Hybrid Model Based Approaches for Systems Health Management and Prognostics

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Credits: NASA, www.nasa.gov

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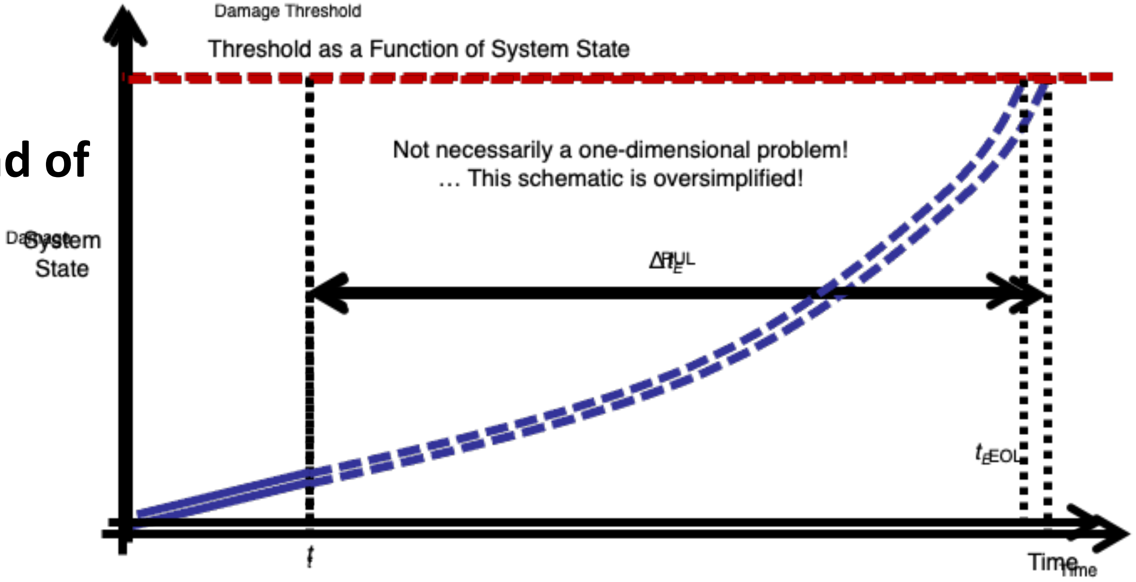
Prof. Felipe Viana, Renato Nascimento - University of Central Florida

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**



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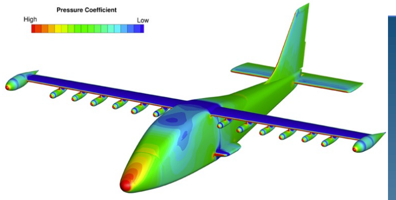
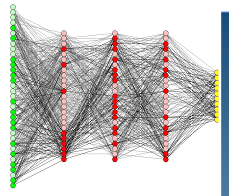
State of the Art



- 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



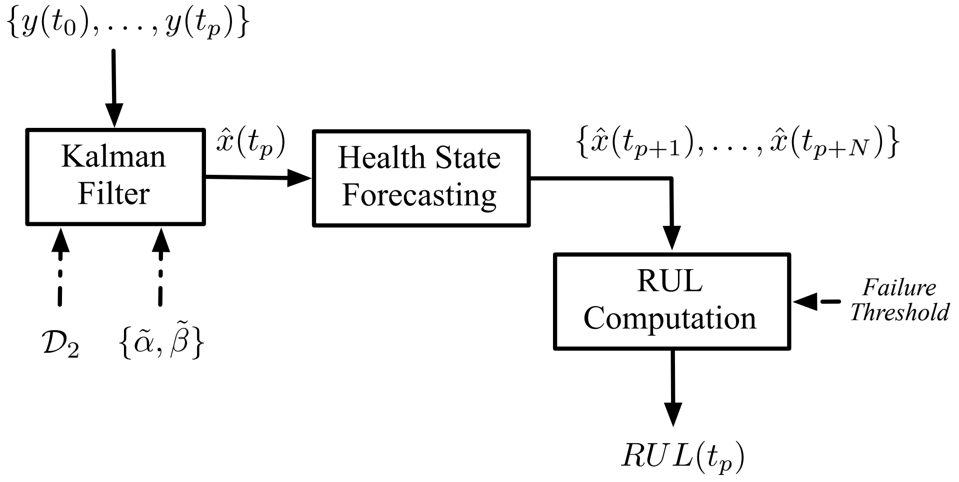
- Easy and Fast to implement
- May identify relationships that were not previously considered
- Requires lots of data and a “balanced” approach”
- Results may be counter(or even un-)intuitive
- Can be computationally intensive, both for analysis and im

