PANEL SESSION 11
THEORETICAL ASPECTS OF PROGNOSTICS

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Motivation

• With the increasing complexity of today’s safety-critical engineering systems, such as transportation, energy generation and distribution, and in manufacturing processes, guaranteeing
  - Safety of systems
  - Optimization of services (gain more with less)
  - Minimization of operational/maintenance costs (life cycle costs)

is becoming a very challenging
Motivation

• With **increased autonomy** demands, these issues are becoming even more central

• The **interconnections between safety, optimization of services, minimization of maintenance costs** provides both challenges and opportunities
  - How do we model and understand the behaviors of these system under different operating conditions?
  - Are there well-defined and closed form analytic formulations of system operations that are computationally feasible?
  - Can we develop algorithms that are robust to uncertainties and disturbances?
  - How do we validate these models and algorithms?

• **Opportunity**: Need to develop more systematic (theoretical) frameworks that link diagnostics, prognostics, control, and maintenance (Decision Making Problem)
What is prognostics?

• ISO13381-1: “an estimation of time to failure (RUL, EOL) and risk for one or more existing and future failure modes”*

- Existing failure modes and deterioration rates,
- Sensitivity of monitoring and analysis techniques to deterioration rates of failure modes
- Interrelationship between failure modes and their deterioration rates,
- Initiation criteria for future failure modes,
- Effect of maintenance on failure degradations
- Conditions and assumptions underlying the prognoses

Traditional Prognostic modeling & analysis

- Known failures and their degradation rates
- What influences these degradation rates?
  - Mode of operation
  - Environmental conditions
  - Operator actions and maintenance actions
- Strong relation between diagnostics and prognostics
Traditional Approaches

- **FDII algorithms** (looking backwards)
  - Estimation task
  - Typically parameterized
  - Involves quantifying the values of deviated parameters

- Prognostics algorithms (looking forward)
  - Prediction task
  - Project forward: how components (represented by parameters) are going to degrade
    - Requires knowing future operating and environmental conditions
    - **Model-driven** (physics of failure); **Data-driven** (Regression; Bayesian, Neural network); **Hybrid** (model- + data-driven)*
      - Methods are necessarily stochastic - predicted value + confidence bounds

What are the limitations of traditional models?

• Typically deal with single components and their degradation modes?
  - Batteries, capacitors, switching elements, bearings, etc.
  - Supports Condition-based maintenance (CBM) & Decision Making for reliability/safety considerations?

• Question: Is this sufficient?
  - What is the effect of multiple degrading components on system behavior and performance? (System-level prognostics)
  - Interactions between failure modes & their deterioration rates (Future Failure mode prognostics)
    • Interactions - high vibration due to bearing degradation accelerates mechanical seal degradation
    • Cascades - one component exceeds specification limits; causes degradation in components down the line
Component → System-level effects

- Simple Example*
- Two 3-capacitor configurations

- Similar capacitors

Degradation model:

\[ C_i(t + \Delta t) = (1 - \alpha_i)C_i(t) \]


Comparison of configuration RUL’s at \( t = 0 \)
System Level RUL prediction

- Khorasgani, Biswas, & Sankararaman (2016)

System model

\[ x_{n+1} = f(x_n, u_n, \theta_n, \omega_x) \]
\[ y_n = h(x_n, u_n, \theta_n, \omega_y) \]

System degradation models; \( D_i, i = 1,2,\ldots,l \)

\[ x_{n+1} = f(x_n, u_n, \theta_n, \omega_x) \]
\[ \theta_{n+1} = g(\theta_n, \alpha_n, x_n, \omega_D) \]
\[ y_n = h(x_n, u_n, \theta_n, \omega_y) \]

\[ p_n = P_S(x_n, \theta_n) \]

System performance; \( p_n \), given constraints, \( R = \{r_i\}_{i=1,\ldots,m} \)

\[ EOL_n = \inf\{k \in Z; k \geq n & T(p_k) = 1\} \]
\[ RUL_n = (EOL_n - n)\Delta t \]

\[ T(p_n) = \begin{cases} 1 & \text{if } 0 \in R(p_n) \\ 0 & \text{if } 0 \notin R(p_n) \end{cases} \]
System Level RUL

- Case Study

Capacitor degradation models

98% bounds on RUL (CoV=0.1)
Evaluation metrics

• Performance of methods
  - Algorithm performance
    • Offline: accuracy, precision, horizon, bounds,
    • Online: precision index; convergence - steadiness index
  - Computational Performance (offline, online)
  - Cost-benefit risk - accuracy of RUL estimate (general); convergence (online methods)

• Applicability criteria (model vs data vs hybrid)
  - Is degradation process model required?
  - Generality and scope
  - How much (online) learning?
  - Assumptions & operating conditions
  - Modeling complexity & computation time
So where is the theory of prognostics?

- Still not widely applicable
  - Component-level prognosis used for CBM
  - System level prognostics in its infancy - used for broader decision making - offline and online components
  - Future failure mode prognosis - still a research problem - will need data driven methods to address; anomaly detection methods are promising; will they generalize?
  - Post Action prognosis -- identifying potential actions that could slow down or temporarily eliminate progression of degradation to critical failure

Risk-based Decision Making Complexity
Need for accurate estimates, confidence bounds

PHM 2018 Panel - Biswas