Development of a Digital Twin for Electrified Aircraft Powertrain Health Management

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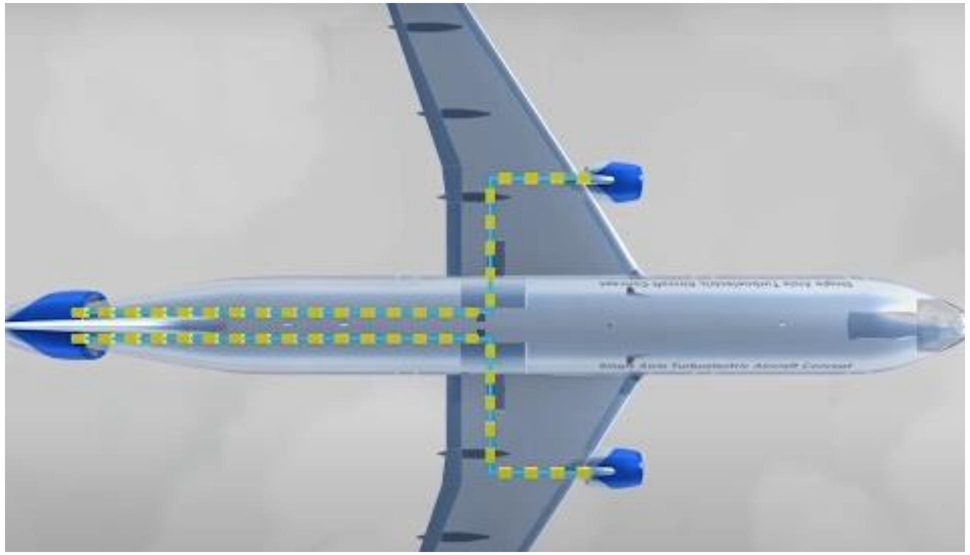
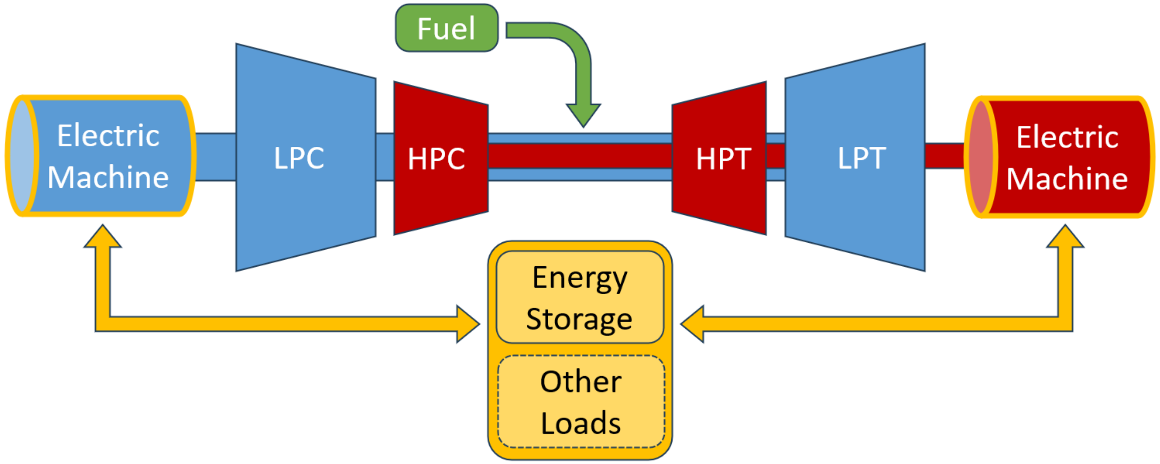
Outline

- Electrified Aircraft Propulsion
- NASA Hybrid Propulsion Emulation Rig (HyPER)
- Digital Twin – What and Why?
- System Model Matching
- Digital Twin Design
- Results
- Summary & Future Work

Electrified Aircraft Propulsion

- Hybrid- and fully-electric powertrains for propulsion
- Improved fuel efficiency, emissions, and noise
- Power extracted from engine using **electric motors/generators**

