

Data Fusion of In-Flight Aerothermodynamic Heating Measurements Using Kalman Filtering

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On February 18th, 2021, the Mars 2020 entry system successfully delivered the Perseverance rover to the surface of Mars at Jezero Crater. The entry capsule carried instrumentation installed on the heatshield and backshell, named the Mars Entry, Descent, and Landing Instrumentation 2. The instruments included pressure transducers, thermocouples, heat flux gauges, and a radiometer to measure the aerodynamic and aerothermodynamic performance of the entry vehicle. Three of these sensors, a thermocouple plug, heat flux gauge, and a radiometer, were co-located on the backshell. The sensors were exposed to roughly the same aerodynamic heating, but measured these environments in different ways, each with its own set of modeling and measurement error complications. This paper develops a method for blending each of these measurements together in a single algorithm to produce estimates of the aerothermodynamic environments at that backshell location. The approach makes use of the Kalman-Schmidt filter/smoothen methodology, where systematic measurement error parameters are modeled as multiplicative states that are estimated by the filter along with the aerothermal states. The results indicate peak convective and radiative heating values of 0.86 and 5.16 W/cm², respectively, compared to the filter predictive model values of 0.67 and 4.83 W/cm².

Nomenclature

A_c, B_c, C_c	=	Convective heating correlation coefficients
A_r, B_r, C_r, D_r	=	Radiative heating correlation coefficients
C	=	State-parameter covariance
c_1	=	Inverse of thermal conductivity coefficient
c_2	=	Surface radiative absorption coefficient
c_3	=	Surface emissivity
c_4	=	Freestream temperature, K
c_5	=	Cold wall heat flux gauge multiplier
c_6	=	Heat flux gauge radiative absorption coefficient
c_7	=	Radiometer view factor coefficient
c	=	Model parameters, $c = [c_1, c_2, c_3, c_4, c_5, c_6, c_7]^T$
F	=	Derivative of f with respect to x
f	=	Process model
G	=	Derivative of ϕ with respect to c

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H	= Derivative of h with respect to x
h	= Measurement model
I	= Identity matrix
K	= Kalman gain
L	= Derivative of h with respect to c
M	= Smoothing gain
k	= Time index
m	= Arbitrary time index
n	= Total number of measurements
P	= Covariance of x
Q	= Covariance of w
q_c	= Convective heat flux, W/cm ²
q_r	= Radiative heat flux, W/cm ²
R	= Covariance of v
T	= Temperature, K
t	= Time, s
u	= Filter process model inputs
V	= Freestream velocity, m/s
v	= Measurement noise
w	= Process noise
x_1	= Filter state corresponding to convective heat rate, W/cm ²
x_2	= Filter state corresponding to radiative heat rate, W/cm ²
x_3	= Filter state corresponding to surface temperature, K
x_4	= Filter state corresponding to surface temperature multiplicative measurement error
x_5	= Filter state corresponding to surface heating multiplicative measurement error
x_6	= Filter state corresponding to heat flux gauge multiplicative measurement error
x_7	= Filter state corresponding to radiometer multiplicative measurement error
x	= Filter state, $x = [x_1, x_2, x_3, x_4, x_5, x_6, x_7]^T$
y_1	= Temperature measurement derived from thermocouple plug, K
y_2	= Total heat flux measurement derived from thermocouple plug, W/cm ²
y_3	= Heat flux gauge measurement, W/cm ²
y_4	= Radiometer measurement, W/cm ²
y	= Filter measurements, $y = [y_1, y_2, y_3, y_4]^T$
κ	= Stefan-Boltzmann constant
ρ	= Freestream atmospheric density, kg/m ³
ρ_{CO}	= Density of CO, kg/m ³
ρ_{CO_2}	= Density of CO ₂ , kg/m ³
σ	= Standard deviation
σ_{y_1}	= Standard deviation of y_1 measurement, K
σ_{y_2}	= Standard deviation of y_2 measurement, W/cm ²
Φ	= State transition matrix, derivative of ϕ with respect to x
ϕ	= State propagation function
Ω	= Covariance of c
$\hat{x}_{k m}$	= Filter estimate at time k given data through time m

I. Introduction

The Mars 2020 entry capsule [1] carried a set of instrumentation installed on the heatshield and backshell, named the Mars Entry, Descent, and Landing Instrumentation 2 (MEDLI2)[2, 3]. MEDLI2 data were collected during the Mars 2020 entry, descent, and landing that occurred on February 18th, 2021, placing the Perseverance rover in Jezero Crater. The MEDLI2 instruments included pressure transducers, thermocouples, heat flux gauges, and a radiometer to measure the aerodynamic and aerothermodynamic performance of the entry vehicle. The MEDLI2 sensor suite built on the success of the Mars Science Laboratory Entry, Descent, and Landing Instrumentation (MEDLI), which flew on the heatshield of the Curiosity rover's entry capsule during its landing on Mars in August, 2012 [4–6]. The MEDLI2 sensor

suite included an enhanced set of instruments to make measurements in flight regimes and locations on the vehicle that were not captured in the MEDLI data, notably including sensors located on the backshell.

The layout of the sensors on the heatshield and backshell is shown in Figure 1. The sensors are designated as pressure sensors or thermal sensors, and by locations on either the heatshield or backshell. For example, MPH01 is the a pressure sensor on the heatshield, and MTB01 is a thermal sensor on the backshell. There a total of eight pressure sensors on the vehicle, seven on the heatshield and one on the backshell. There are a total of twenty thermal sensors, eleven of which are sensor plugs installed into the heatshield Thermal Protection System (TPS) material (Phenolic Impregnated Carbon Ablator) that contain near-surface and in-depth thermocouples. Similarly, there are six thermocouple plugs installed in the backshell TPS material, Super-Lightweight Ablator (SLA-561 V). The backshell instrumentation also included two heat flux gauges (Schmidt-Boelter gauges) and one radiometer (a Schmidt-Boelter gauge behind a sapphire window) to provide direct measurements of the heating environments. Examples of the sensors are shown in Figure 2. Additional details on the instrumentation can be found in [2, 3].

