

Physics Informed Neural Nets for Systems Health Management

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Credit: www.nasa.gov

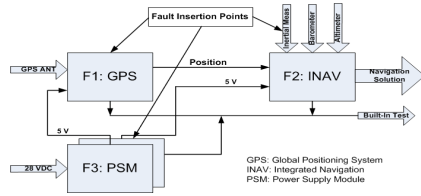


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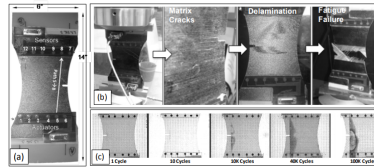


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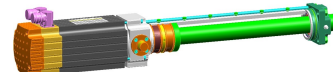
UAM vehicle



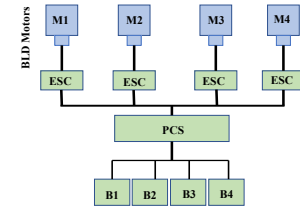
Avionics



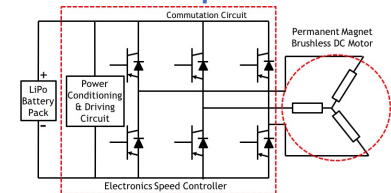
Structures



Actuators

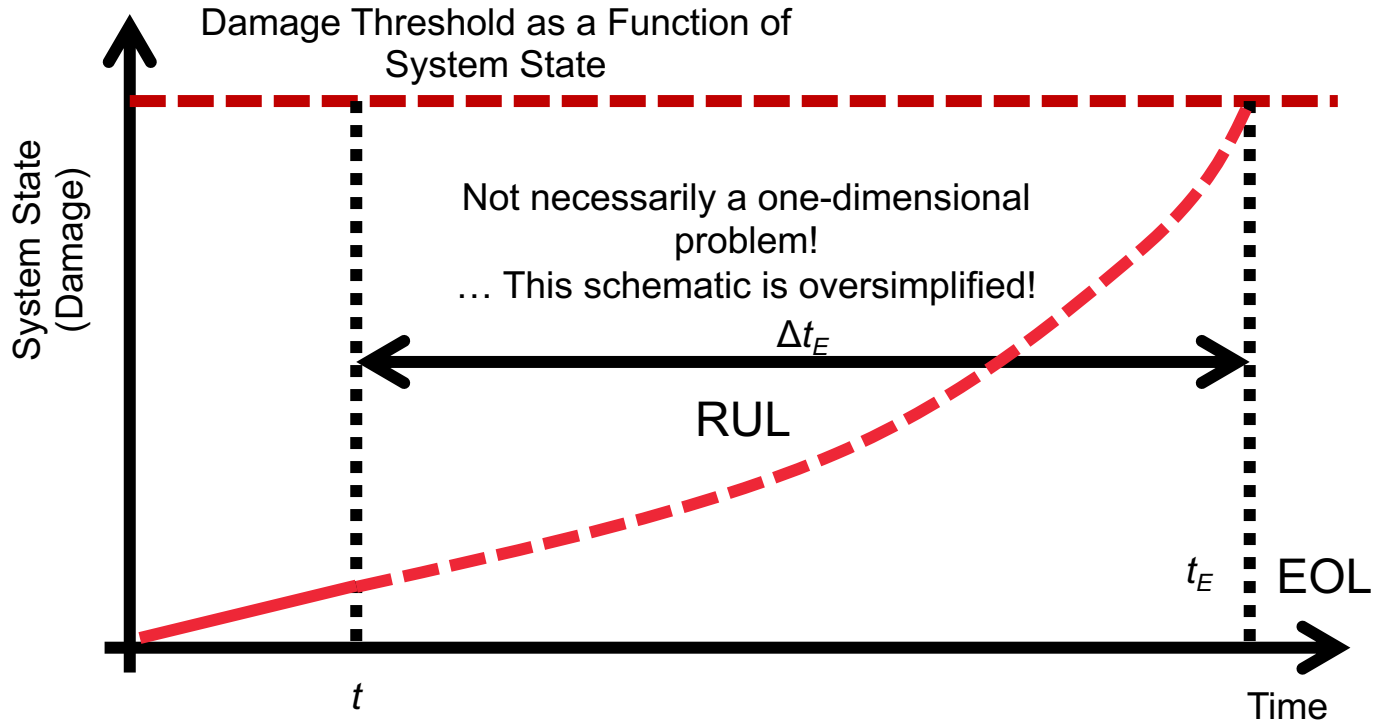


Powertrain



Single Arm - Powertrain

Basic Idea



- **RUL: Remaining Useful Life**

- Model underlying physics of a component/subsystem



- Model physics of damage propagation mechanisms



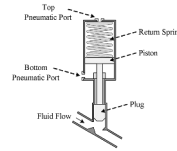
- Determine criteria for End-of-Life threshold



