Health Monitoring and Prognostics for Electric Aircrafts

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Acknowledgement

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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

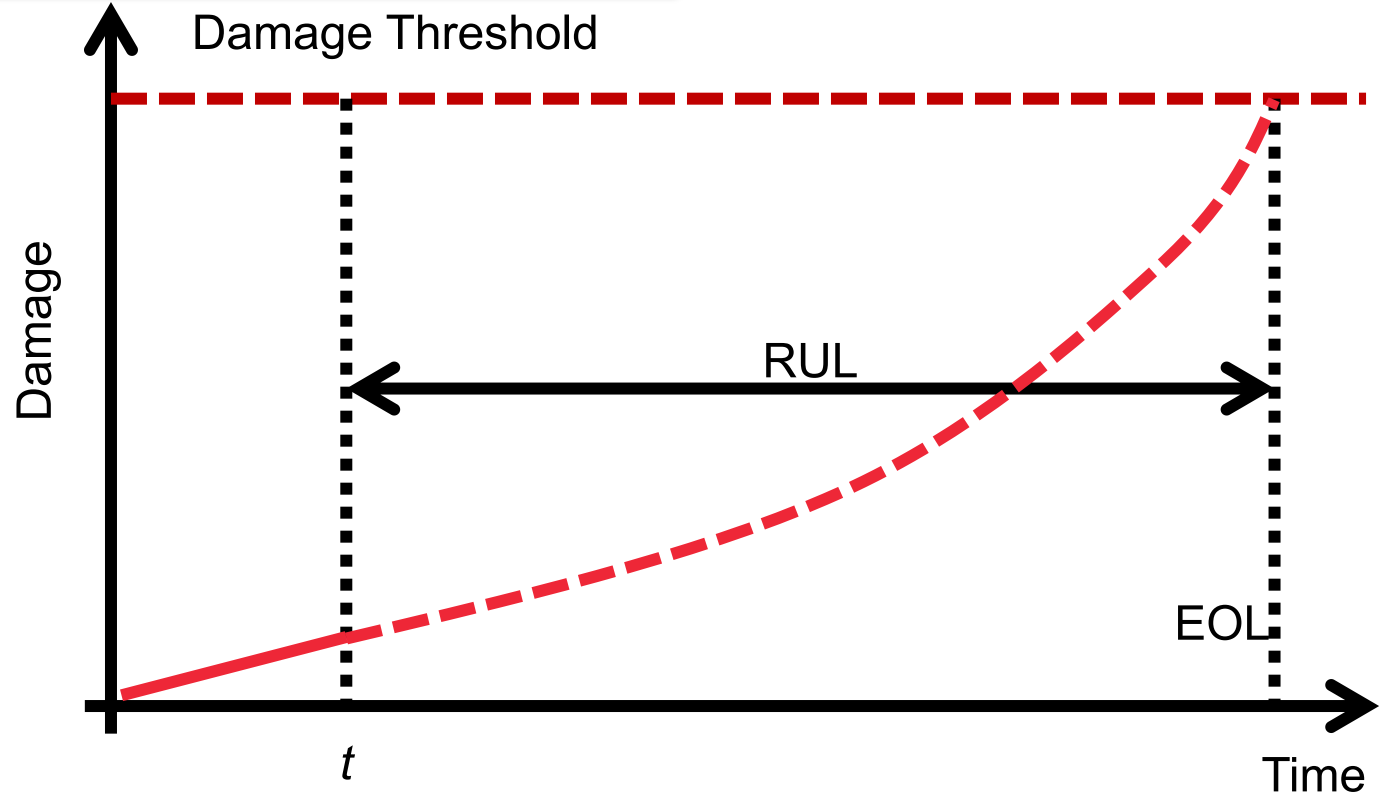
Why Prognostics

- 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

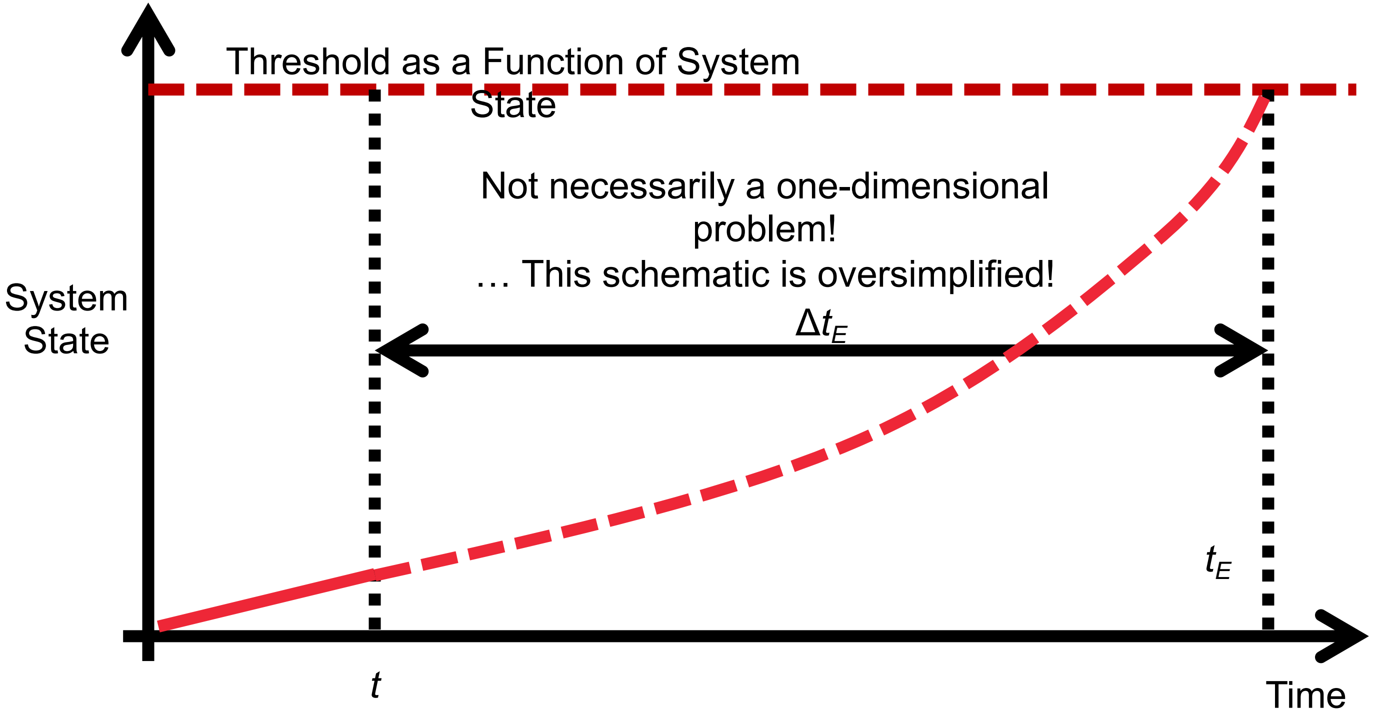
Why Prognostics

- 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

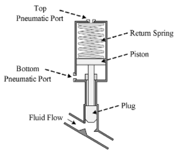


Basic Idea



Threshold as a Function of System State
Not necessarily a one-dimensional problem!
… This schematic is oversimplified!
System State
Δt_E
t_E
t
Time

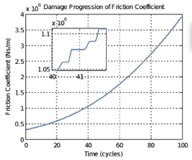
- RUL: Remaining Useful Life
  - Model underlying physics of a component/subsystem
  - Model physics of damage propagation mechanisms
  - Determine criteria for End-of-Life threshold
  - Develop algorithms to propagate damage into future
  - Deal with uncertainty



