Prognostics for Systems Health Management - Model and Hybrid Based Approaches. Where are we heading?

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Acknowledgement

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Collaborators

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Prognostics

- Adopting condition-based maintenance strategies, instead of time-based maintenance
- Optimally scheduling maintenance
- Optimally planning for spare components
- 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
- System operations can be optimized in a variety of ways

Credit: www.nasa.gov

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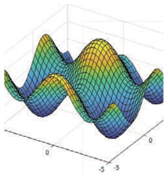
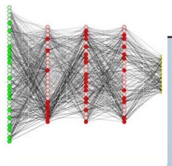
Current State of the Art



- 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



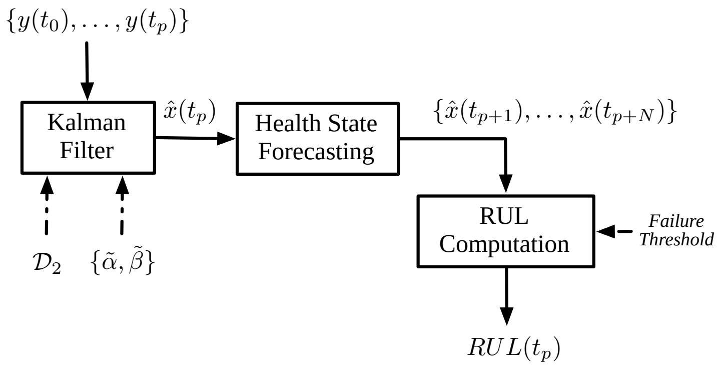
- Easy and Fast to implement
- May identify relationships that were not previously considered
- Requires lots of data and a “balanced” approach”
- Results may be counter(or even un-)intuitive
- Can be computationally intensive, both for analysis and im

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

Model-based prognostics

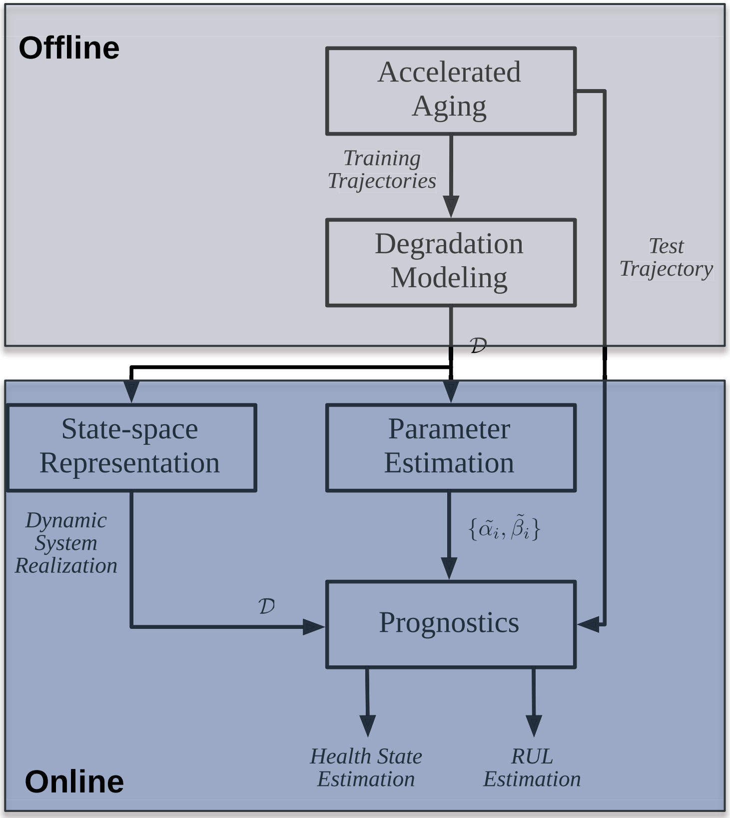
- State vector includes dynamics of normal and degradation process

