Data-Fusion of In-Flight Aerothermodynamic Heating Measurements

Kalman Filtering

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Savio J. Poovathingal[1] Christopher D. Karlgaard[4]

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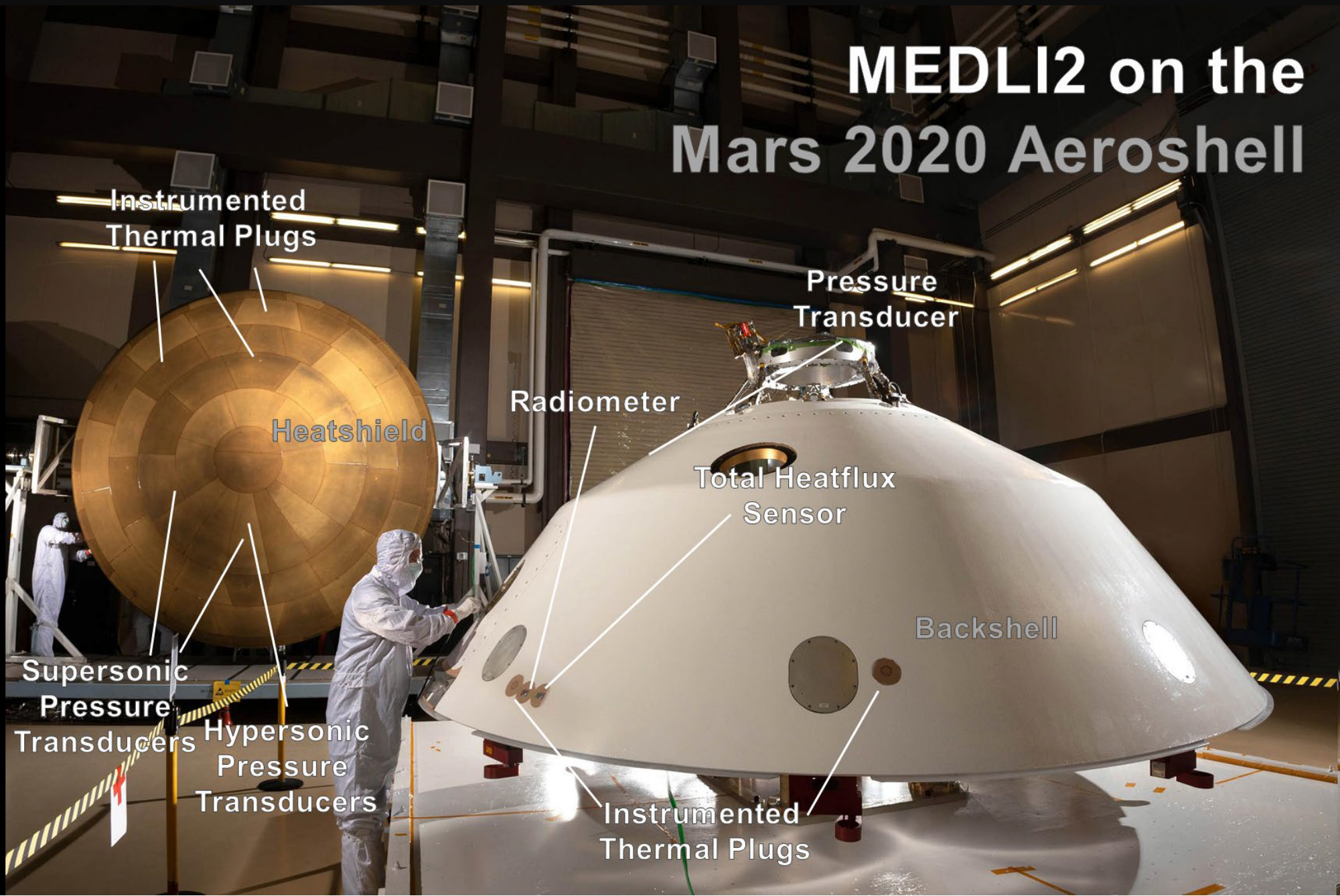
19th International Planetary Probe Workshop

August 11, 2022

Outline

1. Introduction
2. Methods
3. Results
4. Conclusions


MEDLI2 on the
Mars 2020 Aeroshell
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Transducer
Radiometer
Heatshield
Total Heatflux
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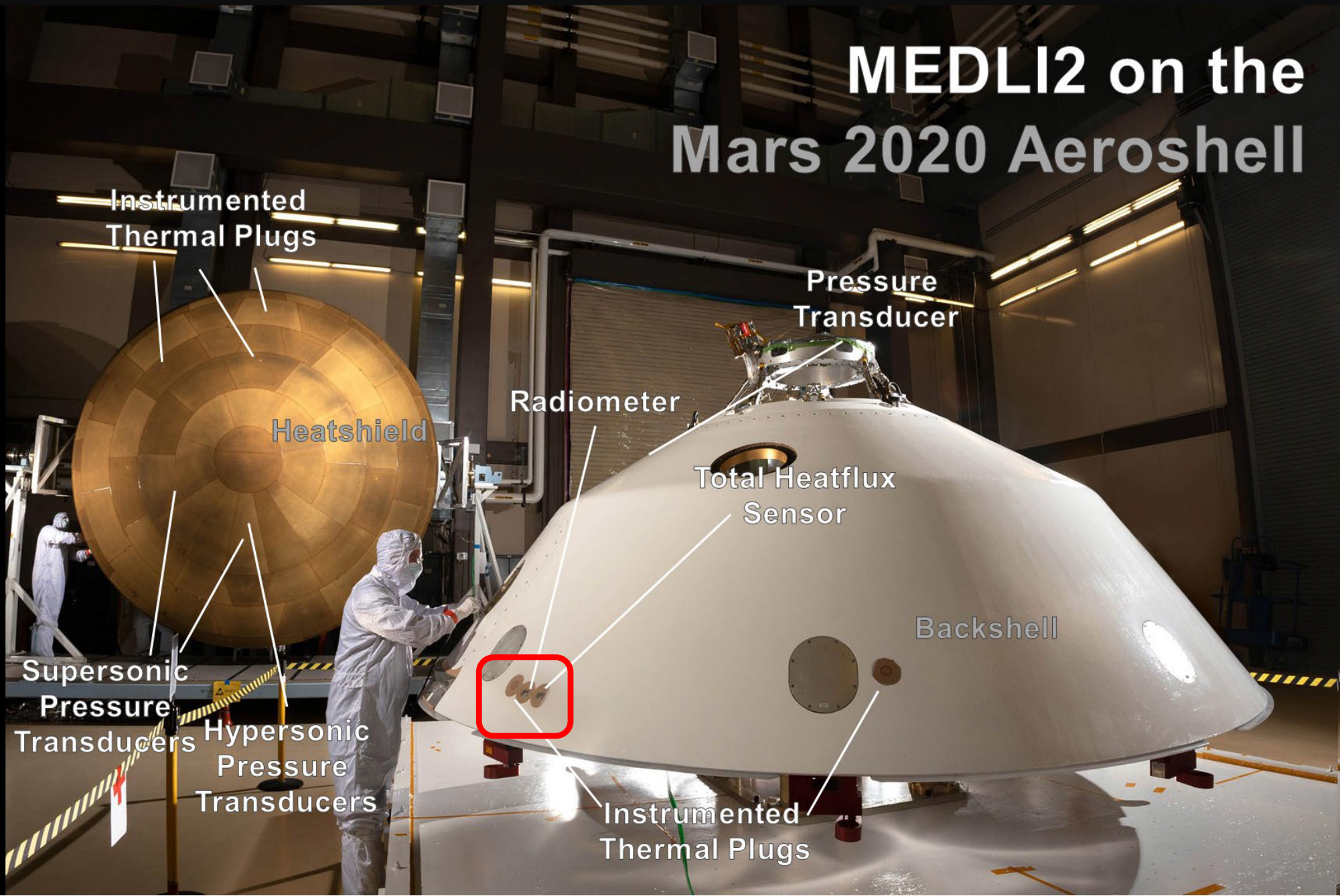
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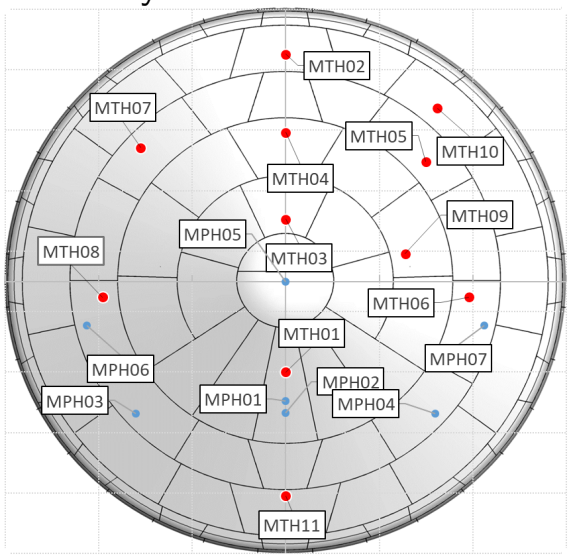

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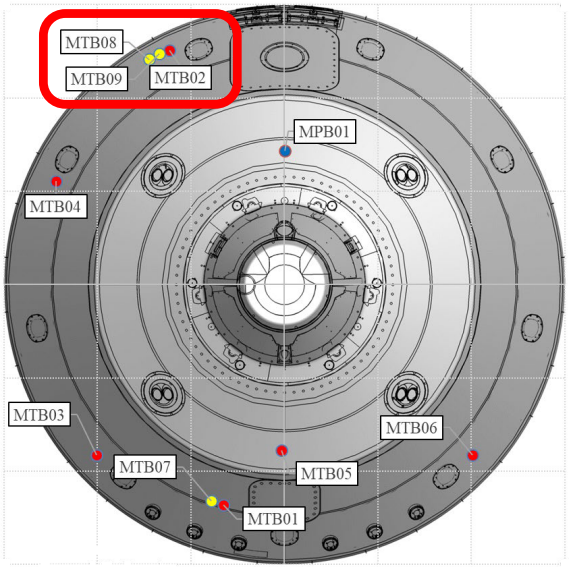
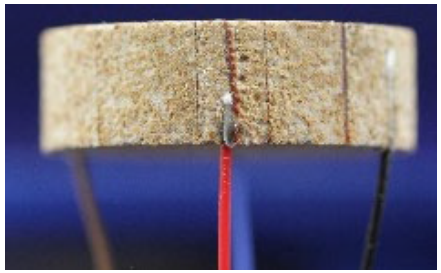


- Three aerothermal sensors colocated on backshell.

