A Prognostics Framework for Battery Health Monitoring Integrated with Thermal Modeling

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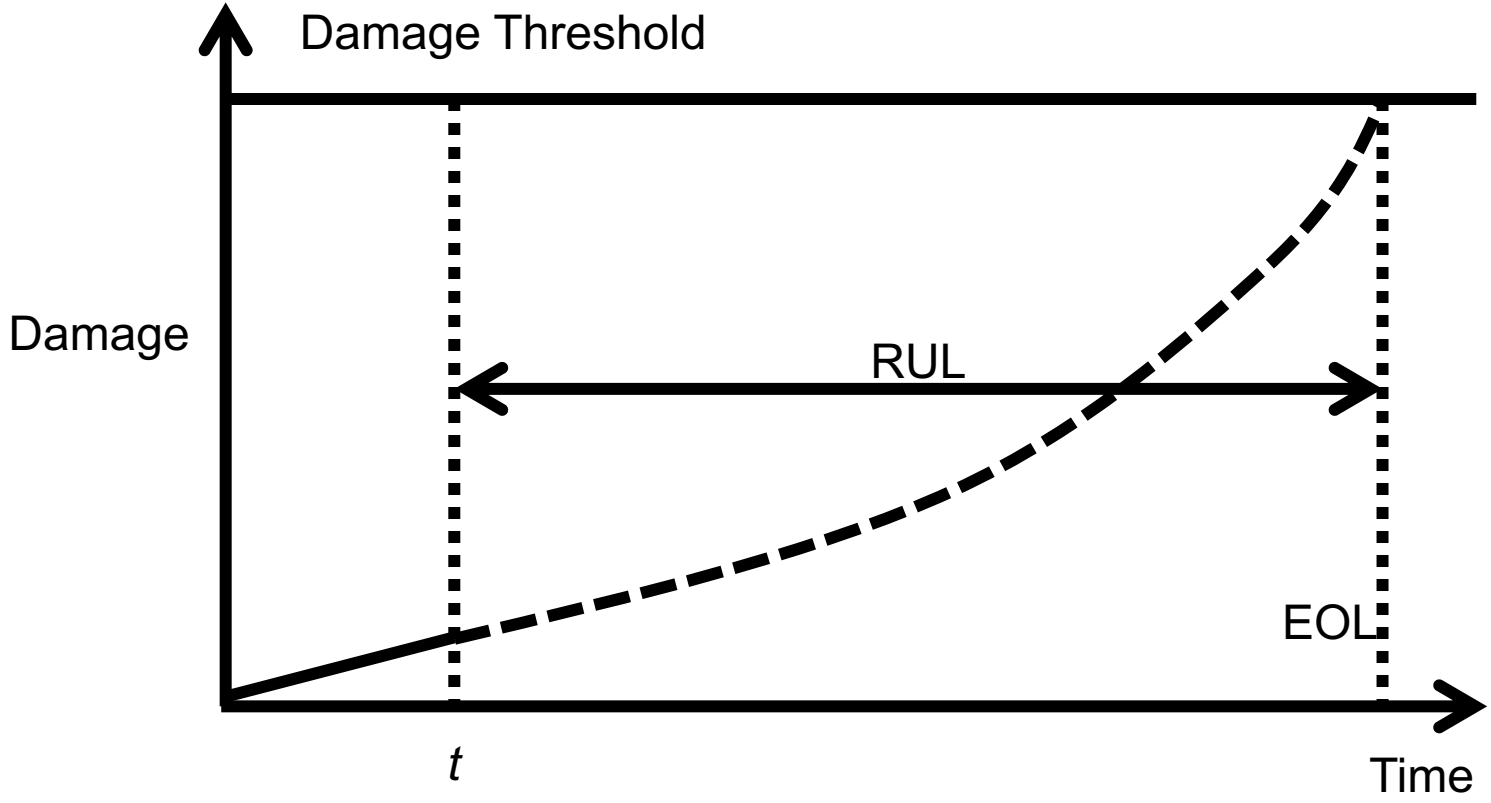
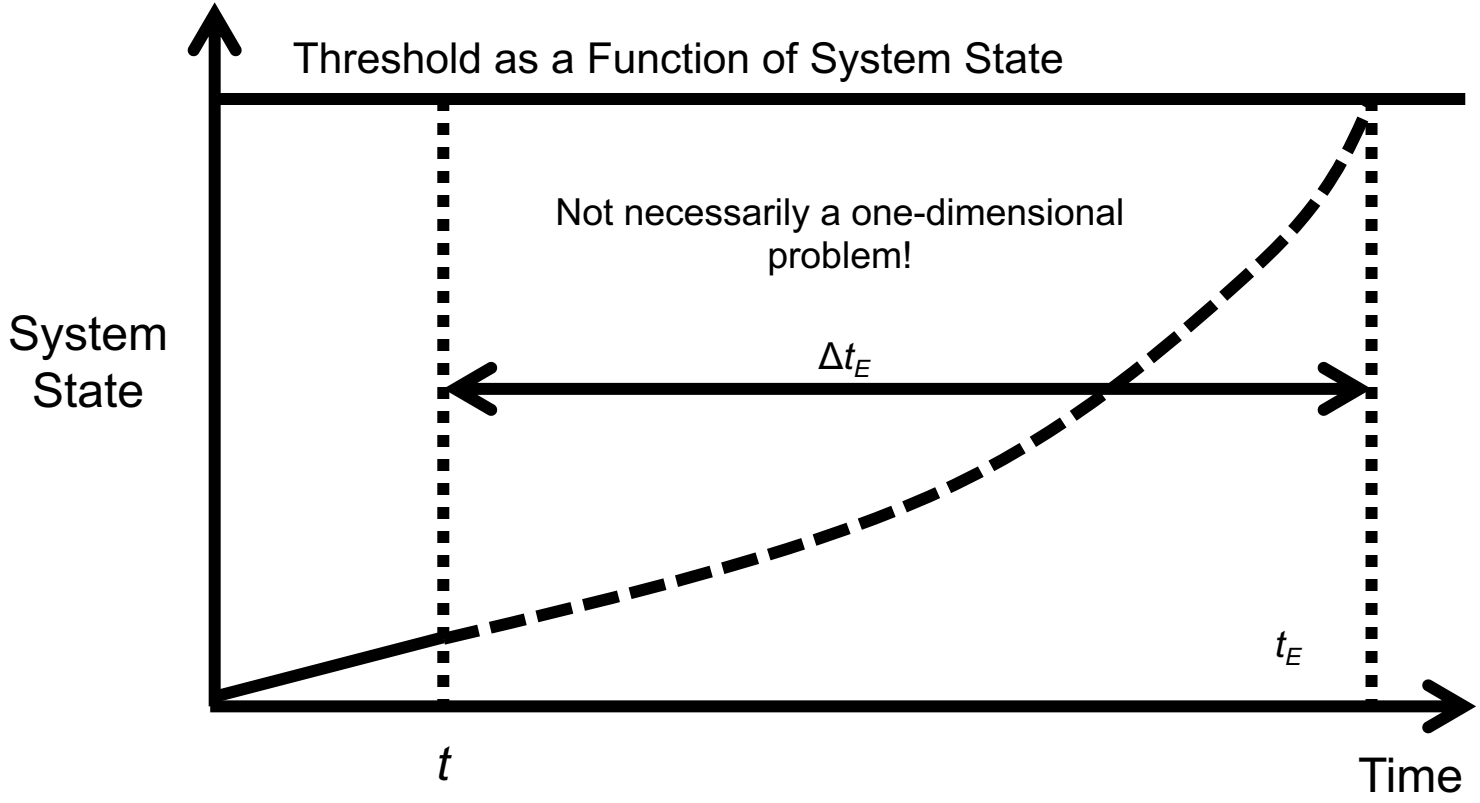
Agenda