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

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

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

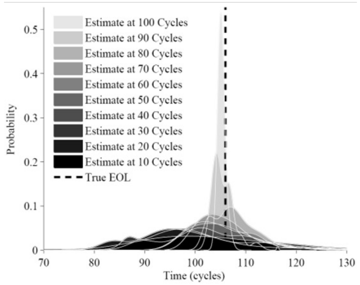


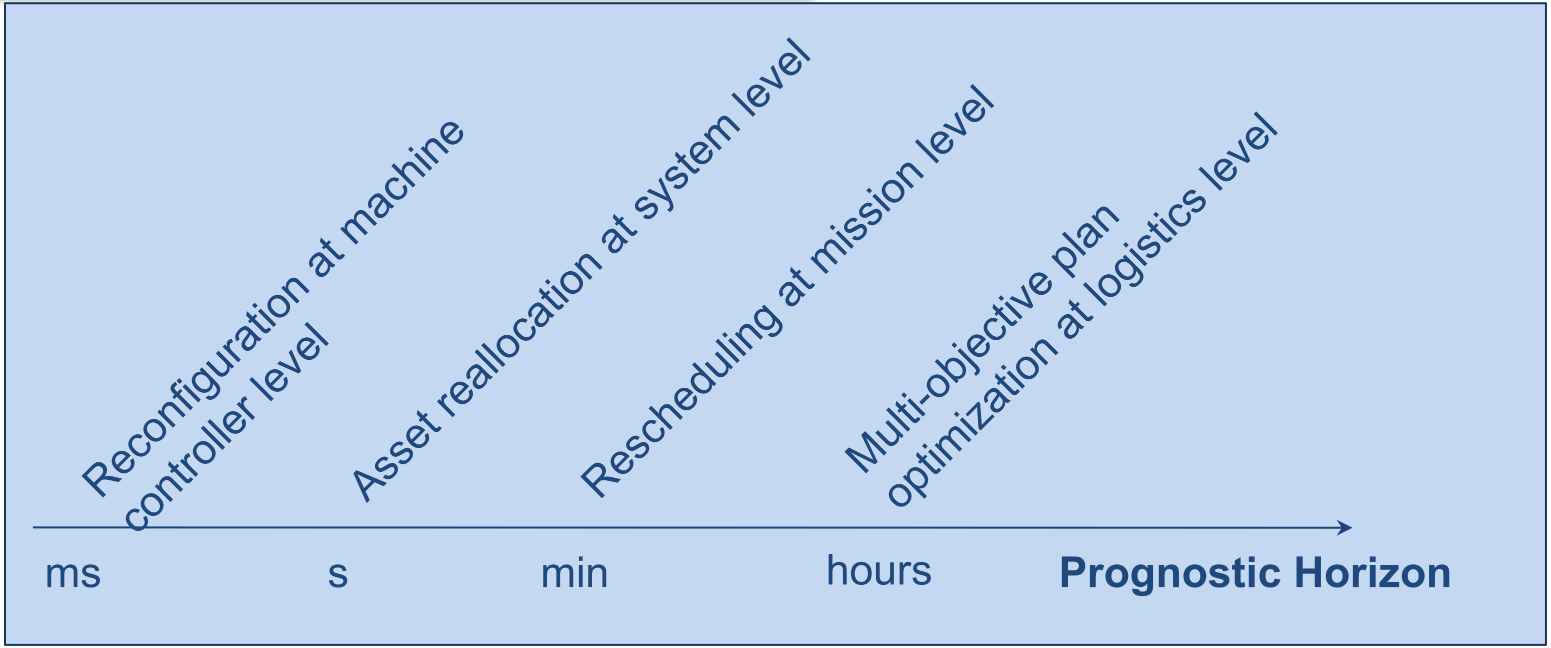
$$\boxed{\dot{r}(t) = w_r |F_f(t) v(t)|}$$

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

Algorithm 2 EOL Prediction

Inputs: $\{(\mathbf{x}^i_{k_P}, \boldsymbol{\theta}^i_k), w^i_{k_P}\}^N_{i=1}$
Outputs: $\{EOL^i_{k_P}, w^i_{k_P}\}^N_{i=1}$
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





Pilots

Air Traffic Control

Autonomy.