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

Model-based prognostics

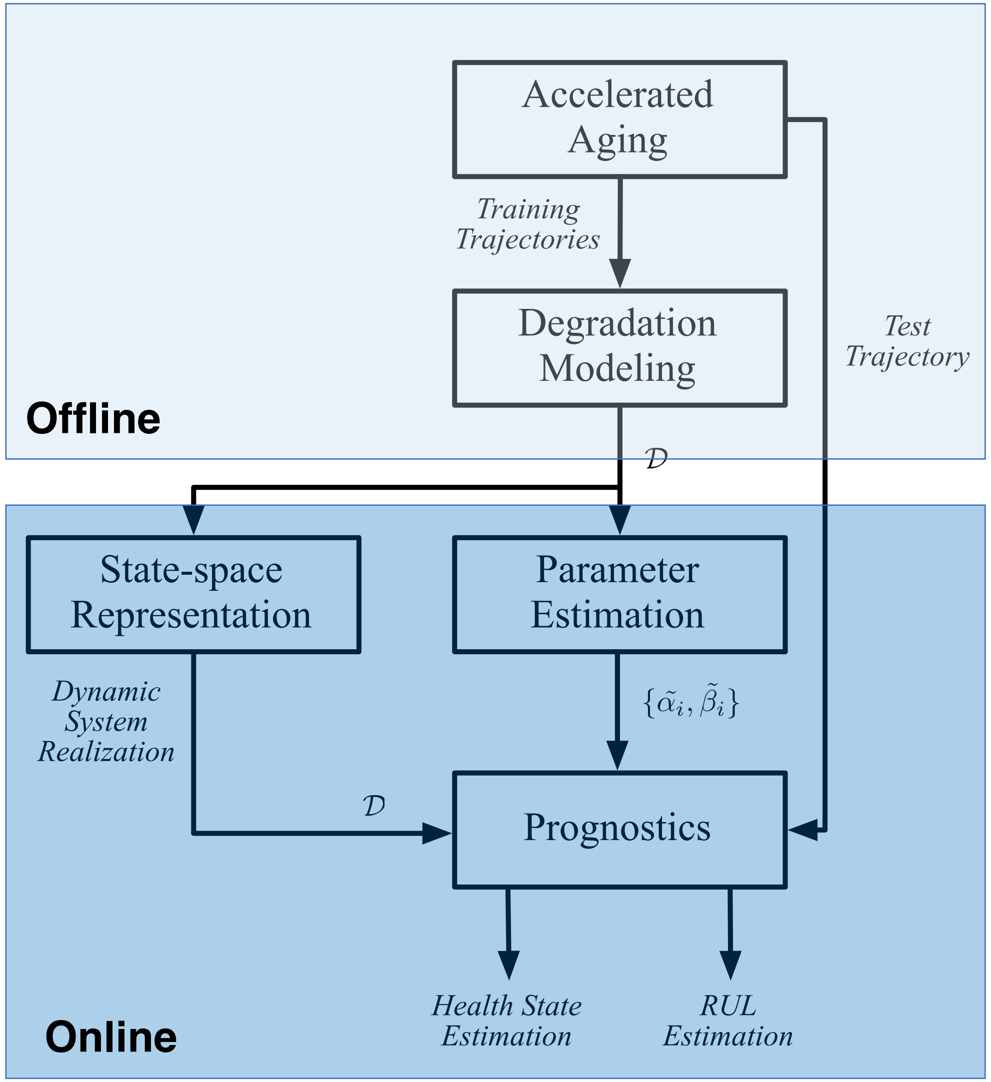
- State vector includes dynamics of normal and degradation process

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



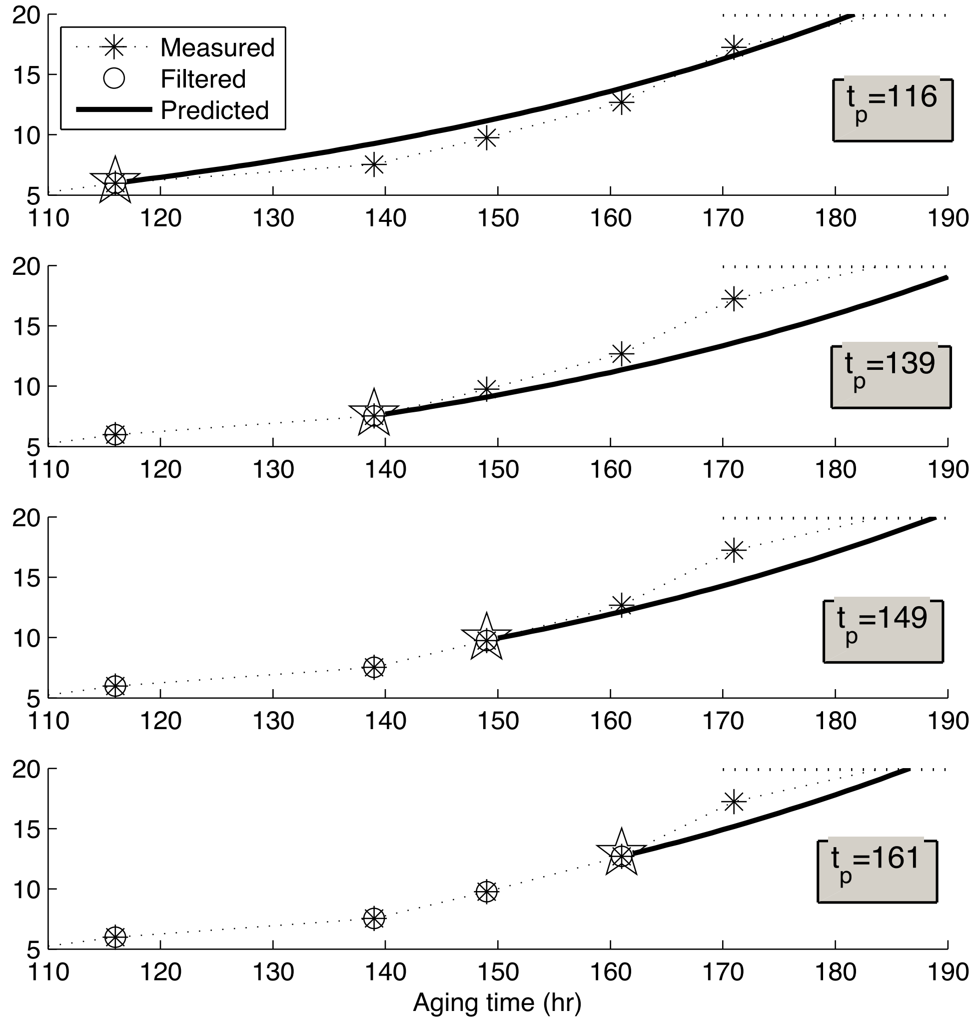
- EOL defined at time in which performance variable cross failure threshold