MTB02



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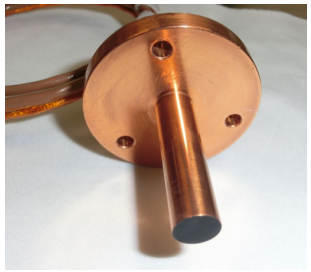

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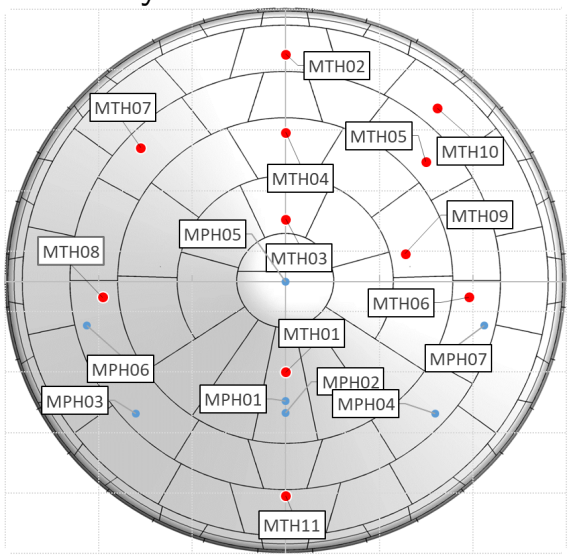

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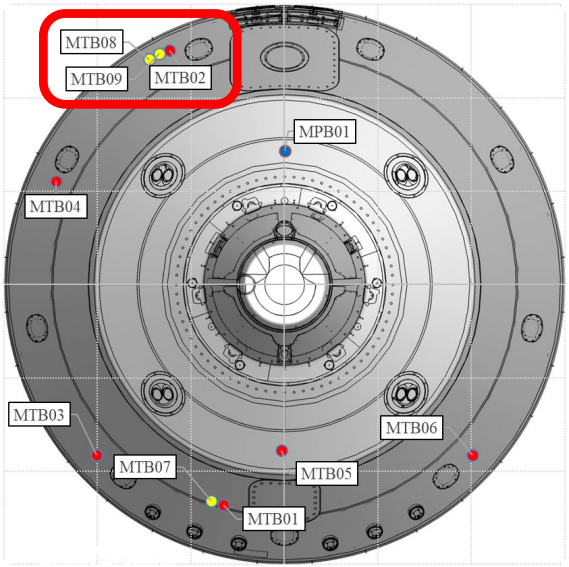

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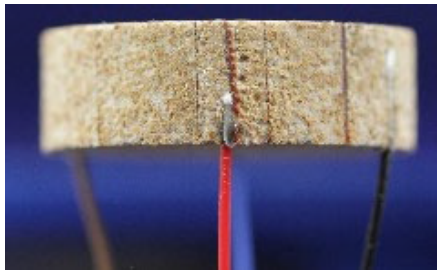

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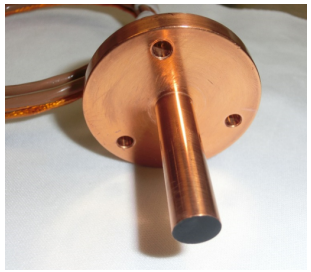

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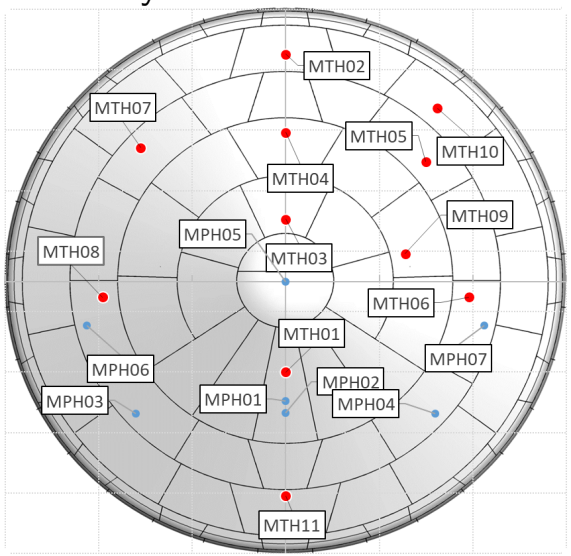

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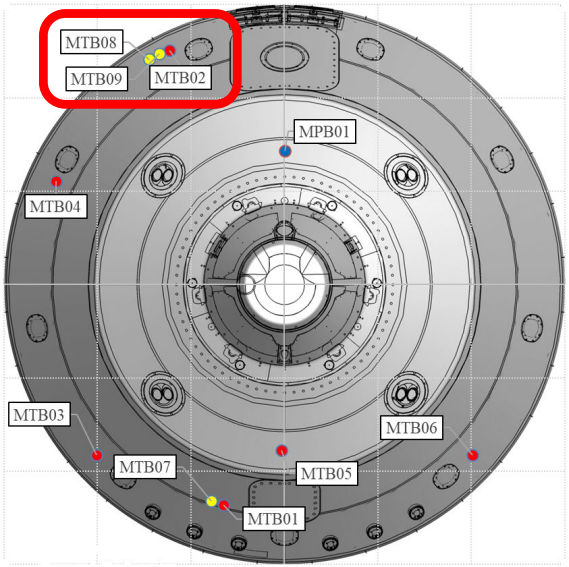

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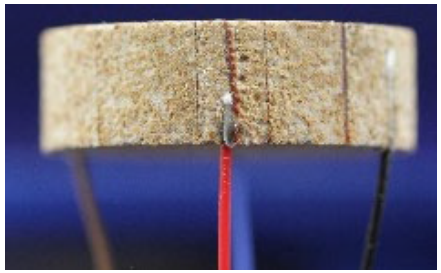

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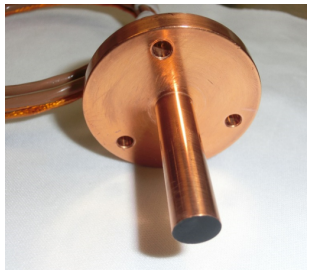

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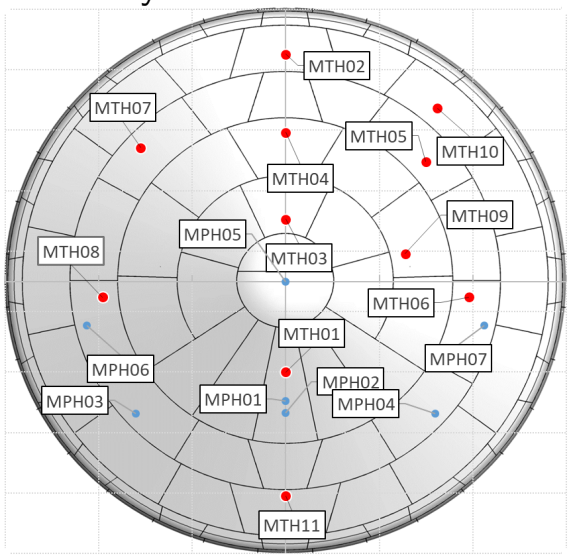

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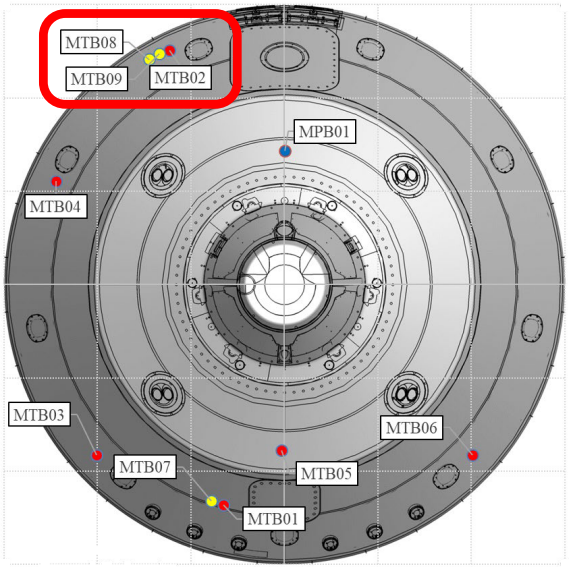

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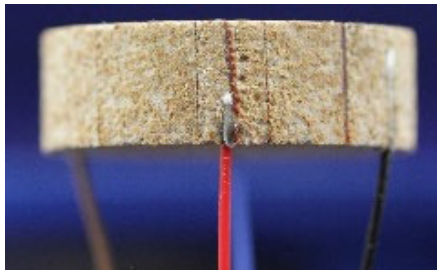

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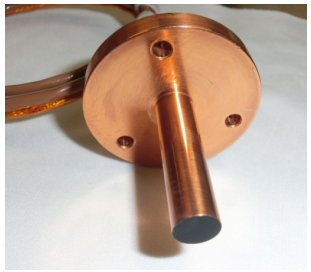

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- MTB09: Radiometer (heat flux gauge behind sapphire window) – isolates the radiative heating.

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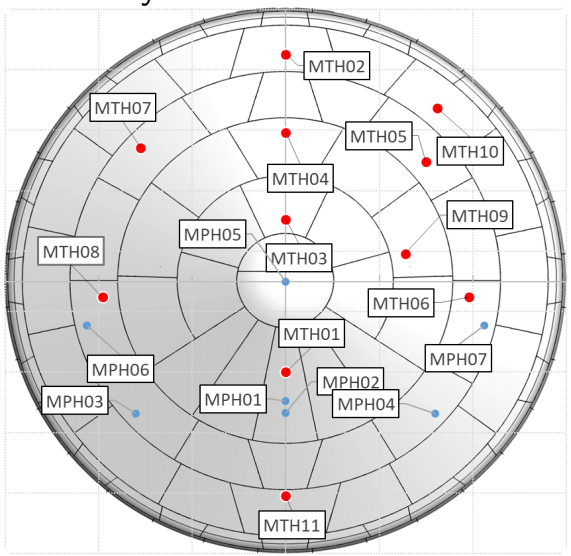

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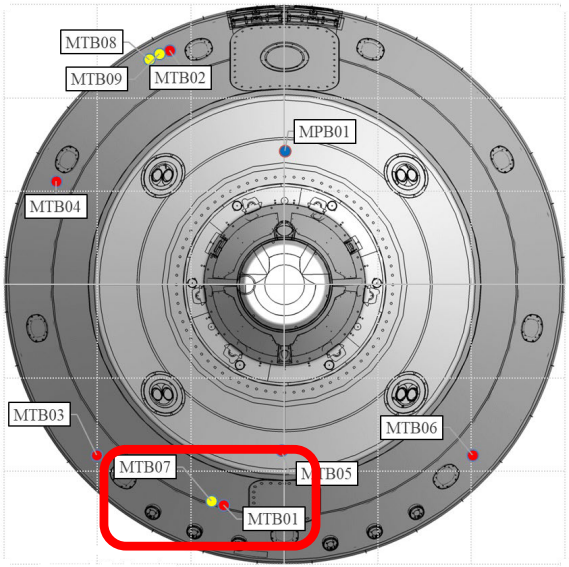

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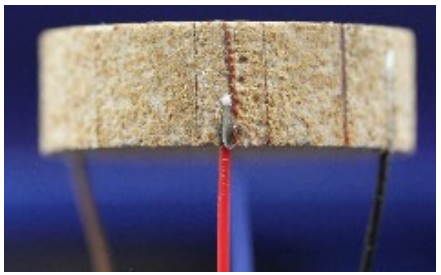

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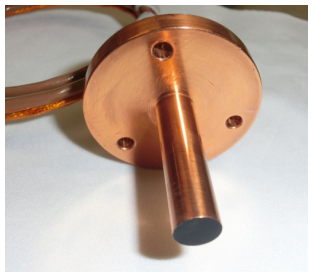