- Basics
- Prognostics Architecture
- Thermal Model Implementation
  - Case Studies
- Closing Remarks

Basic Idea

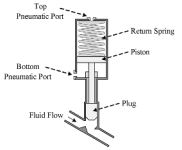


Basic Idea


Threshold as a Function of System State
Not necessarily a one-dimensional problem!
System State
Δt_E
t_E
t
Time

RUL: Remaining Useful Life

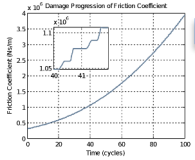
- Model underlying physics of a component/subsystem
- Model physics of damage propagation mechanisms
- Determine criteria for End-of-Life threshold
- Develop algorithms to propagate damage into future
- Deal with uncertainty



$$f_g(p_1,p_2)=\begin{cases} C_s A_s p_1 \sqrt{\frac{\gamma}{ZR_gT}\left(\frac{2}{\gamma+1}\right)^{(\gamma+1)/(\gamma-1)}}, & p_1 \geq p_2 \wedge p_1/p_2 \geq \left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \\ C_s A_s p_1 \sqrt{\frac{2}{ZR_gT}\left(\frac{\gamma}{\gamma-1}\right)\left(\left(\frac{p_2}{p_1}\right)^{2/\gamma}-\left(\frac{p_2}{p_1}\right)^{(\gamma+1)/\gamma}\right)}, & p_1 \geq p_2 \wedge p_1/p_2 < \left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \\ C_s A_s p_2 \sqrt{\frac{\gamma}{ZR_gT}\left(\frac{2}{\gamma+1}\right)^{(\gamma+1)/(\gamma-1)}}, & p_1 < p_2 \wedge p_2/p_1 \geq \left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \\ C_s A_s p_2 \sqrt{\frac{2}{ZR_gT}\left(\frac{\gamma}{\gamma-1}\right)\left(\left(\frac{p_1}{p_2}\right)^{2/\gamma}-\left(\frac{p_1}{p_2}\right)^{(\gamma+1)/\gamma}\right)}, & p_1 < p_2 \wedge p_2/p_1 < \left(\frac{\gamma+1}{2}\right)^{\gamma/(\gamma-1)} \end{cases}$$

$$f_t(t) = f_g(p_t(t), u_t(t))$$
$$f_b(t) = f_g(p_b(t), u_b(t))$$

$$f_v(t) = \frac{x(t)}{L_s} C_v A_v \sqrt{\frac{2}{\rho}|p_{fl} - p_{fr}|}\,\mathrm{sign}(p_{fl} - p_{fr})$$

