node 4 in simplified model = Thermistor 4

Column 5 = Node 5 in simplified model = Thermistor 1

No external thermistors

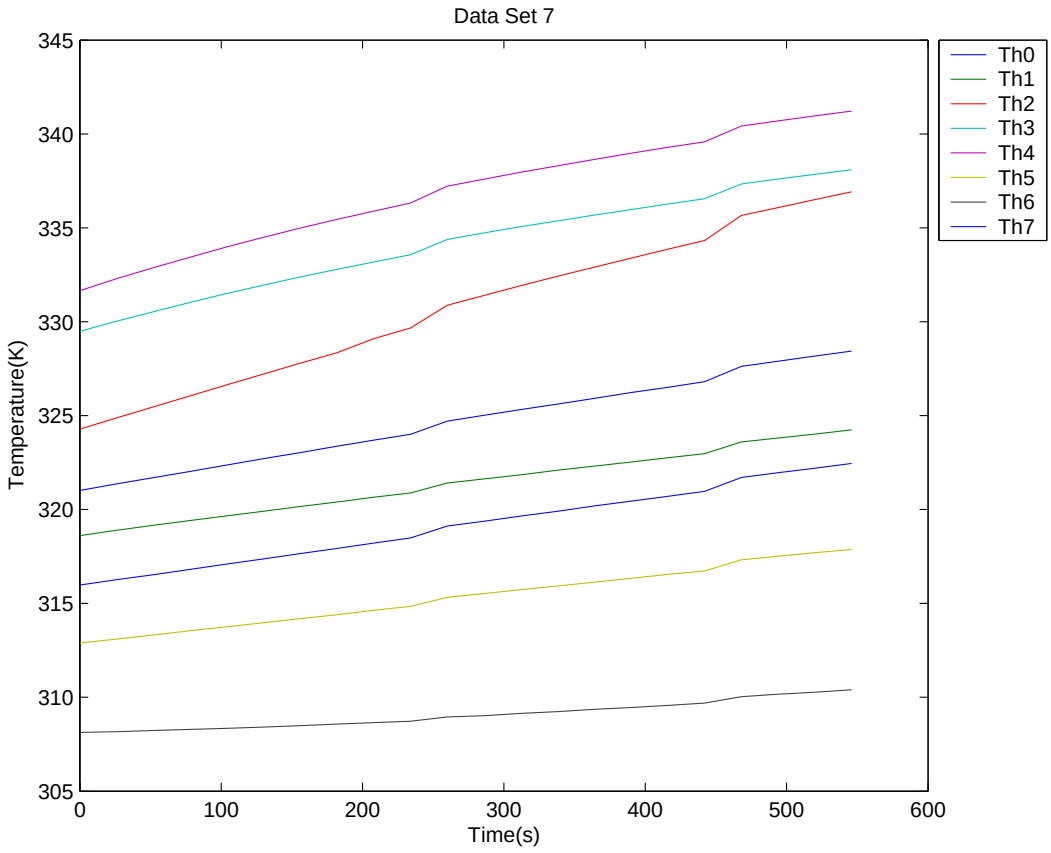


Fig. 40. Data Set 7 Internal Thermistor Readings

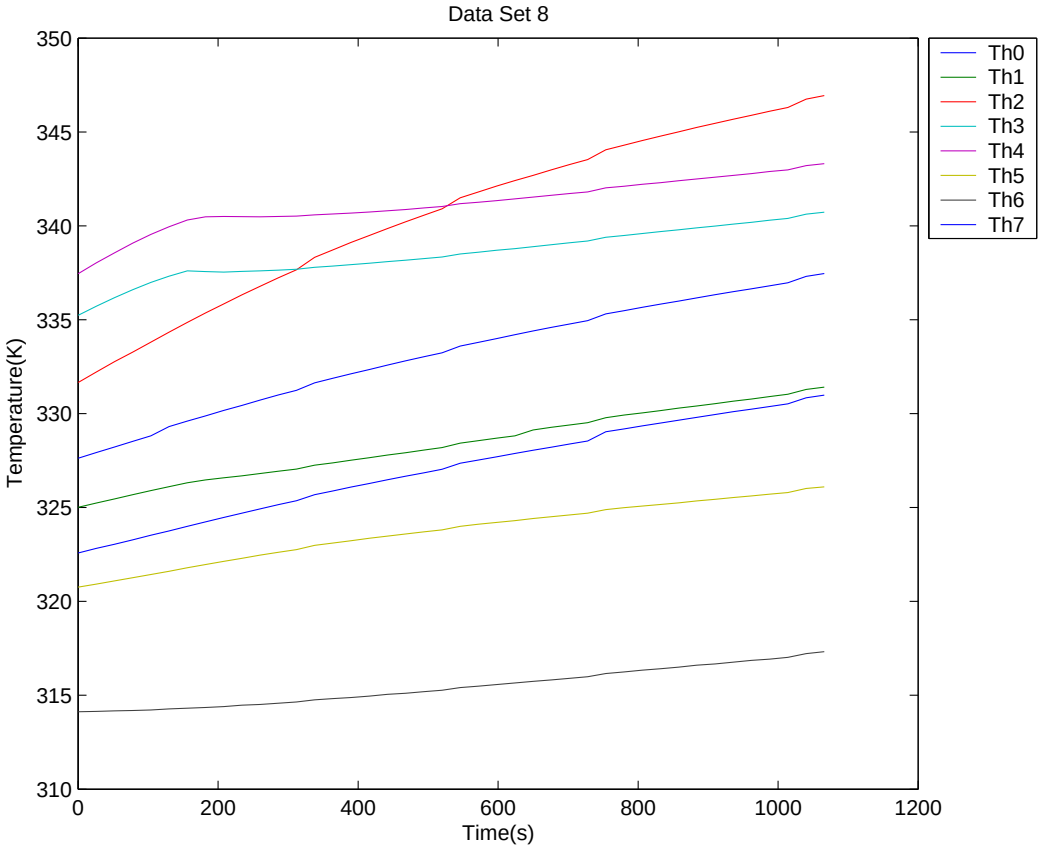


Fig. 41. Data Set 8 Internal Thermistor Readings

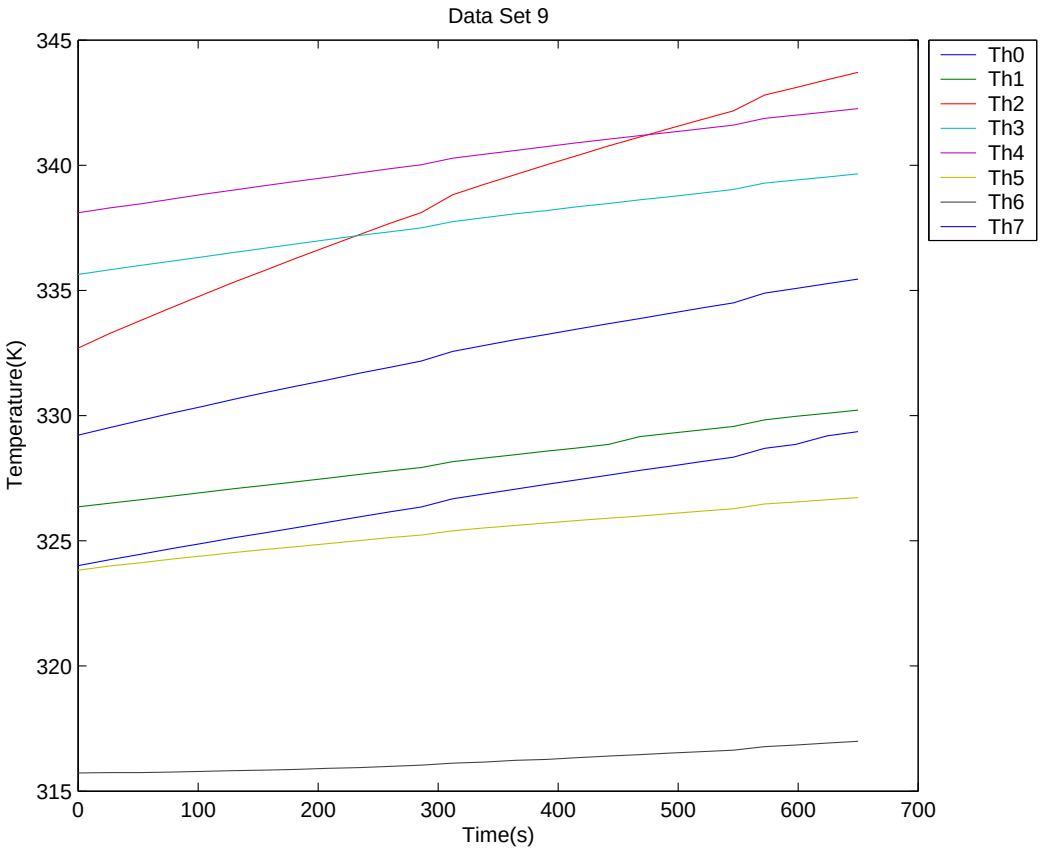


Fig. 42. Data Set 9 Internal Thermistor Readings

D. Test 4 Conducted at Kennedy Space Center - March 2002

This test was conducted in a convective environment at 290k. Its objective was to estimate the contact conductance between the star tracker and the space hab module in the shuttle bay. This test comprised of 9 cycles (Fig. 43 - Fig. 49).