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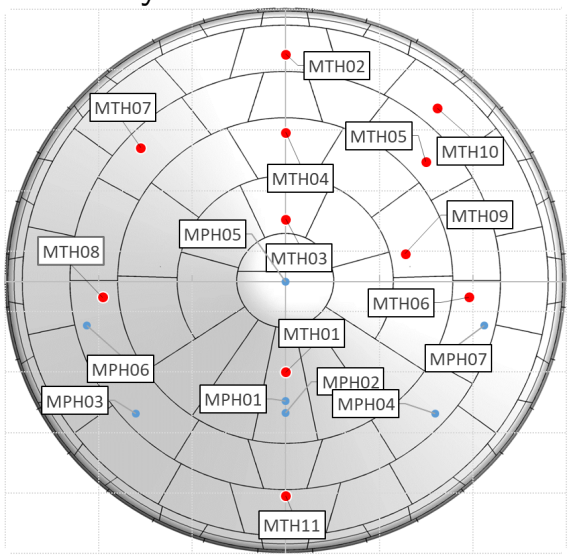

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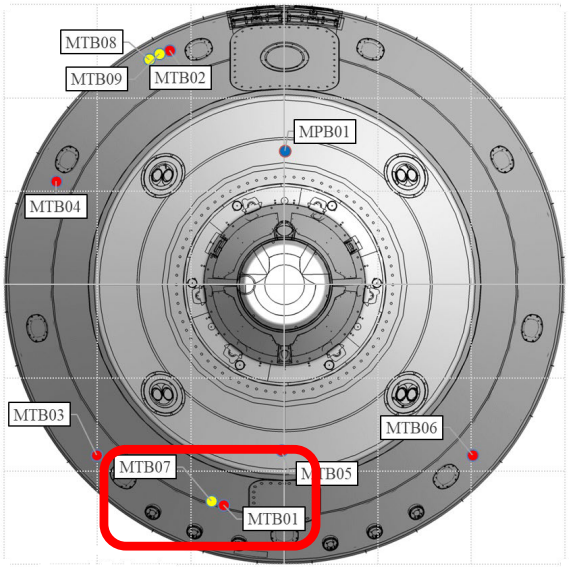

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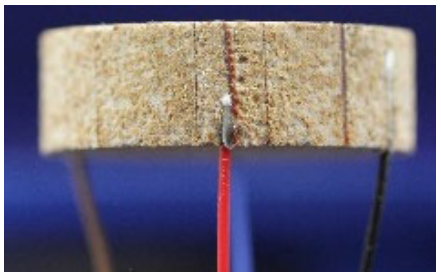

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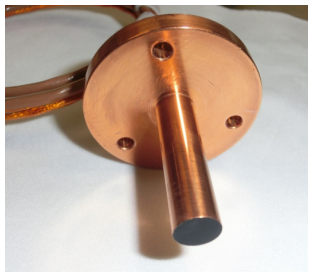

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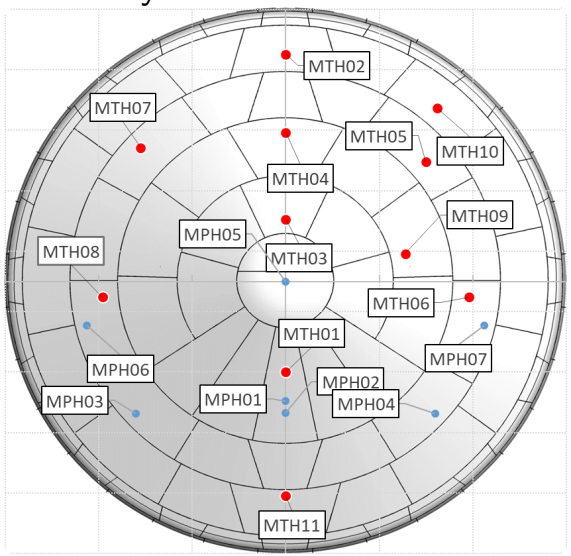

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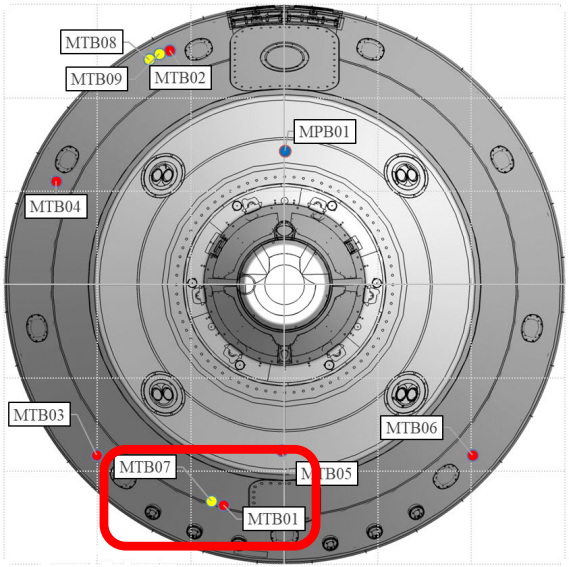

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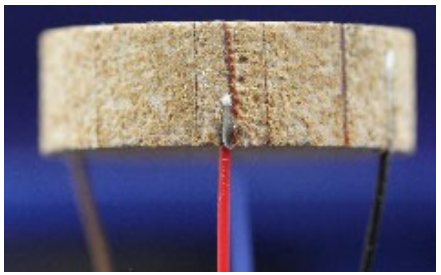

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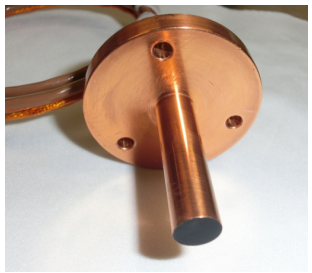

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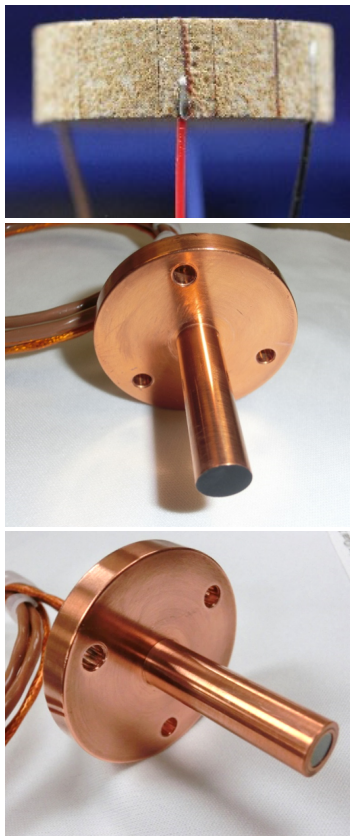
- SLA-561V sensor plug
  - Surface temperature and heating derived from inverse analysis based on material response models.
  - Derived measurements are subject to modeling errors.



Goal

Develop a framework for processing all three measurement sources simultaneously, considering the various sources of measurement errors.

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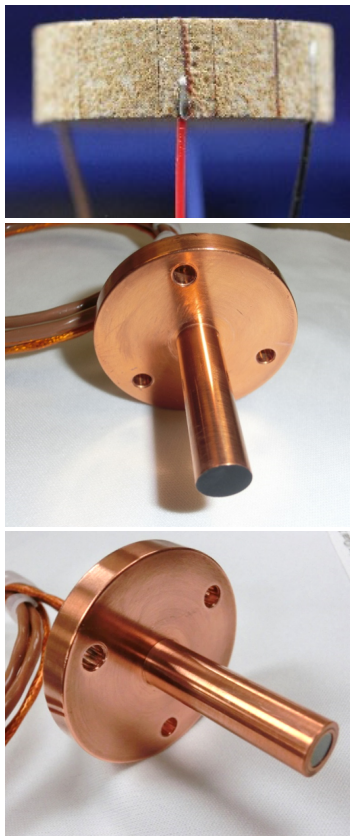
  - Copper housing acts as a heat sink.
  - Cold wall heat flux measurement.



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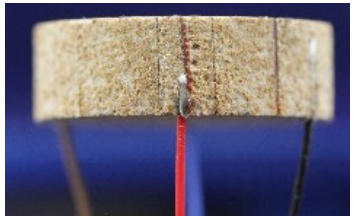
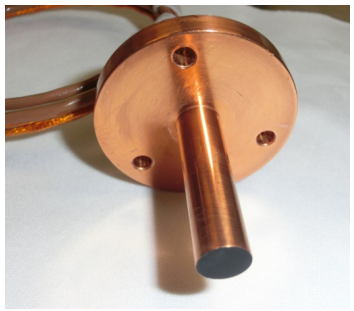
- Radiometer
  - Measurement is subject to attenuation due to ablation products depositing on the sapphire window.





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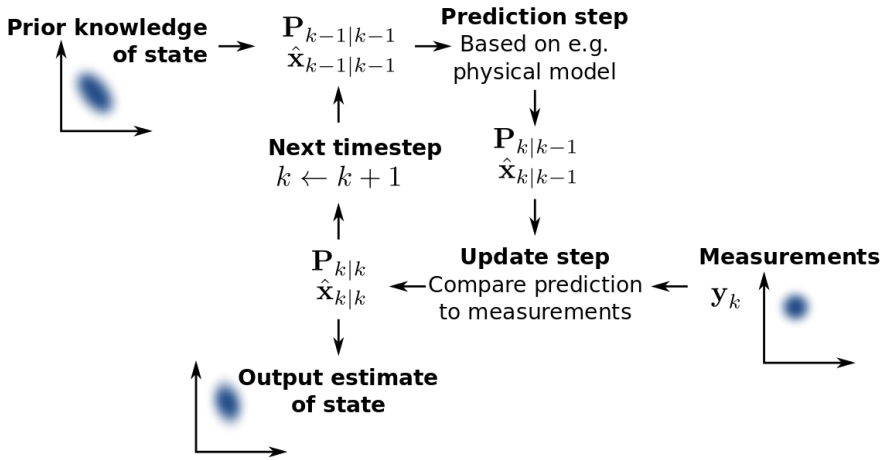
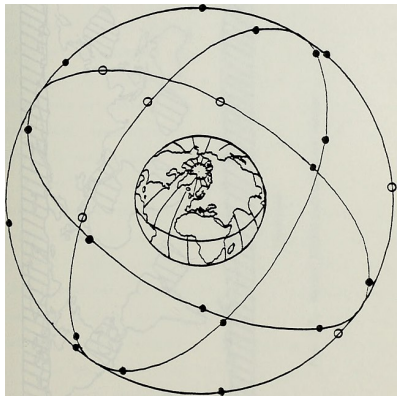
- Also known as *linear quadratic estimation*.
- Produces estimates of unknown states which can be more accurate than single measurements.
- Useful when many noisy measurements are present and the best estimation of some states are desired.



Source: Gufosowa (2019).