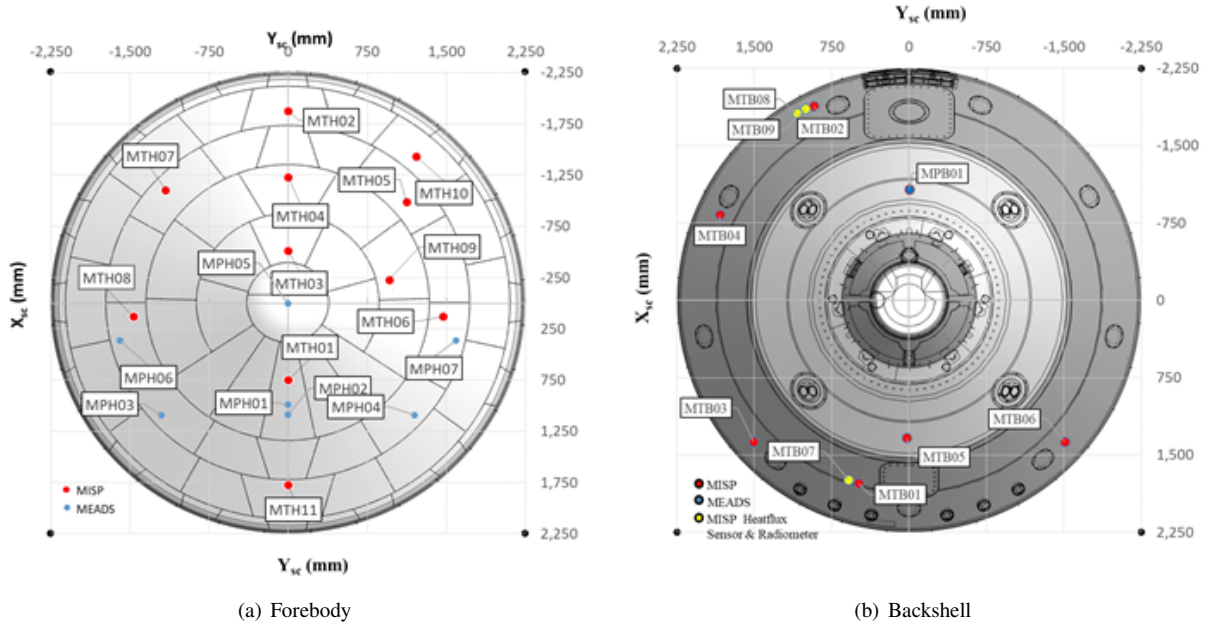


Fig. 1 MEDLI2 Sensor Layout.

Note that three sensors on the backshell were located in close proximity: MTB02, MTB08, and MTB09. MTB02 was a thermocouple plug that measured temperatures at depths within the TPS. The heating environment was then be inferred through an ablator response model using inverse analysis techniques [6–9]. MTB08 was a heat flux sensor that measured the total convective and radiative heating directly, but the measurements were complicated by uncertain effects of catalycity and ablation products obscuring the measurement. The device was placed inside a copper housing, which acts as a heat sink, thus making the sensor output effectively a cold-wall heating measurement [10]. MTB09 is a radiometer, which is essentially the same type of device as MTB08 but the measurement is made through a sapphire window such that the convective component of heating is eliminated. This measurement is complicated by the uncertain effects of ablation products obscuring the window [10, 11]. Reconciling differences in these three co-located sensors is complicated by the different potential sources of measurement error.

The purpose of this work is to develop a numerical approach for blending data from these three sensors to construct a best estimate of the aerothermal environments at the location on the Mars 2020 backshell. The approach makes use of a Kalman filter method [12, 13]. The Kalman filter incorporates models of each individual type of sensor and their associated systematic errors in order to produce an estimate of the aeroheating environment in a single, unified framework. Parameter uncertainties are accounted for by using Kalman-Schmidt filter [14] approach in which the filter covariance is adjusted to account for the parameter uncertainties. A backwards smoother [15] is implemented to map the information accumulated from the forward filtering pass back to the initial time in order to provide best estimates of the states over the entire time interval.

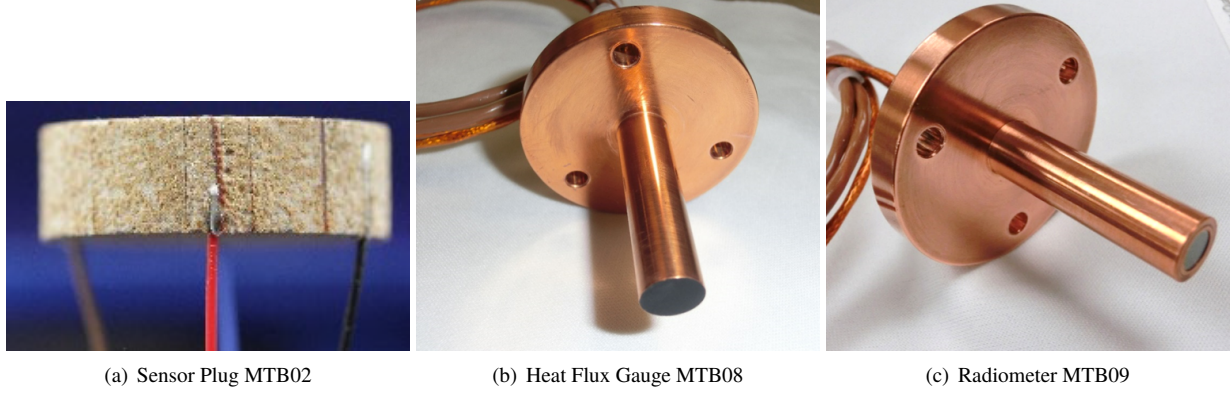


Fig. 2 Aerothermal Sensors.

