Why PHM has H & M, and how to achieve it today and tomorrow?

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[1] A presentation at RRSC Chair Day 2023, Gif-sur-Yvette, France.

Outline

1. Why PHM has H&M?
2. Predictive maintenance of today: A deep learning-based renewal process model
   - RUL prediction through CNN with Monte Carlo dropout
   - Predictive maintenance on single-component level
   - Predictive maintenance on multiple-component level
3. Predictive maintenance for tomorrow: Digital Failure Twin for reliability and maintenance

Outline

Why PHM has H & M?

- H & M? Not the clothing company, but Prognostics and Health Management!

[2] Hu, Y., Miao, X., Si, Y., Pan, E. and Zio, E., 2022. Prognostics and health management: A review from the perspectives of design, development and decision. Reliability Engineering & System Safety, 217, p.108063.

Why PHM has H & M?

- H & M? Not the clothing company, but Prognostics and Health Management!
- Why H& M?
  - Let's look at the definition of PHM.
  - What are the means? What are the ends?

Definition (Definition of PHM [2])

Prognostics and Health Management (PHM) is a cutting-edge integrated technology, which takes knowledge, information and data of system performance, control, operation and maintenance as input to:

- **detect** the initiation of anomalies;
- **isolate/diagnose** the occurring failures;
- **predict** the health state of the system in the future and estimate its **remaining useful life** to dynamically support the maintenance decisions.

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  - P is just the means, while H& M is the end!

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F-35: One of the earliest example of PHM

One paper from USAF releases the basic requirements and system architecture for PHM of F-35 [3]:

"In the context of JSF, PHM includes the following capabilities:

- *Testability/Built-In Test (BIT) capabilities;*
- *Pertinent data acquisition at sensor, component, and subsystem levels;*
- *Enhanced diagnostics, beyond the legacy testability/BIT capabilities, through system models, corroboration, correlation, and information fusion;*
- *Prognostics, including material condition assessment and prediction of the remaining useful life and time to failure of components by modeling fault progression;*
- ***Health management**, including the capabilities to maximize (in conjunction with on-board planners and subsystem managers) system effectiveness in the presence of system anomalies, provide **decision support to optimally plan or defer maintenance**, and manage component life."*

[3] Brown, E. R., N. N. McCollom, E.-E. Moore and A. Hess (2007). Prognostics and health management a data-driven approach to supporting the F-35 lightning II. 2007 IEEE aerospace conference, IEEE.

F-35: One of the earliest example of PHM

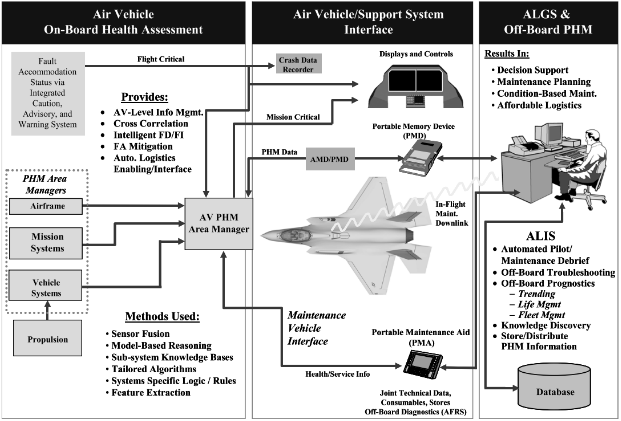

Figure: High-level View of PHM On-board and Off-board Architecture: Example from F-35. [4]

[4] Brown, E. R., N. N. McCollom, E.-E. Moore and A. Hess (2007). Prognostics and health management a data-driven approach to supporting the F-35 lightning II. 2007 IEEE aerospace conference, IEEE.

A short summary

PHM not only concerns P, but also HM:

- RUL prediction is a means, not an end. The ends are the decison-making problems!
- **Predictive maintenance**: Use the predicted RUL to plan maintenance actions.