- Develop algorithms to propagate damage into future



- Deal with uncertainty

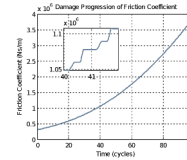


$$f_t(t) = f_g(p_t(t), u_t(t))$$

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

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

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

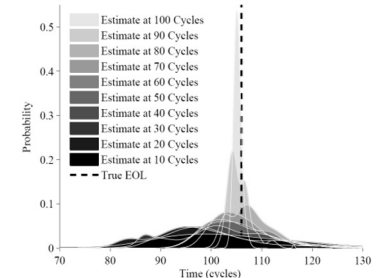


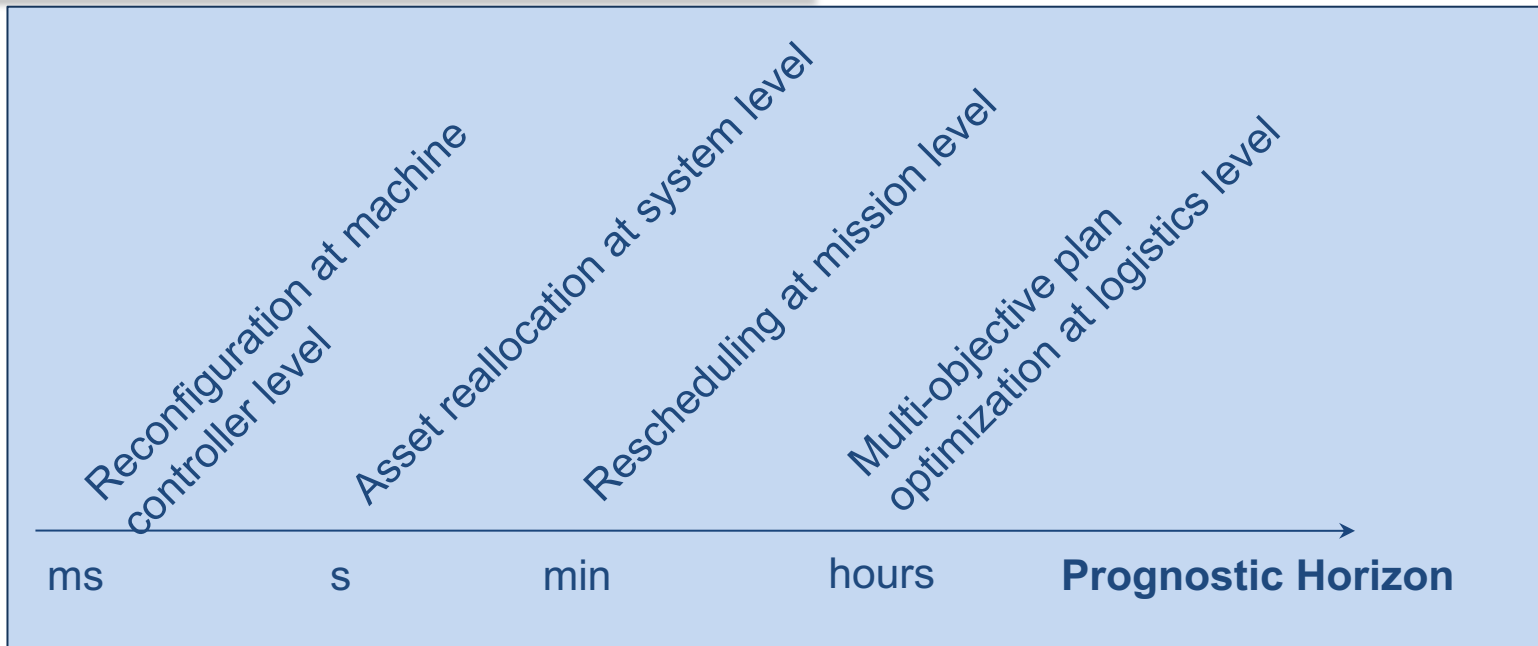
$$\hat{r}(t) = w_r |F_f(t)v(t)|$$

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

Algorithm 2 EOL Prediction

Inputs: $\{\mathbf{x}_{k_p}^i, \boldsymbol{\theta}_k^i, w_{k_p}^i\}_{i=1}^N$
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