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



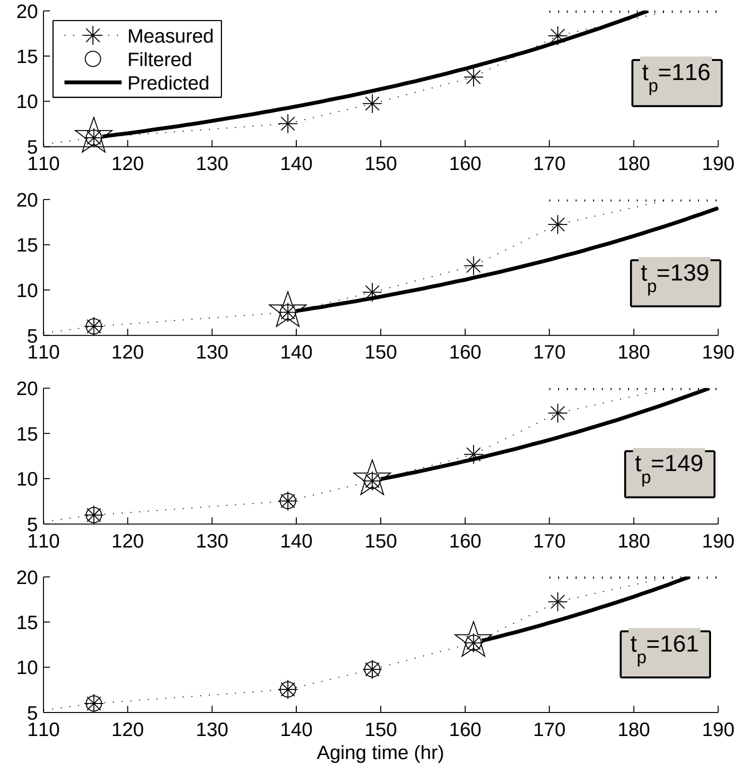
- EOL defined at time in which performance variable cross failure threshold

