

Hybrid Approaches to Systems Health Management and Prognostics

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Acknowledgement

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“Felix, qui potuit rerum cognoscere causas”

“Lucky is he who has been able to
understand the causes of things”

(Virgil 29 BC)

Why Diagnostics

- di·ag·nos·tic
 - a distinctive symptom or characteristic.
 - a program or routine that helps a user to identify errors.
 - the practice or techniques of diagnosis.
 - "advanced medical diagnostics"
 - PHM Community – “Detect and Isolate”
 - Fault Magnitude
 - System/Component

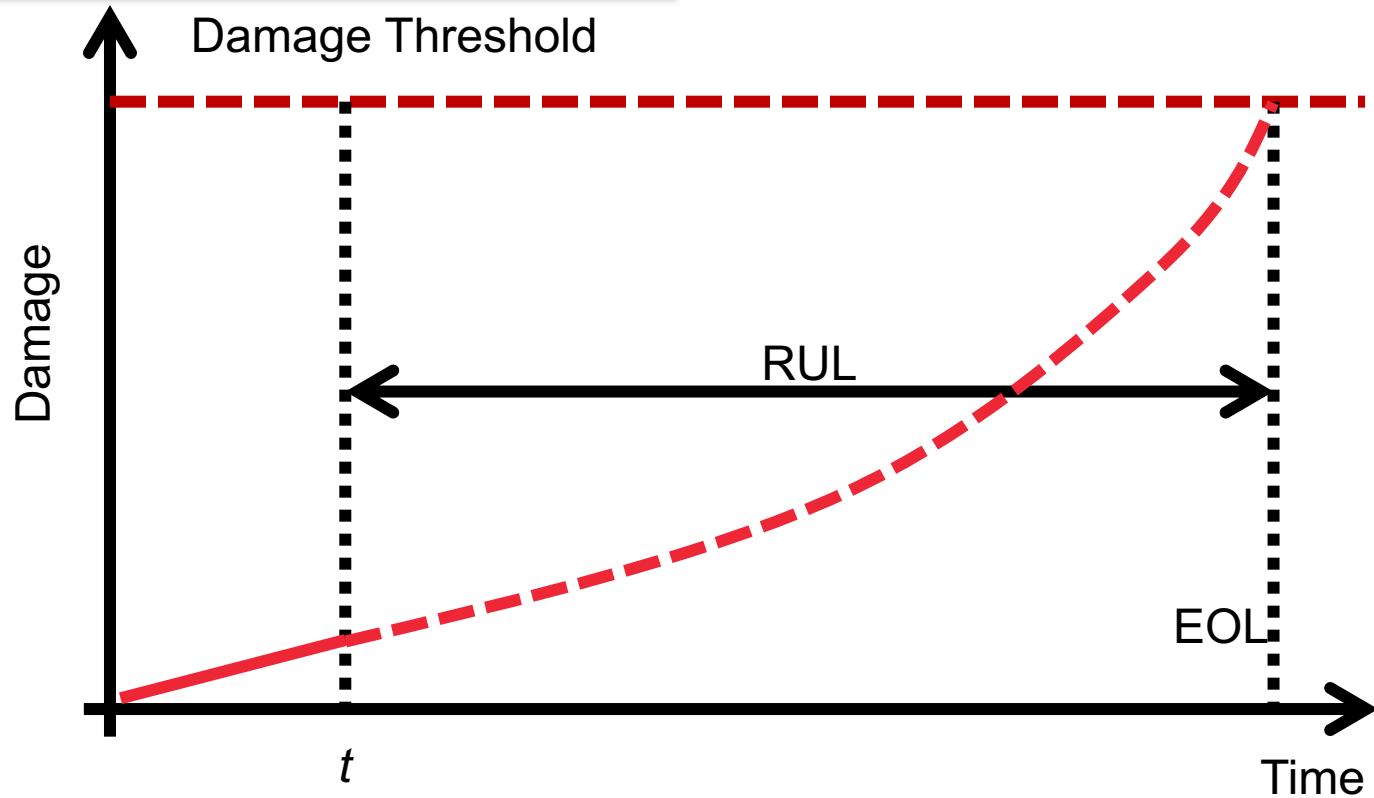
Why Prognostics

- Safety and Decision Making
 - Reconfiguring the system to avoid using the component before it fails
 - Prolonging component life by modifying how the component is used
 - Optimally plan or replan a mission
- Adopting condition-based maintenance strategies, instead of time-based maintenance
 - scheduling maintenance
 - planning for spare components
- System operations can be optimized in a variety of ways