Pilots

Air Traffic Control

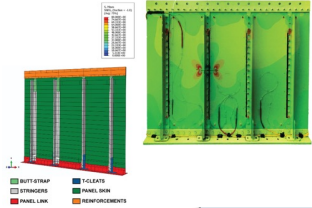
Autonomy

Airline Operators

Operators

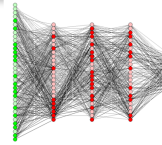
Maintainers

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

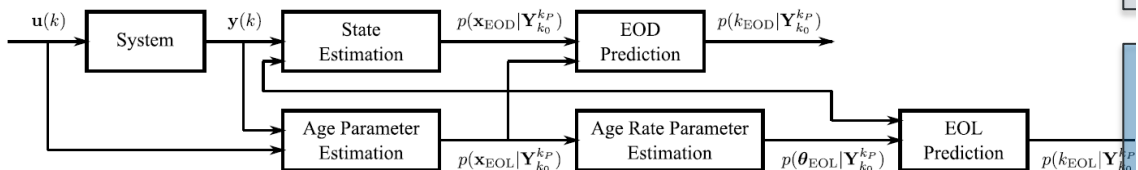
- Regression analysis
- Neural Networks (NN)
- Bayesian updates
- Relevance vector machines (RVM)

Model-based prognostics

- State vector includes dynamics of normal and degradation process

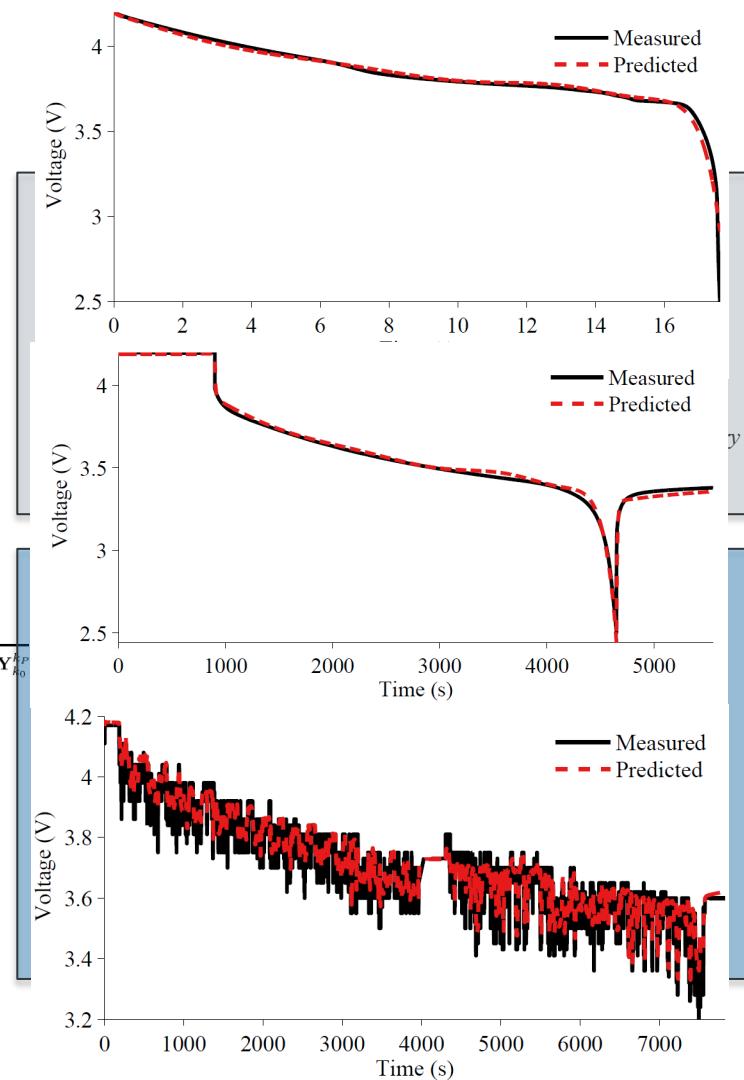
$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$