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

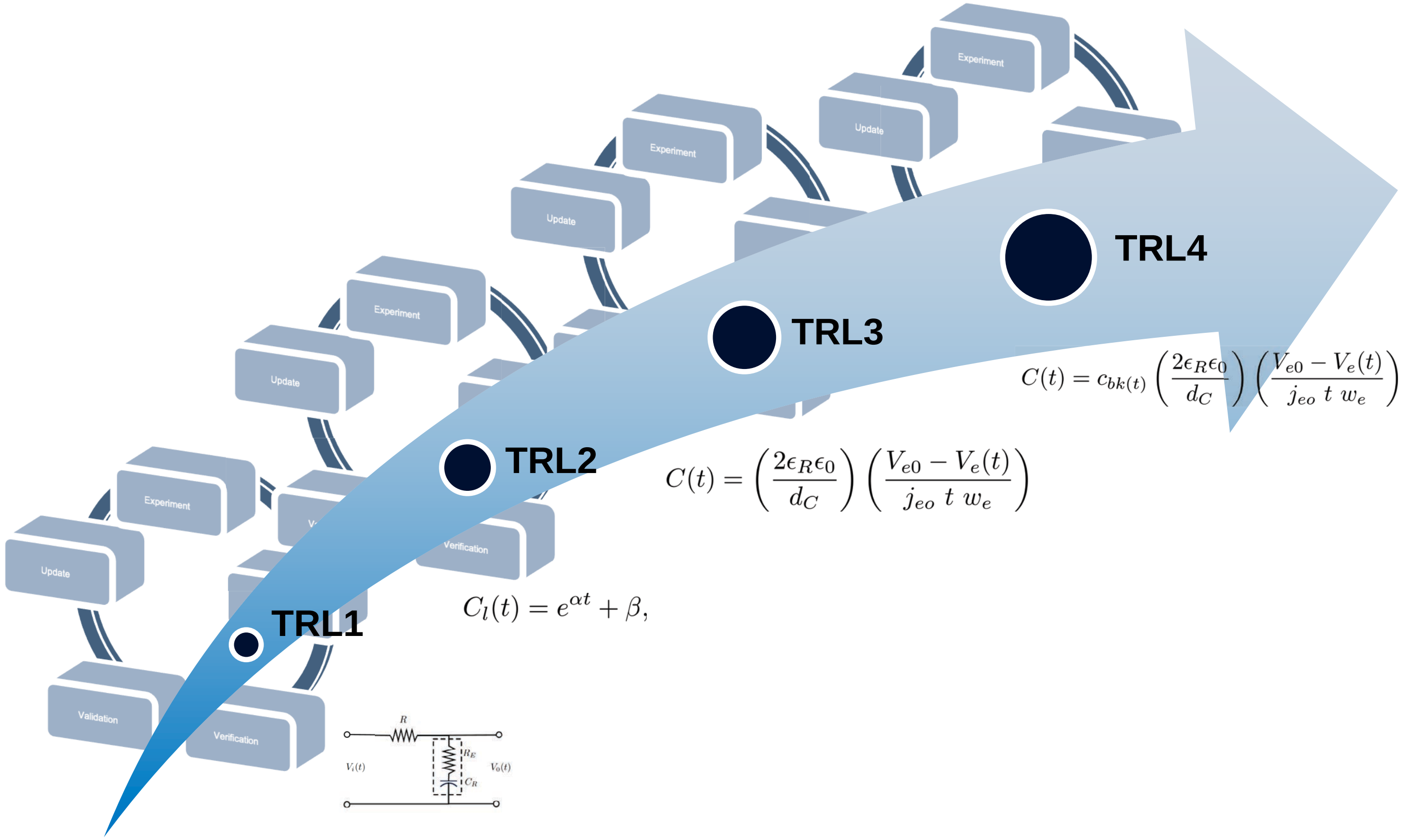


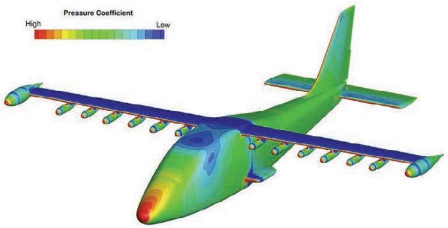
Model-based prognostics

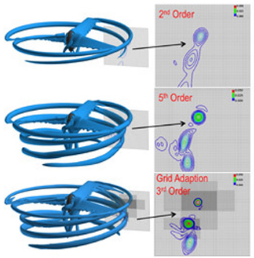
- Tracking of health state based on measurements
- Forecasting of health state until failure threshold is crossed
- Compute RUL as function of EOL defined at time failure threshold is crossed

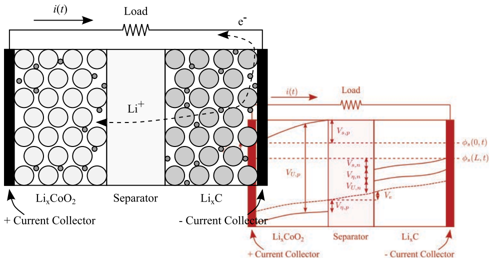


Algorithm and Model Development TRL









Machine Learning underlying physics parameter

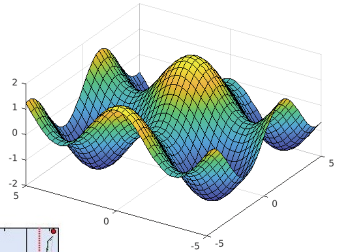
Tensor Flow

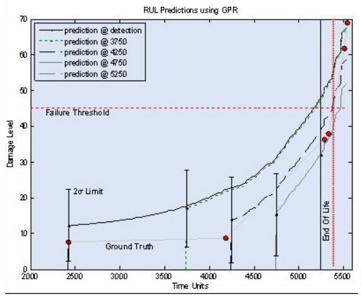
Microsoft Cognitive

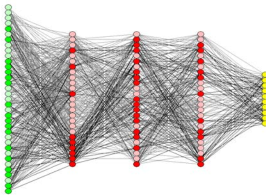
Uber Ludwig

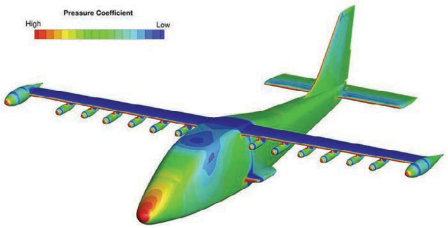
Scikit-learn

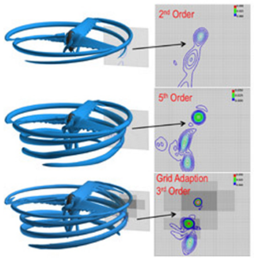
Understanding and Learning underlying Physics for Complex Systems