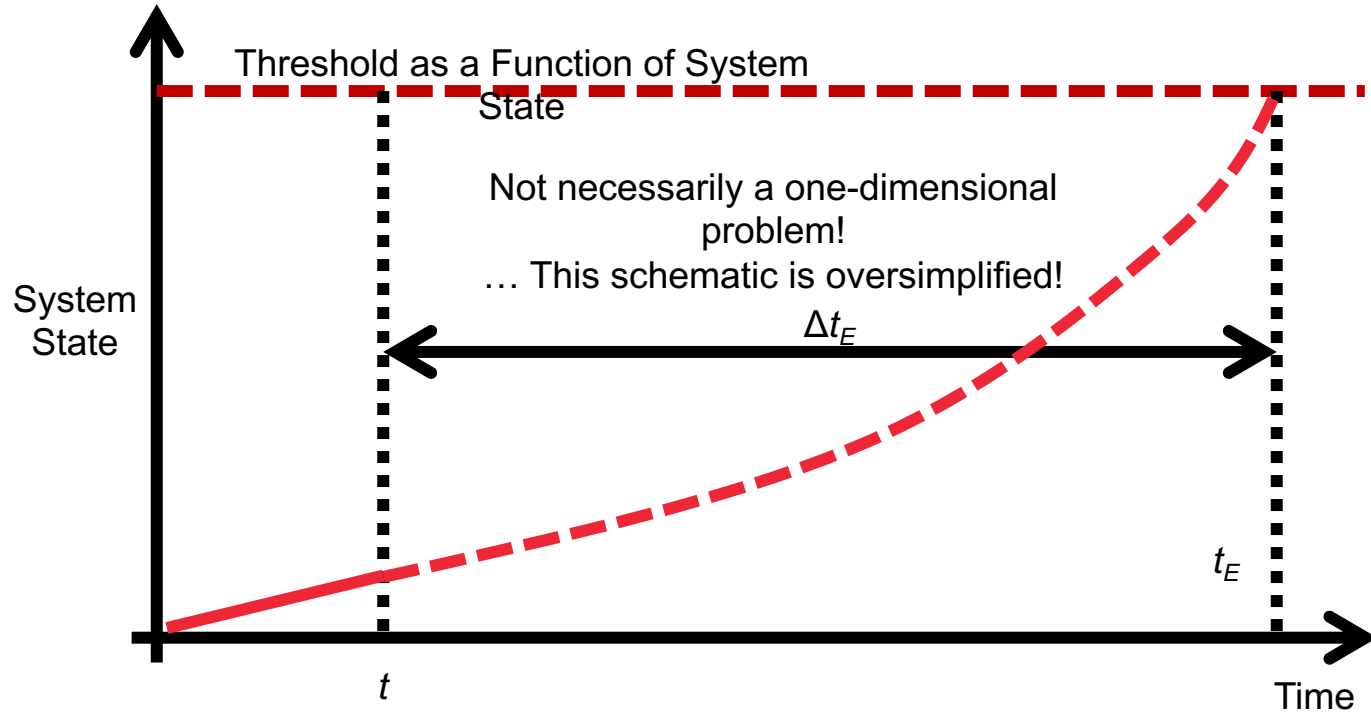
Why Prognostics

- Reliability & Performance
 - product reputation reduced safety factors
- Operational Optimization
 - Prolonging component life by modifying how the component is used (e.g., load shedding/distribution)
 - Optimally plan or replan a mission

Basic Idea

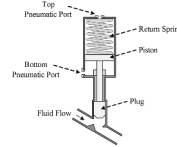


Basic Idea



- **RUL: Remaining Useful Life**

- Model underlying physics of a component/subsystem



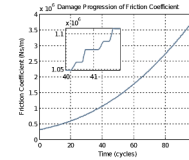
$$f_g(p_1, p_2) = \begin{cases} C_s A_s p_1 \sqrt{\frac{\gamma}{Z R_g T} \left(\frac{2}{\gamma+1} \right)^{(\gamma+1)/(\gamma-1)}}, & p_1 \geq p_2 \wedge p_1/p_2 \geq \left(\frac{\gamma+1}{2} \right)^{\gamma/(\gamma-1)} \\ C_s A_s p_1 \sqrt{\frac{2}{Z R_g T} \left(\frac{\gamma}{\gamma+1} \right) \left(\left(\frac{p_2}{p_1}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

$$f_t(t) = f_g(p_t(t), u_t(t))$$

$$f_b(t) = f_g(p_b(t), u_b(t))$$

$$f_v(t) = \frac{x(t)}{L_s} C_v A_v \sqrt{\frac{2}{\rho} |p_{f1} - p_{fr}| \text{sign}(p_{f1} - p_{fr})}$$

- Model physics of damage propagation mechanisms



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

- Determine criteria for End-of-Life threshold



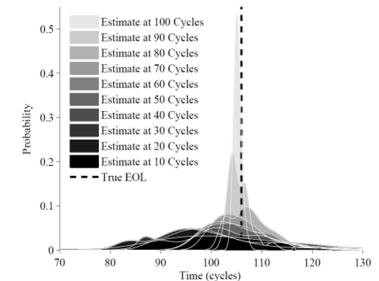
$$EOL(t_P) \triangleq \inf\{t \in \mathbb{R} : t \geq t_P \wedge T_{EOL}(\mathbf{x}(t), \boldsymbol{\theta}(t)) = 1\}$$