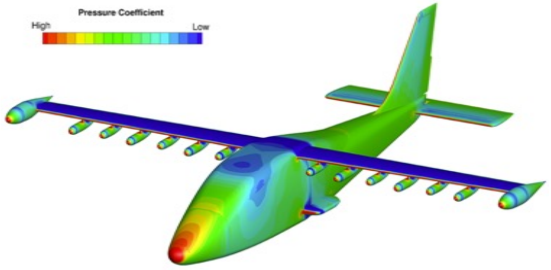
$$R(t_p) = t_{EOL} - t_p$$

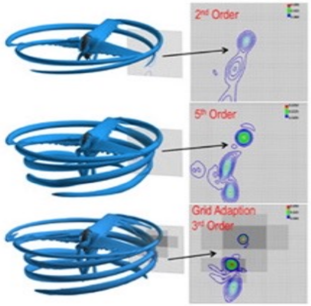


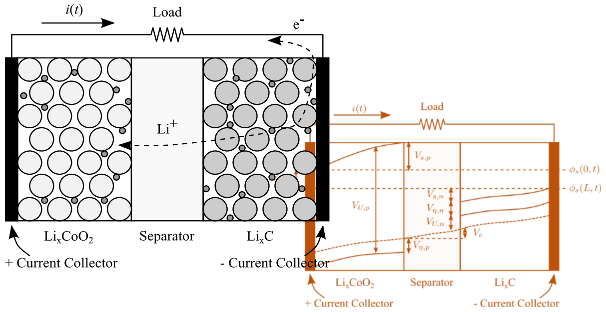
Model-based prognostics

- Tracking of health state based on measurements
- Forecasting of health state until failure threshold is crossed
- Compute RUL as function of EOL defined at time failure threshold is crossed

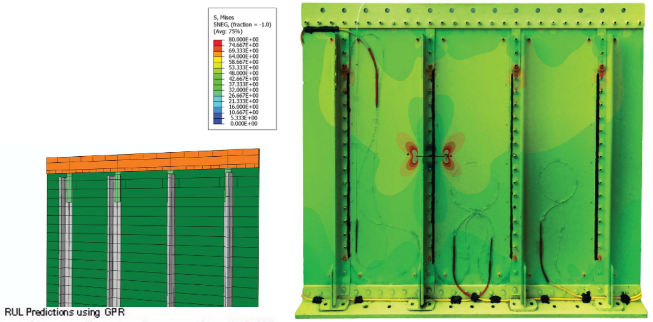


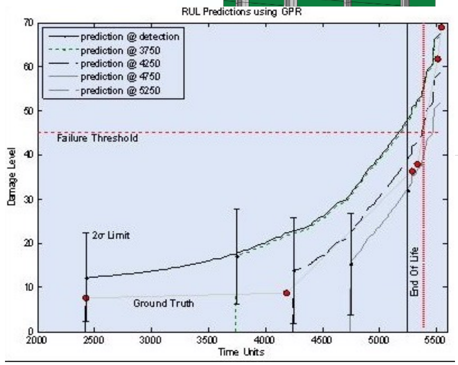

Pressure Coefficient
High
Low

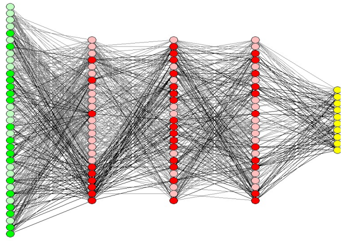

2nd Order
5th Order
Grid Adaption
3rd Order


i(t)
Load
e-
Li+
LixCoO2
Separator
LixC
+ Current Collector
- Current Collector

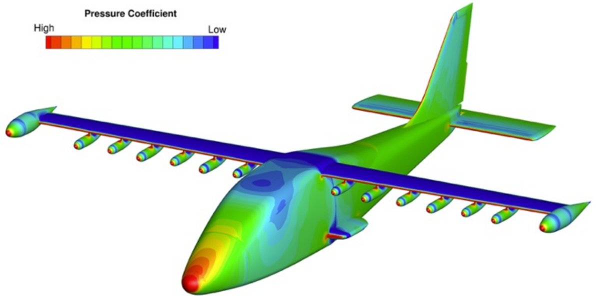
+

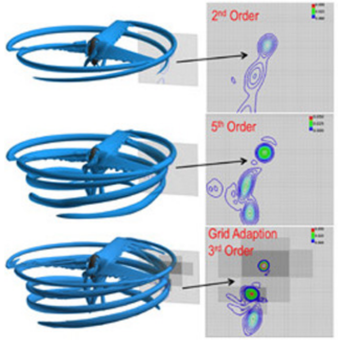


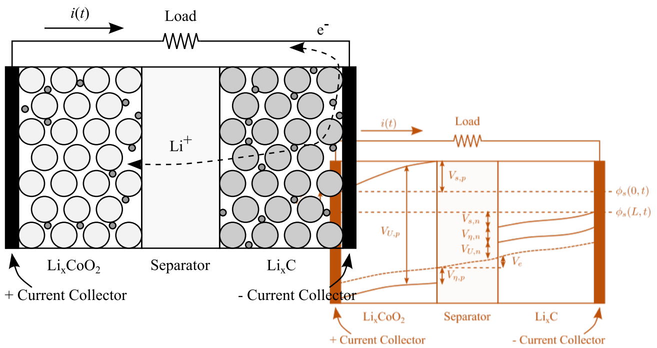

RUL Predictions using GPR
prediction @ detection
prediction @ 3750
prediction @ 4250
prediction @ 4750
prediction @ 5250
Failure Threshold
2σ Limit
Ground Truth
End Of Life
Damage Level
Time Units