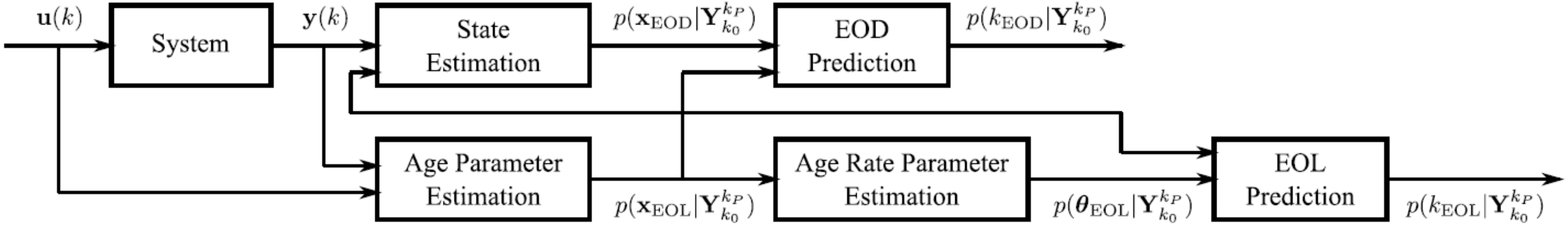
Airline Operators

Operators

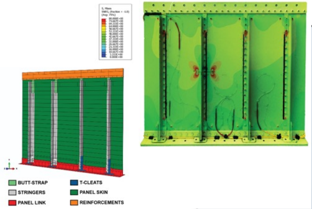
Maintainers

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

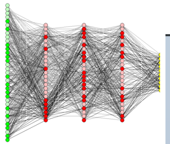


State of the Art



- 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



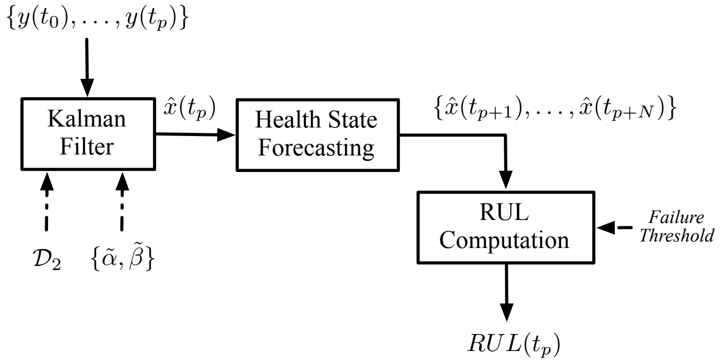
- Easy and Fast to implement
- May identify relationships that were not previously considered
- Requires lots of data and a “balanced” approach”
- Results may be counter(or even un-)intuitive
- Can be computationally intensive, both for analysis and im

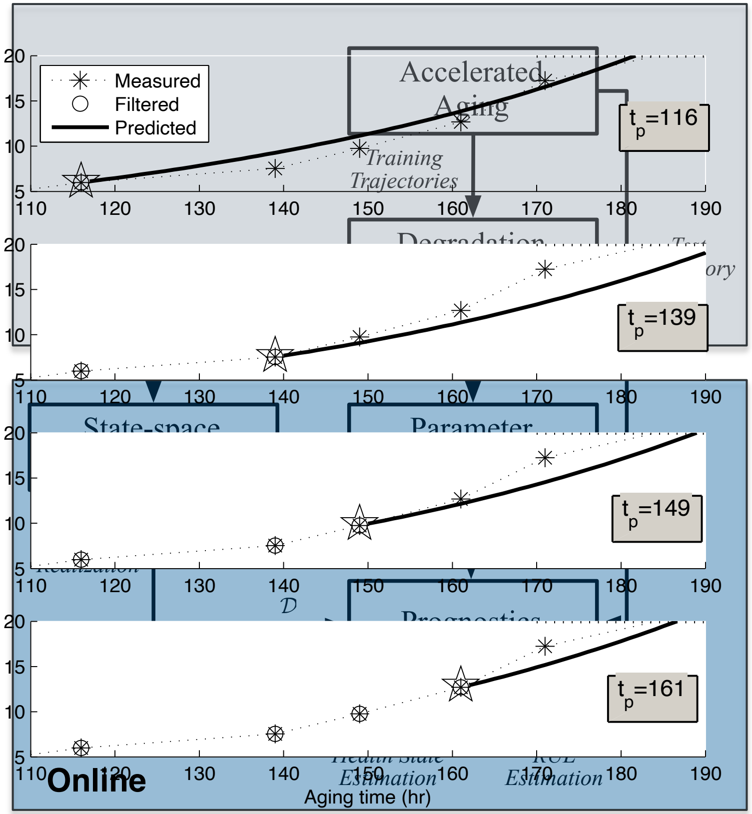
- Regression analysis
- Neural Networks (NN)
- Bayesian updates
- Relevance vector machines (RVM)

Model-based prognostics

- State vector includes dynamics of normal and degradation process

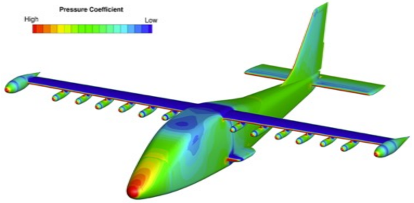
$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$
$$y_k = Hx_k + v_k$$