The following information gives the relation between the the column number in the data file ⇒ its correspondence with the node number in the simplified model ⇒ and to what thermistor reading it corresponds.

For internal thermistor data file:

Column 1 = Array number

Column 2 = Time

Column 3 = Node 3 in simplified model = Thermistor 5

Column 4 = Node 4 in simplified model = Thermistor 4

Column 5 = Node 5 in simplified model = Thermistor 1

No external thermistors

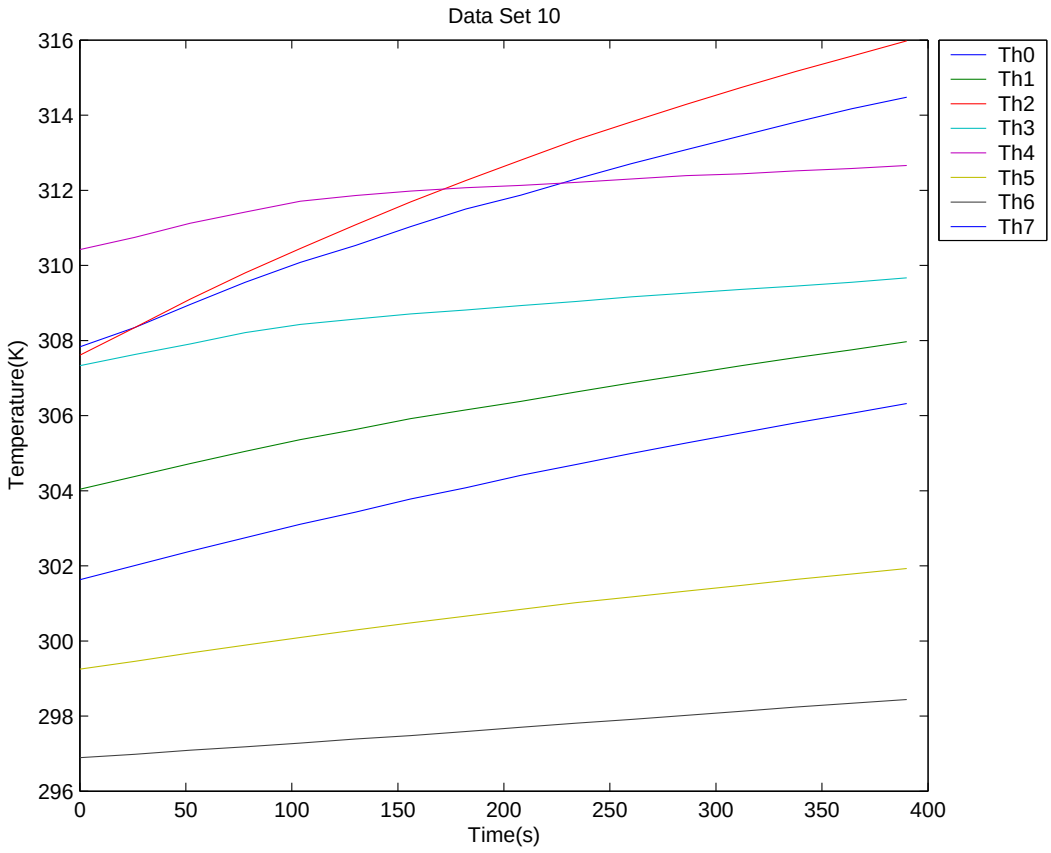