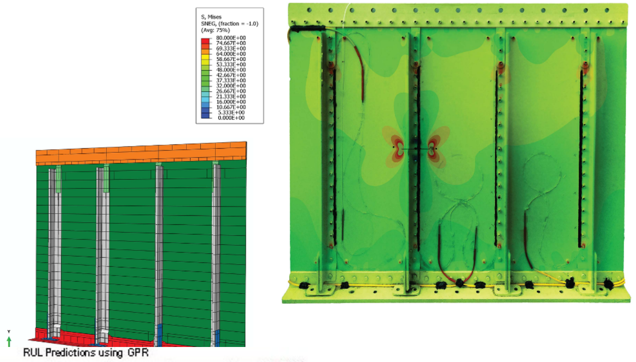
Hybrid Approach

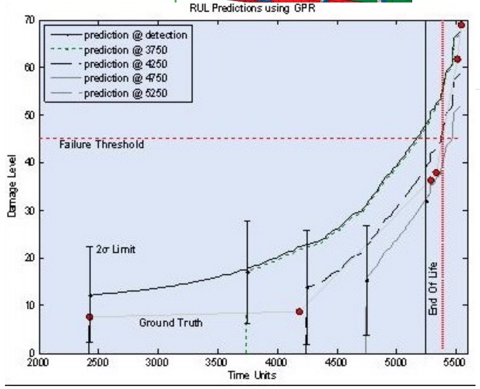






Machine-Learning underlying physics parameters



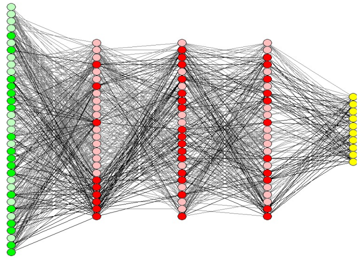


Tensor Flow

Microsoft Cognitive

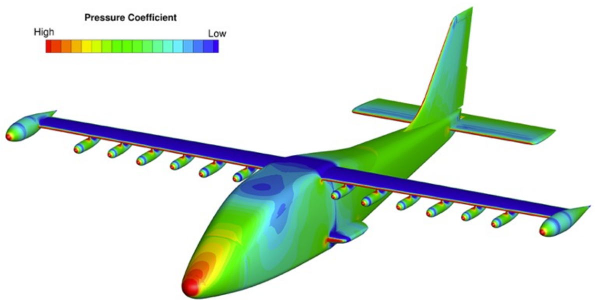
Uber Ludwig

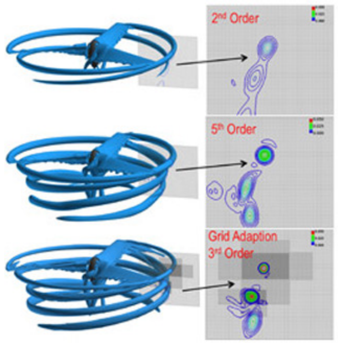
Scikit-learn

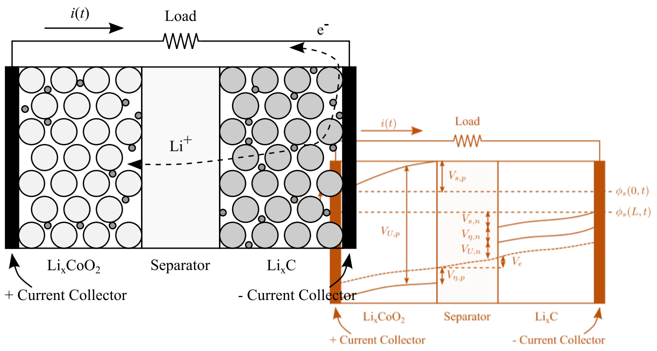


Understanding and Learning underlying Physics for Complex Systems

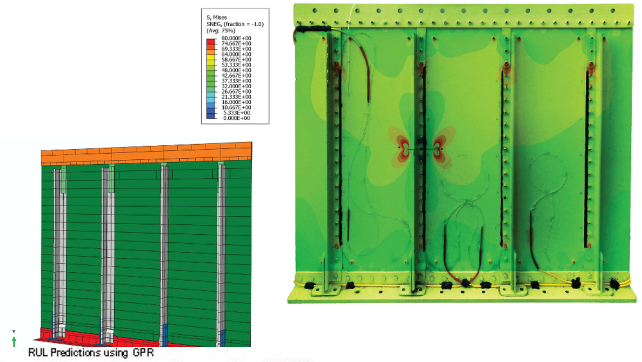
Hybrid Approach

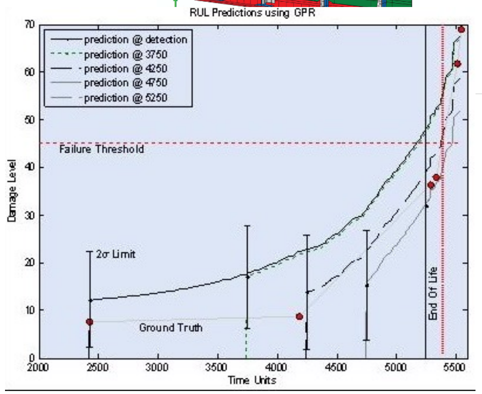