But how to achieve HM?

- However, most of the current literature on PHM focuses only on P. H& M, especially predictive maintenance, is seldom discussed in the literature.

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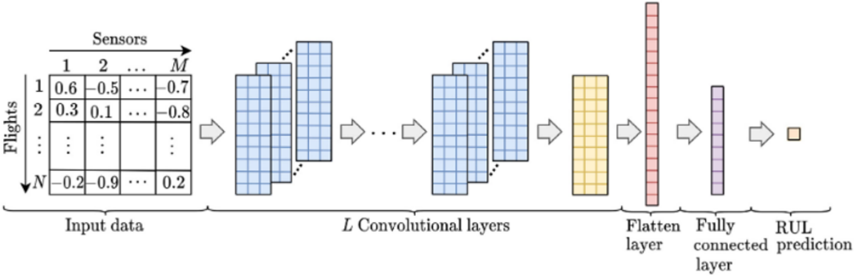
RUL prediction with deep learning - Problems

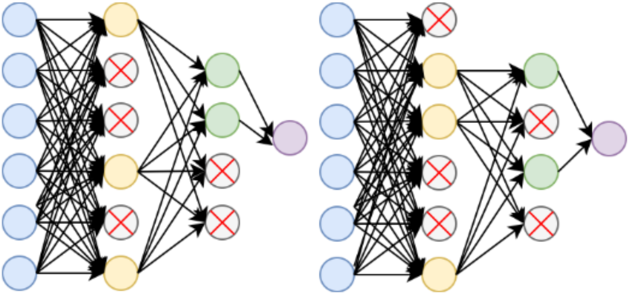
- Deep learning models, e.g., Convolutional Neural Network (CNN), has become state-of-the art approach for data-driven RUL prediction methods.



- Problems of traditional deep learning models for RUL prediction:
  - Require large amount of training data. -> See next section
  - Black box model. Prone to overfitting and hard to generalize. -> Physics-informed deep learning
  - Can only predict a point estimate. Not able to consider the uncertainty due to model structure and selection. -> Monte Carlo dropout

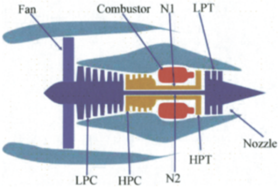
Probabilistic prediction through Monte Carlo dropout

Monte Carlo dropout: How it works



Aircraft turbofan engines - the degradation of engines is simulated using the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) program developed by NASA [5].

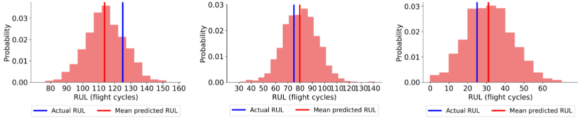
Symbol	*Description*	*Units*
Parameters available to participants as sensor data		
T2	Total temperature at fan inlet	°R
T24	Total temperature at LPC outlet	°R
T30	Total temperature at HPC outlet	°R
T50	Total temperature at LPT outlet	°R
P2	Pressure at fan inlet	psia
P15	Total pressure in bypass-duct	psia
P30	Total pressure at HPC outlet	psia
Nf	Physical fan speed	rpm
Nc	Physical core speed	rpm
epr	Engine pressure ratio (P50/P2)	--
Ps30	Static pressure at HPC outlet	psia
phi	Ratio of fuel flow to Ps30	pps/psi
NRf	Corrected fan speed	rpm
NRc	Corrected core speed	rpm
BPR	Bypass Ratio	--
farB	Burner fuel-air ratio	--
htBleed	Bleed Enthalpy	--



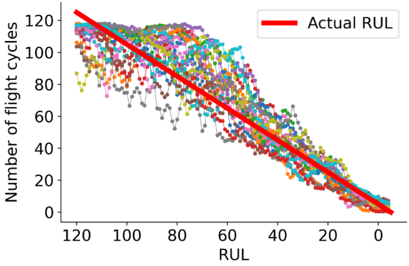
[5] Abhinav Saxena and Kai Goebel. Turbofan engine degradation simulation data set. NASA Ames Prognostics Data Repository.Moffett Field, CA: NASA Ames Research Center; 2008.