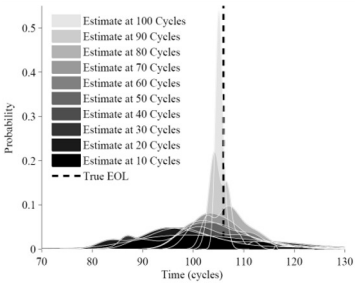


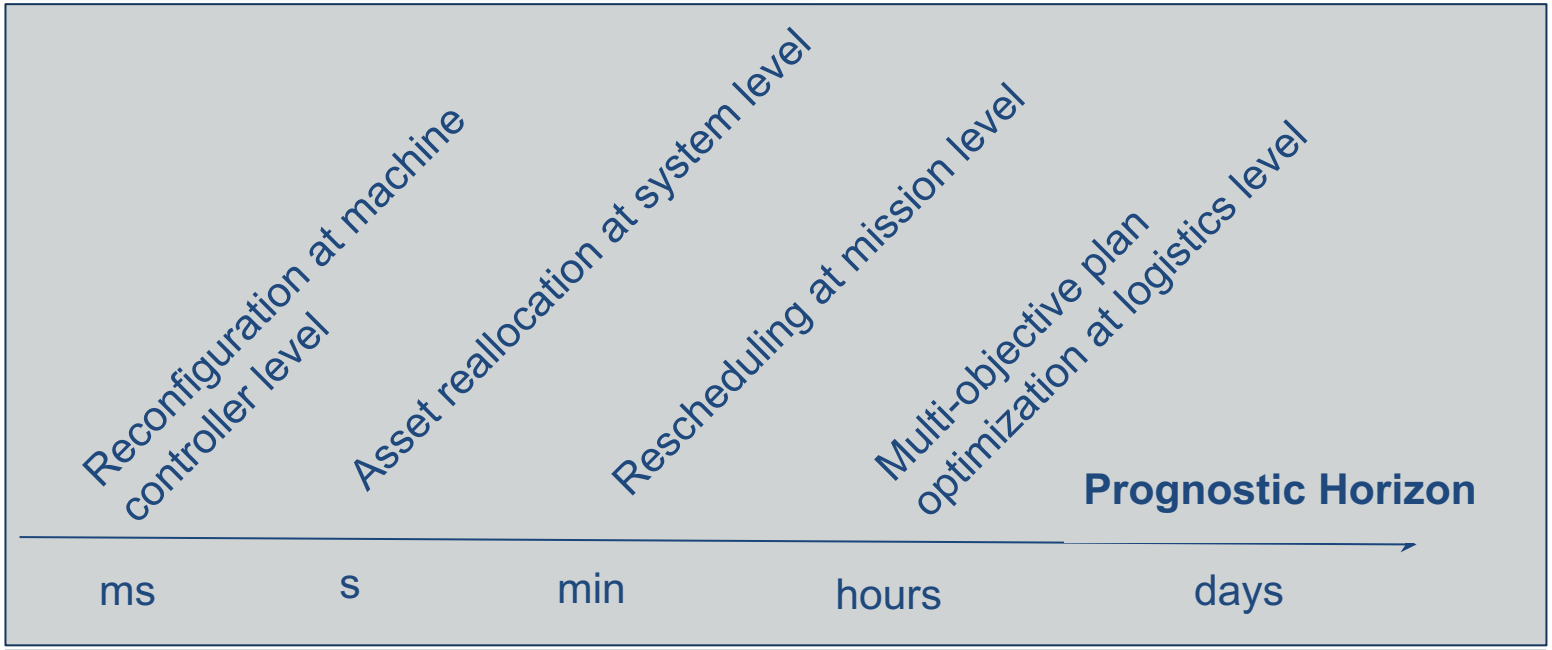
$$\dot{r}(t) = w_r |F_f(t) v(t)|$$

$$EOL(t_P) \triangleq \inf\{t \in \mathbb{R} : t \geq t_P \wedge T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = 1\}$$

Algorithm 2 EOL Prediction

Inputs: $\{(\mathbf{x}^i_{k_P}, \boldsymbol{\theta}^i_{k_P}), w^i_{k_P}\}_{i=1}^N$
Outputs: $\{EOL^i_{k_P}, w^i_{k_P}\}_{i=1}^N$
for $i = 1$ **to** N **do**
  $k \leftarrow k_P$
  $\mathbf{x}^i_k \leftarrow \mathbf{x}^i_{k_P}$
  $\boldsymbol{\theta}^i_k \leftarrow \boldsymbol{\theta}^i_{k_P}$
  while $C_{EOL}(\mathbf{x}^i_k, \boldsymbol{\theta}^i_k) = 0$ **do**
    Predict $\hat{\mathbf{u}}_k$
    $\boldsymbol{\theta}^i_{k+1} \sim p(\boldsymbol{\theta}_{k+1} | \boldsymbol{\theta}^i_k)$
    $\mathbf{x}^i_{k+1} \sim p(\mathbf{x}_{k+1} | \mathbf{x}^i_k, \boldsymbol{\theta}^i_k, \hat{\mathbf{u}}_k)$
    $k \leftarrow k + 1$
    $\mathbf{x}^i_k \leftarrow \mathbf{x}^i_{k+1}$
    $\boldsymbol{\theta}^i_k \leftarrow \boldsymbol{\theta}^i_{k+1}$
  end while
  $EOL^i_{k_P} \leftarrow k$
end for