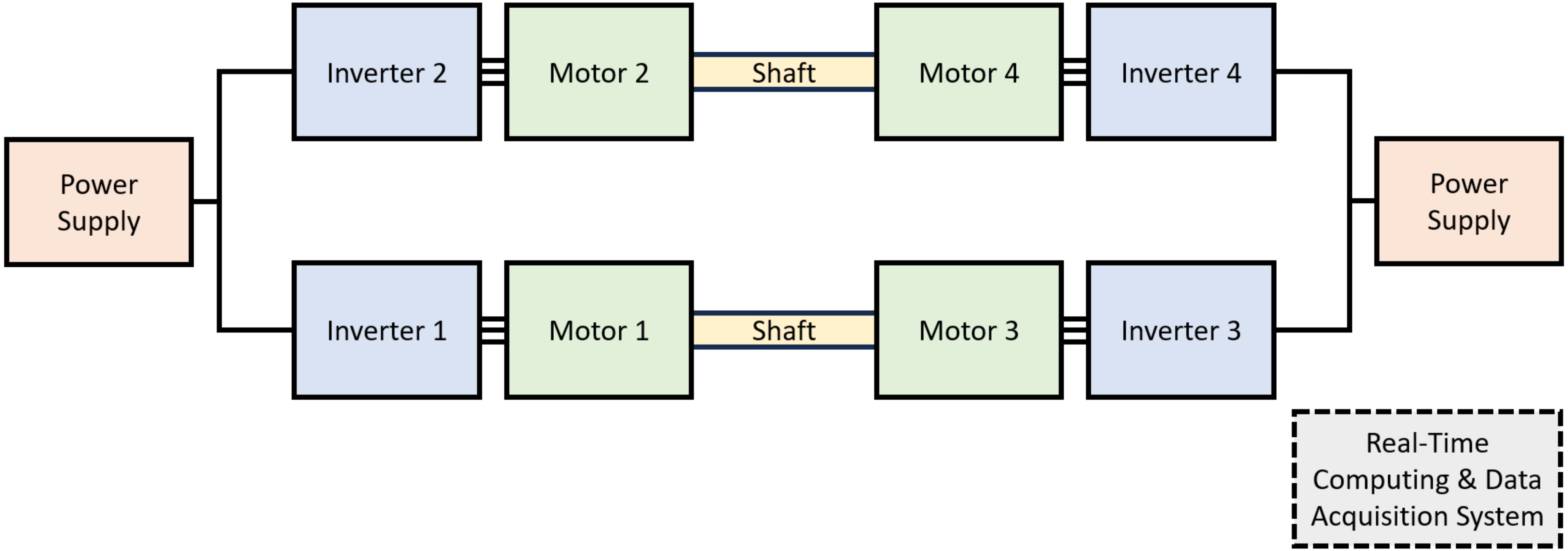




NASA Hybrid Propulsion Emulation Rig (HyPER)

- Located at NASA Glenn Research Center in Cleveland, OH
- HIL evaluation of electrified aircraft propulsion control laws
- Scaling and emulation of 2-spool turbine engine dynamics

NASA Hybrid Propulsion Emulation Rig (HyPER)