$$y_k = Hx_k + v_k$$

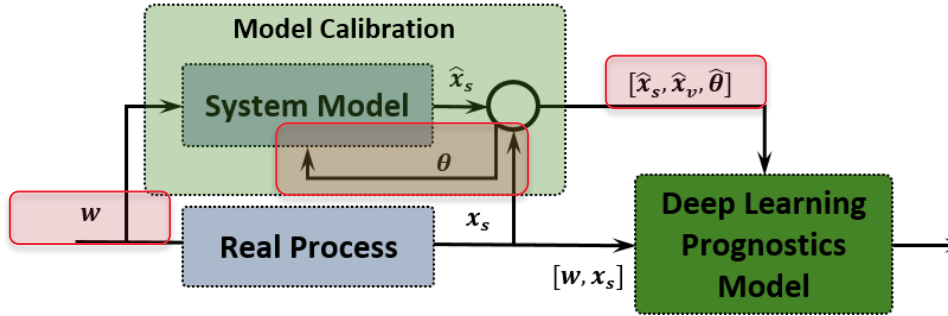


- EOL defined at time in which performance variable cross failure threshold

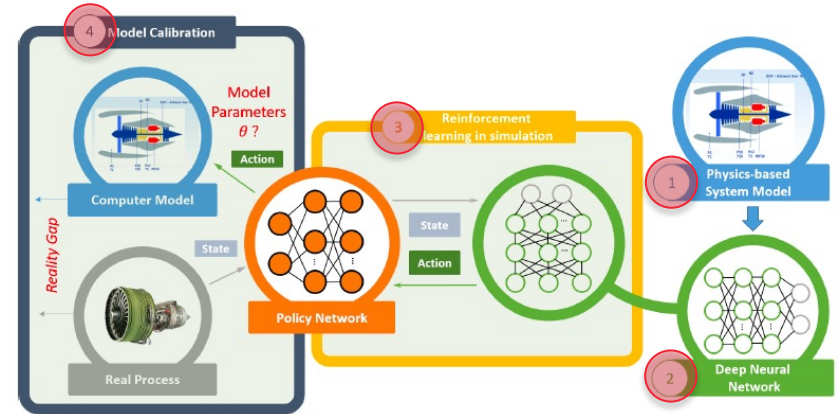
$$R(t_p) = t_{EOL} - t_p$$



Approach 1 : Deep Learning + Physics Model Calibration



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

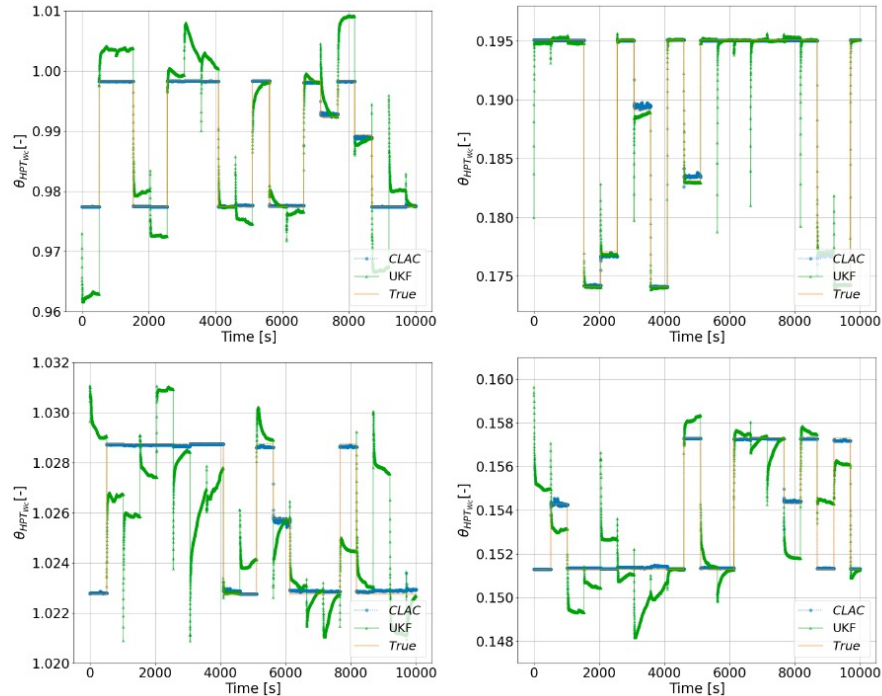


Calibration Policy

M. Chao, Y. Tian, C. Kulkarni, K. Goebel, O. Fink, "Real-Time Model Calibration with Deep Reinforcement Learning", Mechanical Systems and Signal Processing, 2022, ISSN 0888- 3270 * work done during collaboration