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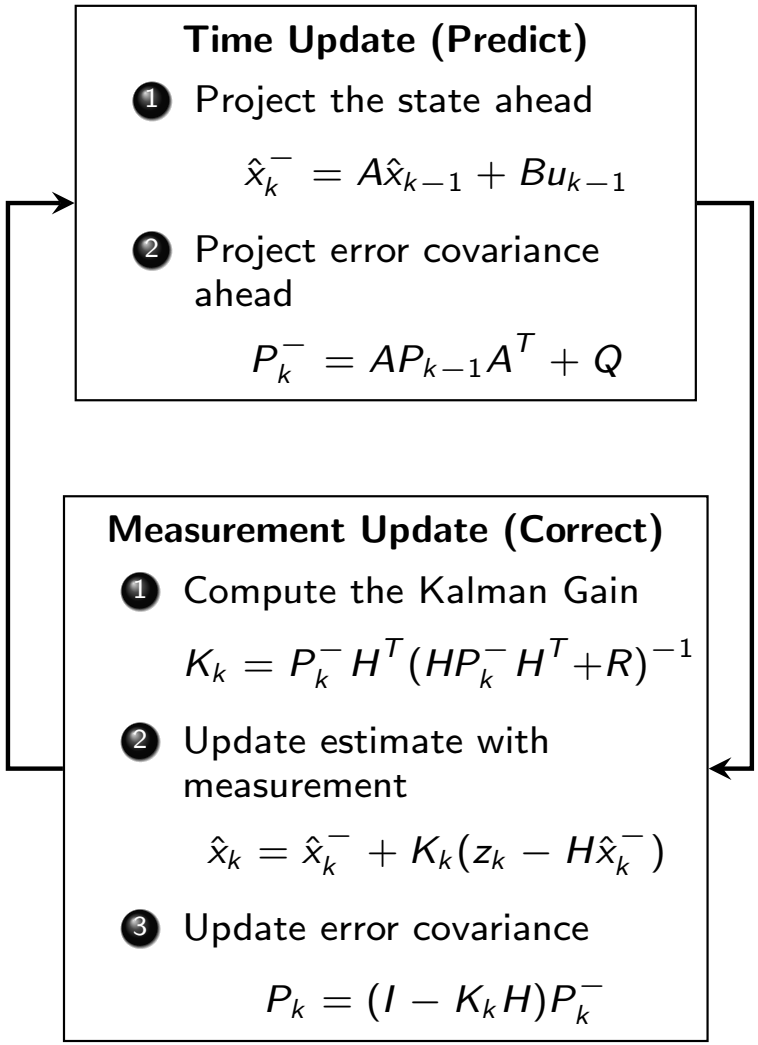
Kalman Filtering Algorithm

Built Matlab program to Kalman filter a general set of measurements/processes.



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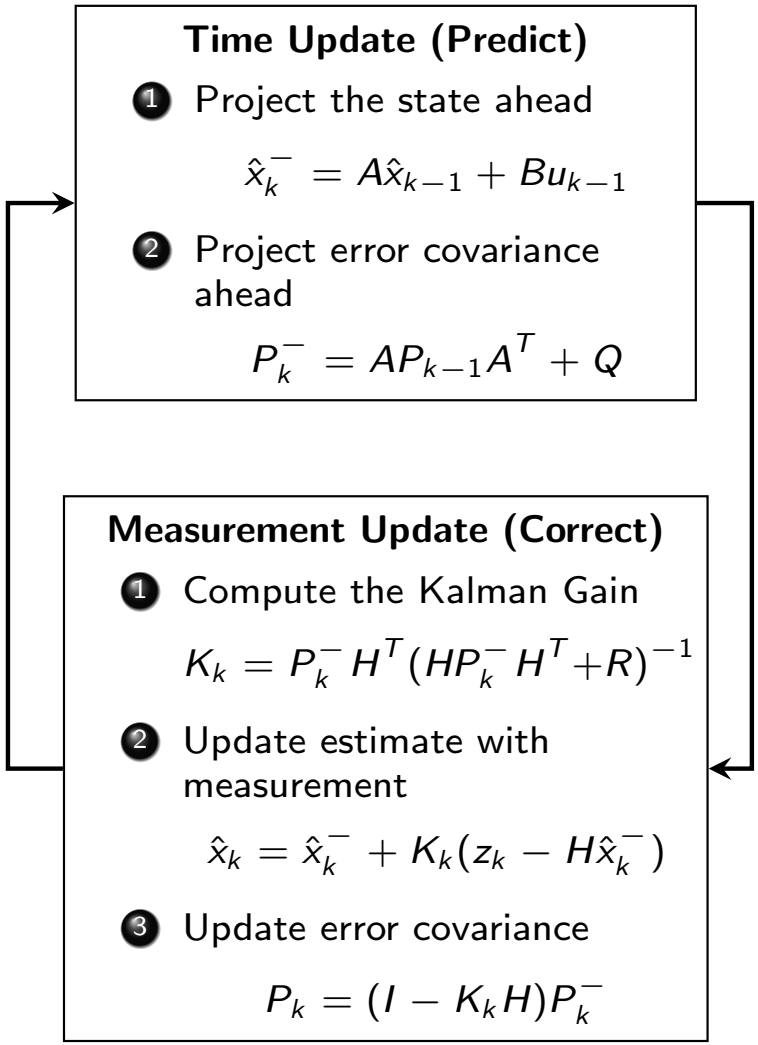

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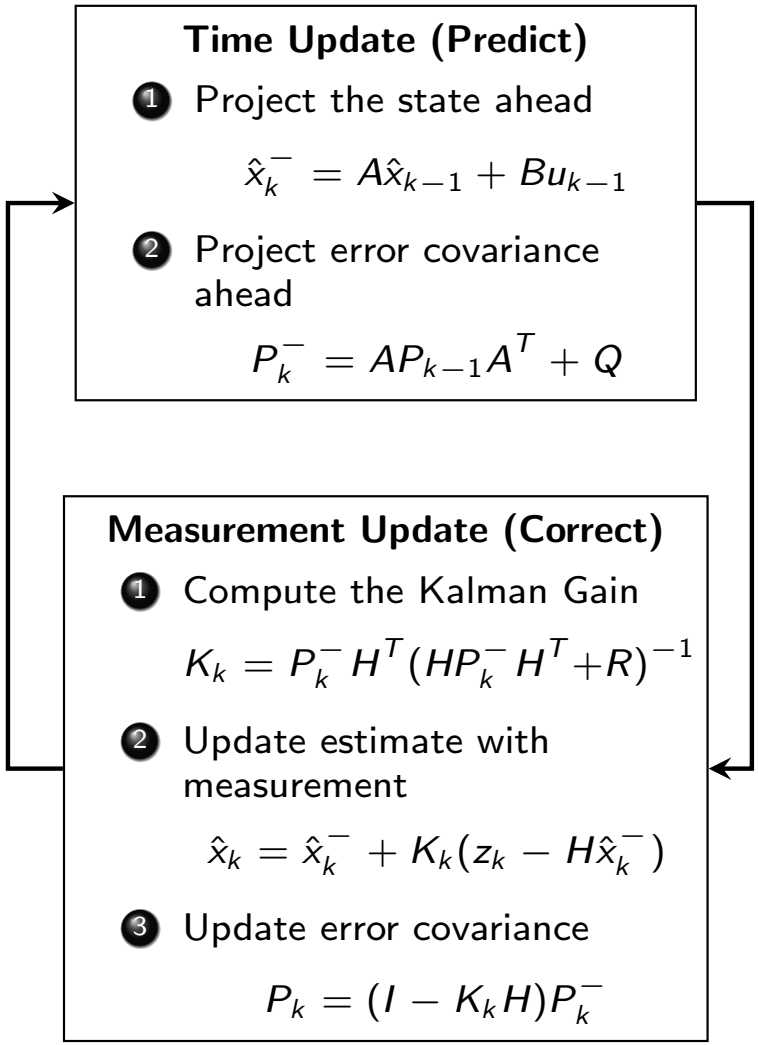

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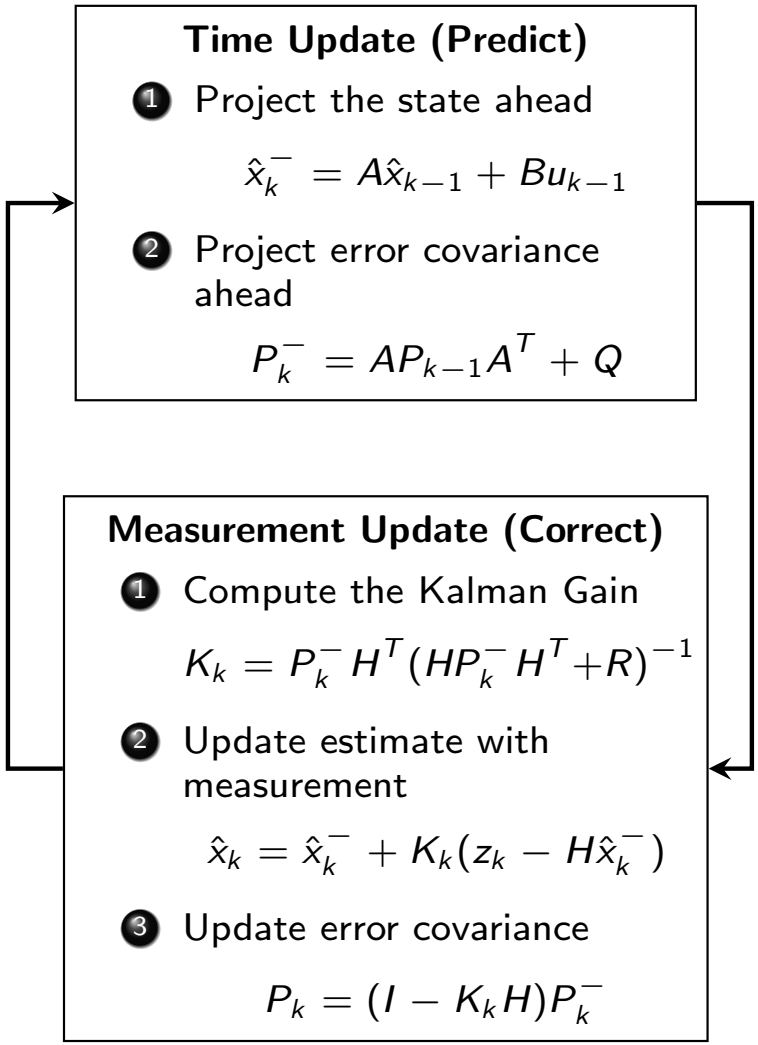

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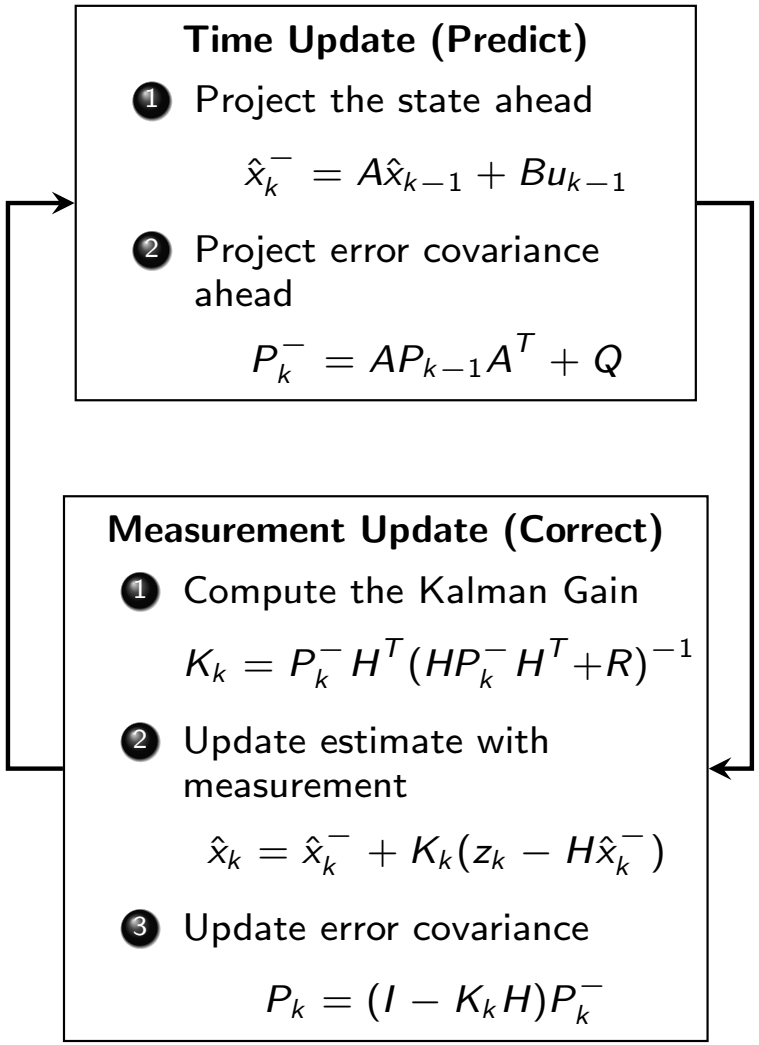
For a nonlinear system the *extended* Kalman filter is required, where $A = \frac{\partial f(x)}{\partial x}$ and $H = \frac{\partial h(x)}{\partial x}$.