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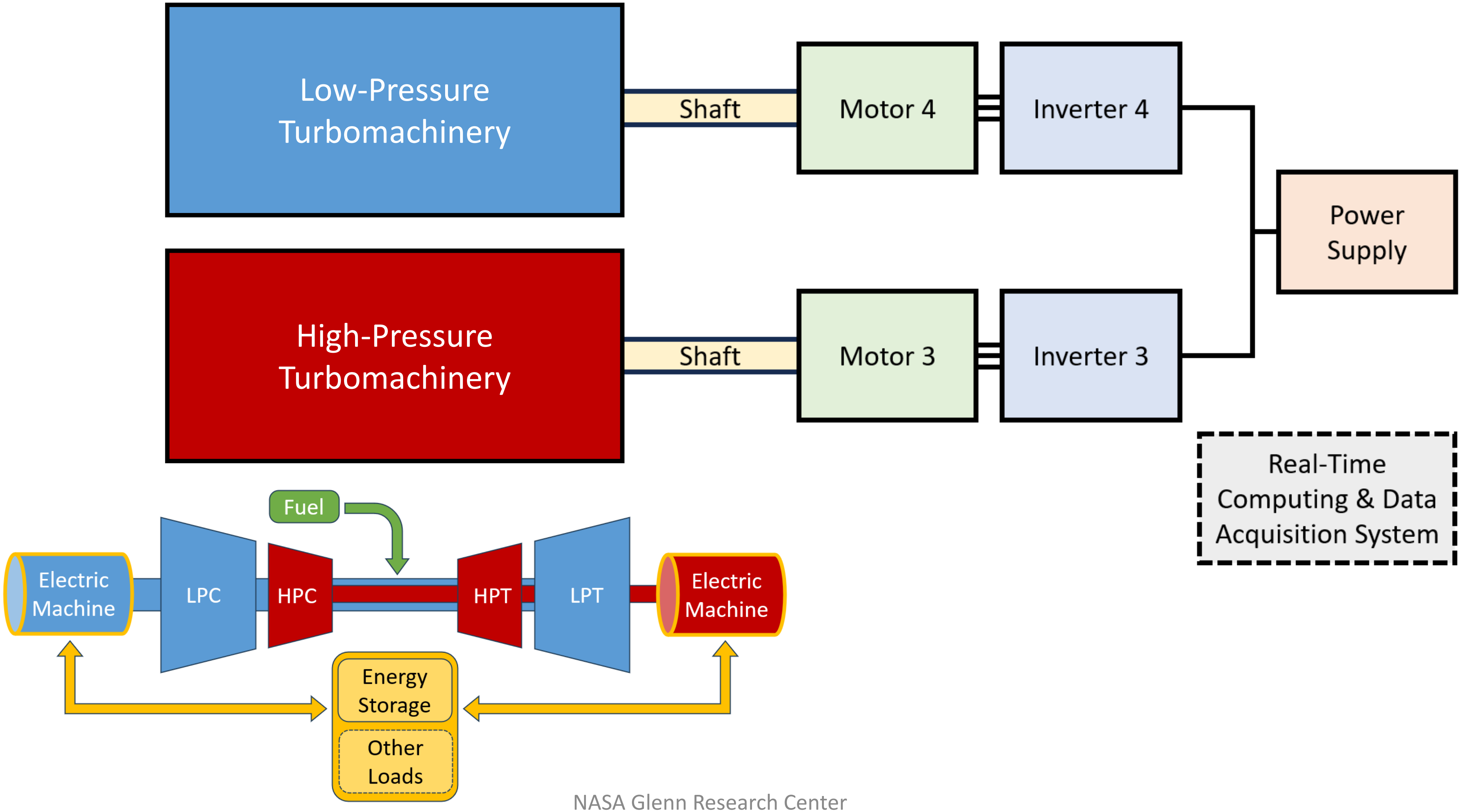

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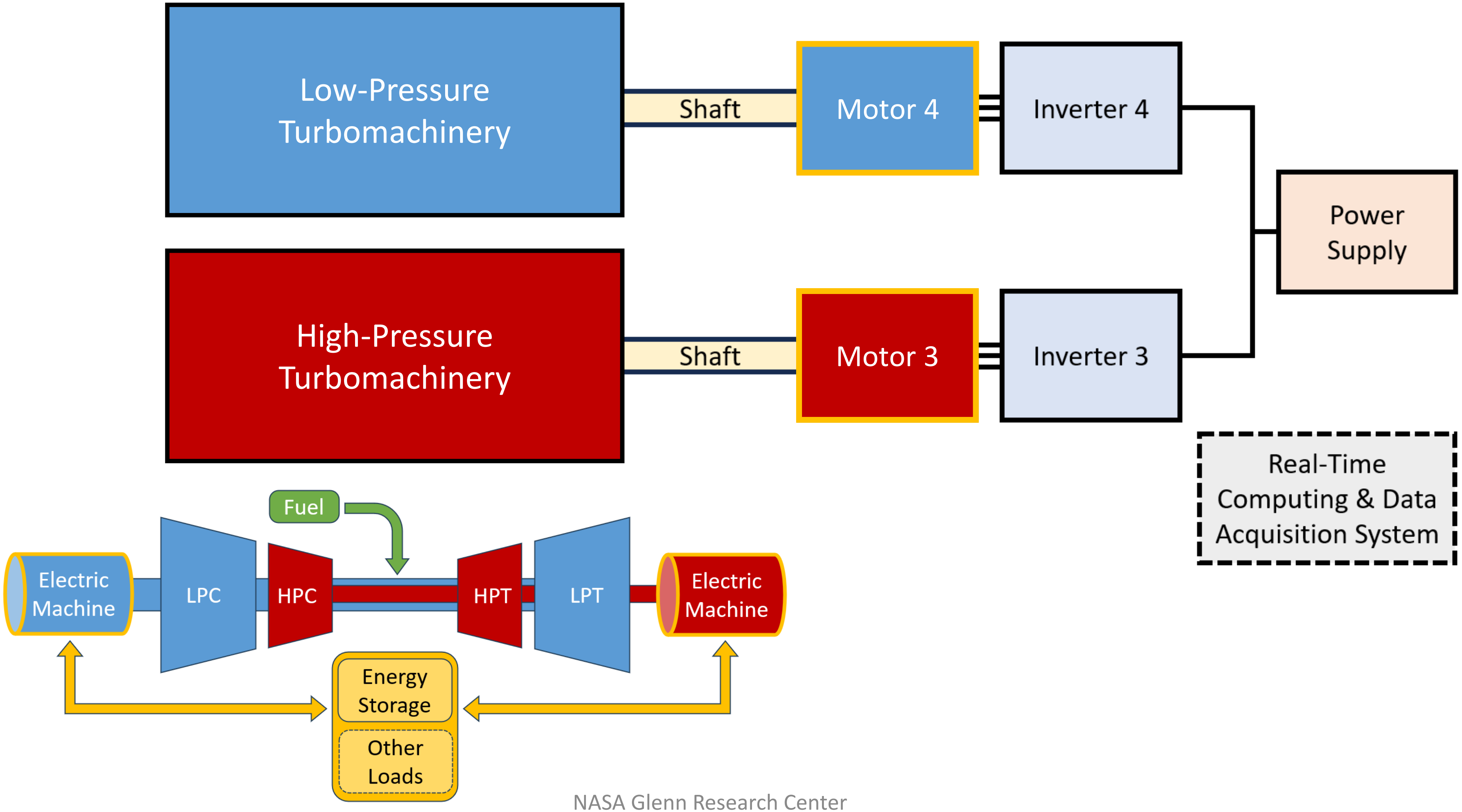