Kalman filter approaches have a wide range of applications in aerospace [16, 17], industry [18], and meteorology [19] for solving various types of state estimation problems. In particular, common applications of Kalman filtering in aerospace have been focused on solving navigation problems, target tracking, and as observers for closed-loop control systems [16, 17]. It is not commonly used for solving aerothermodynamics problems. Some examples include estimation of unsteady heat transfer coefficients [20] and a series of papers describing the estimation of heat source localization from ultrasonic measurements [21–24]. The use of Kalman filtering methods for data fusion of in-flight aerothermal measurements as described in this paper is a new application of the methodology.

The remainder of this paper is organized as follows. Section II describes the Kalman filter implementation for solving the aerothermal sensor fusion problem, including simplified process models and the sensor measurement models. Section III describes application of the method to the MEDLI2 dataset and discussion of results. Concluding remarks are given in Section IV.

II. Sensor Fusion Approach

This section describes the sensor fusion approach for the aerothermal measurements. The method is based on the Kalman-Schmidt Filter and Rauch-Tung-Streifel Smoother [12–15]. Section II.A describes the mathematical formulation of the filter and smoother. The method has a predictor-corrector structure in which filter states are propagated forward in time according to a dynamic model, and the states are then corrected based on measurement data. Section II.B describes the dynamic model developed for solving the aerothermal sensor fusion problem. Section II.C describes the sensor models used by the filter to relate the states to the measurement data.

A. Kalman-Schmidt Filter and Rauch-Tung-Streifel Smoother

The Kalman filter is a linear quadratic optimal estimation technique for blending multiple measurement sources and dynamic models of the process [13]. The Kalman-Schmidt filter is an augmented approach to the Kalman filter in which parameter uncertainties are accounted for in the filtering equations. The filter has a predictor/corrector structure where estimates of the states are propagated forward in time and then corrections are obtained by processing external measurement data. The filter assumes process and measurement models for the system are of the form

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{u}, \mathbf{c}, \mathbf{w}, t) \quad (1)$$

$$\mathbf{y} = \mathbf{h}(\mathbf{x}, \mathbf{u}, \mathbf{c}, \mathbf{v}, t) \quad (2)$$

The prediction step propagates the estimated states and covariance forward in time from measurement time t_{k-1} to time t_k according to the relations

$$\hat{\mathbf{x}}_{k|k-1} = \boldsymbol{\phi}(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_{k-1}, \mathbf{c}_{k-1}, \hat{\mathbf{w}}_{k-1}) \quad (3)$$

$$\hat{\mathbf{P}}_{k|k-1} = \boldsymbol{\Phi}_{k-1} \hat{\mathbf{P}}_{k-1|k-1} \boldsymbol{\Phi}_{k-1}^T + \boldsymbol{\Phi}_{k-1} \mathbf{C}_{k-1|k-1} \mathbf{G}_{k-1}^T + \mathbf{G}_{k-1} \mathbf{C}_{k-1|k-1} \boldsymbol{\Phi}_{k-1}^T + \mathbf{G}_{k-1} \boldsymbol{\Omega}_{k-1} \mathbf{G}_{k-1}^T + \mathbf{Q}_{k-1} \quad (4)$$

$$\hat{\mathbf{C}}_{k|k-1} = \boldsymbol{\Phi}_{k-1} \hat{\mathbf{C}}_{k-1|k-1} + \mathbf{G}_{k-1} \boldsymbol{\Omega}_{k-1} \quad (5)$$

where ϕ represents numerical propagation of Eq. 1 from time t_{k-1} to t_k . For reasonably fast time steps the numerical propagation can take for the form of an Euler integration of the form

$$\phi = \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{f}(\hat{\mathbf{x}}_{k-1|k-1}, \mathbf{u}_{k-1}, \mathbf{c}_{k-1}, \hat{\mathbf{w}}_{k-1})(t_k - t_{k-1}) \quad (6)$$

It then follows that $\Phi_{k-1} = \mathbf{I} + \mathbf{F}_{k-1}(t_k - t_{k-1})$.

The measurement update at time t_k takes the form

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k [\mathbf{y}_k - \mathbf{h}(\hat{\mathbf{x}}_{k|k-1}, \mathbf{u}_k, \mathbf{c}_k, \hat{\mathbf{v}}_k, t)] \quad (7)$$

$$\hat{\mathbf{P}}_{k|k} = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \hat{\mathbf{P}}_{k|k-1} (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)^\top + \mathbf{K}_k \mathbf{R}_k \mathbf{K}_k^\top \quad (8)$$

$$\hat{\mathbf{C}}_{k|k} = \hat{\mathbf{C}}_{k|k-1} - \mathbf{K}_k (\mathbf{H}_k \hat{\mathbf{C}}_{k|k-1} + \mathbf{L}_k \mathbf{\Omega}_k) \quad (9)$$

where $\mathbf{K}_k = (\bar{\mathbf{P}}_k \mathbf{C}_k^\top + \hat{\mathbf{C}}_{k|k-1} \mathbf{L}_k^\top) (\mathbf{H}_k \bar{\mathbf{P}}_k \mathbf{H}_k^\top + \mathbf{H}_k \hat{\mathbf{C}}_{k|k-1} \mathbf{L}_k^\top + \mathbf{L}_k \hat{\mathbf{C}}_{k|k-1}^\top \mathbf{H}_k^\top + \mathbf{R}_k)^{-1}$.