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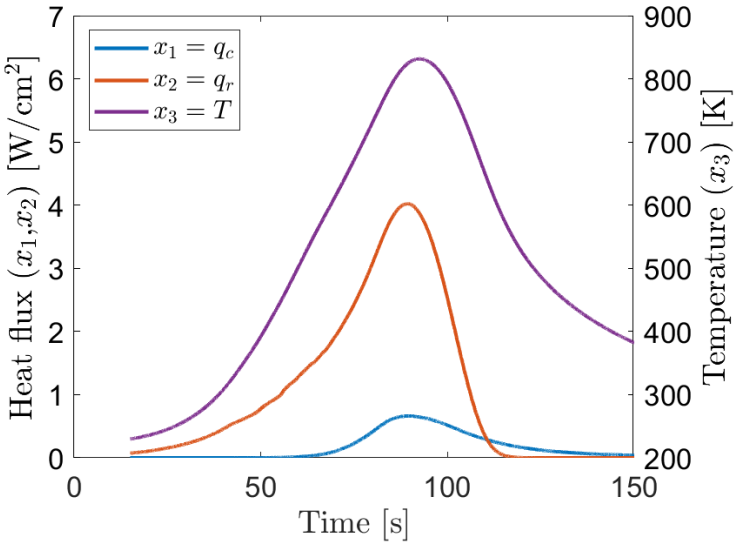
$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, t) + \mathbf{B}\mathbf{u}$$



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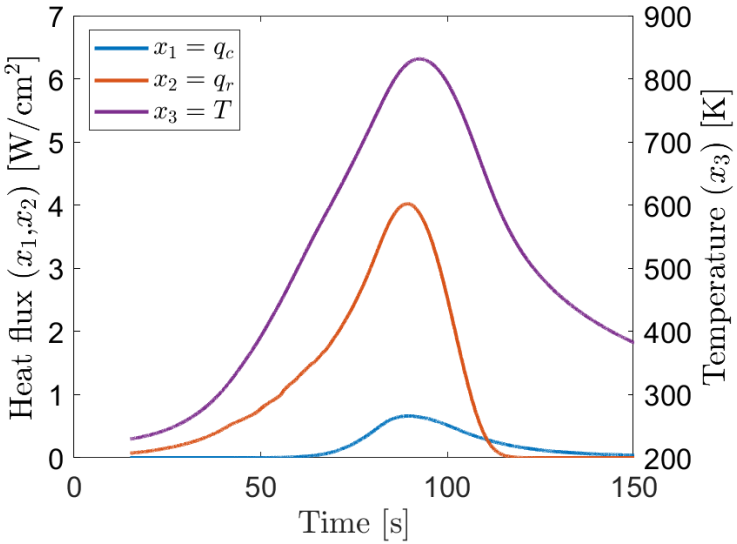
Convective/radiative heating correlations:

$$q_c = A_c \rho^{B_c} V^{C_c}$$

$$q_r = A_r \left(\rho_{\mathrm{CO}}\right)^{B_r} \left(\rho_{\mathrm{CO_2}}\right)^{C_r} T^{D_r}$$

Surface temperature based on energy balance without blowing or ablation:

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



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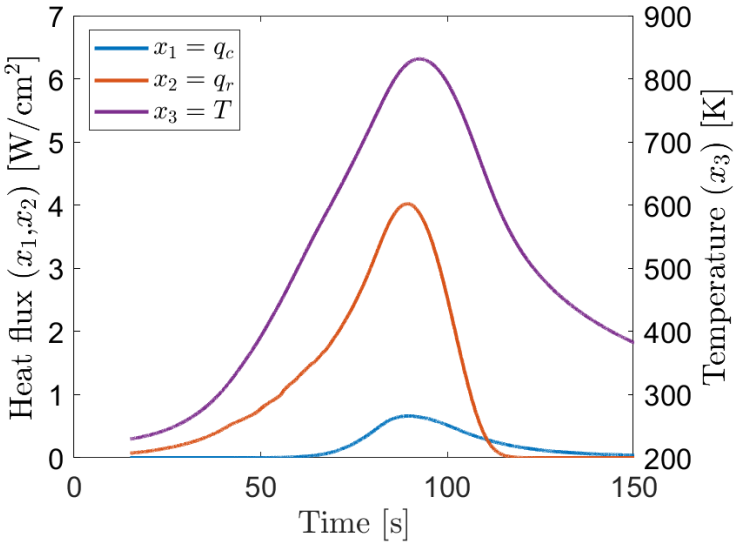
$$\dot{T} = c_1 \left(q_c + c_2 q_r\right) - c_1 c_3 \kappa \left(T^4 - c_4^4\right)$$



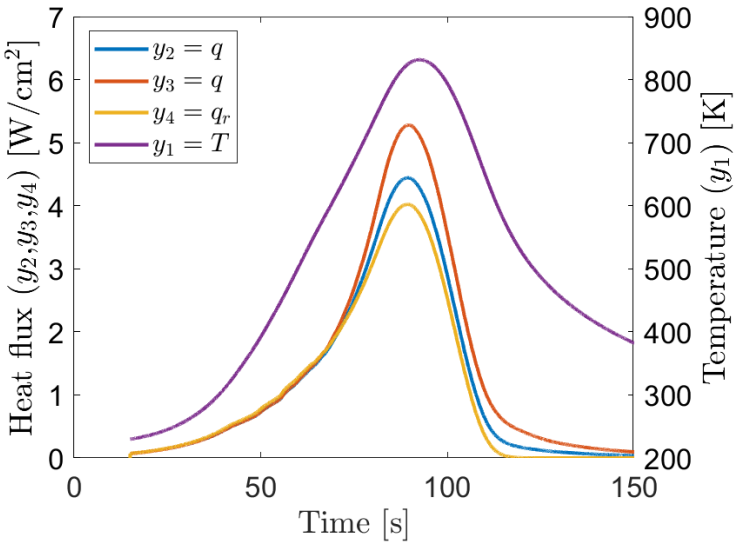
Process model:

- x_1: Convective heat rate
- x_2: Radiative heat rate
- x_3: Surface temperature
- $x_4 - x_7$: Multiplicative error states

$$\mathbf{x} = \begin{bmatrix} q_c \\ q_r \\ T \\ x_4 \\ x_5 \\ x_6 \\ x_7 \end{bmatrix}, \quad \mathbf{u} = \begin{bmatrix} \dot{q}_c \\ \dot{q}_r \end{bmatrix}, \quad \mathbf{f} = \begin{bmatrix} 0 \\ 0 \\ \dot{T} \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad \mathbf{B} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Measurements:

- y_1: Surface temperature derived from TC plug inverse analysis
- y_2: Heat rate derived from TC plug inverse analysis
- y_3: Total heat rate measurement from heat flux gauge
- y_4: Radiative heating component from radiometer



[2] J. Monk et al. *AIAA SciTech 2022 Forum*. 2022, p. 0549.
[3] R. A. Miller et al. *2018 Joint Thermophysics and Heat Transfer Conference*. 2018, p. 3590.

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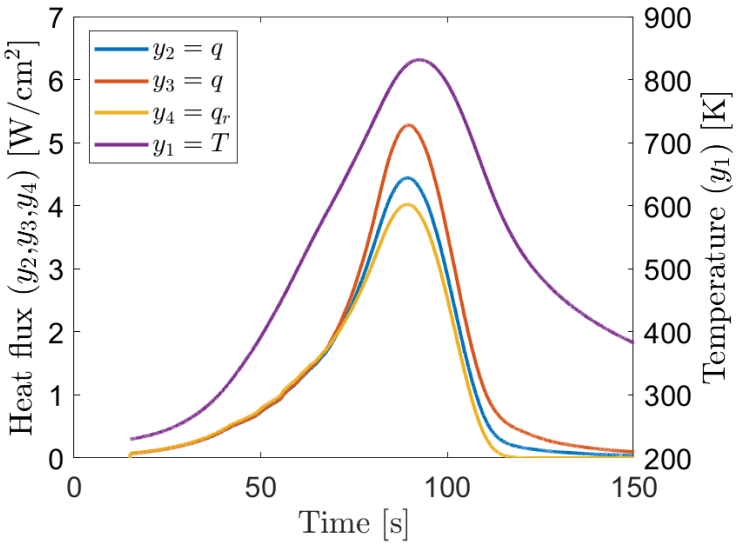

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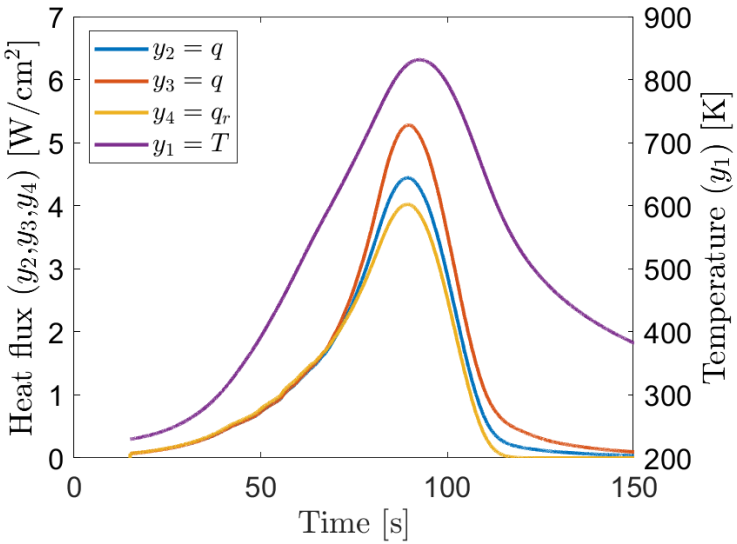

Parameters:

- c_1: Inverse of thermal conductivity.[2]
- c_2: SLA-561V radiative absorption coefficient.
- c_3: Surface emissivity.
- c_4: Freestream temperature.
- c_5: Cold wall heat flux correction factor.[3]
- c_6: Heat flux gauge radiative absorption coefficient.
- c_7: Radiometer view factor.

[2] J. Monk et al. *AIAA SciTech 2022 Forum*. 2022, p. 0549.
[3] R. A. Miller et al. *2018 Joint Thermophysics and Heat Transfer Conference*. 2018, p. 3590.