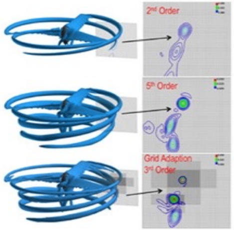


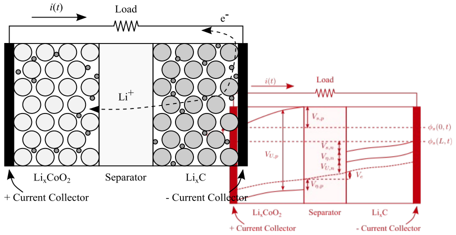


- EOL defined at time in which performance variable cross failure threshold

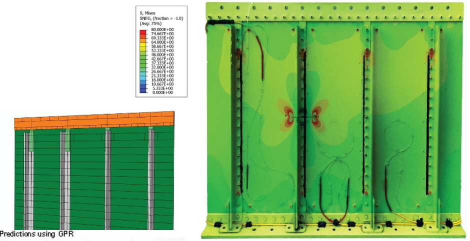
$$R(t_p) = t_{EOL} - t_p$$

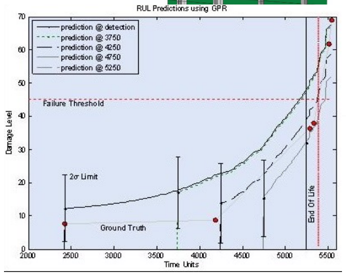

Pressure Coefficient
High
Low

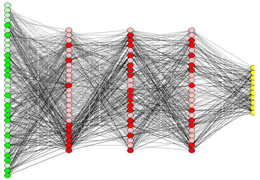

2nd Order
5th Order
Grid Adaption
3rd Order


$i(t)$
Load
e^-
Li^+
Li_xCoO_2
Separator
Li_xC
+ Current Collector
- Current Collector

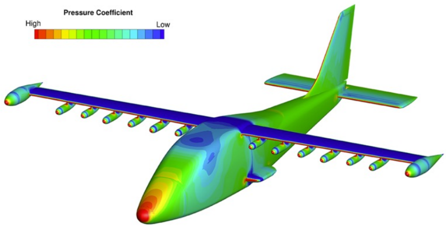
+

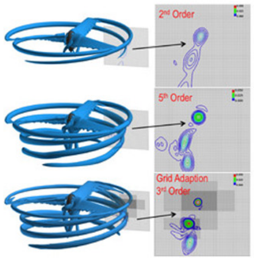


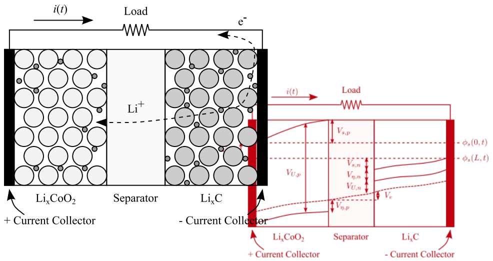

RUL Predictions using GPR
prediction @ detection
prediction @ 3750
prediction @ 4250
prediction @ 4750
prediction @ 5250
Failure Threshold
2σ Limit
Ground Truth
End Of Life
Damage Level
Time Units



Hybrid Approach







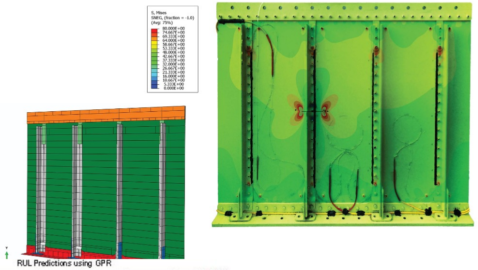
Machine-Learning underlying physics parameters