- Develop algorithms to propagate damage into future



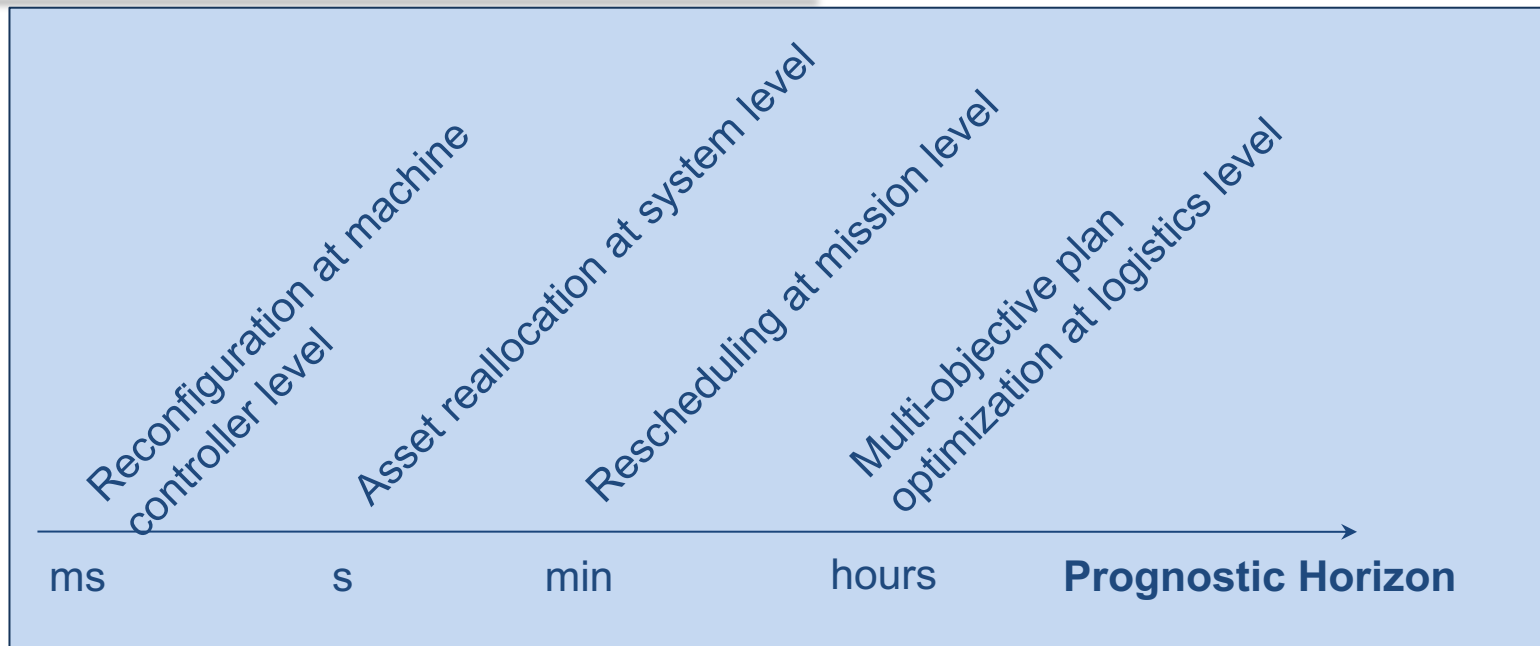
Algorithm 2 EOL Prediction

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



- Deal with uncertainty





Pilots

Autonomy.

Operators

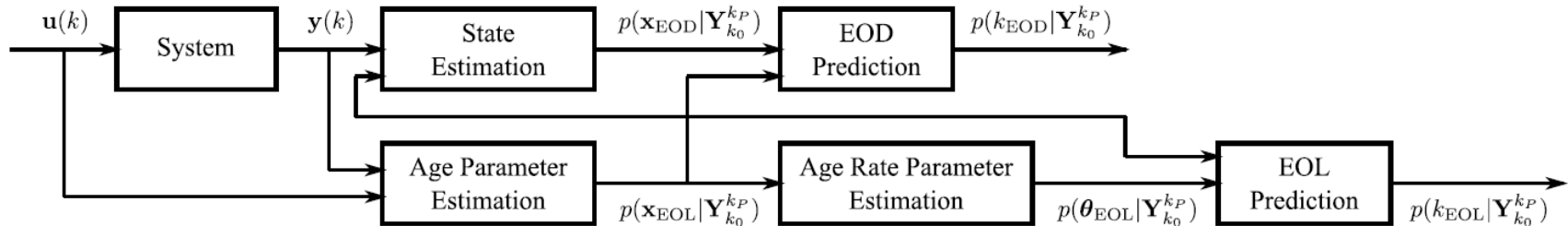
Air Traffic Control

Airline Operators

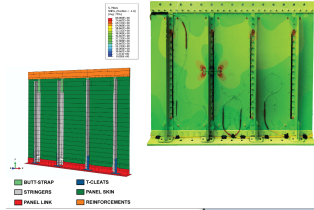
Maintainers

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 parameter estimation computes estimates of age parameters
- 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