Once all n measurements have been processed by the Kalman filter, the information content contained in $\hat{\mathbf{x}}_{n|n}$, $\hat{\mathbf{P}}_{n|n}$, and $\hat{\mathbf{C}}_{n|n}$ can be mapped backward in time to the beginning of the measurements at time index $k = 1$ by means of the Rauch-Tung-Striebel (RTS) smoother [13]. The smoother initializes at time index $k + 1 = n$ and maps the information content back to $k = 1$ using the recursions

$$\hat{\mathbf{x}}_{k|n} = \hat{\mathbf{x}}_{k|k} + \mathbf{M}_k (\hat{\mathbf{x}}_{k+1|n} - \hat{\mathbf{x}}_{k+1|k}) \quad (10)$$

$$\hat{\mathbf{P}}_{k|n} = \hat{\mathbf{P}}_{k|k} + \mathbf{M}_k (\hat{\mathbf{P}}_{k+1|n} - \hat{\mathbf{P}}_{k+1|k}) \mathbf{M}_k^\top \quad (11)$$

where $\mathbf{M}_k = \hat{\mathbf{P}}_{k|k} \Phi_k \hat{\mathbf{P}}_{k+1|k}^{-1}$.

B. Process Model

For application to the aerothermal sensor fusion problem, the states to be estimated include the convective and radiative heating components (q_c and q_r , respectively) and the temperature at the surface of the TPS, indicated by T . The Kalman filter requires a process model in order to propagate the states forward through the measurement data. Analytic approximate models can be utilized for this purpose. These relations take the form [25, 26]

$$q_c = A_c \rho^{B_c} V^{C_c} \quad (12)$$

$$q_r = A_r (\rho_{CO})^{B_r} (\rho_{CO_2})^{C_r} T^{D_r} \quad (13)$$

These relations are evaluated along the reconstructed entry trajectory and atmosphere [27, 28]. Note that the radiative heating relation requires evaluation of post-shock equilibrium flowfield parameters from the Chemical Equilibrium with Applications (CEA) [29] code. Once evaluated, the relations are functions of time, which can be differentiated numerically to provide the dynamics model describing the rate of change of the heating states along the trajectory.

The temperature state dynamics can be modeled using relations involving the temperature rate of change to the total heat rate and re-radiation. A surface energy balance without surface ablation or blowing yields a model of the form

$$\dot{T} = c_1 (q_c + c_2 q_r) - c_1 c_3 \kappa (T^4 - c_4^4) \quad (14)$$

Multiplicative systematic measurement error terms are also included as filter states. These states are modeled as random walk processes of the form $\dot{x}_i = w_i$ where w is a random noise, for $i = 4 - 7$. The measurement error states will be described further in the next section.

In summary, the process model takes the form $\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, \mathbf{c}, t) + \mathbf{G}\mathbf{u}$ where

$$\mathbf{x} = \begin{Bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 & x_6 & x_7 \end{Bmatrix}^T \quad (15)$$

$$\mathbf{u} = \begin{Bmatrix} u_c & u_r \end{Bmatrix}^T \quad (16)$$

$$\mathbf{f} = \begin{Bmatrix} 0 \\ 0 \\ c_1(x_1 + c_2x_2) - c_1c_3\kappa(x_3^4 - c_4^4) \\ 0 \\ 0 \\ 0 \\ 0 \end{Bmatrix} \quad (17)$$

$$\mathbf{G} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (18)$$

where $x_1 = q_c$, $x_2 = q_r$, $x_3 = T$, and u_c and u_r are the time derivatives of equations 12 and 13, respectively.

C. Measurement Models

The measurement data to be processed in the Kalman filter consists of the temperature and heat rate derived from the inverse analysis of the thermocouple sensors, the total heat rate measured by the heat flux gauge, and the radiative heat rate component measured by the radiometer. The measurement model takes the form $\mathbf{y} = \mathbf{h}(\mathbf{x}, \mathbf{c})$ where

$$\mathbf{y} = \begin{Bmatrix} y_1 & y_2 & y_3 & y_4 \end{Bmatrix}^T \quad (19)$$

$$\mathbf{h}(\mathbf{x}, \mathbf{c}) = \begin{Bmatrix} x_4x_3 \\ x_5(x_1 + c_2x_2) \\ x_6(c_5x_1 + c_6x_2) \\ c_7x_7x_2 \end{Bmatrix} \quad (20)$$

The first two measurements correspond to the surface temperature and total heat flux estimates derived from the inverse analysis of the in-depth thermocouple measurements [9], respectively. The third and fourth measurements correspond to the heat flux gauge and the radiometer [10], respectively. The parameters in the model include the SLA-561V radiative absorption coefficient (c_2), a correction factor for cold wall heat flux measurements (c_5), heat flux gauge radiative absorption coefficient (c_6), and radiometer view factor compensation (c_7). The states x_4 through x_7 are multiplicative systematic error terms to be estimated in the filter to reduce uncertainties.

III. Application to the MEDLI2 Dataset

This section describes the application of the Kalman filter framework to the MEDLI2 data set acquired during Mars 2020 EDL on February 18th, 2021. The flight measurements for the sensor fusion problem are shown in Figure 3 along with comparisons to the Kalman filter predictive model given by Equations 15–18. Recall that the temperature and total heat flux (y_1 and y_2 , respectively) are derived from the in-depth thermocouple measurements recorded from the instrumented sensor plug using an inverse analysis and material response model [9]. Measurements y_3 and y_4 are heating measurements from the total heat flux gauge and the radiometer, respectively [10]. The nominal predictive models provide a reasonable initial estimate of the measurement data. The peak measured temperature was 886.1 K whereas the peak model prediction was 848.6 K. The peak heat flux derived from the sensor plug was 4.47 W/cm², where the peak model prediction was higher at a value of 5.50 W/cm². The nominal model also overpredicted the heat flux gauge measurement with a peak value of 6.05 W/cm² where the peak measured value was 5.10 W/cm². The nominal model underpredicted the peak radiative heating measurement with a value of 2.29 W/cm² compared to the peak measured value of 3.32 W/cm².