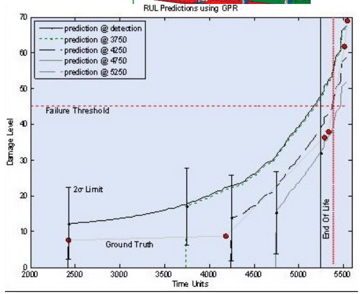
Tensor Flow

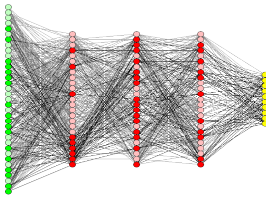
Microsoft Cognitive

Uber Ludwig

Scikit-learn

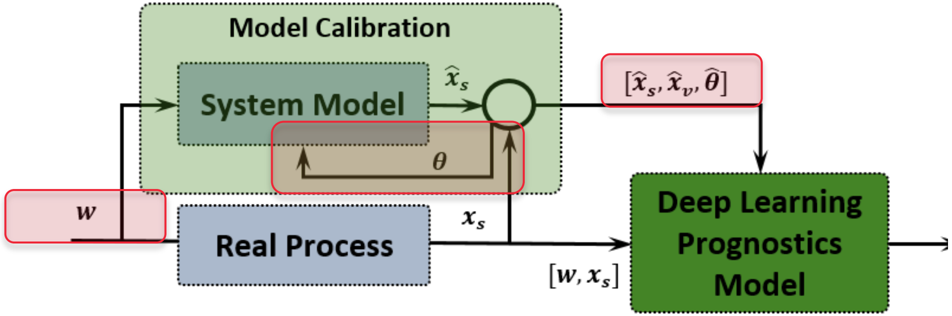




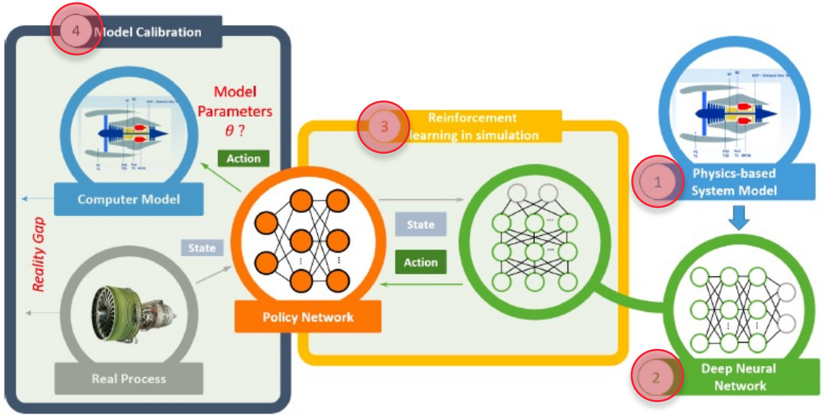


Understanding and Learning underlying Physics for Complex Systems

Approach 1 : Deep Learning + Physics Model Calibration



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

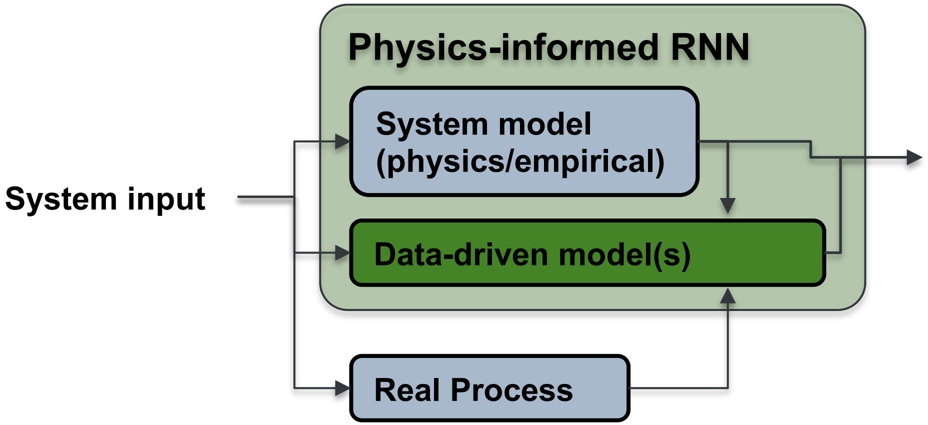


Calibration Policy

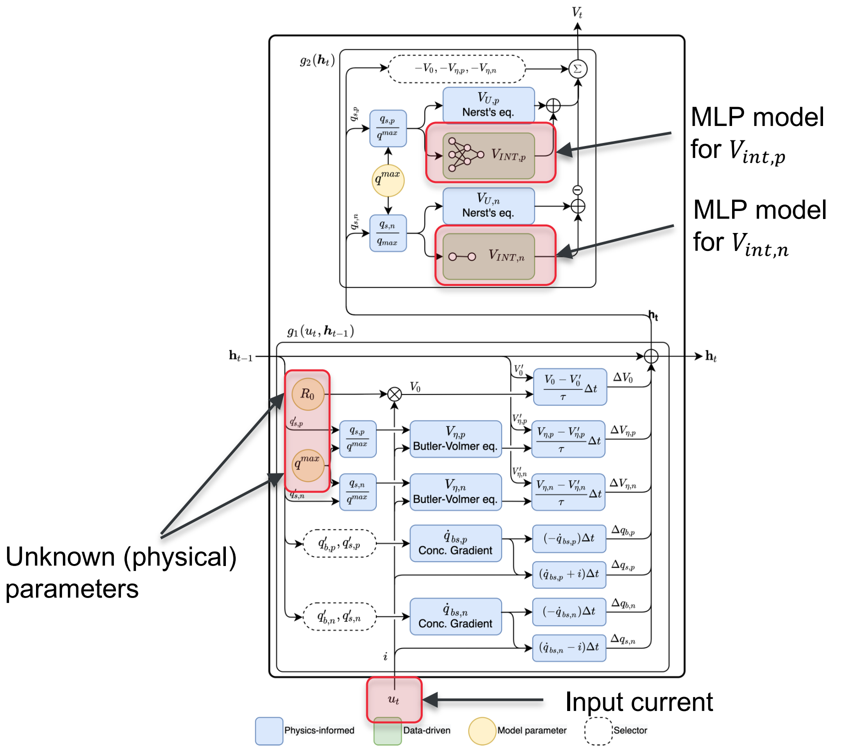
Yuan Tian, Manuel Arias Chao, Chetan Kulkarni, Kai Goebel, Olga Fink, “Real-Time Model Calibration with Deep Reinforcement Learning”, arXiv:2006.04001