Result: RUL prediction for aircraft engines through CNN with Monte Carlo dropout

Results - Probabilistic RUL prognostics



(a) Actual RUL = 125 flight cycles (b) Actual RUL = 75 flight cycles (c) Actual RUL = 25 flight cycles



Results - RUL prognostics

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A motivating example

- Suppose our RUL prediction algorithm gives us a predicted distribution of the RUL.
- How to decide when to replace?
- A straightforward idea could be minimizing:

$$Expected\ Cost(T) = c_1 P(RUL < T) + c_2(1 - P(RUL < T)). \quad (1)$$

- Is that OK to proceed like this?

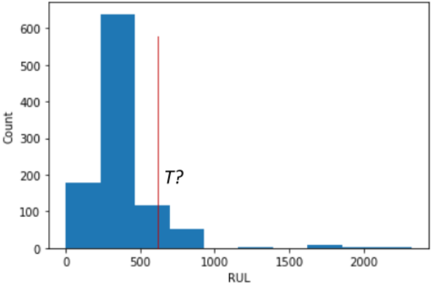


Figure: An example of the predicted RUL distribution.

Why cannot directly use the cost?

$$\begin{aligned} cost(T) &= c_1 P(RUL < T) + c_2(1 - P(RUL < T)) \\ &= c_2 + (c_1 - c_2)P(RUL < T). \text{ (Usually one has} c_1 >> c_2.) \end{aligned} \quad (2)$$

- If we directly minimizing $cost(T)$, the optimal sulotion will always be $T = 0$, which indicates that whenever we did a RUL prediction, we should replace the item immediately.
- This is because in this way of formulation, no penalty on wasting remaining useful life!

Two possible ways of dealing with this problem.

- Introduce a penalty cost associated with the wasted RUL. For example,

$$cost(T) = c_1 P(RUL < T) + c_2(1 - P(RUL < T)) + \alpha E(RUL(T)) \quad (3)$$

- Use expected cost rate instead of $cost(T)$: Renewal process theory.

Basics of renewal process theory: A recap

$\{N(t), t \geq 0\}$ - renewal process that regenerates when a replacement occurs:

- Suppose we do a preventive replacement when the age of the item reaches t_p.
- The replacement is corrective if time-to-failure $t_f < t_p$,
- is preventive is $t_f > t_p$.

Expected cost rate is defined as:

$$\lim_{t \to \infty} = \frac{\sum_{i=1}^{N(t)} C_i}{t} \tag{4}$$

- Physical meaning of expected cost rate: If we operate the item for a long period of time, what is the average operation cost per unit of time.

Basics of renewal process theory: A recap

From renewal reward process theory:

$$\lim_{t\to\infty} \frac{C(t)}{t} = \frac{\mathbb{E}[C_1]}{\mathbb{E}[L_1]}.$$

To determine an optimal replacement time, analyze the long-term average cost per unit of time:

$$\frac{\mathbb{E}(\text{cost incurred during one cycle})}{\mathbb{E}(\text{length of one cycle})}.$$

Optimal predictive maintenance planning

At current time k, interested in the optimal time to replace t_k^*, i.e., an optimal time to replace the engine, which minimizes the long-term average cost per unit of time:

$$t_k^* = argmin_{t_k} \frac{\mathbb{E}[C(k, t_k)]}{\mathbb{E}[L(k, t_k)]},$$

where

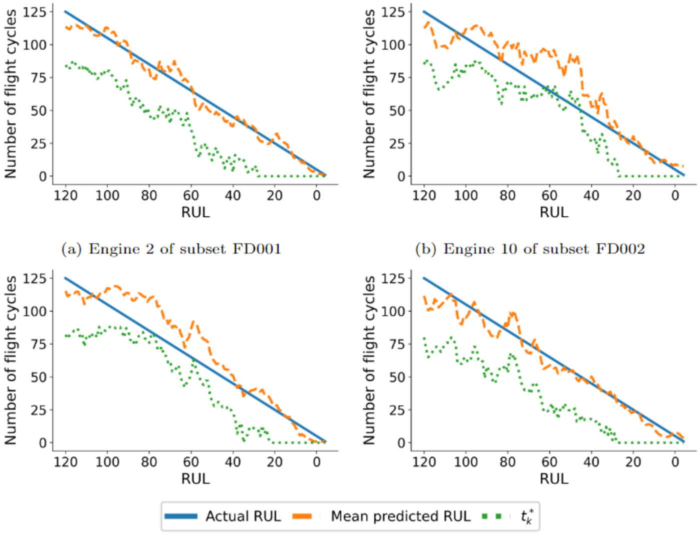
$$\mathbb{E}[C(k, t_k)] = c_\mathrm{f} \sum_{i=0}^{t_k-1} \phi_k(i) + c_\mathrm{r} \left(1 - \sum_{i=0}^{t_k-1} \phi_k(i)\right),$$

and

$$\mathbb{E}[L(k, t_k)] = k + \sum_{i=0}^{t_k-1} i \cdot \phi_k(i) + t_k \left(1 - \sum_{i=0}^{t_k-1} \phi_k(i)\right).$$

where $\phi_k(i)$ is the predicted probability mass function of the RUL distribution at time i.

Results - Single engine maintenance planning



(a) Engine 2 of subset FD001

(b) Engine 10 of subset FD002

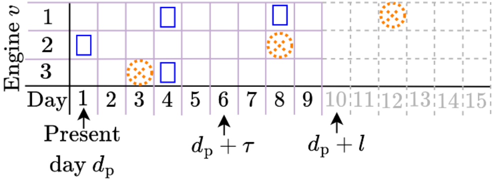
(c) Engine 2 of subset FD003

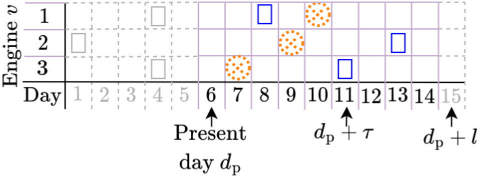
(d) Engine 3 of subset FD004

Outline

V - a set of engines
$S^v, v \in V$ - set of time slots when engine v can be maintained
S_g - set of generic slots
Constraint: at most h engines maintained in one day

Rolling-horizon planning: optimisation window $[d_p, d_p + l)$





Maintenance costs

Cost of maintenance in slot s:

$$c_s^v = \frac{c_\mathrm{f} \sum_{i=0}^{t_\mathrm{p}^s - 1} \phi_{k_\mathrm{p}}^v(i) + (c_\mathrm{r} + c_\mathrm{g}\mathcal{I}_\mathrm{g}(s)) \left(1 - \sum_{i=0}^{t_\mathrm{p}^s - 1} \phi_{k_\mathrm{p}}^v(i)\right)}{(d_\mathrm{p} - d_0^v) + \sum_{i=0}^{t_\mathrm{p}^s - 1} i\phi_{k_\mathrm{p}}^v(i) + t_\mathrm{p}^s \left(1 - \sum_{i=0}^{t_s^p - 1} \phi_{k_\mathrm{p}}^v(i)\right)},$$

Cost of not maintaining in current window, but having a failure:

$$c_\mathrm{DN}^v = \frac{c_\mathrm{f} \sum_{i=0}^{l-1} \phi_{k_\mathrm{p}}^v(i)}{(d_\mathrm{p} - d_0^v) + \sum_{i=0}^{l-1} i\phi_{k_\mathrm{p}}^v(i) + l\left(1 - \sum_{i=0}^{l-1} \phi_{k_\mathrm{p}}^v(i)\right)}.$$