M. Chao, C. Kulkarni, K. Goebel, O. Fink, "Fusing Physics-based and Deep Learning Models for Prognostics", Reliability Engineering & System Safety, Volume 217, 2022, ISSN 0951-8320 * work done during collaboration

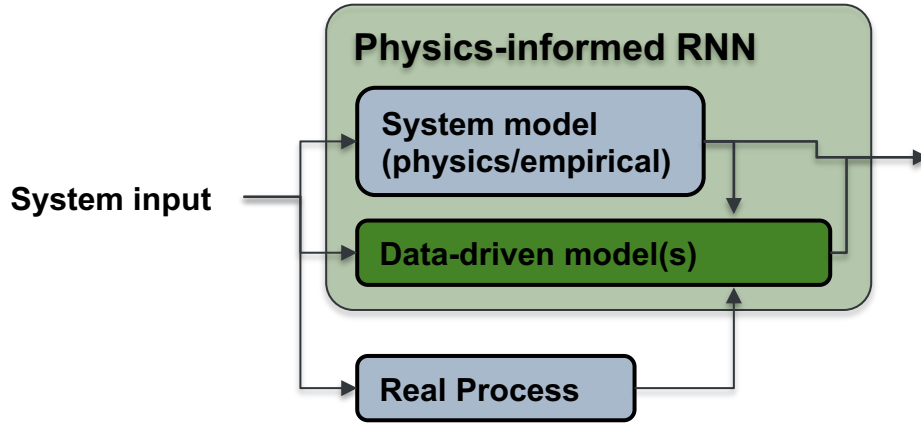
Approach 1 : Deep Learning + Physics Model Calibration



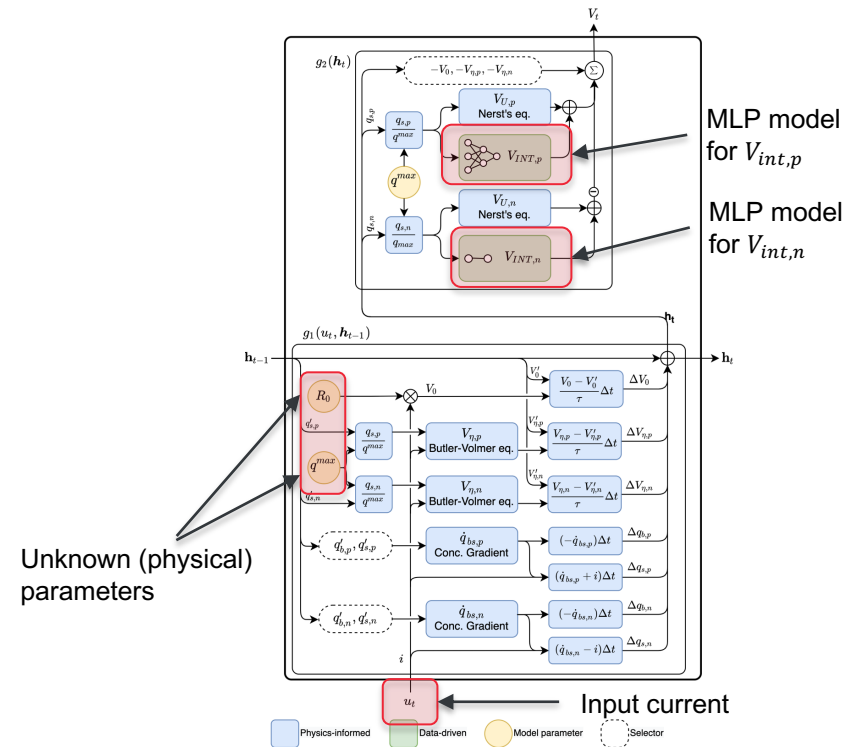
M. Chao, Y. Tian, C. Kulkarni, K. Goebel, O. Fink, "Real-Time Model Calibration with Deep Reinforcement Learning", *Mechanical Systems and Signal Processing*, 2022, ISSN 0888- 3270 * work done during collaboration