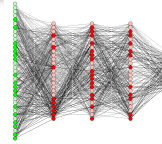


State of the Art



- Results tend to be intuitive
- Models can be reused
- If incorporated early enough in the design process, can drive sensor requirements
- Computationally efficient to implement
- Model development requires a thorough understanding of the system
- High-fidelity models can be computationally intensive

- Paris-Erdogan Crack Growth Model
- Taylor tool wear model
- Corrosion model
- Abrasion model



- Easy and Fast to implement
- May identify relationships that were not previously considered
- Requires lots of data and a “balanced” approach”
- Results may be counter(or even un-)intuitive
- Can be computationally intensive, both for analysis and implementation

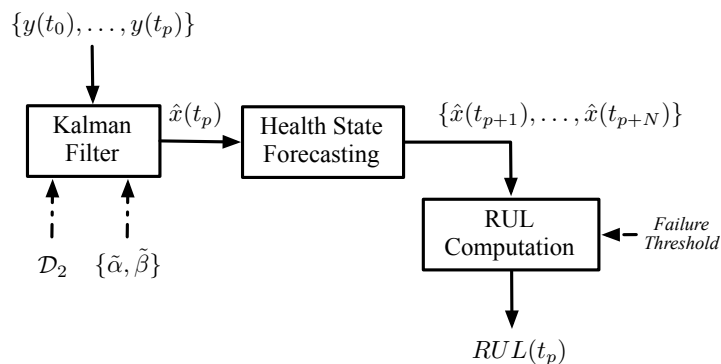
- Regression analysis
- Neural Networks (NN)
- Bayesian updates
- Relevance vector machines (RVM)

Model-based prognostics

- State vector includes dynamics of normal and degradation process

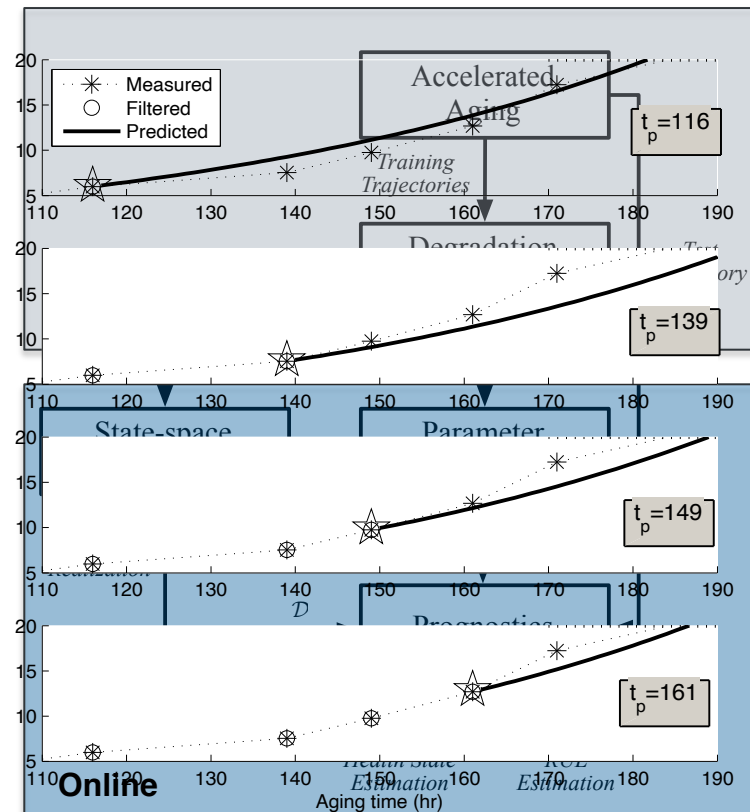
$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$

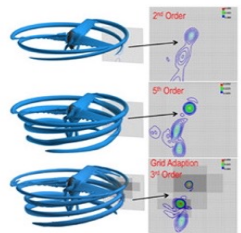
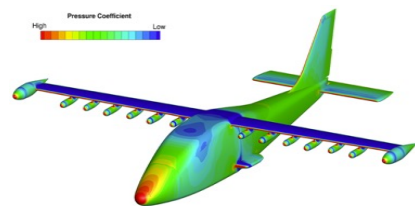
$$y_k = Hx_k + v_k$$