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

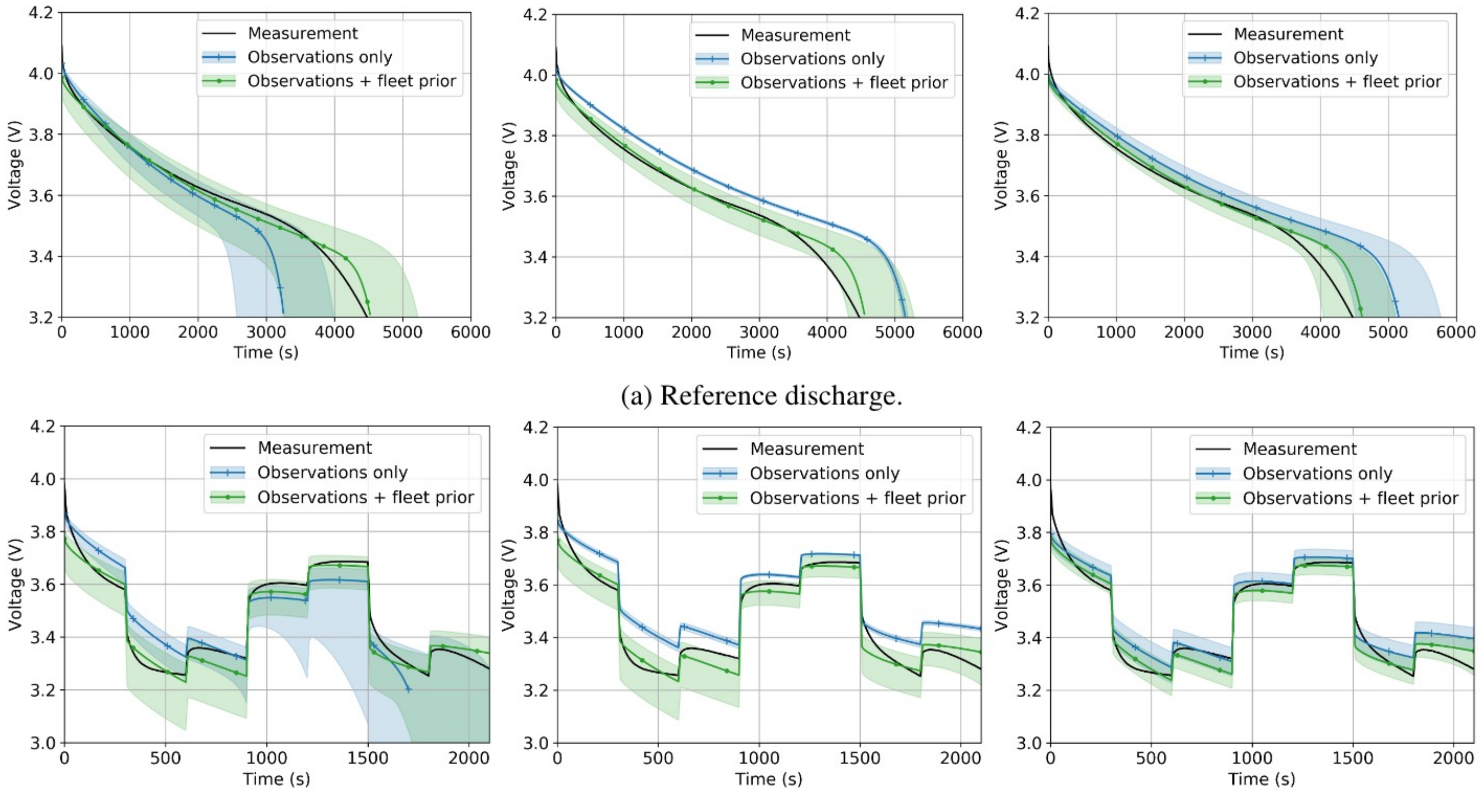


Physics-informed neural network framework for Li-ion Battery SOC estimation

Nascimento, R.G. & Viana, F. A. & Corbetta, M. & Kulkarni, C. S. (2021). "Usage-based Lifing 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)

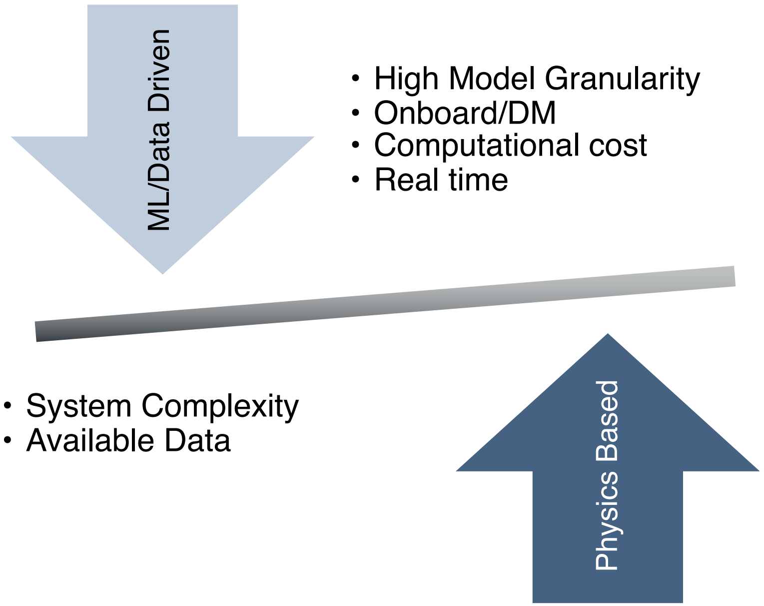