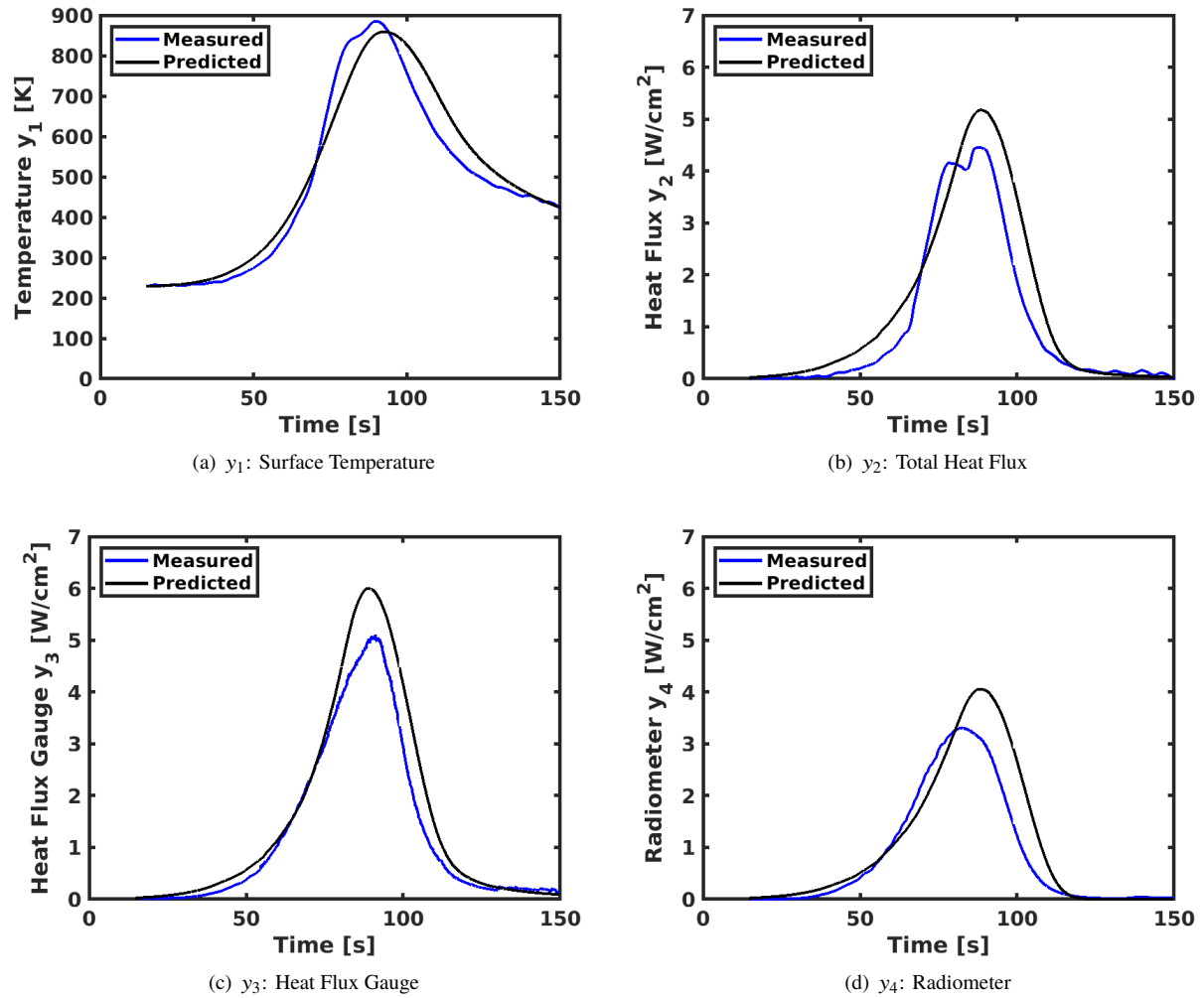


Fig. 3 Comparison of In-Flight Measurements to Predictions.

The measurement data were processed using the Kalman-Schmidt filter and RTS smoother. The filter initial conditions, initial covariance, process noise covariance, and measurement noise covariance used for the analysis are shown in Eqs. 21–24. The filter was initialized at a time of 15 s after entry interface and terminated at a time of 150 s after entry interface. The temperature and heat rate uncertainties from the in-depth thermocouple measurements are based on the inverse reconstruction uncertainty analysis [9] and are shown in Figure 4(a). The heat flux gauge and

radiometer measurement noise uncertainties are based on sensor calibrations [10]. Engineering judgement was used to tune the process noise assumptions to provide a reasonable amount of model uncertainty. Parameters c_1 , c_2 , and c_3 are based on the SLA-561V material properties. For this work, the parameter c_1 is treated as a constant. Temperature variations as given in [30] are not considered. The background temperature c_4 is based on the reconstructed atmosphere conditions along the Mars 2020 as-flown trajectory [27, 28] and is shown in Figure 4(b). The cold wall measurement compensation factor c_5 is based on Computational Fluid Dynamics (CFD) simulations [10] and shown in Figure 4(b). The heat flux gauge absorption coefficient c_6 is based on the sensor specifications, and the radiometer view factor coefficient is derived from the geometry of the sensor housed behind the sapphire window [10].