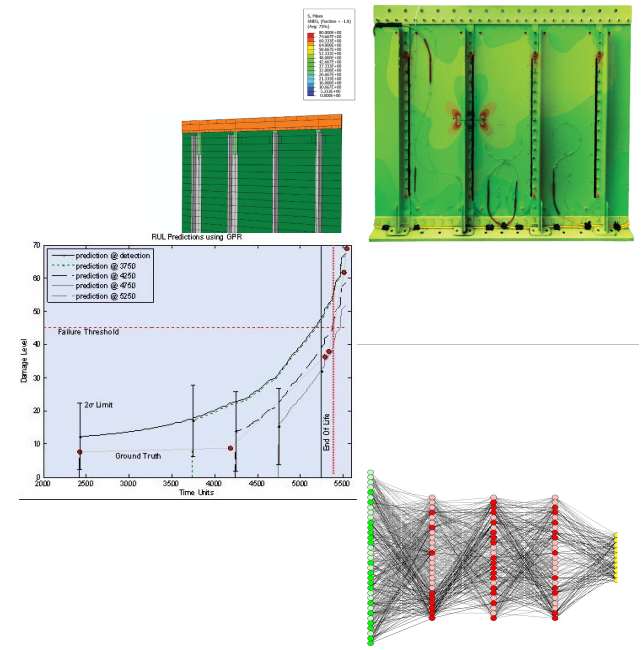
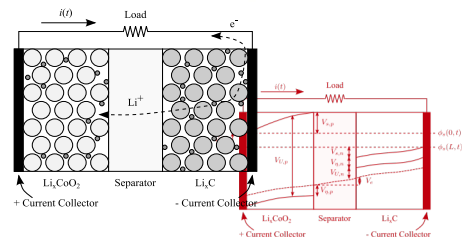
- EOL defined at time in which performance variable cross failure threshold

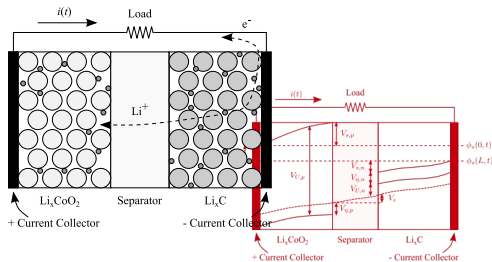
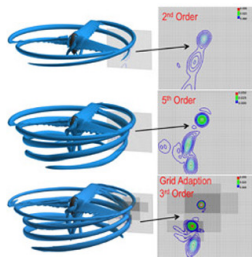
$$R(t_p) = t_{EOL} - t_p$$





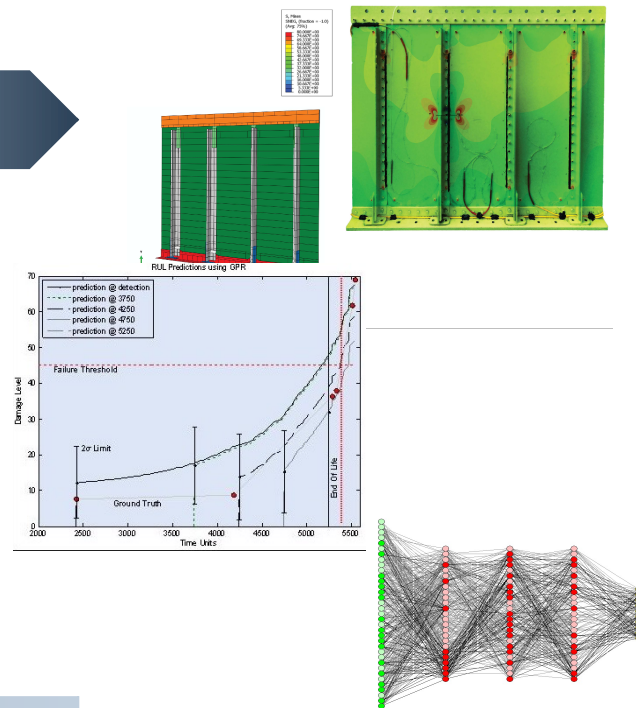
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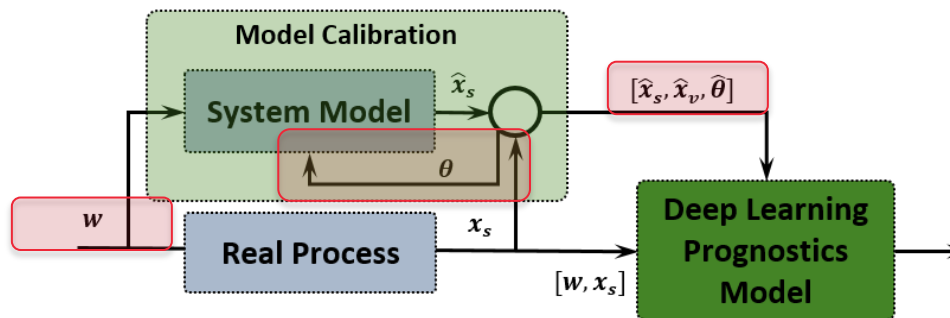