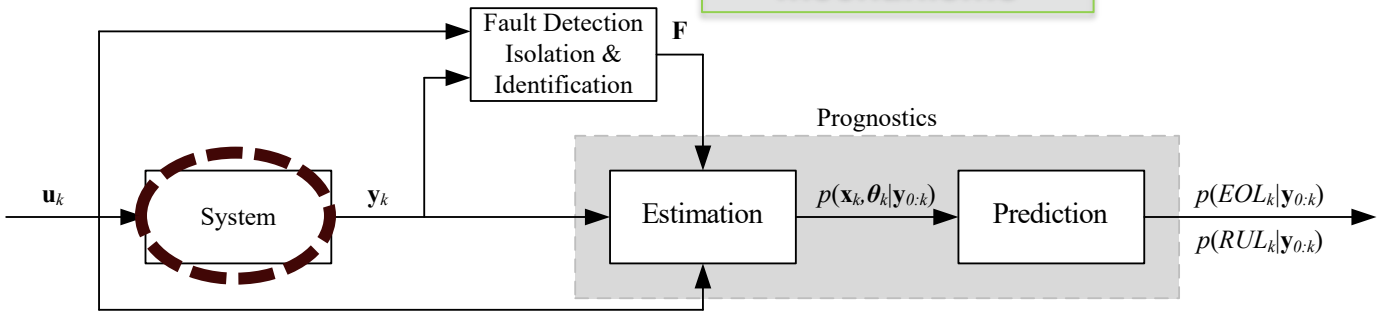
Autonomy

Pilots	**Airline Operators**	**Operators**
Air Traffic Control		**Maintainers**

Model-Based Architecture

1 System receives inputs, produces outputs

2 Identify active damage mechanisms

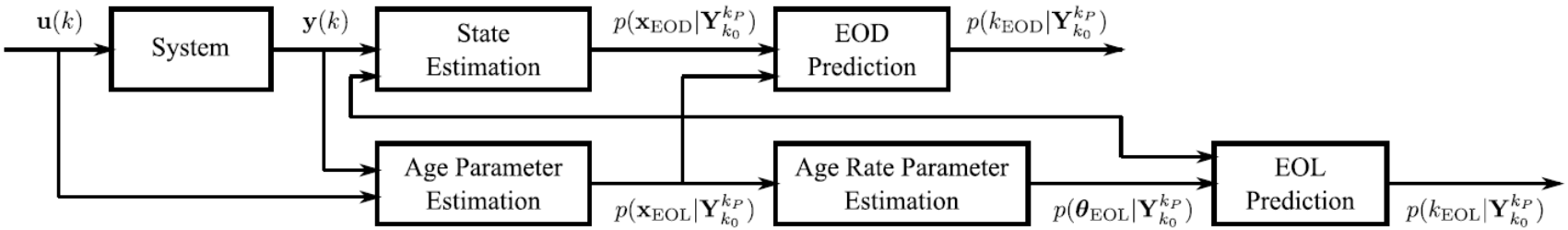


3 Estimate current state and parameter values

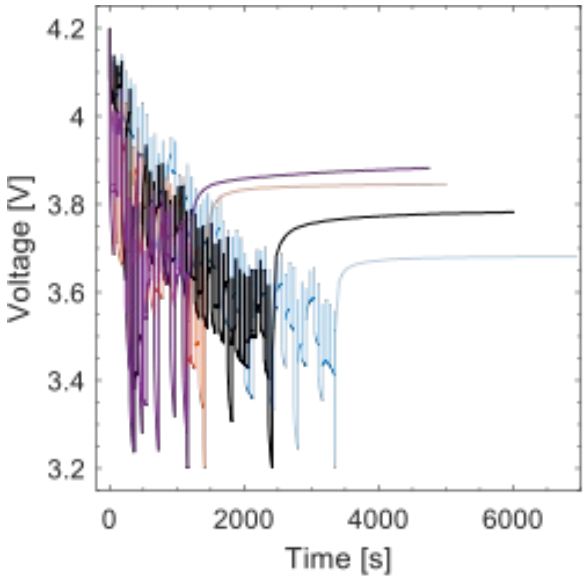
4 Predict EOL and RUL as probability distributions

Integrated Prognostics Architecture

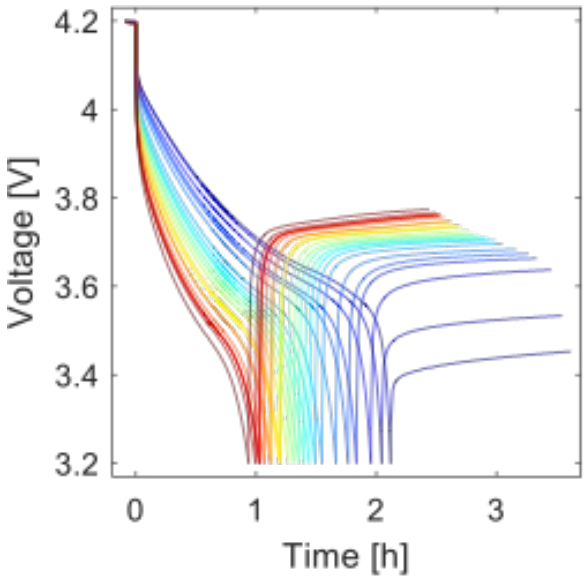
- System (battery) gets inputs (current) and produces outputs (voltage)
- State estimation computes estimate of state given estimates of age parameters
- EOD prediction computes prediction of time of EOD, given state and age parameter estimates
- Age rate parameter estimation computes parameters defining aging rate progression
- EOL prediction computes prediction of time of EOL, given age parameter and age rate parameter estimates