$$\hat{\mathbf{x}}_{0|0} = \begin{Bmatrix} 0 & 0.034 & 229.83 & 1 & 1 & 1 & 1 \end{Bmatrix}^T \quad (21)$$

$$\hat{\mathbf{P}}_{0|0} = \text{diag} \left\{ 0.01 \quad 0.01 \quad 1 \quad 0.01 \quad 0.01 \quad 0.01 \quad 0.01 \right\} \quad (22)$$

$$\mathbf{Q}_k = 10^{-4} \cdot \text{diag} \left\{ 0.25 \quad 0.25 \quad 0.25 \quad 0.0625 \quad 0.0625 \quad 0.0625 \quad 0.0625 \right\} \quad (23)$$

$$\mathbf{R}_k = \text{diag} \left\{ \sigma_{y_1}^2 \quad \sigma_{y_2}^2 \quad 0.0745 \quad 0.0745 \right\} \quad (24)$$

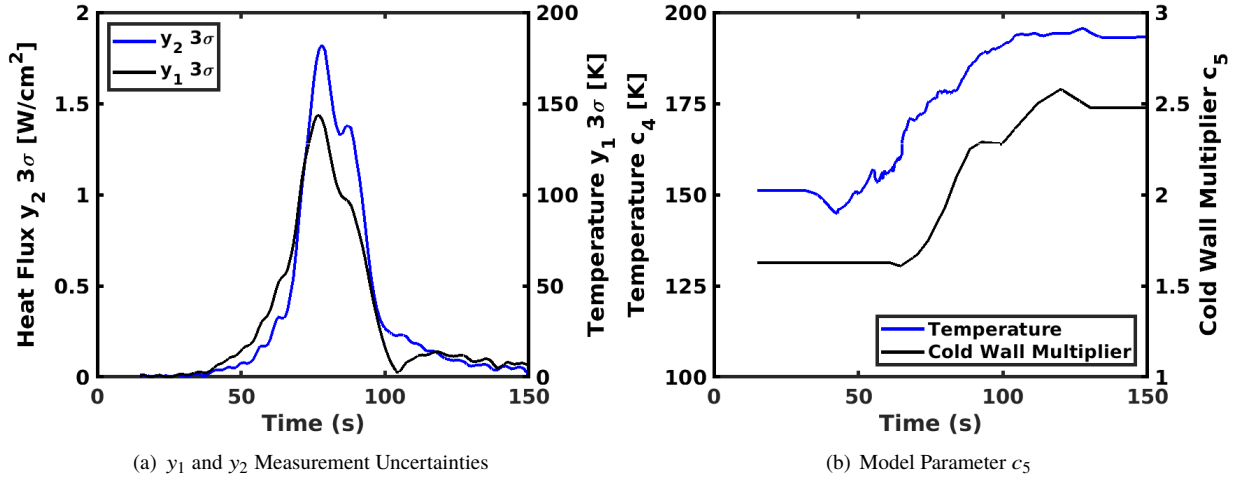


Fig. 4 Measurement Uncertainties and Model Parameters.

The filter residuals, defined as $\Delta \mathbf{y}_k = \mathbf{y}_k - \mathbf{h}(\hat{\mathbf{x}}_{k|n}, \mathbf{c}_k)$, are shown in Figure 5 along with the 3σ uncertainty bounds calculated from the residual covariance. In each case the measurement residuals are within the uncertainty bounds estimated by the filter, indicating the filter provides a reasonable estimate of the state and the corresponding uncertainties.