Machine-Learning underlying physics parameters





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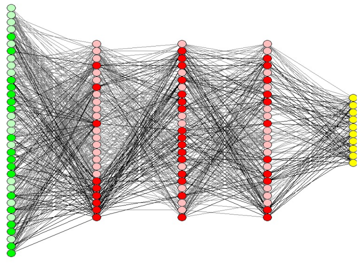
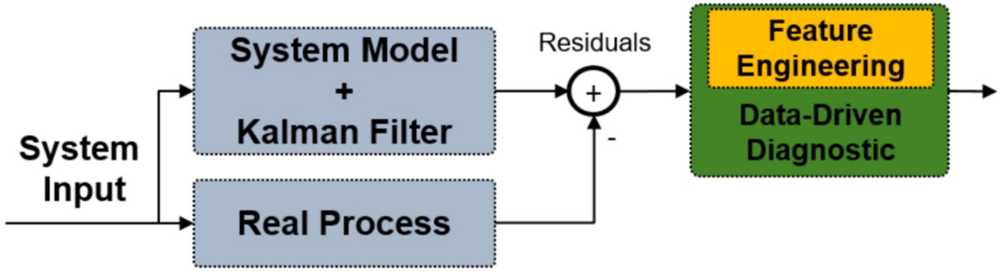
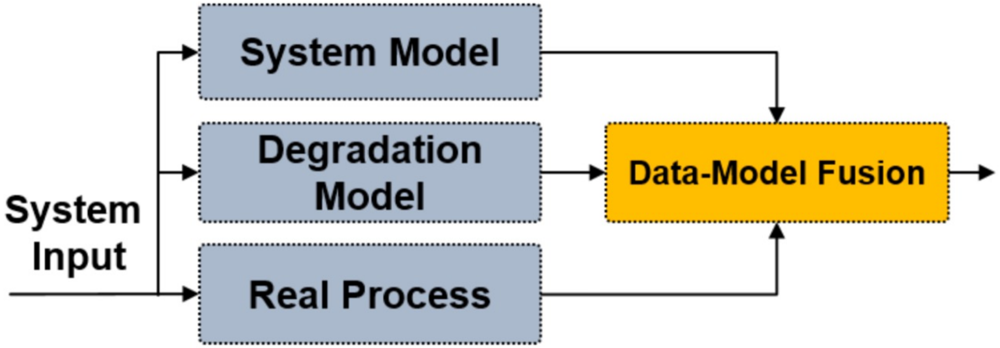


Understanding and Learning underlying Physics for Complex Systems

Hybrid Approaches : Prior Work

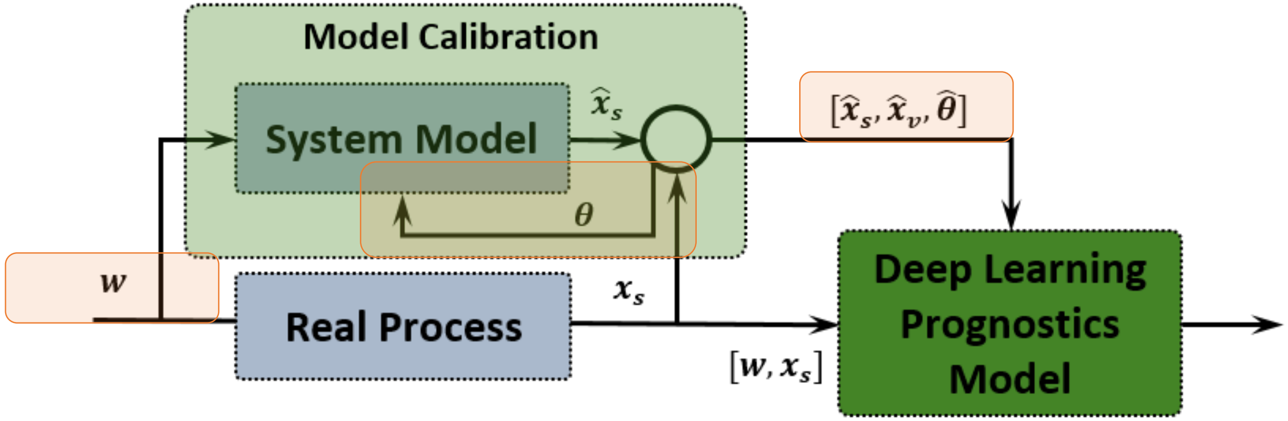


Overall architecture of the residual-based hybrid diagnostics (Rausch et al., 2005).

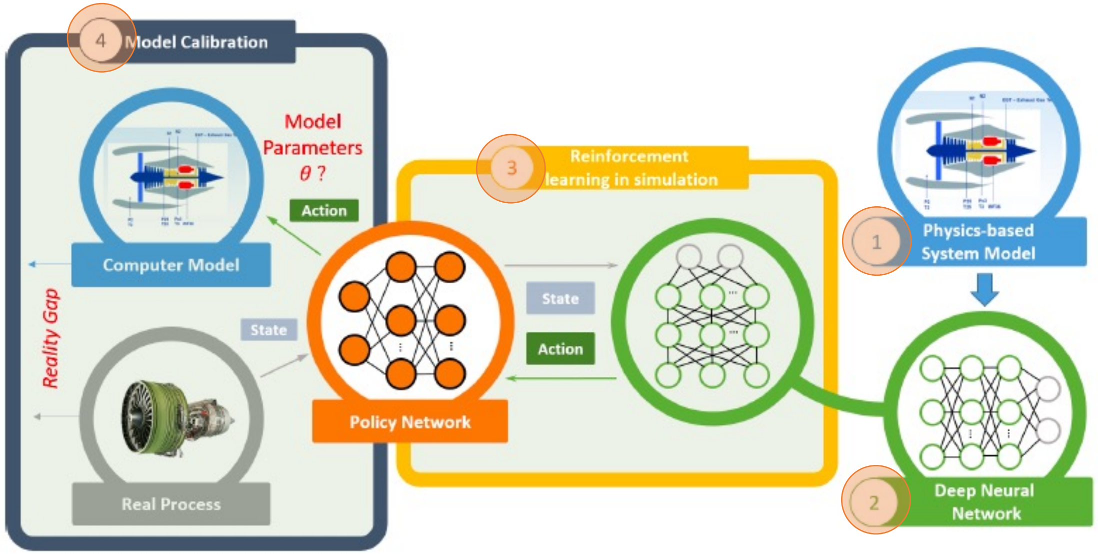


(Hanachi et al., 2017).