What is a Digital Twin?

"A set of information constructs that mimics the structure, context and behavior of an individual asset, is dynamically updated with data from its physical twin throughout its life cycle, and informs decisions that realize value"

- AIAA/AIA Position Paper, 2020

- Logical way to organize vast amounts of data (e.g. fleet data)
- **Defining feature: Updates based on data from physical counterpart**

Why use a Digital Twin?

- Up-to-date model of physical system
  - Model-based engineering

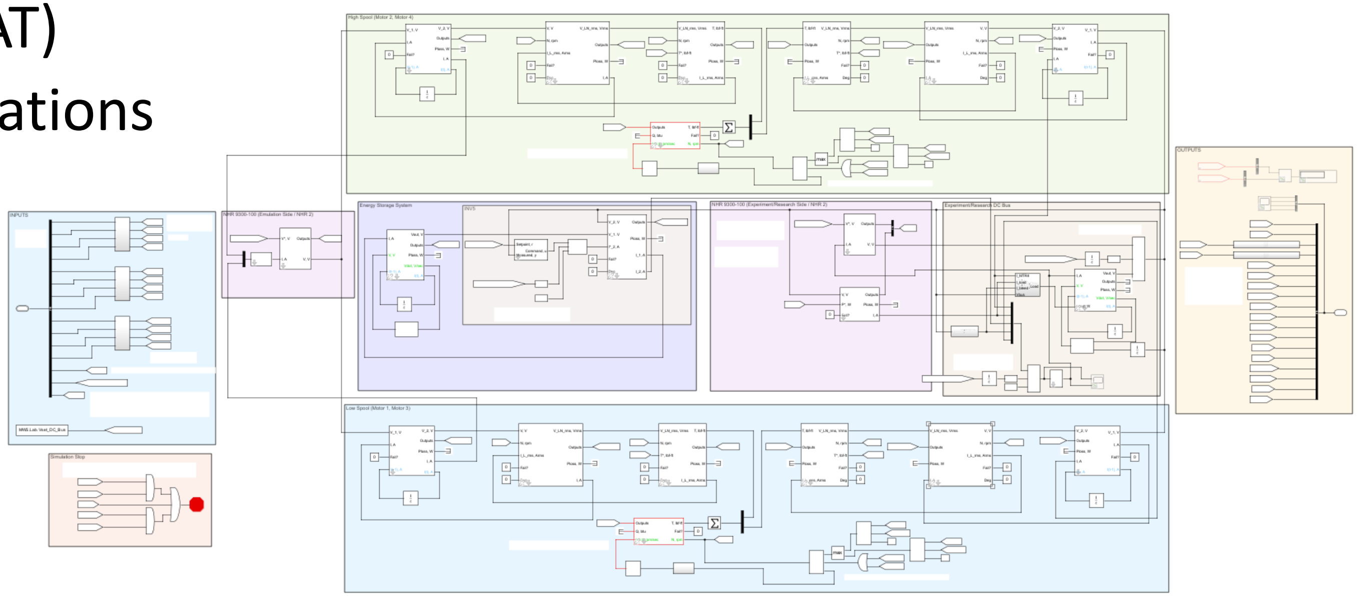
- System health insight
  - Condition-based maintenance

These mean:

Cost savings for system operators

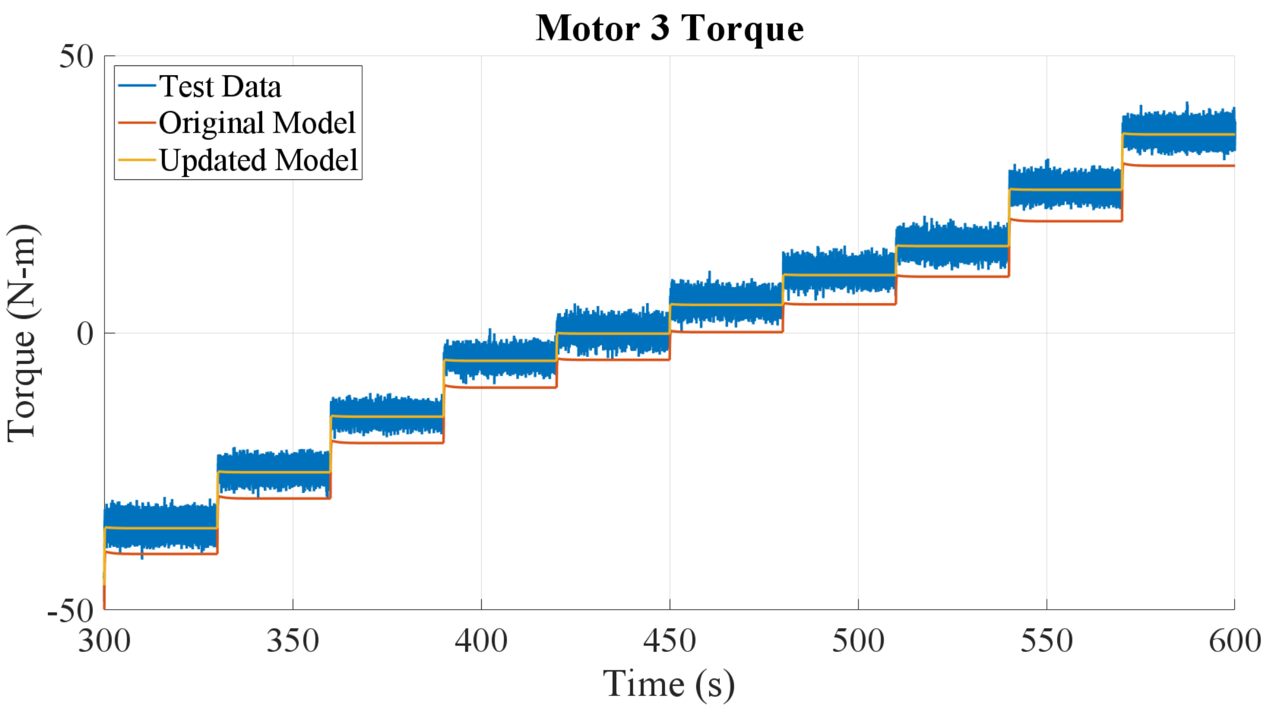
System Model Matching

- Previously-developed nonlinear system model in MATLAB/Simulink
  - NASA's Electrical Modeling and Thermal Analysis Toolbox (EMTAT)
  - Based off manufacturer specifications
- 15 ms timestep
  - Turbomachinery dynamics



System Model Matching

- Collected test data across operating envelope
- Fitted model parameters to data to improve matching
- This established a ‘baseline’ for health monitoring
  - Kalman filter will track deviation from this using *health parameters*



Digital Twin Design

- Uses Kalman filter to automatically update model from measurements
  - Optimal linear state observer
  - Infers states from measurements

$$\Delta\hat{x}_k^- = A\Delta\hat{x}_{k-1}^+ + B\Delta u_k$$

$$\Delta\hat{x}_k^+ = \Delta\hat{x}_k^- + K(\Delta y_k - C\Delta\hat{x}_k^- - D\Delta u_k)$$

$$\hat{x}_k = x_0 + \Delta\hat{x}_k^+$$

$x_k = State\ vector$
$x_0 = Nominal\ state$
$u_k = Inputs\ vector$
$y_k = Measurements\ vector$
$K = Kalman\ gain\ matrix$
$A, B, C, D = State\ space\ matrices$

- State vector: Shaft speeds
  - **Augmented with *health parameters* representing deviation from baseline**

$$\boxed{x = [\underbrace{N}_{\text{Shaft Speed}} \quad \underbrace{\delta V_{S,1} \quad \delta\eta_{I,1} \quad \delta\eta_{M,1} \quad \delta V_{S,3} \quad \delta\eta_{I,3} \quad \delta\eta_{M,3} \quad \delta\tau_3}_{\text{Health Parameters}}]^T}$$