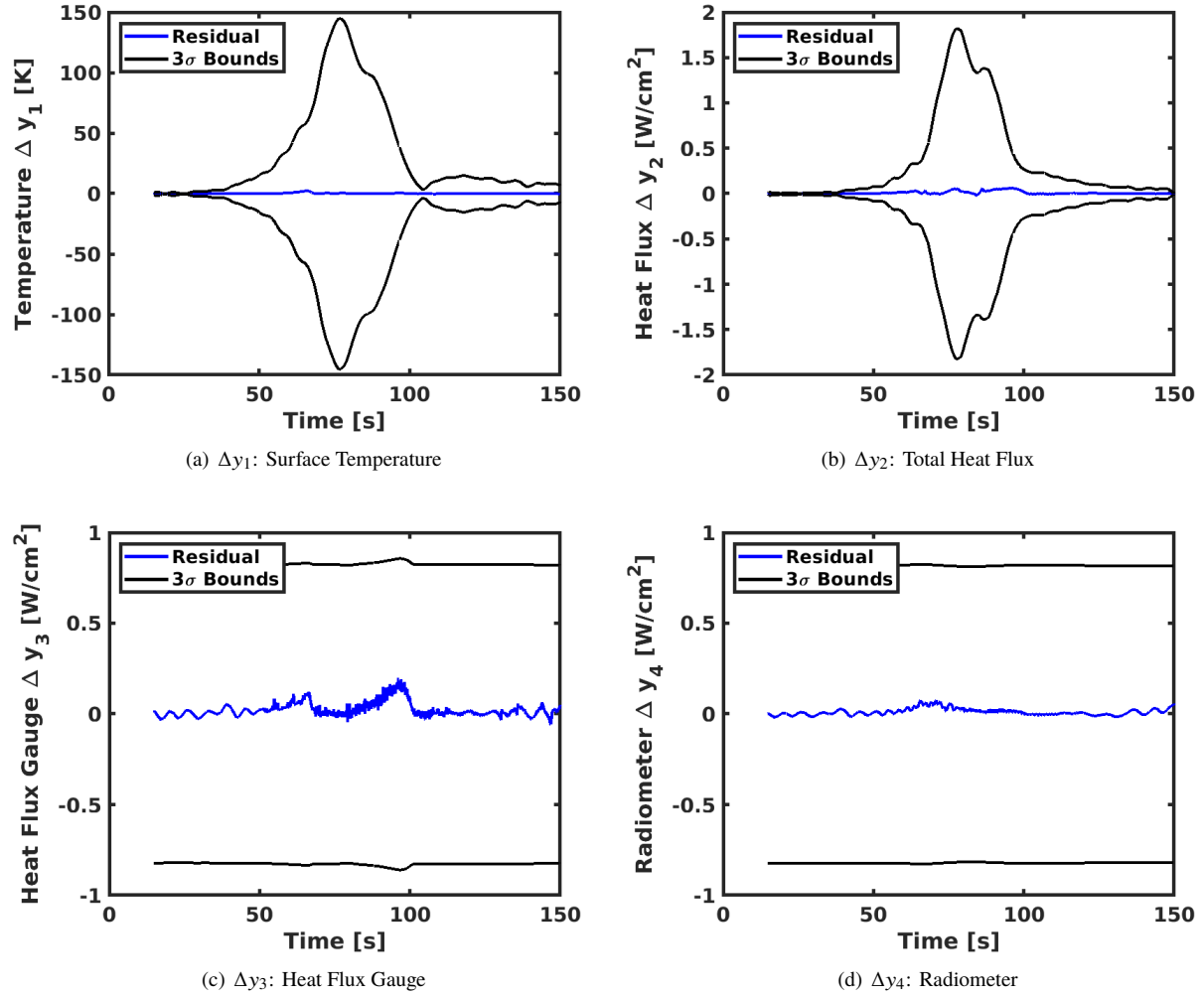


Fig. 5 Measurement Residuals.

The filter state outputs corresponding to the thermal state are shown in Figure 6. The model predictions are also shown for comparison. Figure 6(a) shows the thermal states corresponding to the convective heating (x_1), Figure 6(b) shows the radiative heating (x_2), and Figure 6(c) shows the temperature (x_3). The estimated convective heating is higher than predicted, with a peak value of 0.86 W/cm² compared to the prediction of 0.67 W/cm². The radiative heating component is also higher than predictions with a peak value of 5.16 W/cm² compared to the prediction of 4.83 W/cm². The filter estimate of the peak total heating ($x_1 + x_2$) has a value of 6.01 W/cm² where the prediction was 5.47 W/cm². The peak reconstructed temperature value is 907.3 K compared to the peak prediction based on the filter model of 848.6 K. The thermal state uncertainties are shown in Figure 6(d). The peak convective heating component 3-sigma uncertainty is 0.47 W/cm² and that of the radiative heating component is 0.50 W/cm². The peak 3-sigma reconstructed temperature uncertainty is 39.1 K. Note that the differences between the reconstructed heating values and the predicted values corresponds to the simplified analytical model used in the filter, and not to high-fidelity CFD solutions.