Filter model:

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}, t) + \mathbf{B}\mathbf{u}$$

Convective/radiative heating correlations:

$$q_c = A_c \rho^{B_c} V^{C_c}$$

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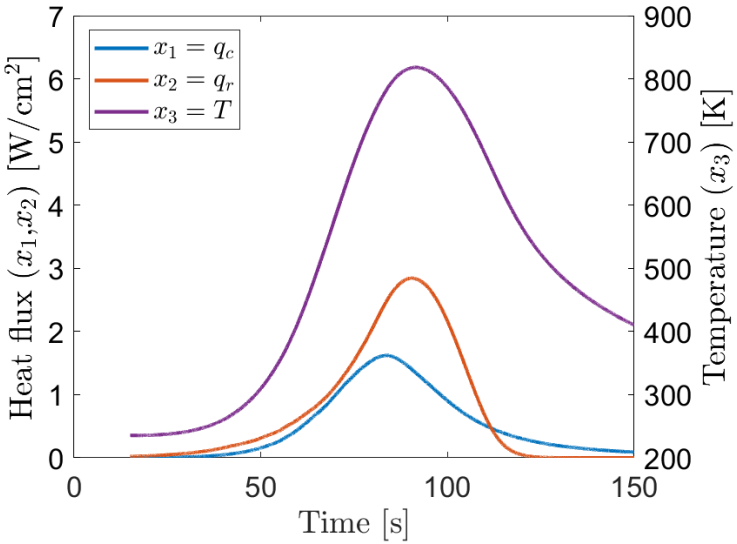

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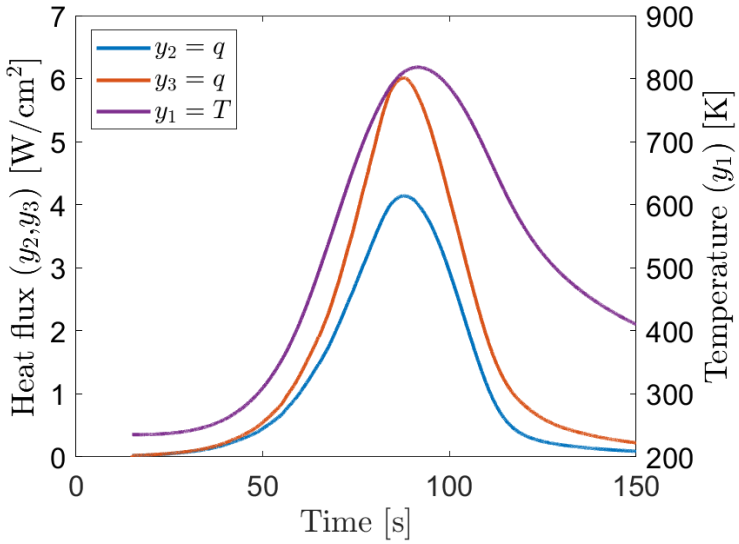

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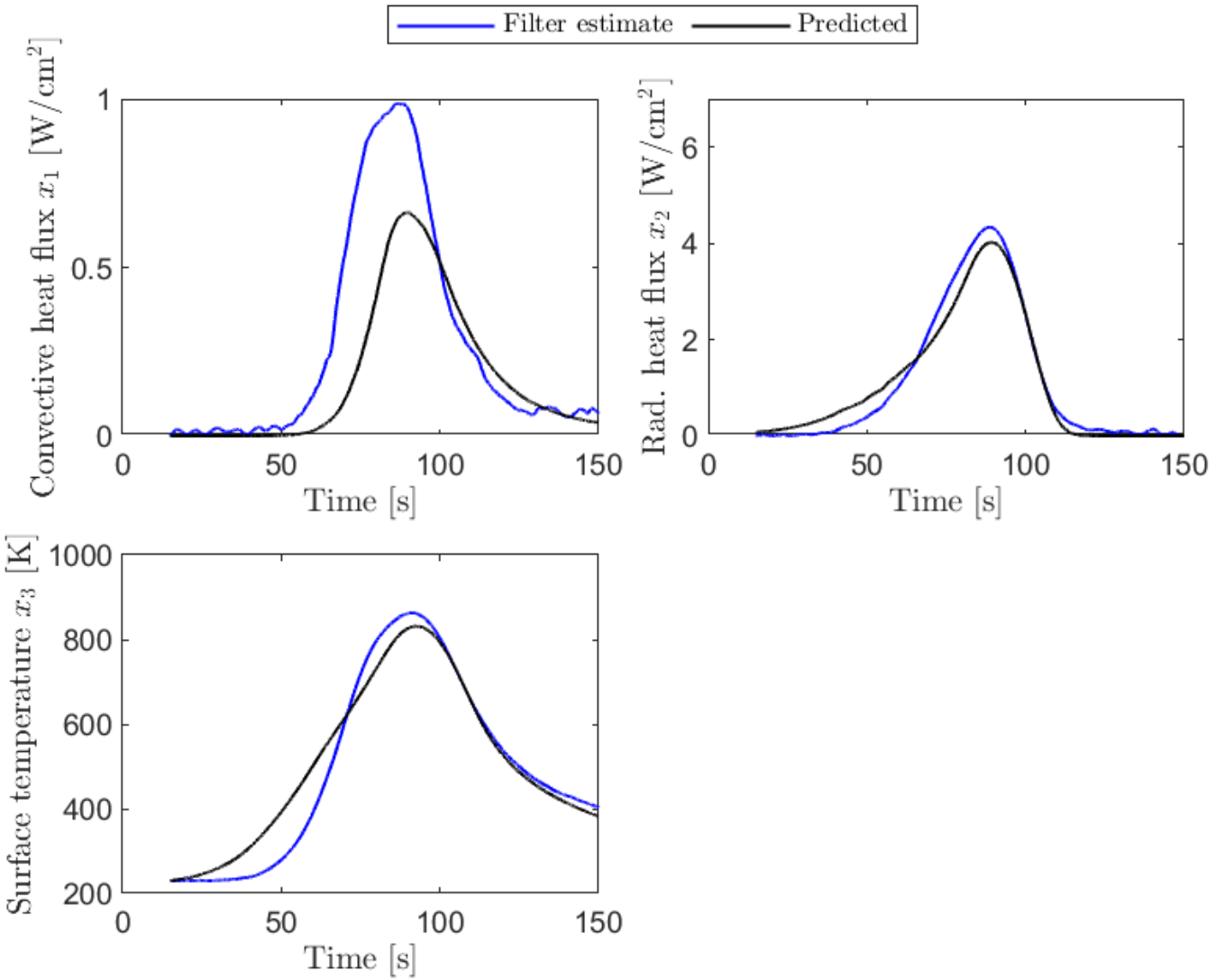

Figure: States predicted by the filter model and the filtered result.

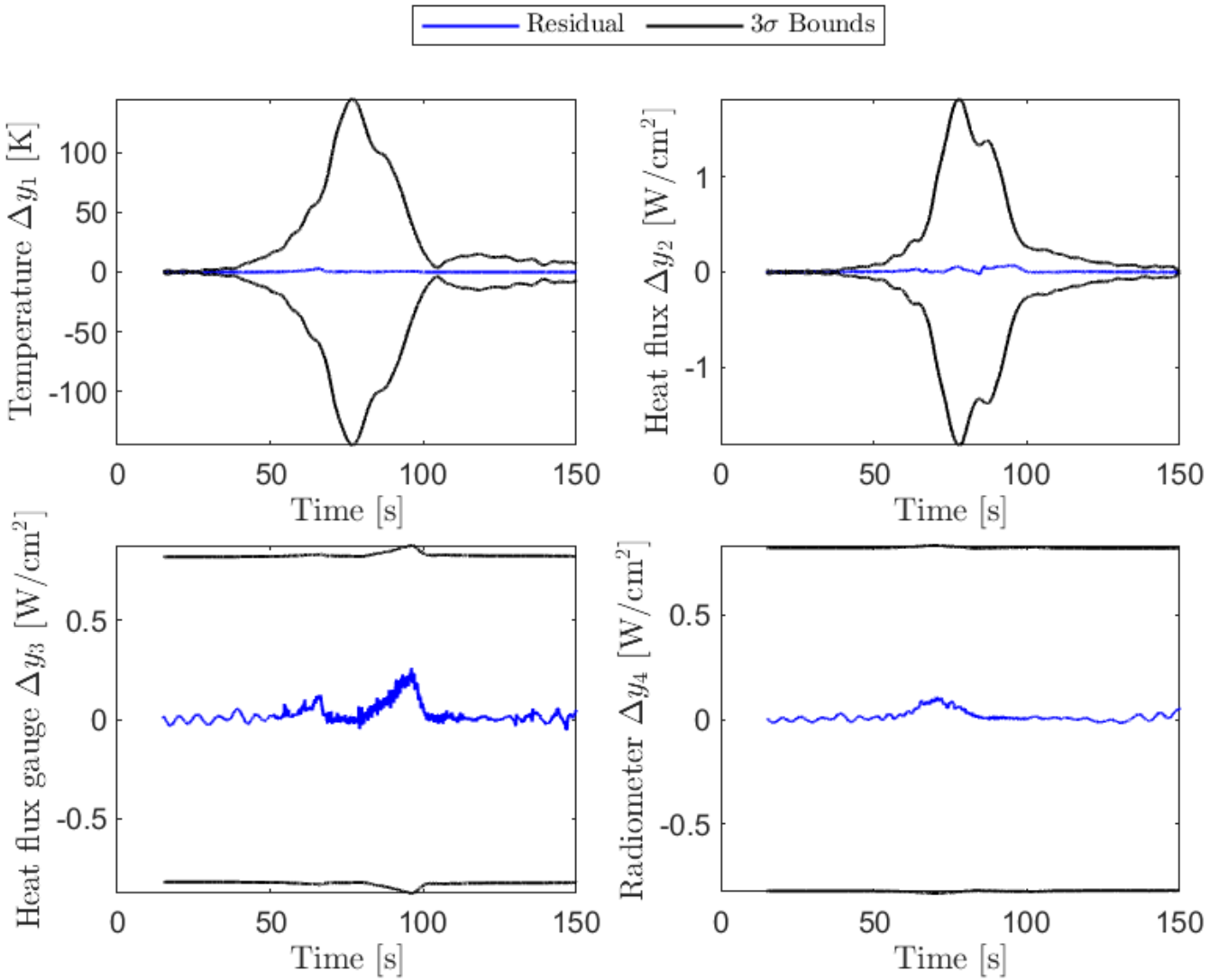

Figure: Measurement residuals.

$$\mathbf{y} = \begin{bmatrix} T_{\text{MTB02}} \\ q_{\text{MTB02}} \\ q_{\text{MTB08}} \\ q_{\text{r,MTB09}} \end{bmatrix} = \begin{bmatrix} x_4 x_3 \\ x_5 \left(x_1 + c_2 x_2\right) \\ x_6 \left(c_5 x_1 + c_6 x_2\right) \\ c_7 x_7 x_2 \end{bmatrix} = \mathbf{h}(\mathbf{x}, \mathbf{c})$$

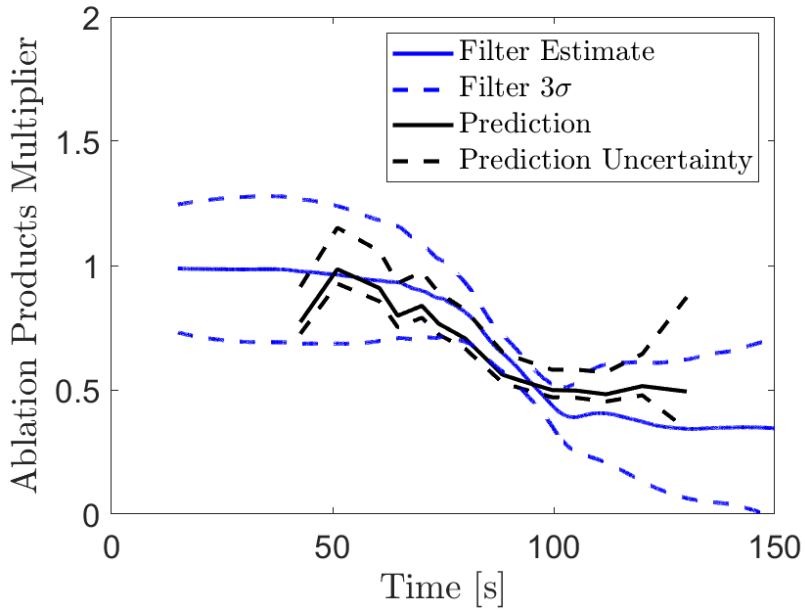

Figure: Filter estimate of ablation products blockage factor.