Digital Twin Design

Estimated States:

- Shaft speeds
- Motor efficiency biases
- Inverter efficiency biases
- Power supply voltage biases
- Shaft torque bias

Measurements:

- DC voltages & currents
- AC powers
- Motor torques
- Shaft speeds

$$x = [\underset{\substack{\uparrow \\ \text{Shaft Speed}}}{N} \quad \underbrace{\delta V_{S,1} \quad \delta\eta_{I,1} \quad \delta\eta_{M,1} \quad \delta V_{S,3} \quad \delta\eta_{I,3} \quad \delta\eta_{M,3} \quad \delta\tau_3}_{\text{Health Parameters}}]^T$$

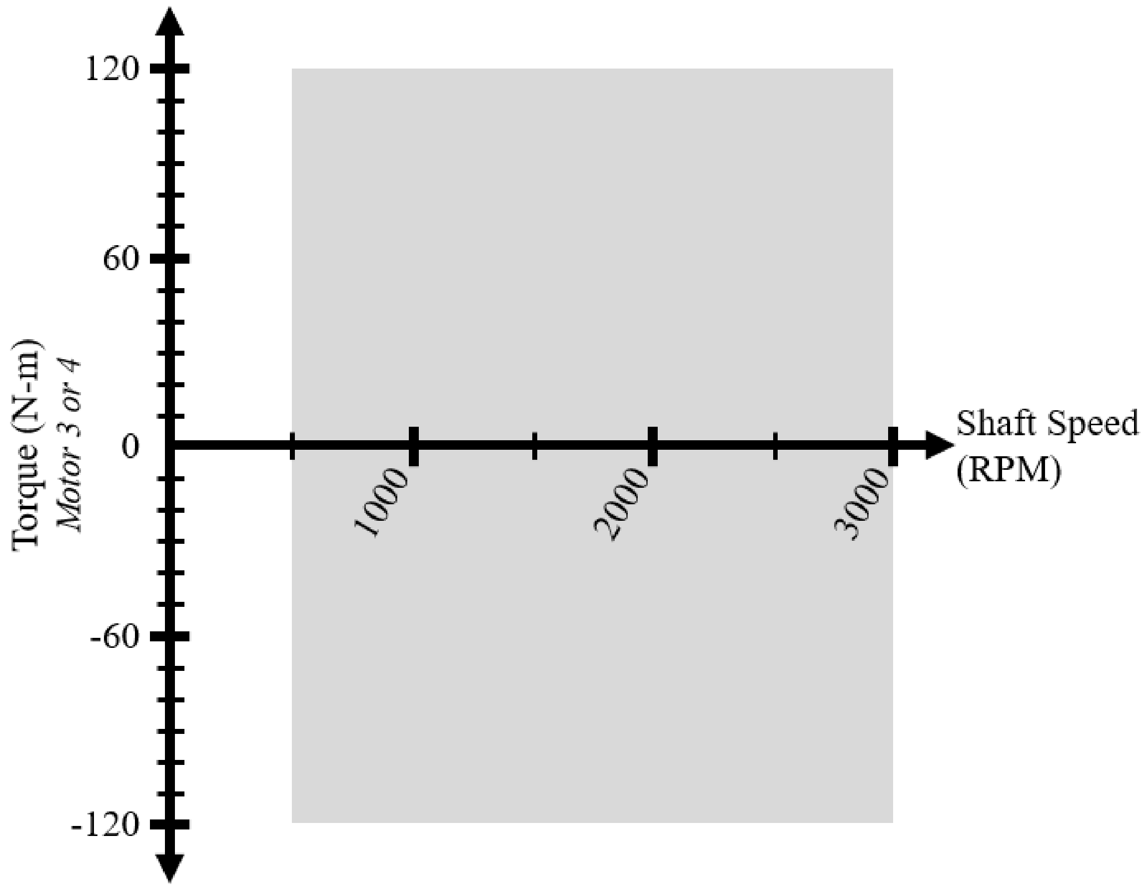
Digital Twin Design

1. Measurement covariance matrix *R* calculated from test data

2. System linearized by perturbing nonlinear model

3. Kalman gain matrix computed

4. Steps 1-3 repeated across operating envelope



Digital Twin Design

- Process covariance matrix Q designed as diagonal matrix
- Scaled to tune state estimates' adaptation rates
  - Higher magnitude -> Faster adaptation
- Adaptation rate was designed empirically through iteration
  - Balanced adaptation rate and noise susceptibility