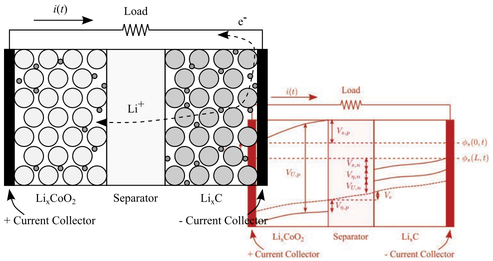




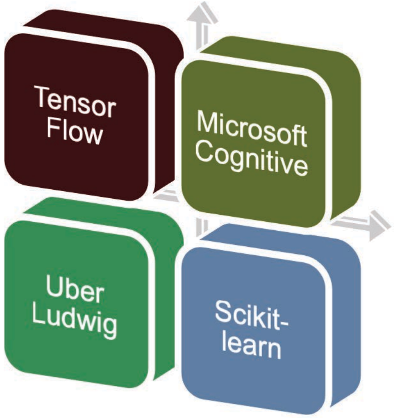




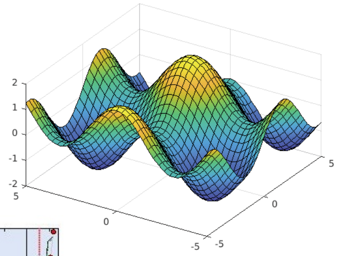


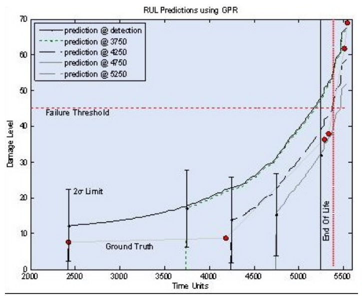


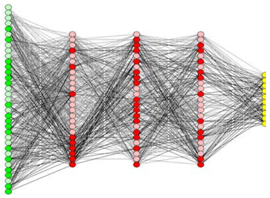
Machine Learning underlying physics parameter

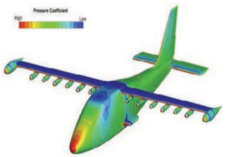


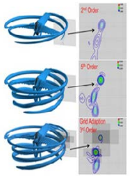
Understanding and Learning underlying Physics for Complex Systems

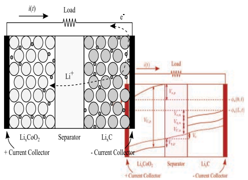




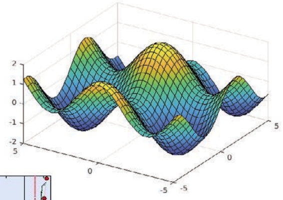


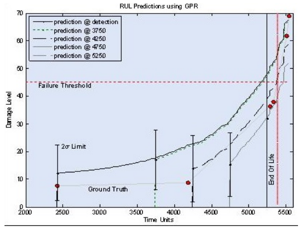

Pressure Coefficient
High
Low

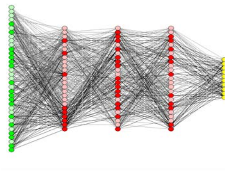



i(t)
Load
Li+
Separator
+ Current Collector
- Current Collector

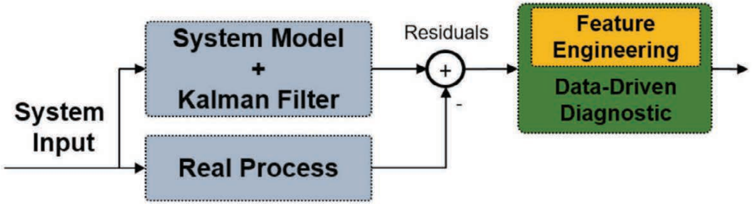
+



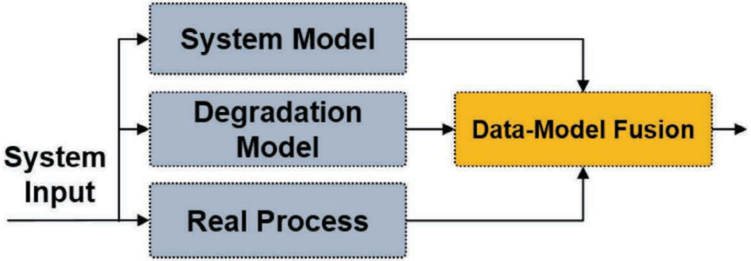

RUL Predictions using GPR
prediction @ detection
prediction @ 3750
prediction @ 4250
prediction @ 4750
prediction @ 5250
Failure Threshold
2σ Limit
Ground Truth
End Of Life
Damage Level
Time Units