Maintenance planning

Decision variable:

$$x_{vs} = \begin{cases} 1, & \text{component } v \in V \text{ is replacedin slot } s \in S^v \cup S_{\mathrm{g}} \\ 0, & \text{otherwise.} \end{cases}$$

Objective:

$$\min \sum_{v \in V} \left(\sum_{s \in S^v \cup S_{\mathrm{g}}} c_s^v x_{vs} + c_{\mathrm{DN}}^v \left(1 - \sum_{s \in S^v \cup S_{\mathrm{g}}} x_{vs} \right) \right),$$

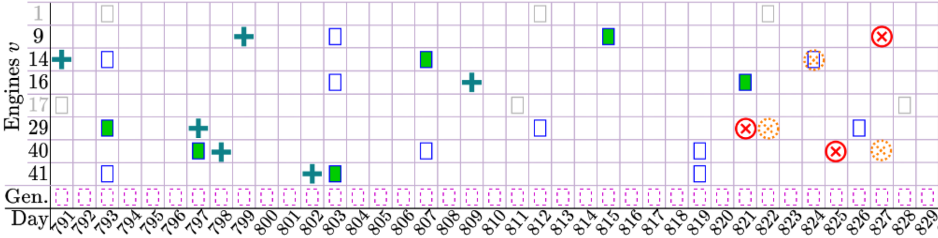
Constraints:

$$\sum_{s \in S^v \cup S_{\mathrm{g}}} x_{vs} \leq 1, \quad \forall v \in V$$

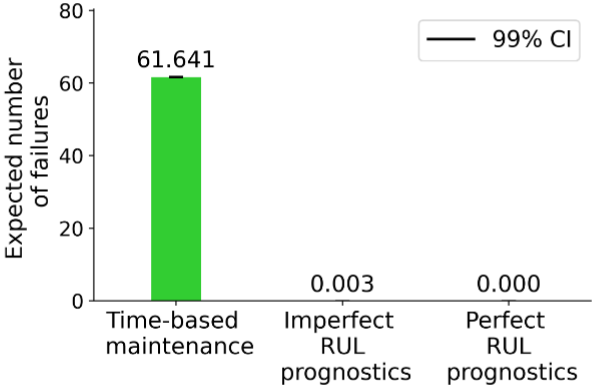
$$\sum_{v \in V} \sum_{s \in S^d} x_{vs} \leq h, \quad \forall d \in [d_{\mathrm{p}}, d_{\mathrm{p}} + l)$$

A set of $|V| = 50$ engines.
At most $h = 1$ engine per day maintained; Maintenance slots known $l = 50$ days ahead. Frozen maintenance planning $\tau = 10$ days. Costs: $c_r = 10$, $c_g = 10$, $c_f = 50$.
Maintenance for $T = 10 \times 365$ days.

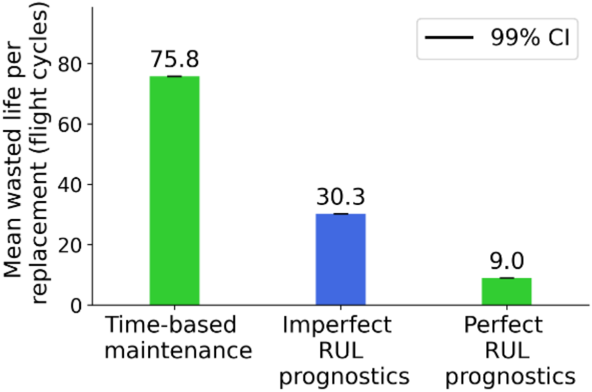
Snapshot present day $d_p = 791$:



Results - Number of failures



Results - Expected Wasted Life of engines



A short summary

Conclusions

- Deep learning for RUL prediction with Monte Carlo dropout - Predict not only point estimate, but also uncertainty!
- Predictive maintenance based on renewal theory
  - Single-component level
  - System-level

Remaining Challenges

- Theoretical analysis of the results: Given different properties of the RUL distribution, what will be the optimal maintenance time?
- Consider further dependencies on the system-level, e.g., economic dependency, structural dependency.