Case 1 : Randomized Discharge Data

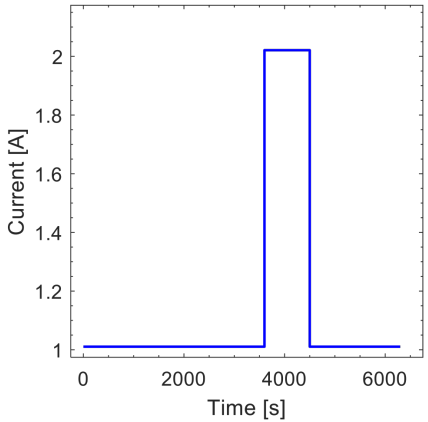


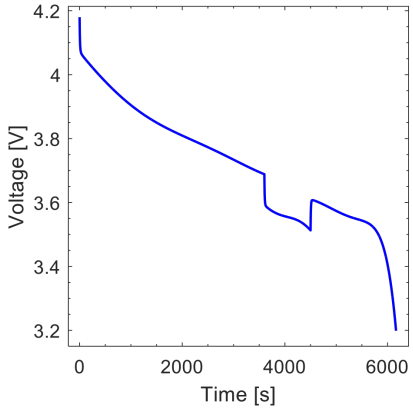
Random Discharge Profiles

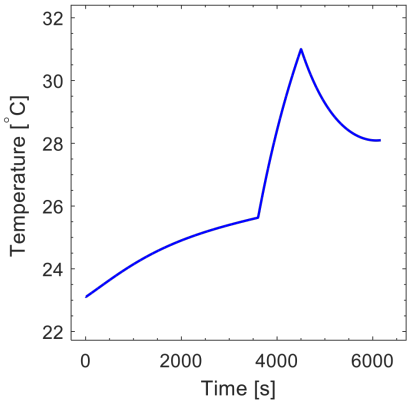


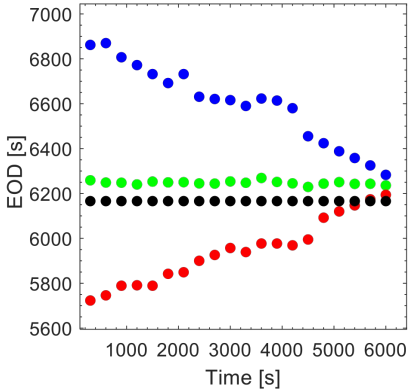
1C Reference Discharge Profiles

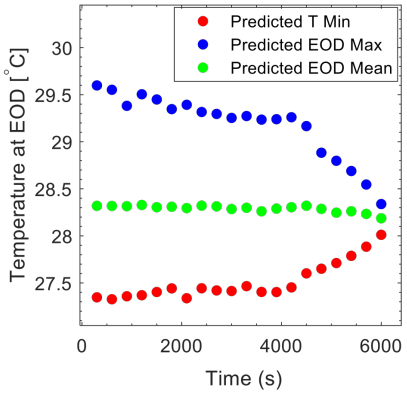
Case 1 : Randomized Discharge Data

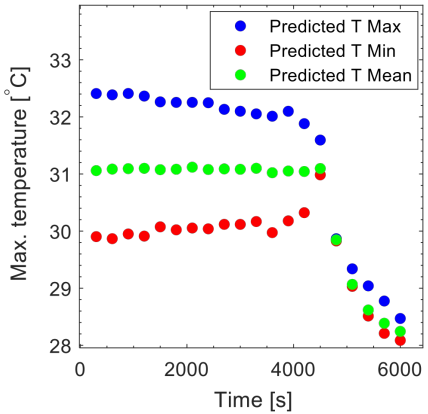




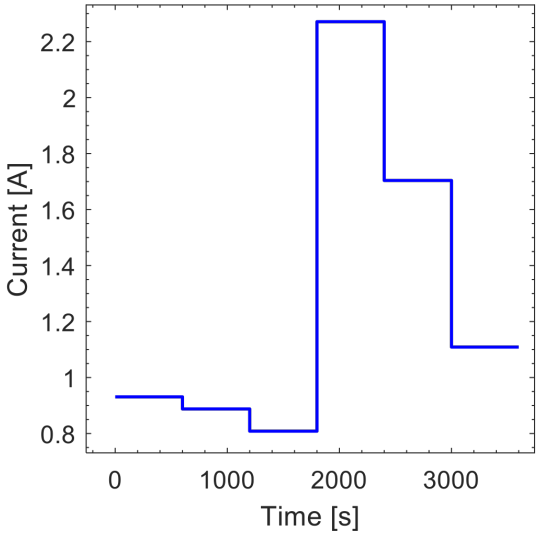


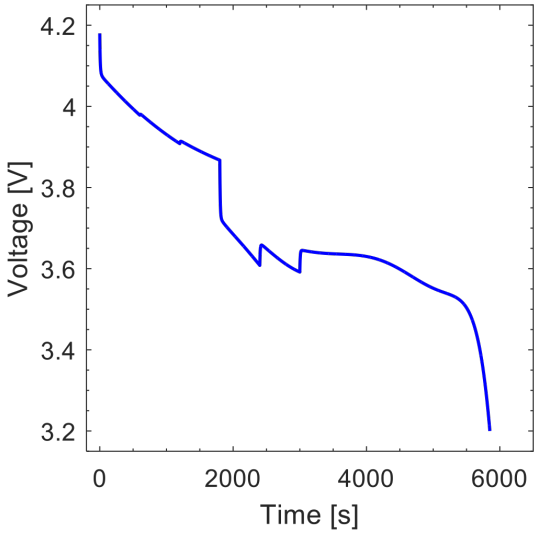


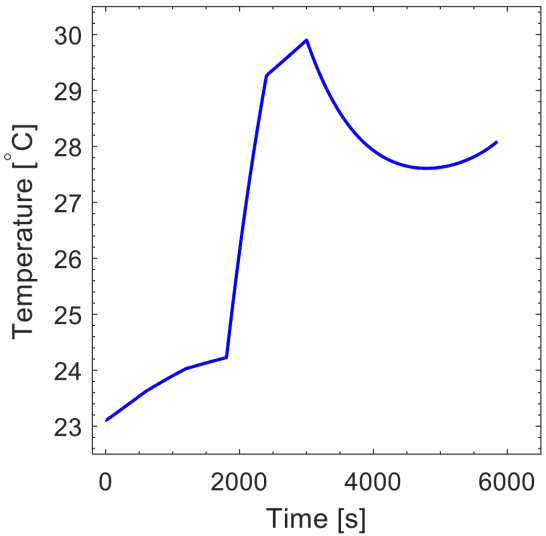




Case 2 : Simulated Flight Profile (SFP)