Fig. 43. Data Set 10 Internal Thermistor Readings

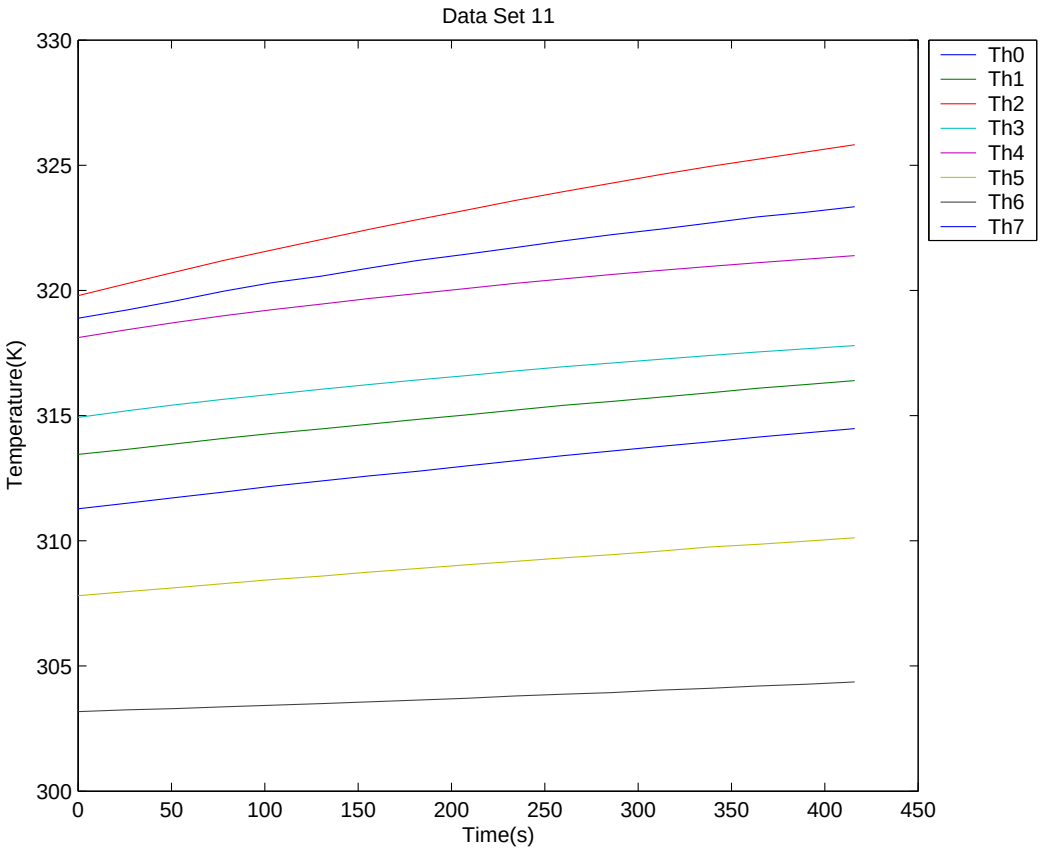


Fig. 44. Data Set 11 Internal Thermistor Readings

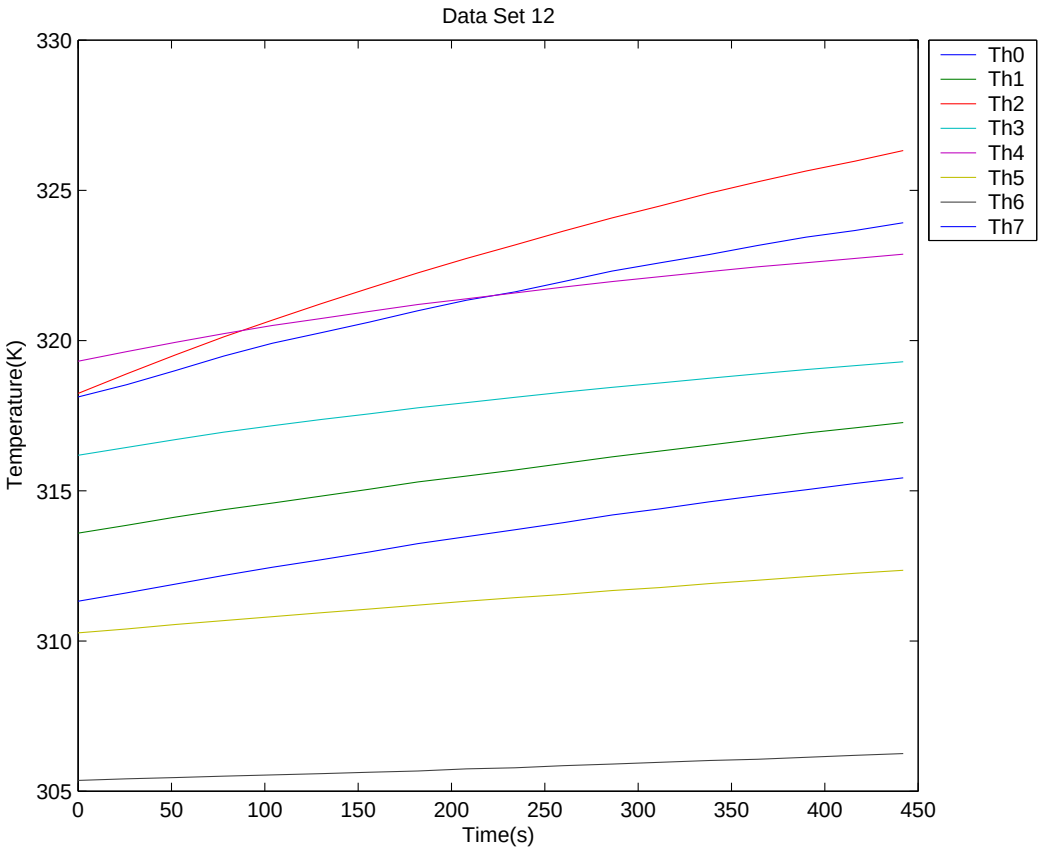


Fig. 45. Data Set 12 Internal Thermistor Readings