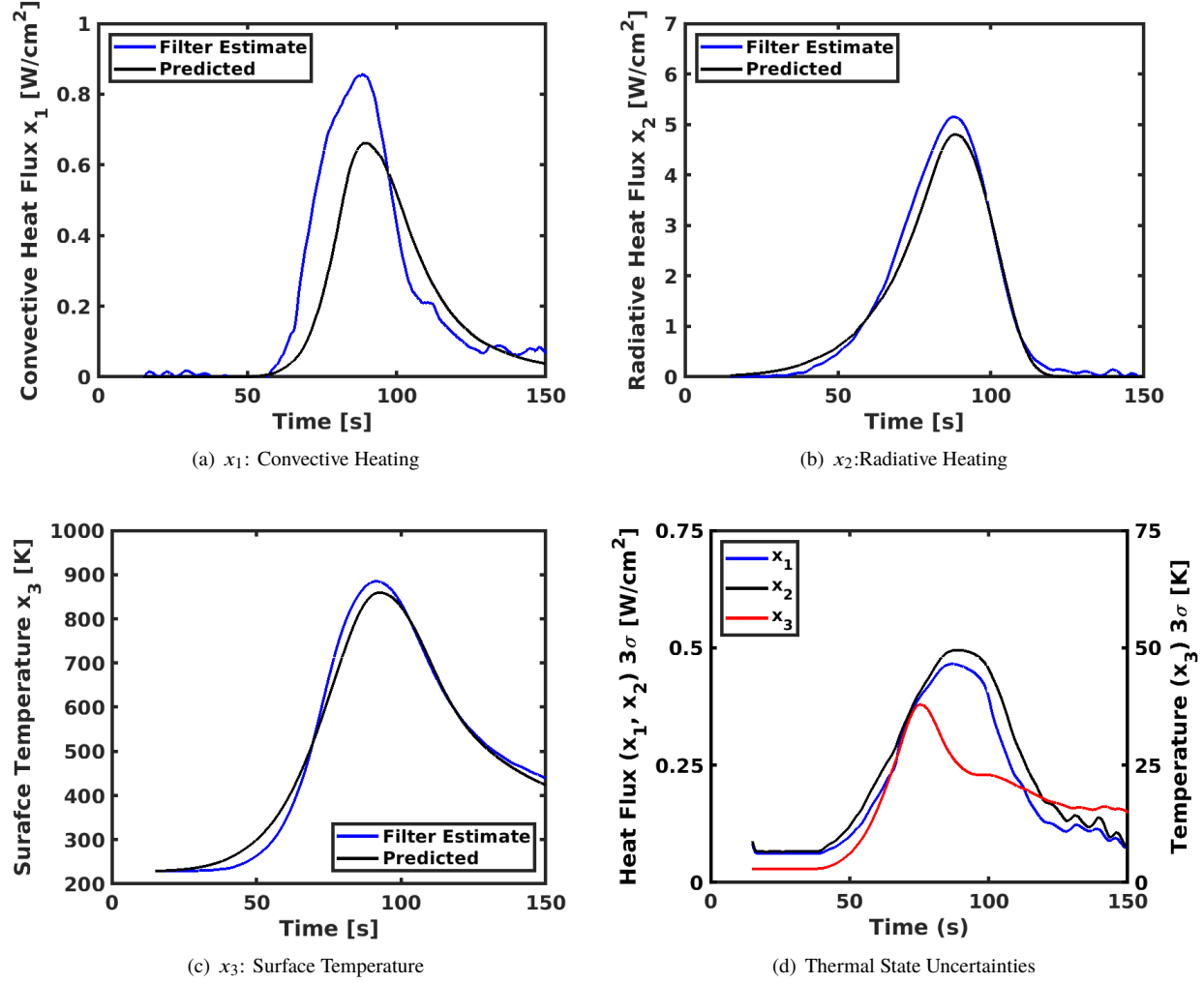


Fig. 6 Comparison of Filter States to Predictions.

The filter multiplicative measurement error state outputs and uncertainties are shown in Figure 7. Figure 7(a) shows the estimates of the multiplicative systematic error parameters corresponding to each measurement equation. The uncertainty estimates based on the filter covariance are shown in Figure 7(b).

The measurement multiplier states take on values that provide a best fit to the measurement data combined with the process model. These states absorb the effects of sensor systematic errors and any unmodeled dynamics neglected by the filter models. The multiplier on the thermal plug-derived temperature and heat rate measurements (x_4 and x_5 , respectively) could make up for potential time lags involved in the material response as part of the inverse analysis [9]. The multiplier on the heat flux gauge measurement (x_6) could compensate for uncertainties in the cold wall correction factor and the sensor's radiative absorption coefficient.

The state x_7 is a multiplier on the radiometer measurement, and represents effects and error sources not captured in the predictive model. One such model inadequacy is believed to be the deposition of ablation products onto the radiometer window, which would attenuate the incoming radiation. The estimate is shown in Figure 8 along with the predicted multiplier from [10], derived from arc-jet testing used to simulate ablation product deposition on radiometer windows. The filter estimate indicates approximately 60% signal loss due to attenuation through the heat pulse. This filter output provides a reasonable estimate of the effect of ablation products obscuring the radiometer measurement compared to testing.

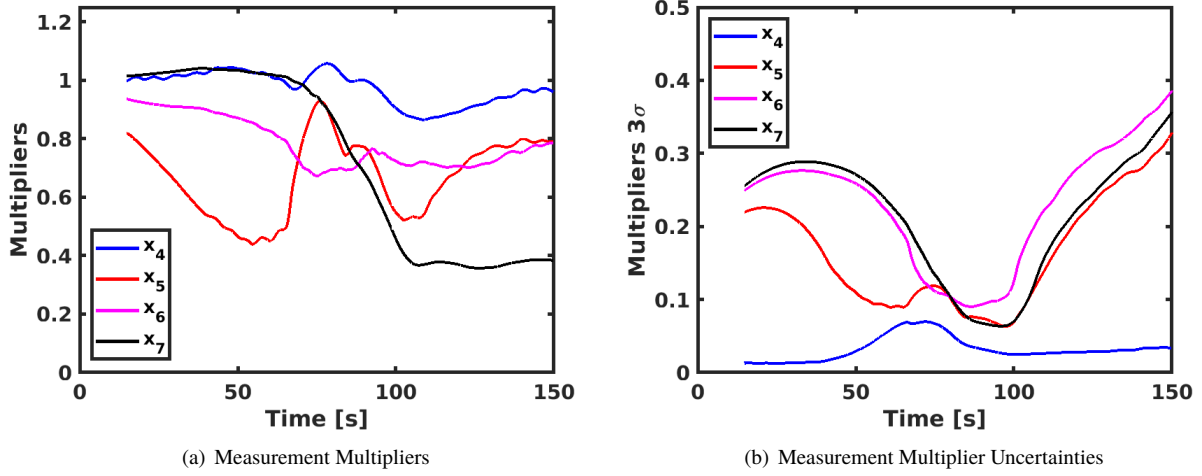


Fig. 7 Filter States and Uncertainties.

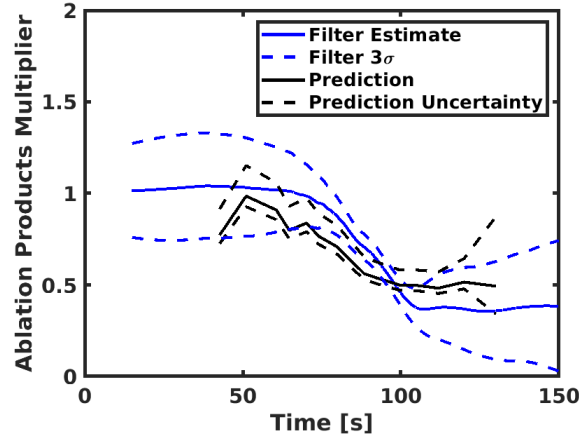


Fig. 8 Ablation Product Multiplier.

IV. Conclusions

A Kalman-Schmidt filter and Rauch-Tung-Striebel smoother approach has been implemented for solving a sensor fusion problem involving three sources of aerothermal measurements co-located on the backshell of the Mars 2020 entry vehicle. A simplified analytical model is used as the basis for the filter state propagation. The measurement update makes use of data from reconstructed surface temperature and total heat rate derived from inverse analysis of embedded thermocouple measurements, and direct measurements of the heating environment from a heat flux gauge and a radiometer. Systematic error parameters are also estimated within the filter-smoother framework. The results of applying the approach to data acquired during the Mars 2020 entry, descent, and landing indicate peak convective and radiative heating values of 0.86 and 5.16 W/cm², respectively, compared to the filter predictive model values of 0.67 and 4.83 W/cm².

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