M. Chao, C. Kulkarni, K. Goebel, O. Fink, "Fusing Physics-based and Deep Learning Models for Prognostics", *Reliability Engineering & System Safety*, Volume 217, 2022, ISSN 0951-8320 * work done during collaboration

Approach 2 : Physics + RNN



Architecture of the physics-informed recurrent neural network

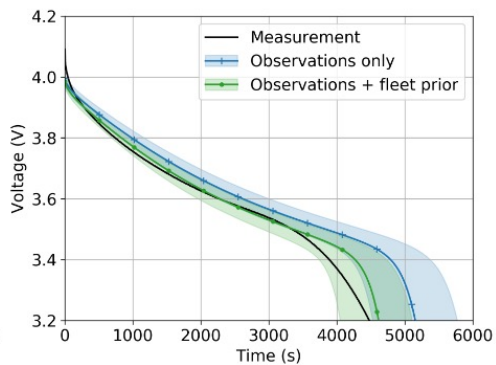
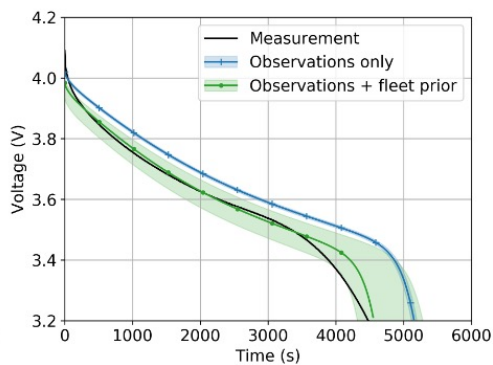
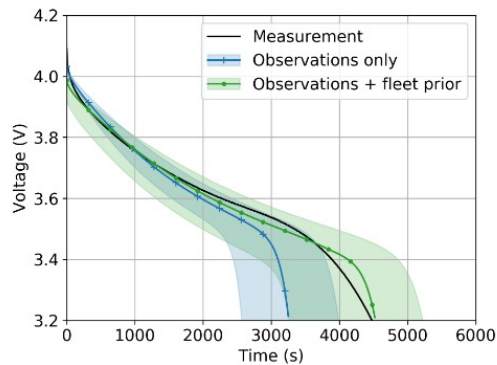


Physics-informed neural network framework for Li-ion Battery SOC estimation

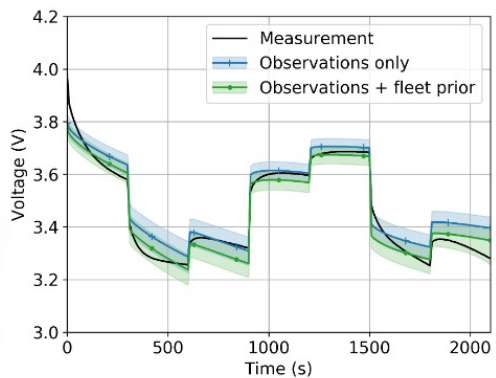
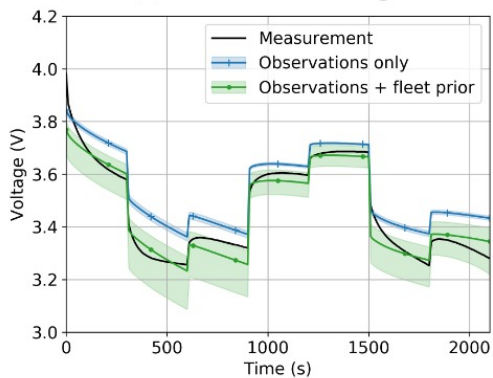
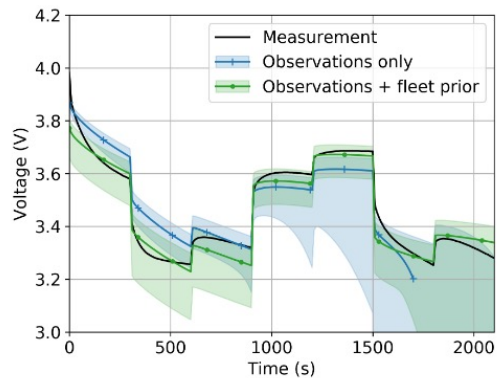
R G. Nascimento; M. Corbetta; C. Kulkarni; F. A.C. Viana, "Hybrid Physics-Informed Neural Networks for Lithium-Ion Battery Modeling and Prognosis", Journal of Power Sources, Volume 513, 2021, ISSN 0378-7753