[6] R. A. Miller et al. *AIAA SciTech 2022 Forum*. 2022, p. 0551.

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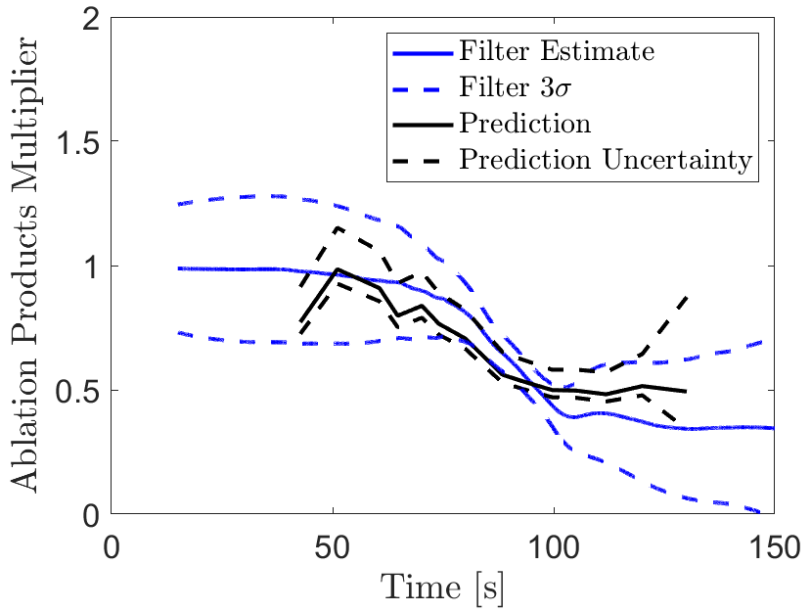

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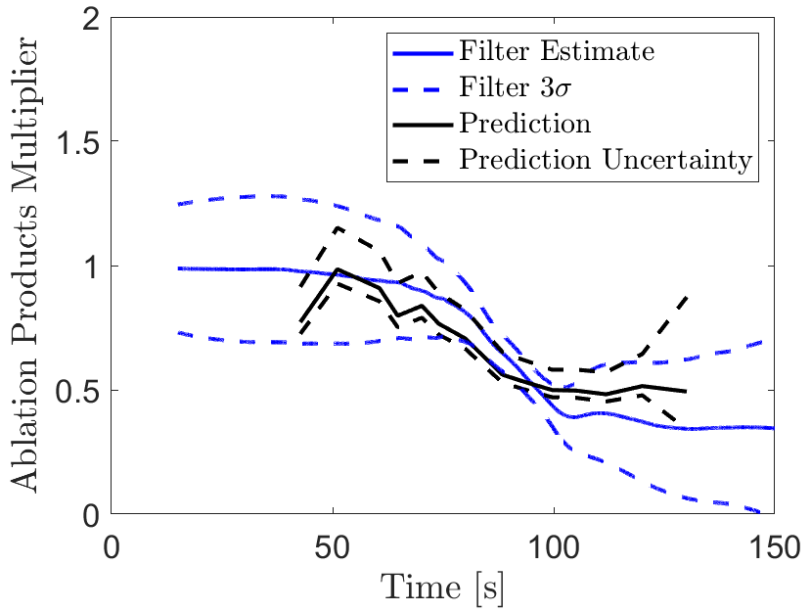

Figure: Filter estimate of ablation products blockage factor.

- Ablation products blockage factor x_7 compares well with predictions by Miller et al.[6]

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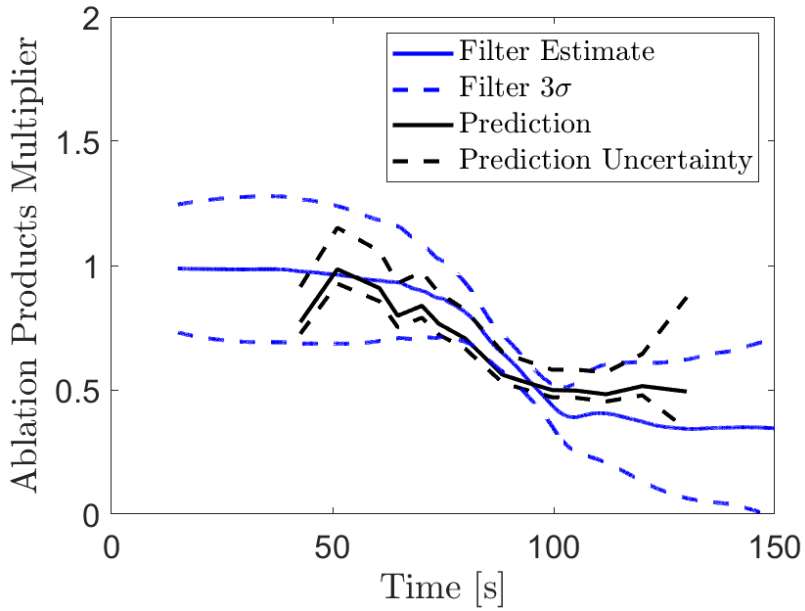

Figure: Filter estimate of ablation products blockage factor.

- Ablation products blockage factor x_7 compares well with predictions by Miller et al.[6]
- Up to ≈60% loss in radiometer signal at the end of entry sequence.

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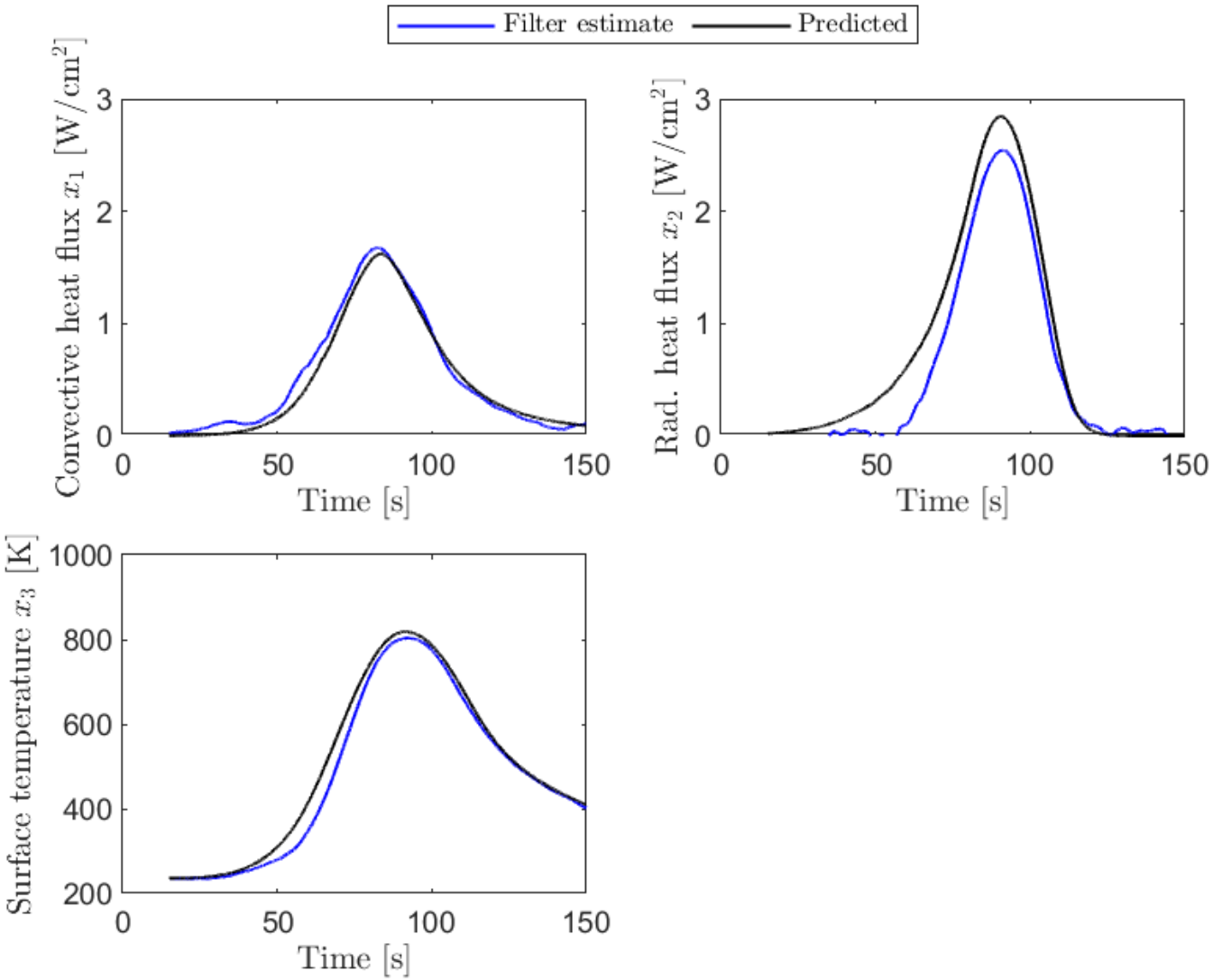

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Future work:

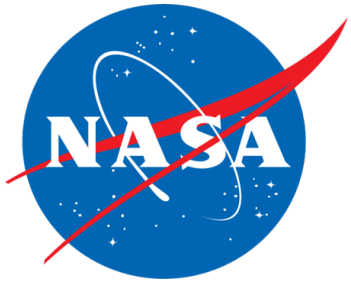
- Further investigate cold wall correction factor.
- Develop future applications of this approach for aerothermal problems.

Acknowledgements

Thank you!

- Mentors Chris Karlgaard and Tom West
- Ruth Miller
- Joshua Monk
- Todd White
- Aaron Brandis

Supported in part by NASA Kentucky Space Grant Fellowship #80NSSC20M0047.