Prior Work

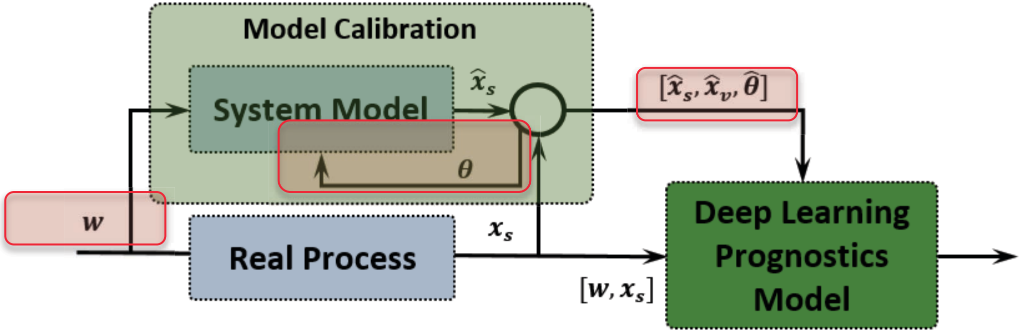


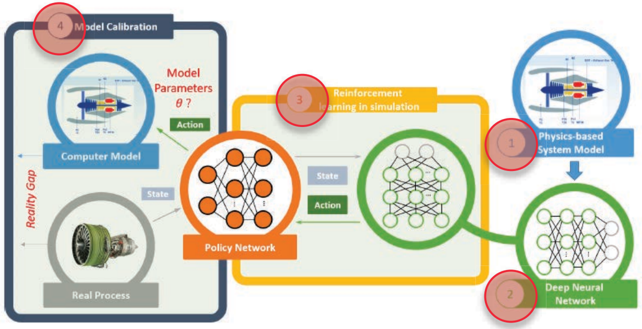
Overall architecture of the residual-based hybrid diagnostics (Rausch et al., 2005).



(Hanachi et al., 2017).

Deep Learning + Physics Model Calibration





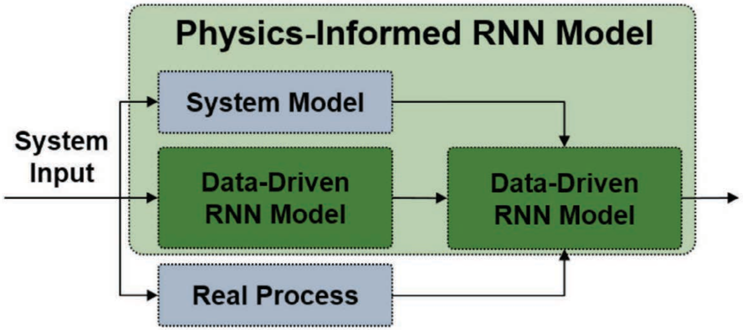
Overall architecture of the hybrid prognostics framework fusing physics-based and deep learning models.

Calibration Policy

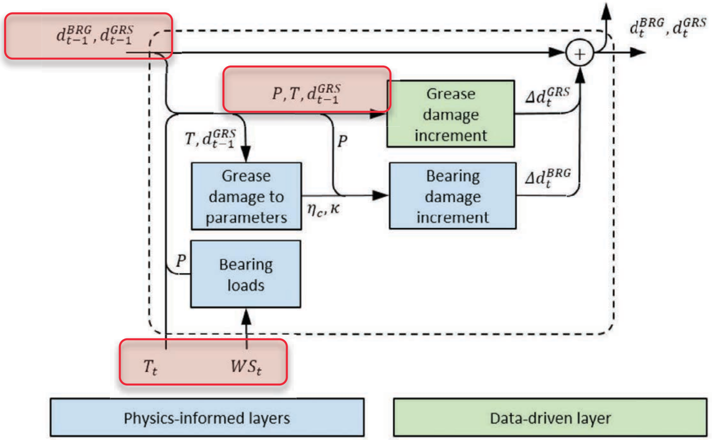
Yuan Tian, Manuel Arias Chao, Chetan Kulkarni, Kai Goebel, Olga Fink, "Real-Time Model Calibration with Deep Reinforcement Learning", arXiv:2006.04001

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

Physics + RNN



Overall architecture of the physics-informed recurrent neural network



Physics-informed neural network framework for main bearing fatigue and grease degradation

Nascimento, R. G., & Viana, F. A. (2019). Fleet prognosis with physics-informed recurrent neural networks. In Structural health monitoring 2019: Enabling intelligent life-cycle health management for industry internet of things (iiot) - proceedings of the 12th international workshop on structural health monitoring (Vol. 2, pp. 1740–1747).