Approach 1 : Deep Learning + Physics Model Calibration



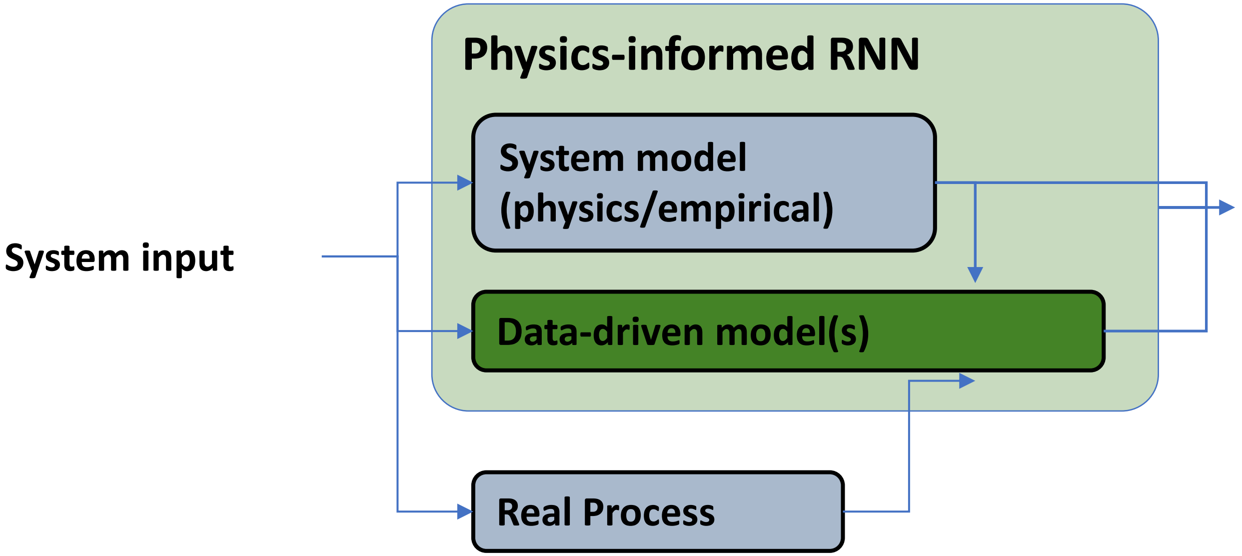
Overall architecture of the hybrid prognostics framework fusing physics-based and deep learning models.