Anomaly Detection Filter

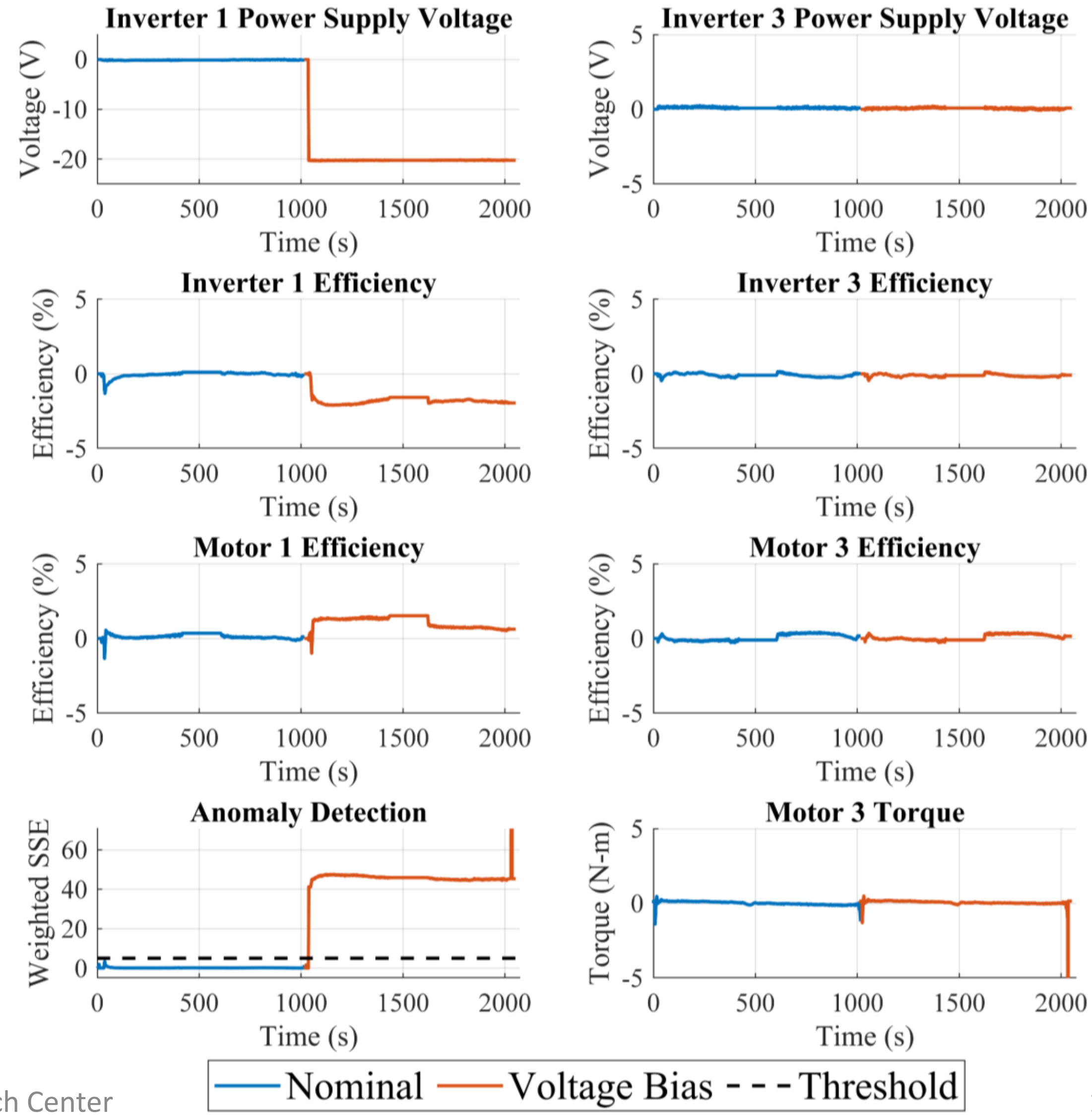
- Sum of squared health parameters compared against threshold

- Exceeding threshold -> anomaly present
  - Gradual degradation
  - Internal faults
  - Misconfiguration

- Threshold designed empirically through iteration
  - Stochastic methods possible – future work