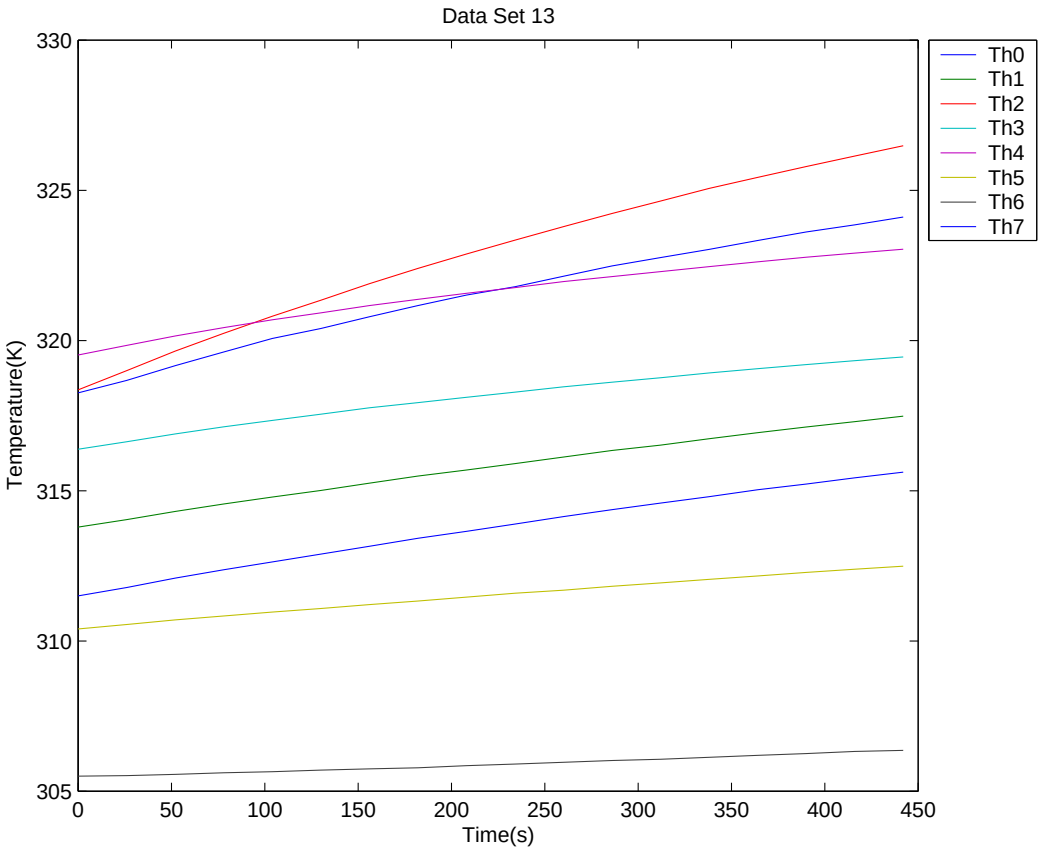


Fig. 46. Data Set 13 Internal Thermistor Readings

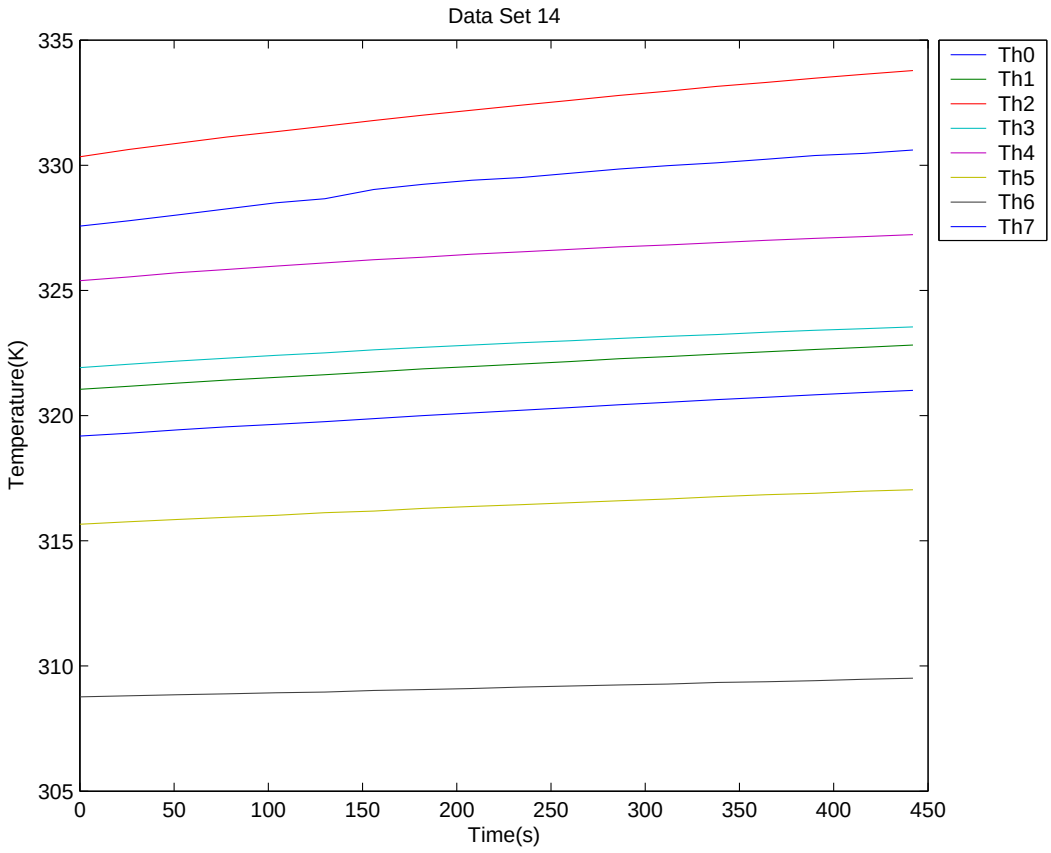


Fig. 47. Data Set 14 Internal Thermistor Readings

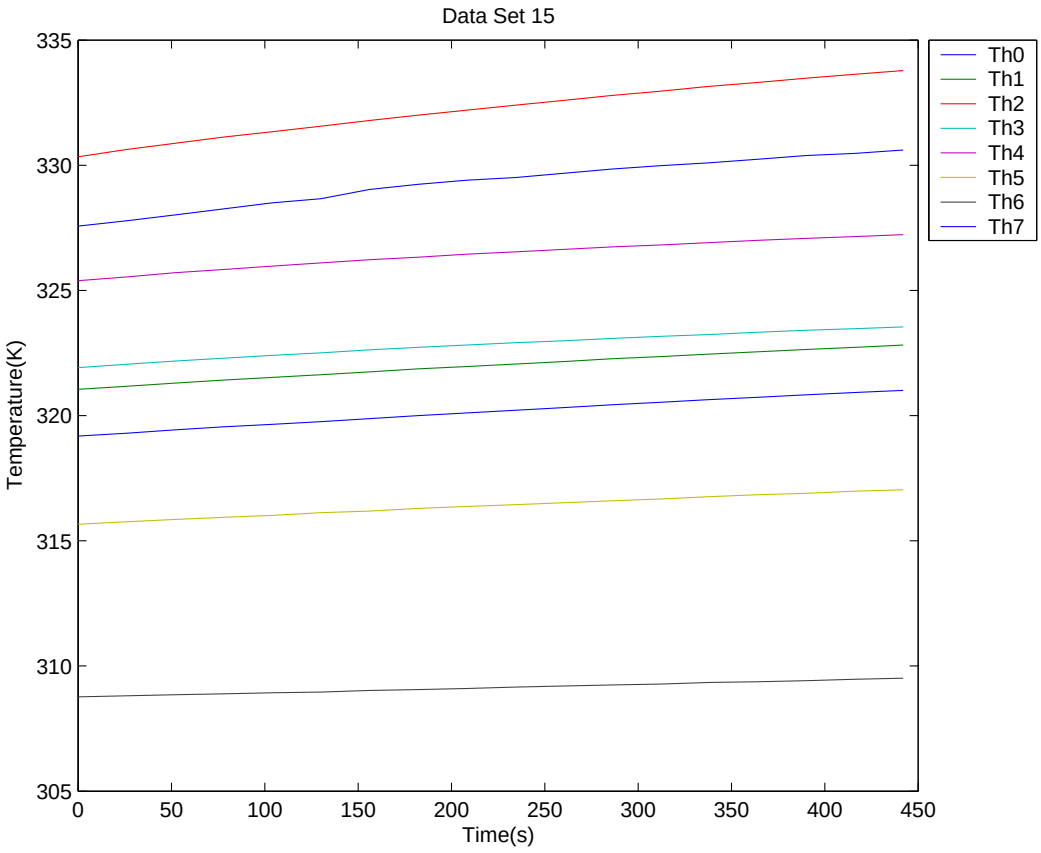