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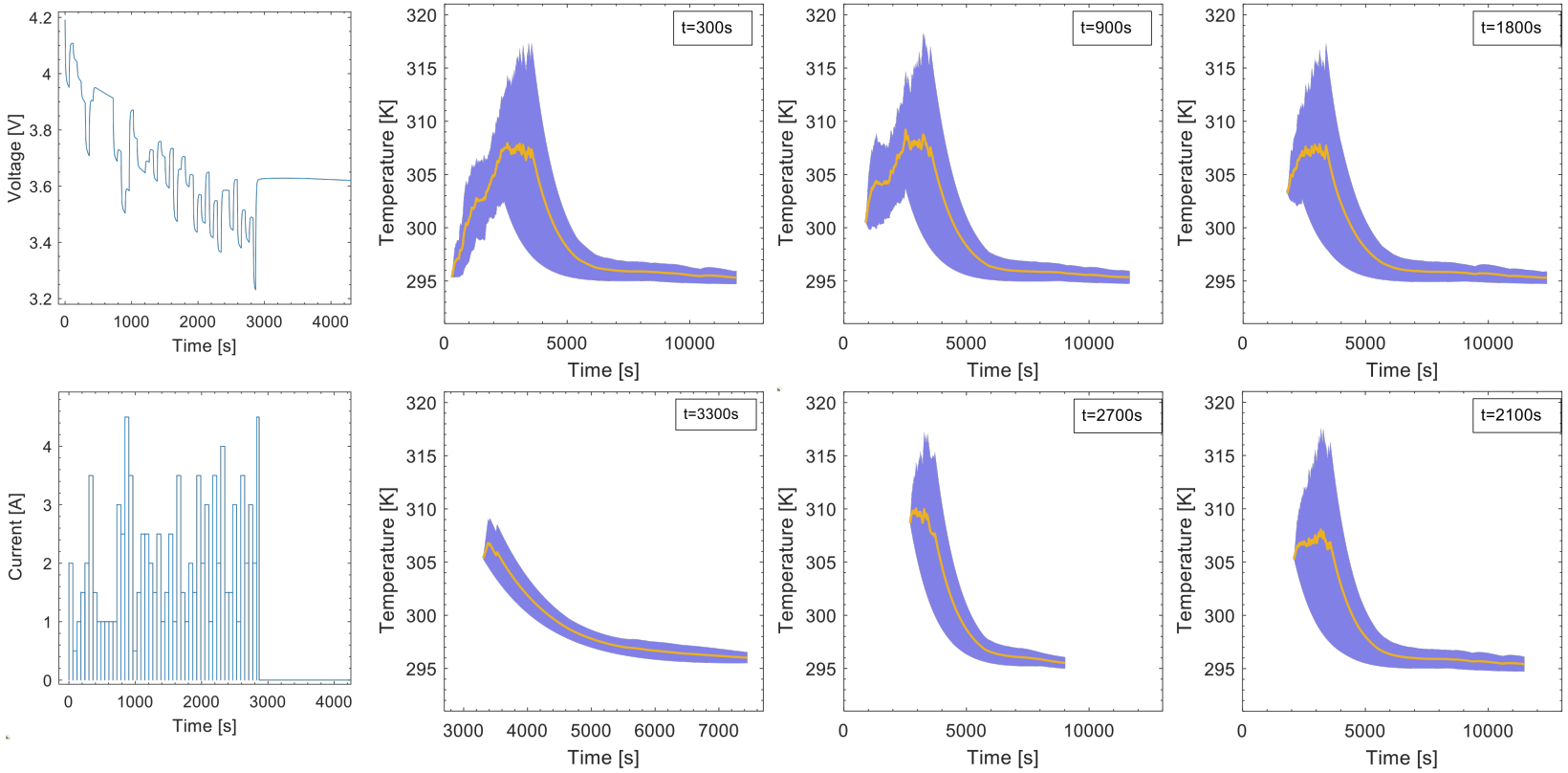
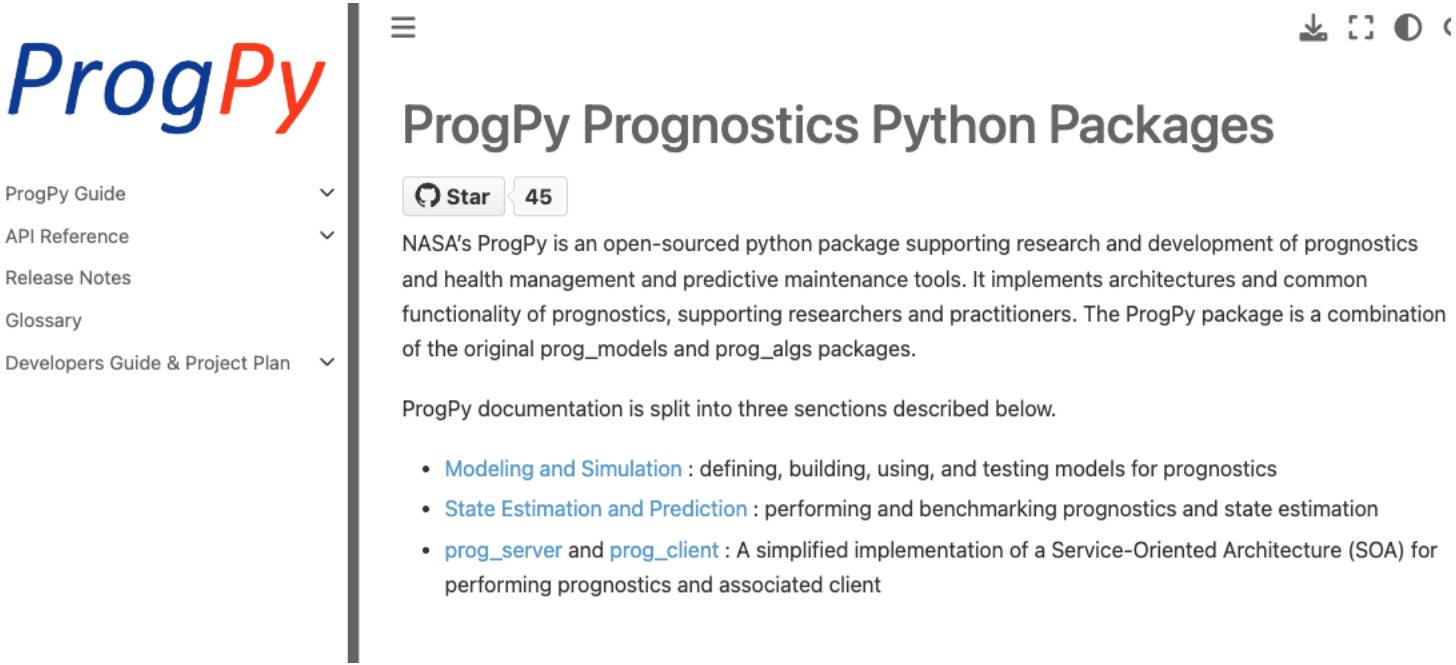


NASA SOY Award 2024



Next Steps : Looking Ahead

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Thermal data-driven model reduction for enhanced battery health monitoring

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HIGHLIGHTS

- Identifying battery model parameters from flight data is challenging.
- Prognostic algorithms require models which are both predictive and identifiable.
- Data-driven reduction applied to a physics-based thermal model.
- Model reduction results in a model identifiable from flight data.
- Developed an identifiable thermal reduced-order model.

https://spinoff.nasa.gov/Spinoff2019/t_1.html

Concluding Remarks

- Predicted state-of-charge (SOC), state-of-health (SOH) and Temperature (T)
  - Instrumental in making informed decisions and optimizing scheduling
  - Particularly in the realm of autonomous systems.

- The integration of accurate battery prognostics with decision-making algorithms holds significant promise
  - enhancing the efficiency, safety, and longevity of battery-powered autonomous vehicles.

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