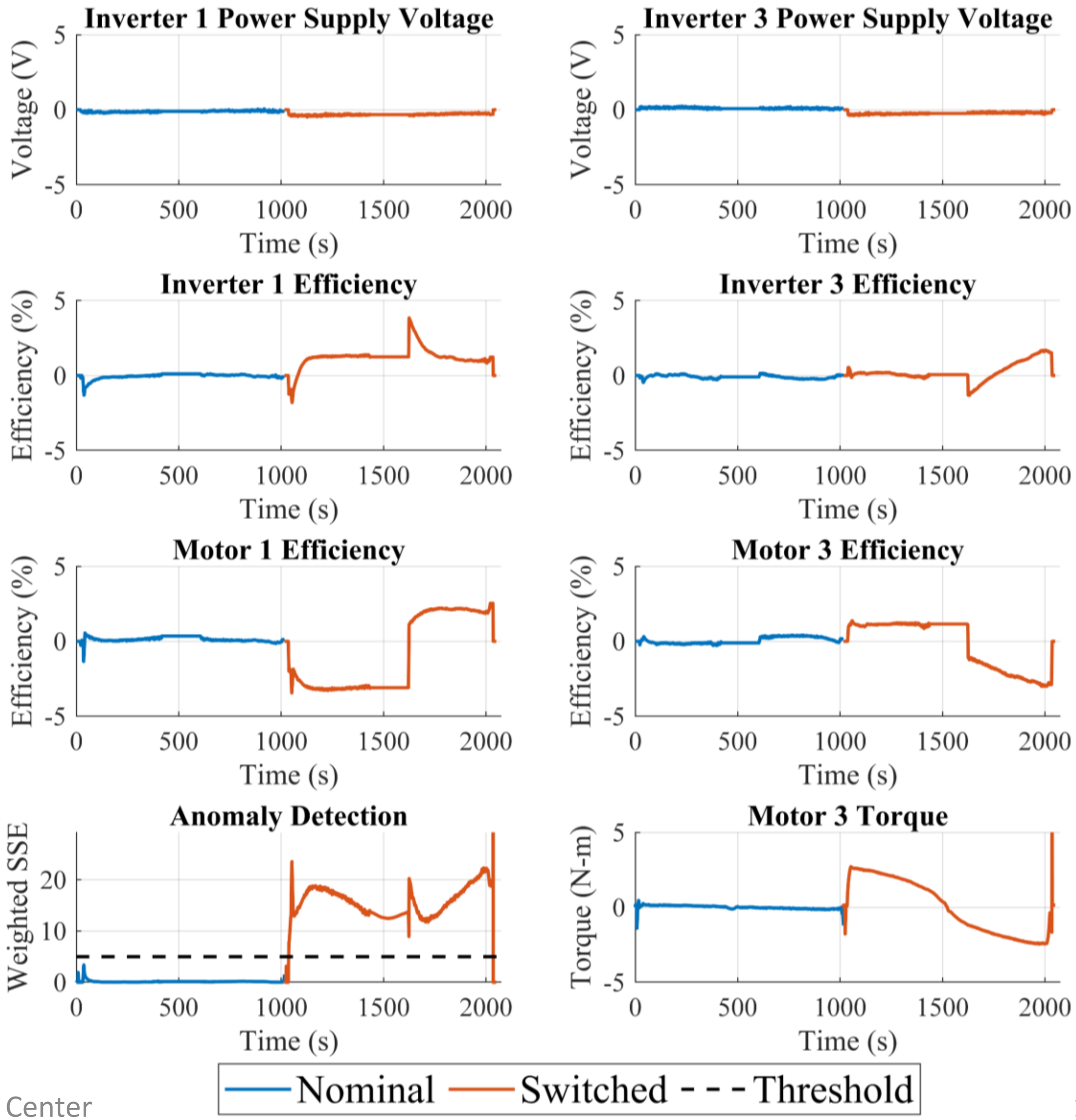
Results – Voltage Anomaly

- Intentionally biased one DC power supply by -20V (*t = ~1000 s)*
- Kalman filter's health parameters responded
- Anomaly detection filter correctly identified an anomalous condition



Results – Shaft Data Swap

- Swapped measurement data between shafts/motors/inverters
  - Same makes and models
- Kalman filter's health parameters responded to account for unit-to-unit differences
  - Tolerances, etc.
- *Demonstrated that the digital twin is sensitive and asset-specific*



Summary

- Model of a NASA EAP controls testbed was matched to test data
  - NASA's Electrical Modeling and Thermal Analysis Toolbox (EMTAT)
- Kalman filter implemented to **track system health parameters**
- Anomaly detection filter created to **flag off-nominal conditions**
- Kalman filter and anomaly detection filter were demonstrated against nominal and off-nominal conditions

Future Work

- Enhancement of anomaly detection
  - More intelligent thresholding method
  - E.g. Stochastic methods

- Real-time fault detection and isolation

- Application to more complex EAP systems

Acknowledgments

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