Approach 2 : Physics + RNN



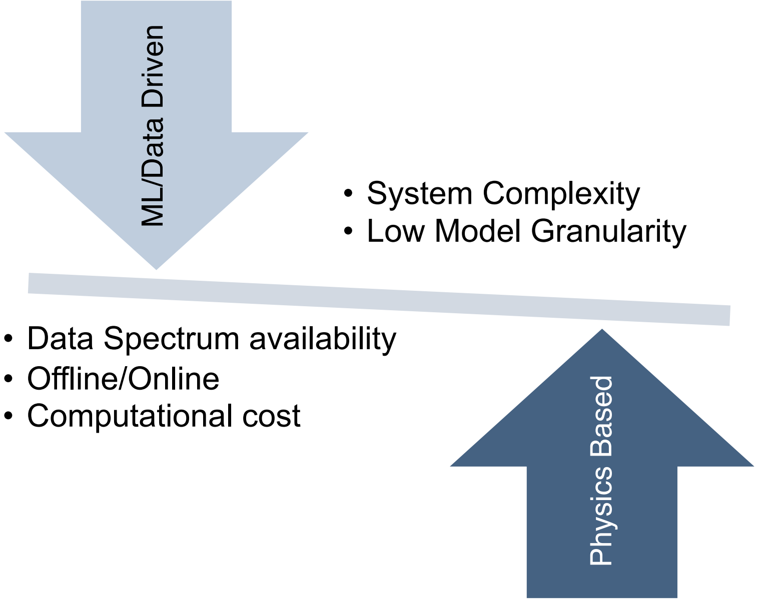
(a) Reference discharge.

(b) Random-loading discharge.

Next Steps : Looking Ahead



Next Steps : Looking Ahead



Next Steps : Looking Ahead

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 two 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/