R G. Nascimento; M. Corbetta; C. Kulkarni; F. A.C. Viana, "A Hybrid Variational Physics- Informed Neural Network with Complete and Censored Data for Battery Prognosis", Journal of Reliability Engineering & System Safety

Approach 2 : Physics + RNN

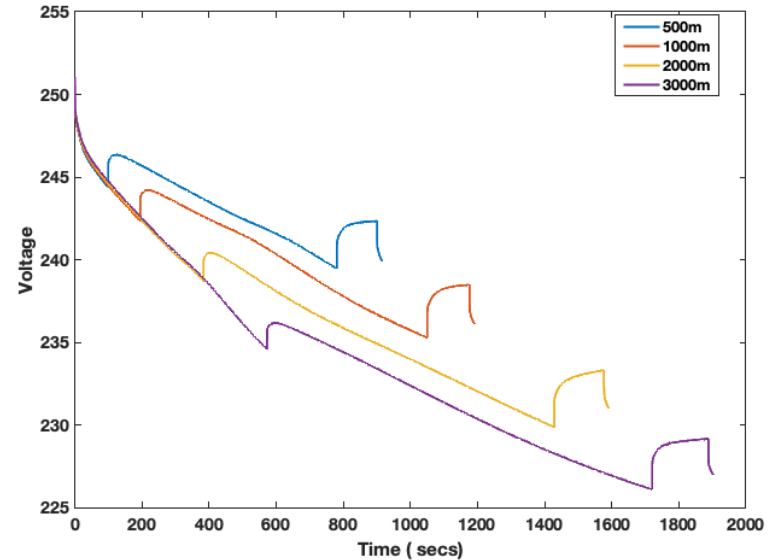
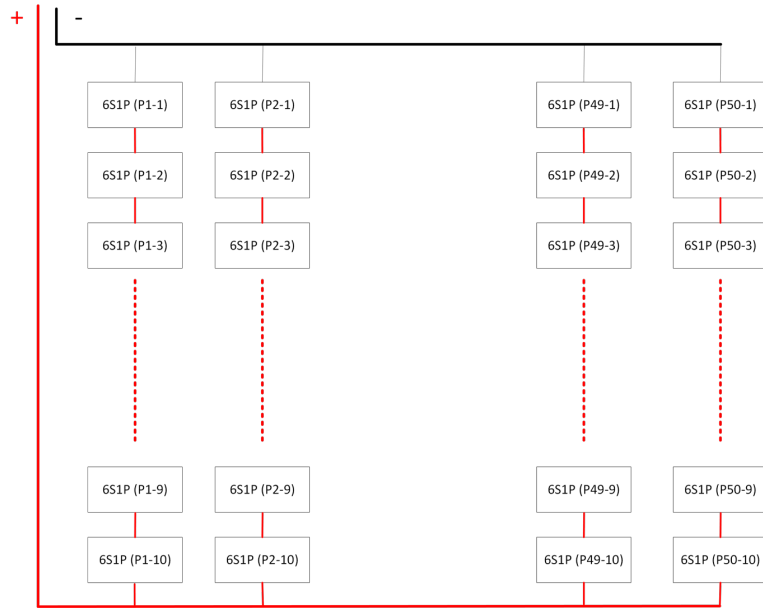


(a) Reference discharge.



(b) Random-loading discharge.

Approach 2 : Physics + RNN – Multi cell Application



C. Kulkarni; P. Pradeep and G. Chatterjee, "Simulation Studies for an Urban Air Mobility Aircraft using Hardware-In-Loop Experiments" AIAA Aviation 2022

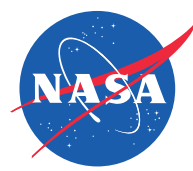
Next Steps : Looking Ahead



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/>