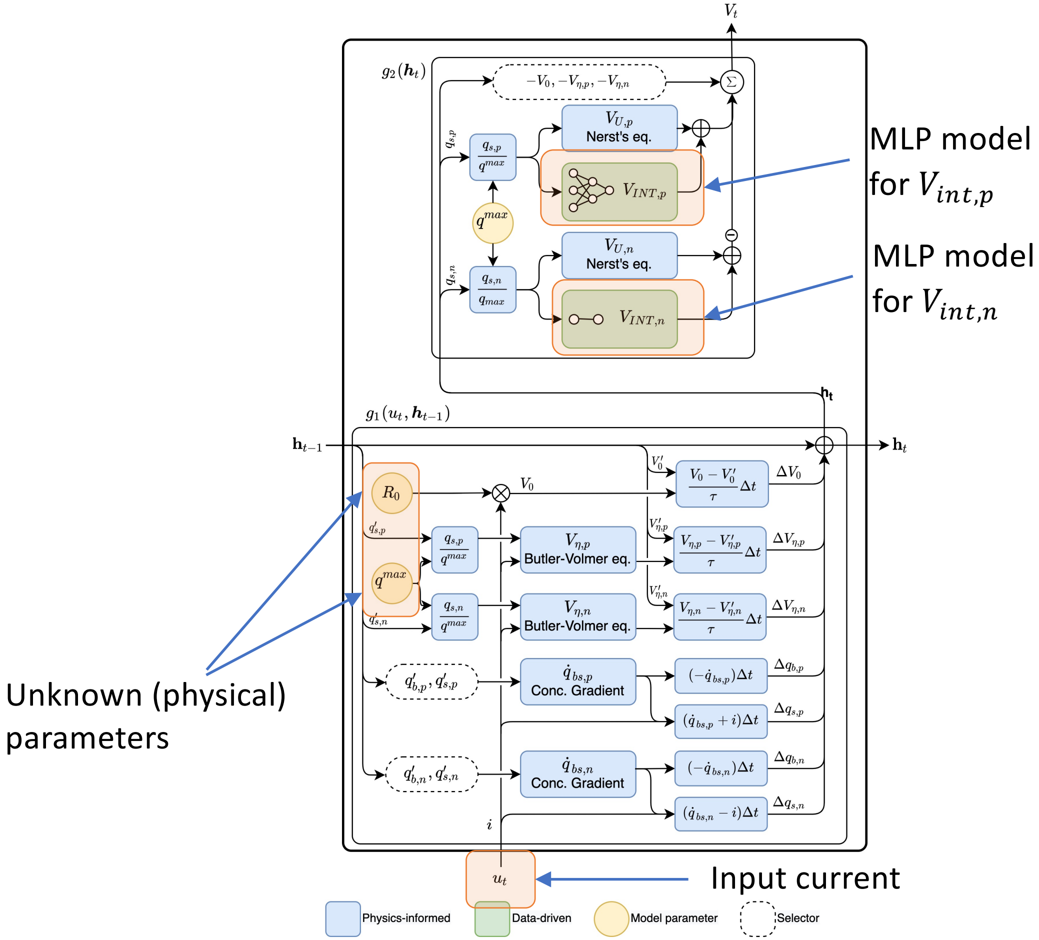
Calibration Policy

- Chao, Manuel A.; Kulkarni, Chetan; Goebel, Kai; Fink, Olga, “Fusing Physics-based and Deep Learning Models for Prognostics”, Reliability Engineering & System Safety, Volume 217, 2022
- Chao, Manuel A.; Kulkarni, Chetan; Goebel, Kai; Fink, Olga. 2021. "Aircraft Engine Run-to-Failure Dataset under Real Flight Conditions for Prognostics and Diagnostics" Data 6, no. 1: 5.
- https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/#turbofan-2

Approach 2 : Physics + RNN



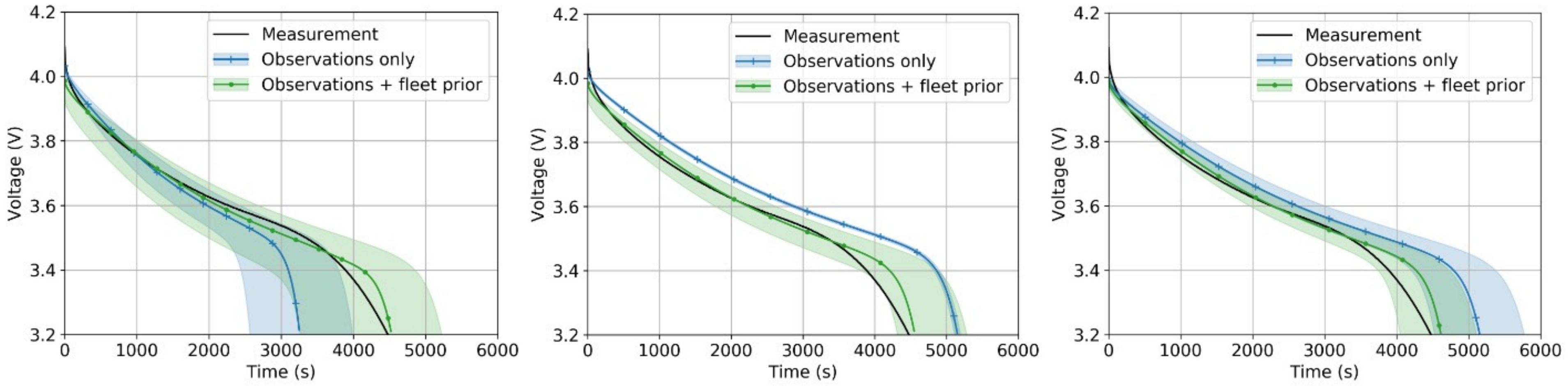
Overall architecture of the physics-informed recurrent neural network



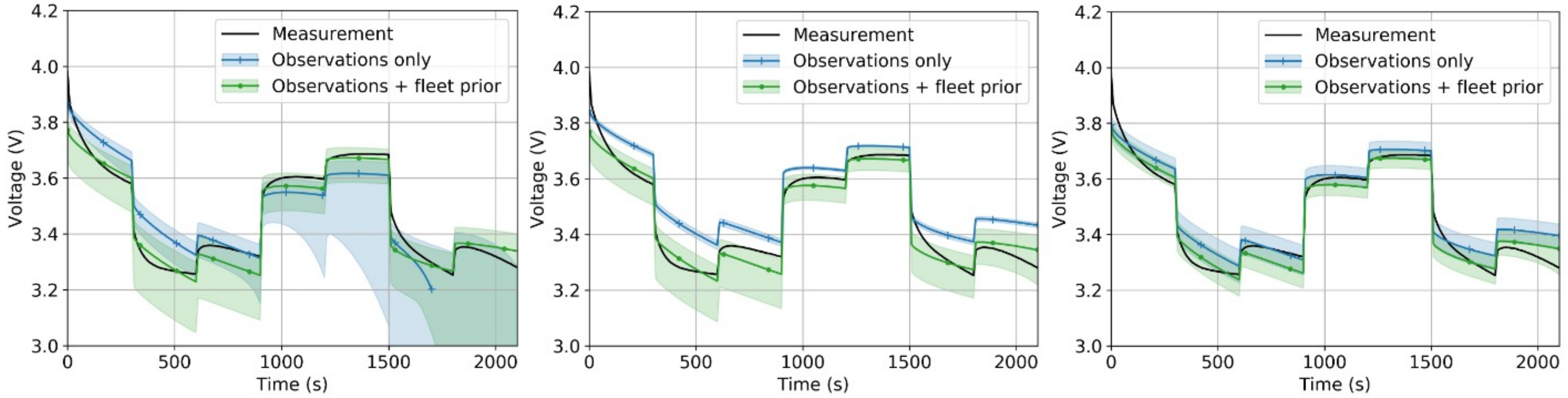
Physics-informed neural network framework for Li-ion Battery SOC estimation

- Nascimento, R.G. & Viana, F. A. & Corbetta, M. & Kulkarni, C. S. , "Usage-based Lifing of Lithium-Ion Battery with Hybrid Physics-Informed Neural Networks," AIAA Aviation 2021.
- Nascimento, R.G. & Viana, F. A. & Corbetta, M. & Kulkarni, C. S, “Hybrid Physics-Informed Neural Networks for Lithium-Ion Battery Modeling and Prognosis Journal of Power Sources 2021

Approach 2 : Physics + RNN



(a) Reference discharge.