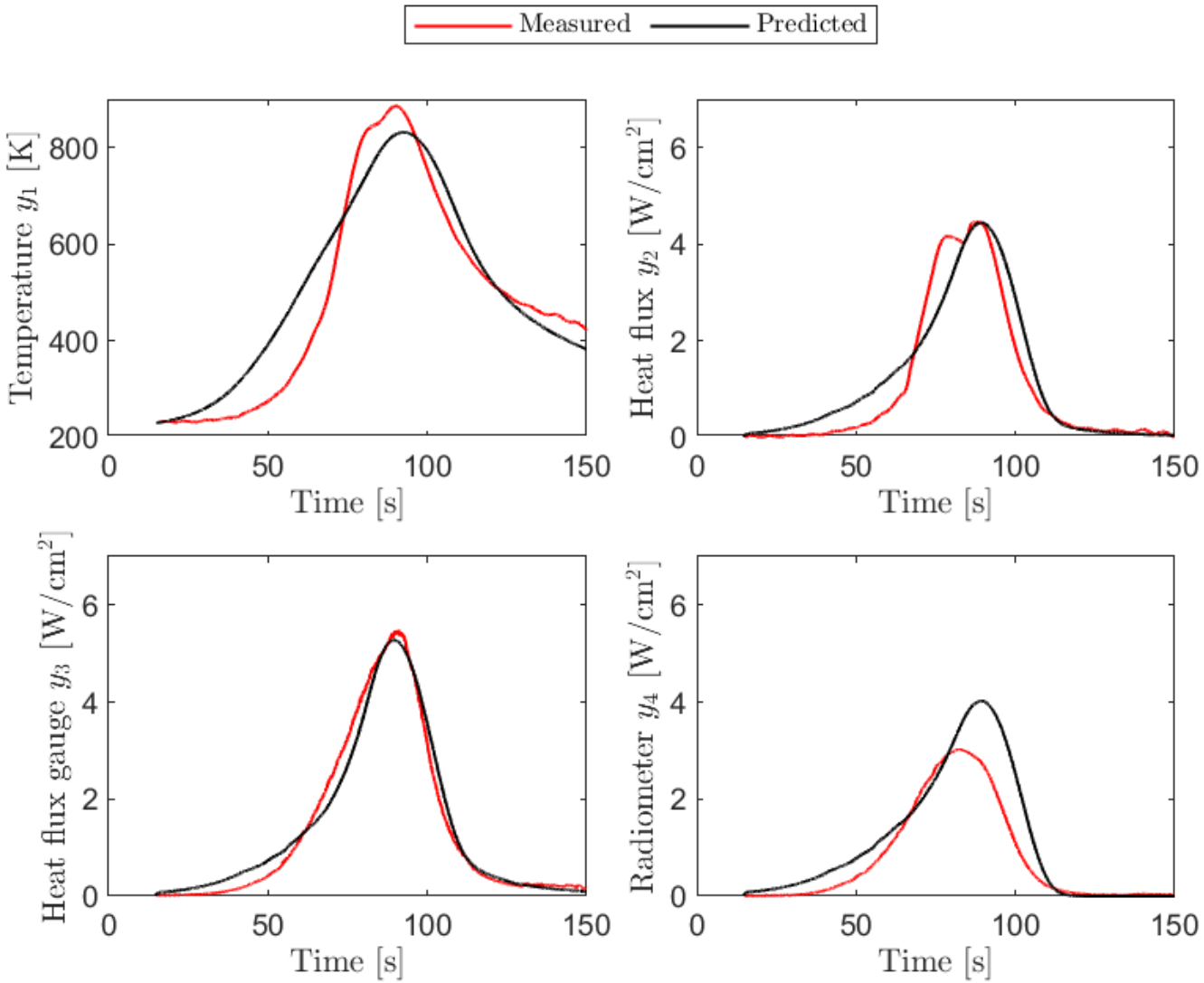
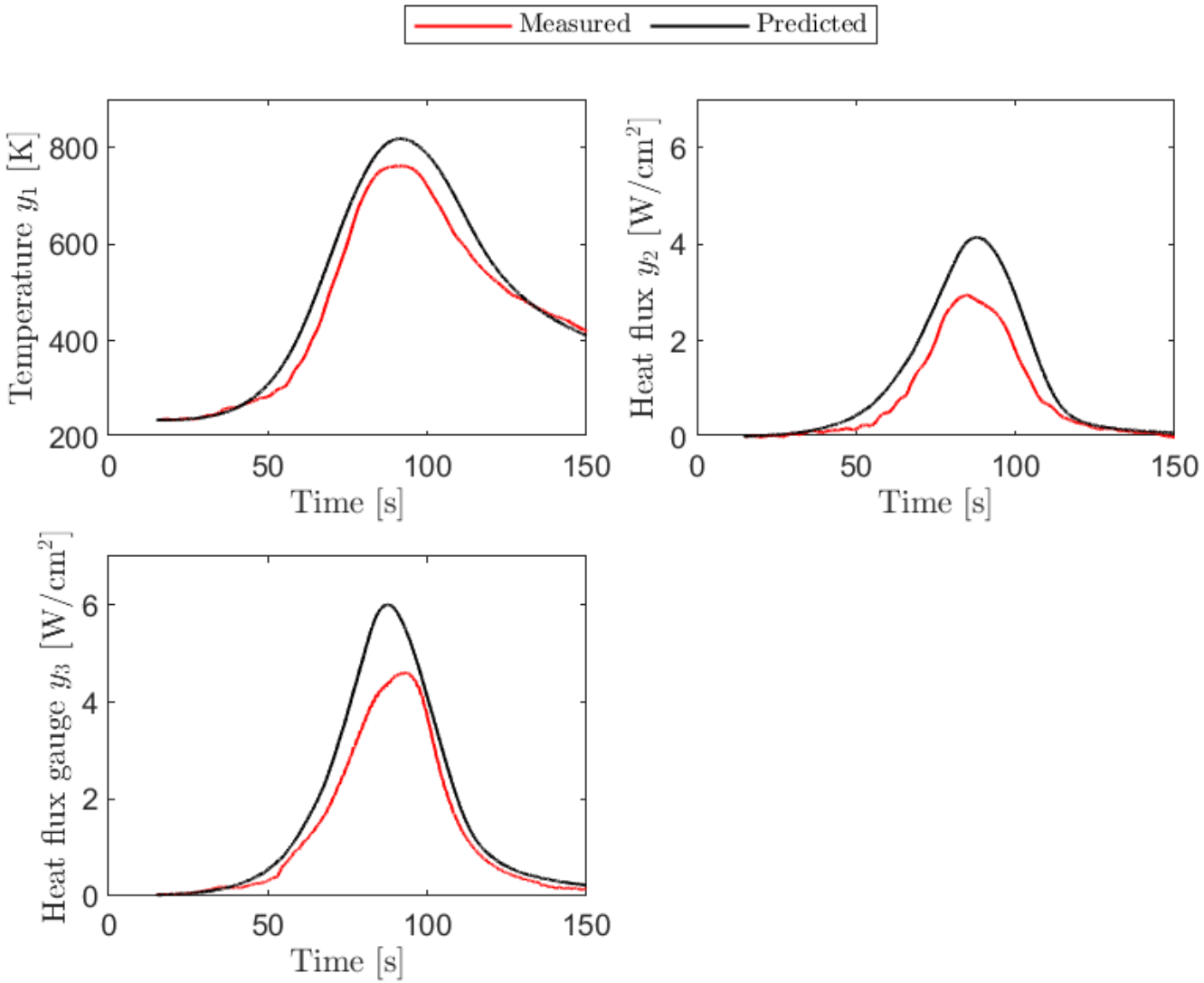


Figure: Measurements made by the instrumentation and predicted by the filter model.



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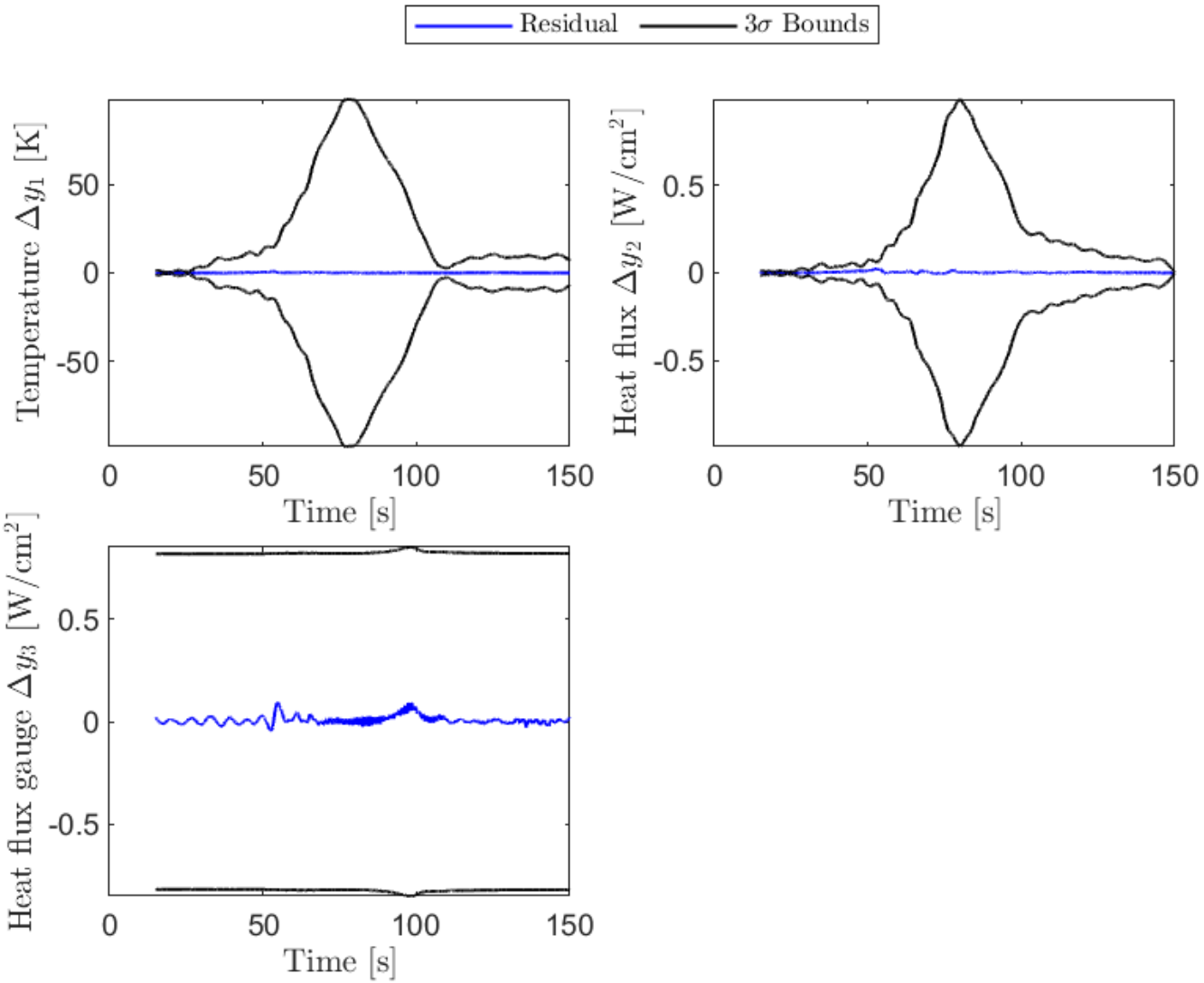
Measurement Residuals

Two Sensor Location



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