Fig. 48. Data Set 15 Internal Thermistor Readings

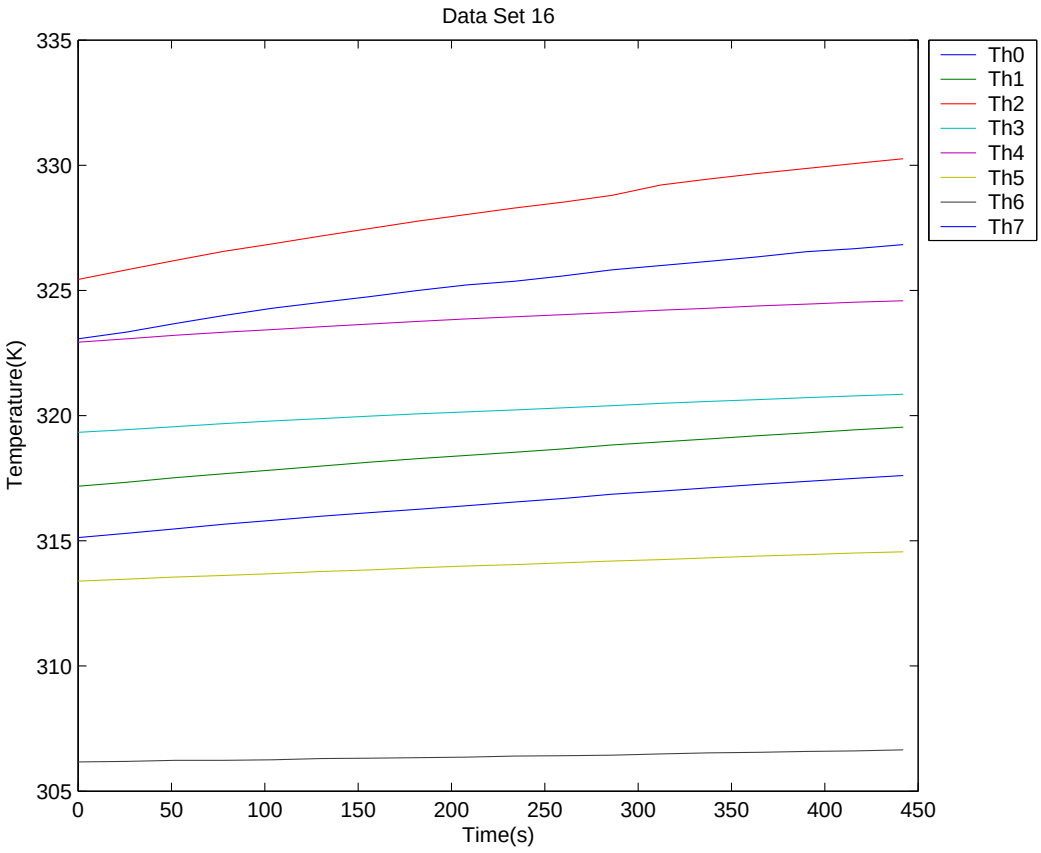
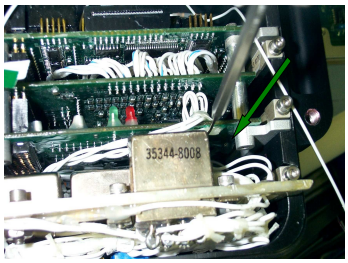
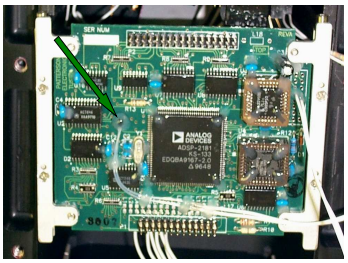


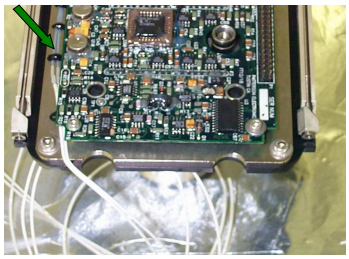
Fig. 49. Data Set 16 Internal Thermistor Readings