(b) Random-loading discharge.

Next Steps : Looking Ahead

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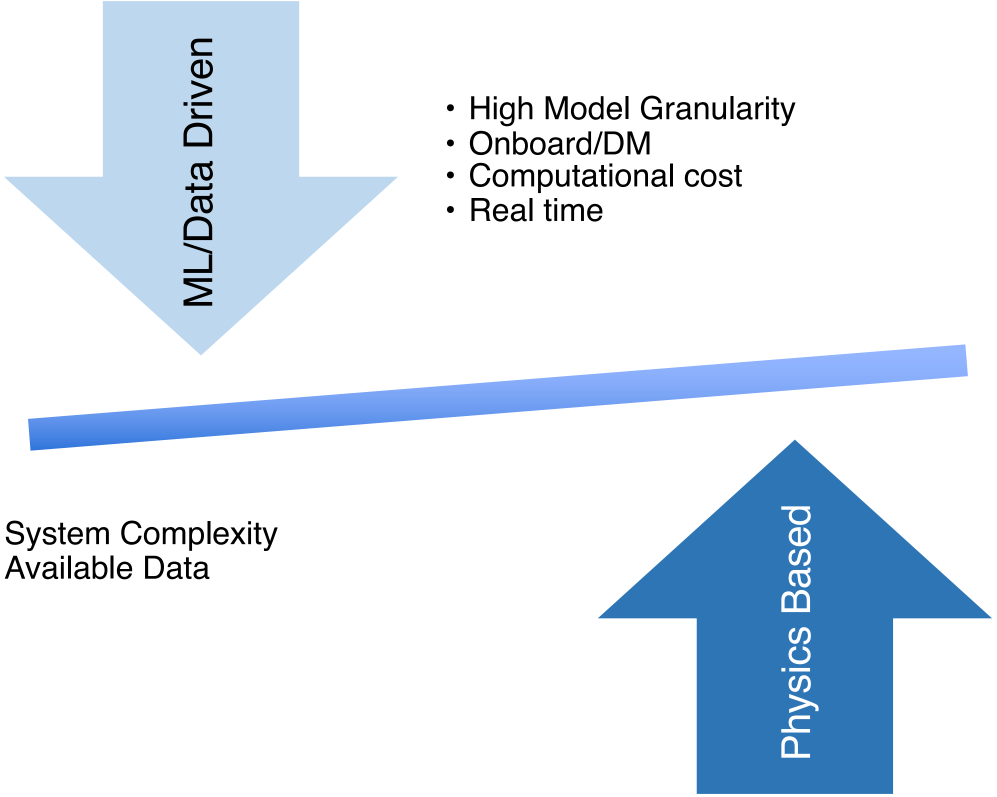
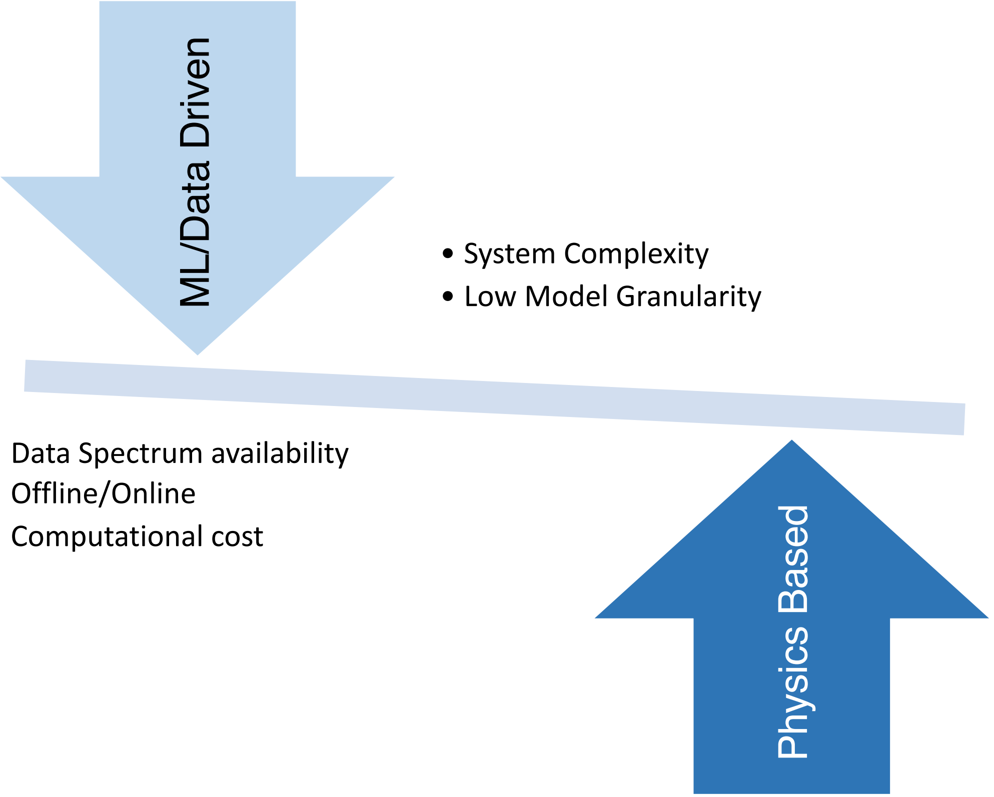


- High Model Granularity
- Onboard/DM
- Computational cost
- Real time

- System Complexity
- Available Data

Next Steps : Looking Ahead



- System Complexity
- Low Model Granularity

- Data Spectrum availability
- Offline/Online
- Computational cost

Concluding Remarks

- **Prognostics 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 for online applications
  - 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

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