A diagram showing four machine learning frameworks arranged in a square pattern, each in a colored rounded square box with a white border. The boxes are: Tensor Flow (dark red, top-left), Microsoft Cognitive (olive green, top-right), Uber Ludwig (green, bottom-left), and Scikit-learn (blue, bottom-right). Grey arrows indicate relationships: a vertical arrow pointing up from Uber Ludwig to Tensor Flow, a vertical arrow pointing down from Microsoft Cognitive to Uber Ludwig, a horizontal arrow pointing right from Tensor Flow to Microsoft Cognitive, and a horizontal arrow pointing left from Scikit-learn to Uber Ludwig. Additionally, a diagonal arrow points from the bottom-left towards the top-right, passing between the boxes.

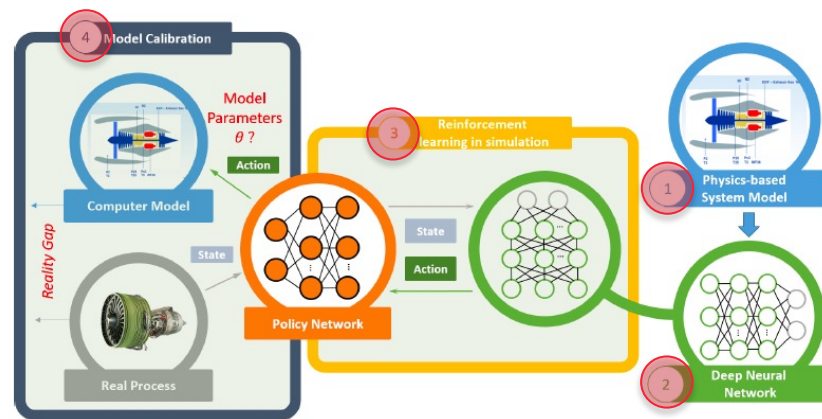
Understanding and Learning underlying Physics for Complex Systems



Approach 1 : Deep Learning + Physics Model Calibration



Overall architecture of the hybrid prognostics framework fusing physics-based and deep learning models.

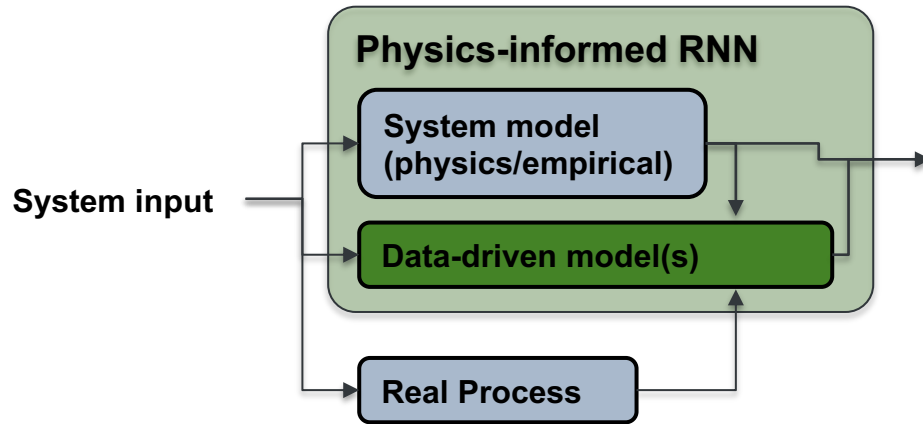


Calibration Policy

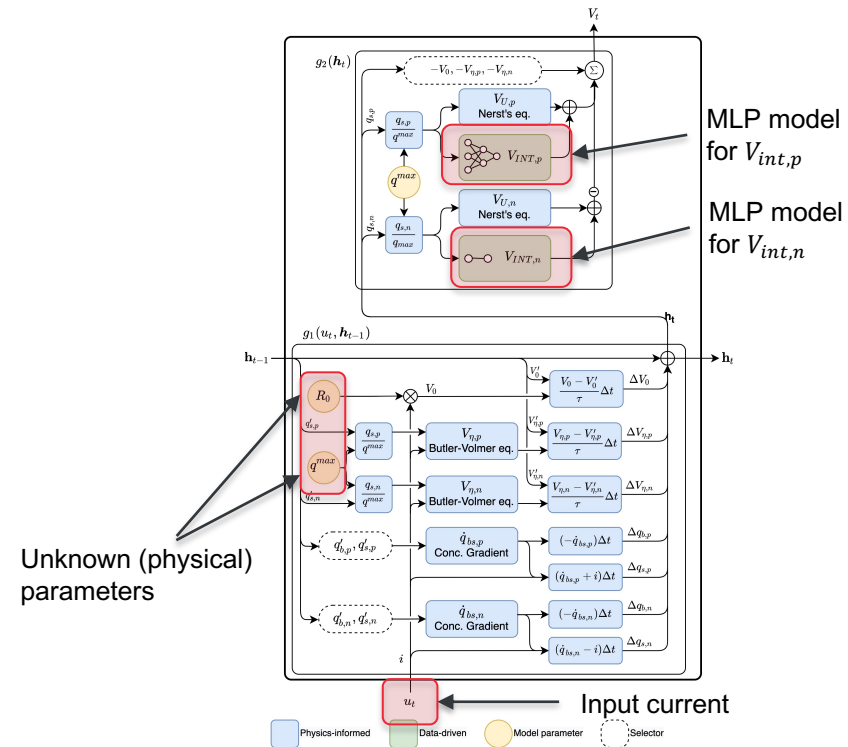
Yuan Tian, Manuel Arias Chao, Chetan Kulkarni, Kai Goebel, Olga Fink, "Real-Time Model Calibration with Deep Reinforcement Learning", arXiv:2006.04001