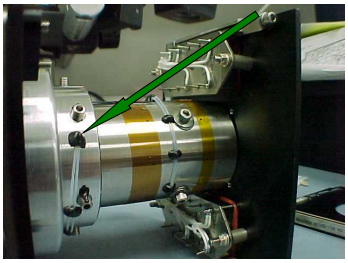
50.1: T1 Thermistor 1



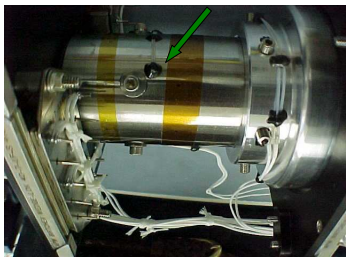
50.2: T2 Thermistor 2



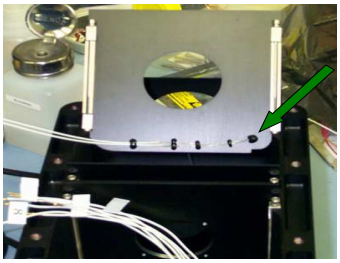
50.3: T3 Thermistor 3



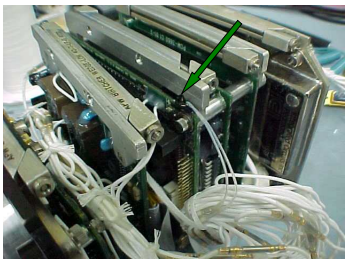
50.4: T4 Thermistor 4



50.5: T5 Thermistor 5



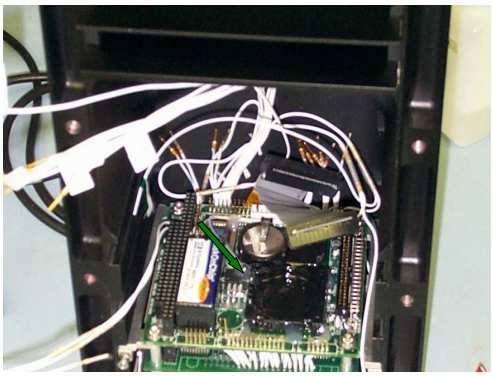
50.6: T5 Thermistor 6



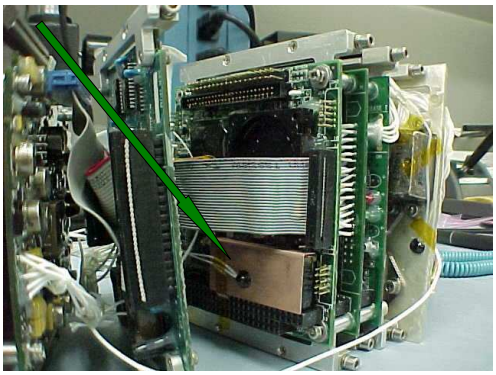
50.7: T6 Thermistor 7

Fig. 50. Location of Internal Thermistors on StarNavI

Fig. 50 gives the location of the internal thermistors 1 - 7. The location of thermistor 0 is different in Test-1 compared to Test2-Test4. Fig. 51 gives the location of thermistor 0 for Test-1 and Test-2-Test4. Fig. 52 gives the location of external thermistors for Test-1.

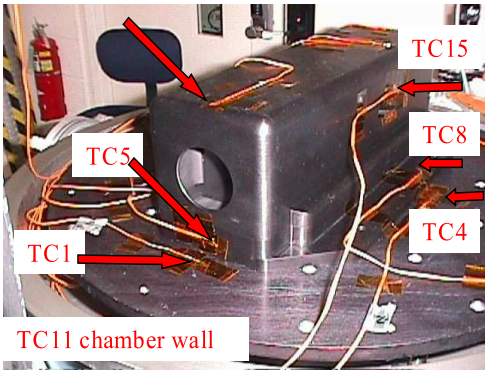


51.1: T0 Thermistor 0 for Test 1

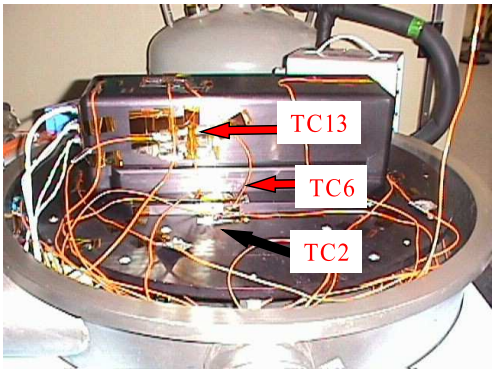


51.2: T0 Thermistor 0 for Test 2-Test 4

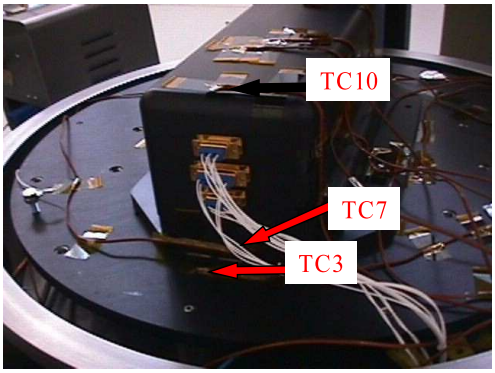
Fig. 51. Location of Internal Thermistor T0 on StarNavI



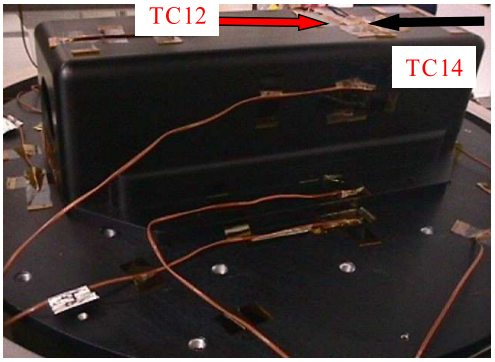
52.1:



52.2:



52.3:



52.4:

Fig. 52. Location of External Thermistors on StarNavI for Test-1

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