Y. A. Yucesan and F. A. C. Viana, "A physics-informed neural network for wind turbine main bearing fatigue," International Journal of Prognostics and Health Management, Vol. 11 (1), 2020. (ISSN: 2153-2648).

Next Steps : Looking Ahead

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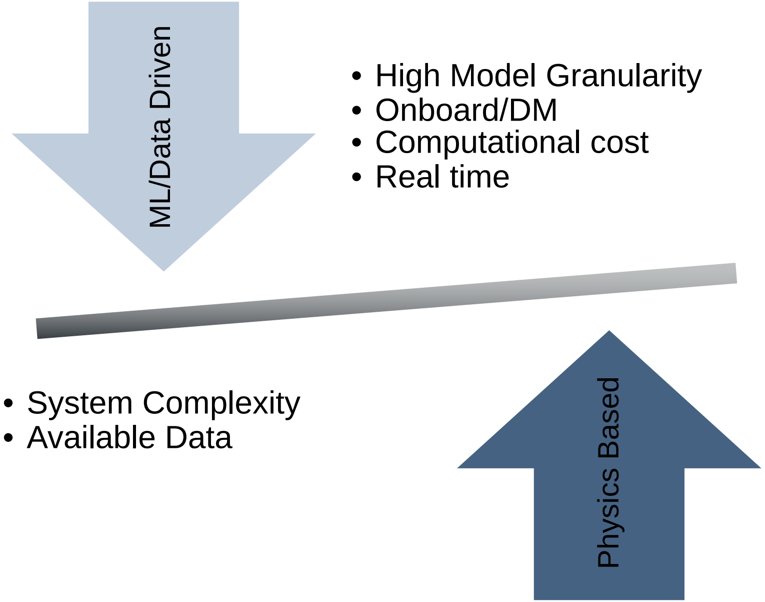
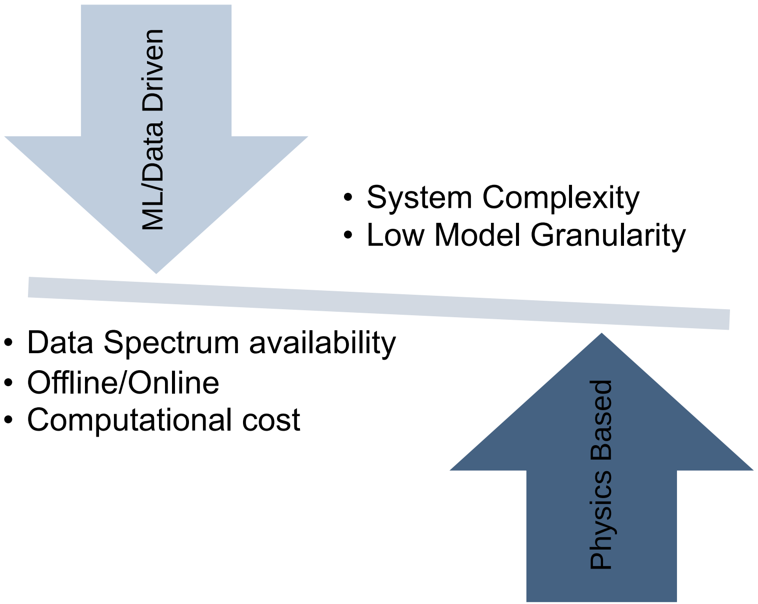


- High Model Granularity
- Onboard/DM
- Computational cost
- Real time

- System Complexity
- Available Data

Next Steps : Looking Ahead



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.
  - With availability of test and field data, machine learning able to blend the digital data fabric for model update
  - Uncertainty Quantification
- Framework still in early stages and needs maturation
- Requirements for autonomous systems

Thank You

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