Manuel Arias Chao, Chetan Kulkarni, Kai Goebel, Olga Fink, "Fusing Physics-based and Deep Learning Models for Prognostics", arXiv:2003.00732

Approach 2 : Physics + RNN



Overall architecture of the physics-informed recurrent neural network

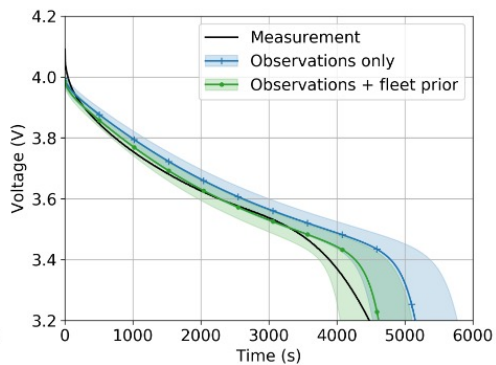
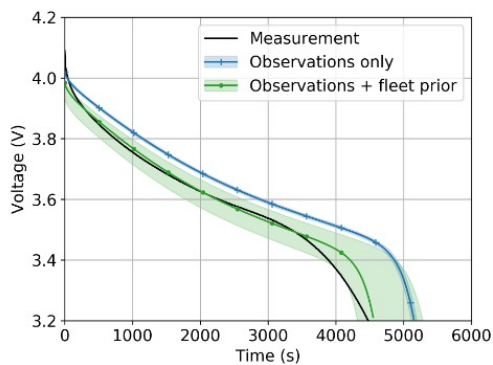
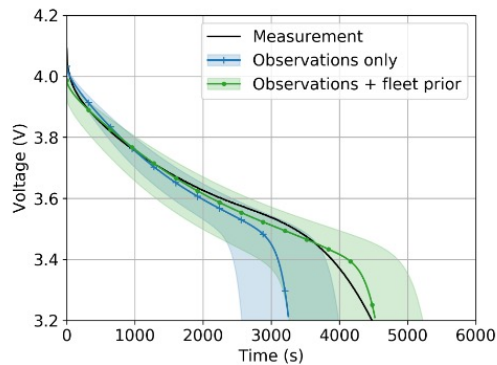


Physics-informed neural network framework for Li-ion Battery SOC estimation

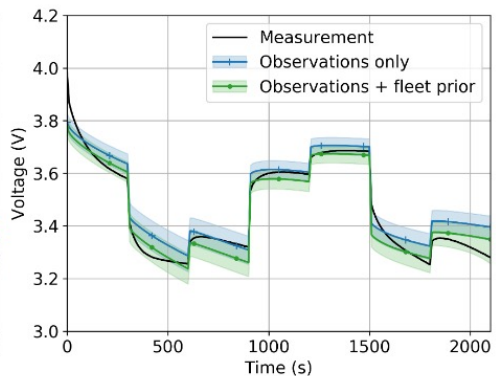
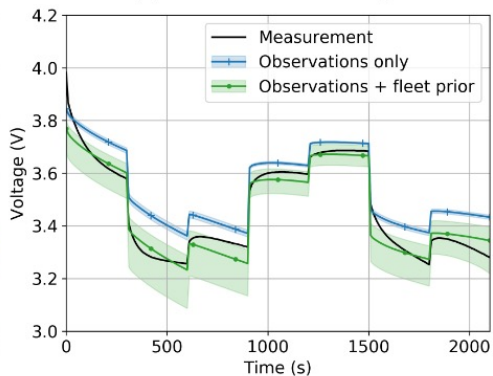
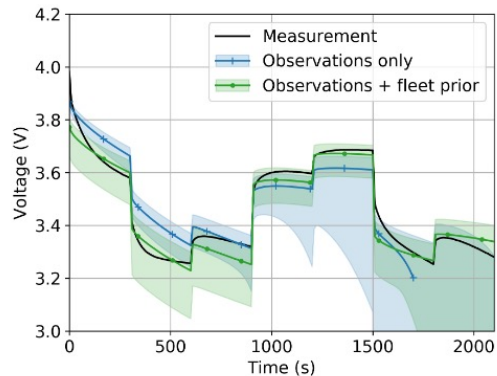
Nascimento, R.G. & Viana, F. A. & Corbetta, M. & Kulkarni, C. S. (2021). "Usage-based Lifting of Lithium-Ion Battery with Hybrid Physics-Informed Neural Networks," AIAA Aviation 2021.

Renato G. Nascimento; Matteo Corbetta; Chetan S. Kulkarni; Felipe A.C. Viana, "Hybrid Physics-Informed Neural Networks for Lithium-Ion Battery Modeling and Prognosis". Journal of Power Sources 2021 (accepted)

Approach 2 : Physics + RNN

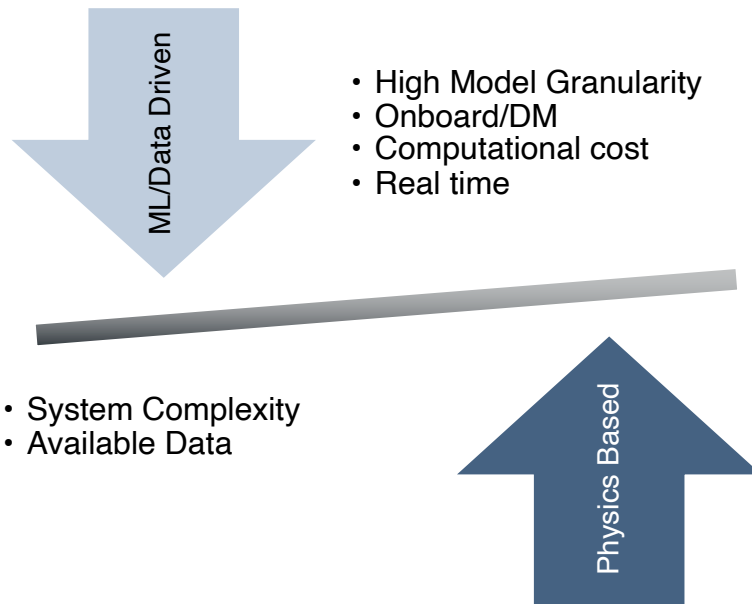


(a) Reference discharge.

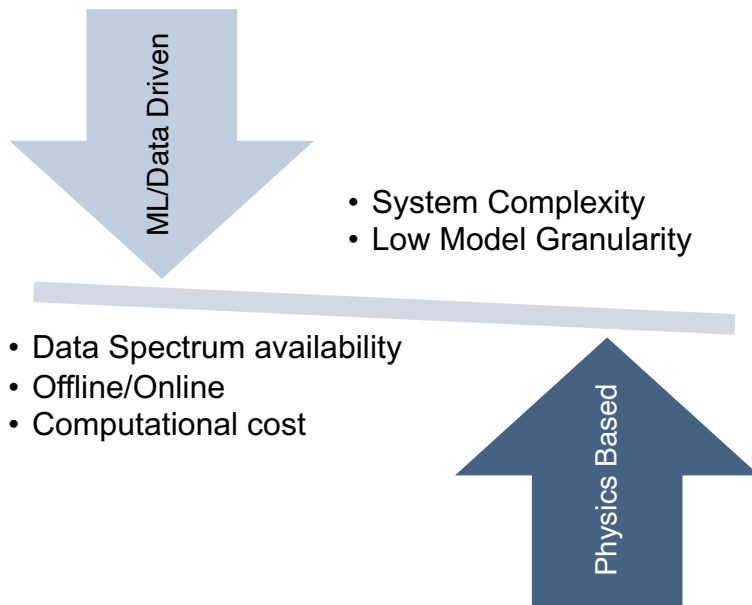


(b) Random-loading discharge.

Next Steps : Looking Ahead



Next Steps : Looking Ahead



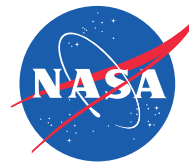
Next Steps : Looking Ahead



Credit: www.nasa.gov

Concluding Remarks

- Health Management framework helps enable
 - Systems safe and efficient
 - Decision making
- Hybrid Approaches
 - Physics based methods can be combined with machine learning to determine and evaluate models for complex physical systems.
 - High Fidelity simulation
 - Field and Tests
 - These models enable in verification and validation for autonomy in shorter period of time than current state of the art.
 - Computational tools are too slow.
 - With availability of test and field data, machine learning able to blend the digital data fabric for model update
 - Uncertainty Quantification
- Requirements for autonomous systems
- Framework still in early stages and needs maturation



Thank You

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<https://ti.arc.nasa.gov/tech/dash/groups/pcoe/>