For details, please refer to our recent paper [6].

[6] Based on our recent publication: Mitici, M., de Pater, I., Barros, A. and Zeng, Z., 2023. Dynamic predictive maintenance for multiple components using data-driven probabilistic RUL prognostics: The case of turbofan engines. Reliability Engineering & System Safety, 234, p.109199.

Outline

Problems of today

- Every one is talking about: Lack of data.
- But why lacking data is a problem?
  - Because we do not have the capability to model how the system works, and how it does not work!
  - What if we have? Then we can use simulation to generate the data!

- A deeper question: If we have enough data, do we solve all the problem in reliability engineering?

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  - What if we have? Then we can use simulation to generate the data!

- A deeper question: If we have enough data, do we solve all the problem in reliability engineering?
  - NO! Because data are always after failure.
  - Then, you can only "react" to failure, but not anticipate before failure and design to prevent failure.
- So what we really need is not data, but a "digital twin" for failure behavior!

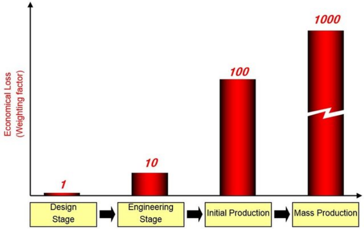
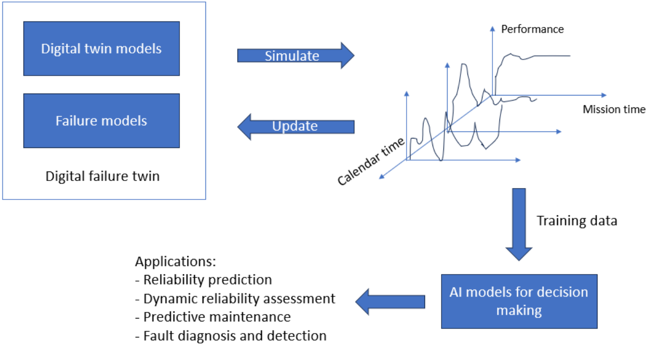


Figure: Failure cost in different phases of product life cycle.

Visions for tomorrow



- Create a modeling approach for digital failure twin:
  - simulate system normal behavior as well as failure behavior.
  - connect to physical system and able to update the model in realtime.
- Use the digital failure twin to develop AI-based algorithms for predictive maintenance:
  - training data for deep learning;
  - environment for reinforcement learning.

An experimental platform for digital twin enabled intelligent predictive maintenance

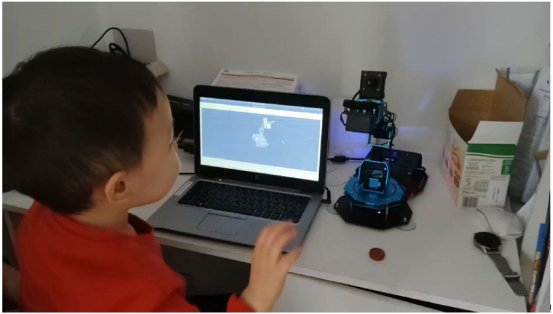
- Supported by ANR JCJC.
- System composition:
    - Robots: 2
    - Conveyer: 1
    - Stock shelfs: 4
- Robot:
    - 6 degree of freedom
    - Based on ROS and Rapsberry Pi
    - 6 motors are servo motors:
        - Feedback signal: Position, temperature, voltage

From 2:41'

View the video here!

An experimental platform for digital twin enabled intelligent predictive maintenance

Till now, we mainly worked on robot level and obtained a preliminary digital twin:



Watch the demo here!

The platform – Next steps

Robot level: From digital twin to digital failure twin

- If motor degrades, how will the performance of the robot be impacted (Forward problem)?
  - Motor degradation model + Robot level simulation
  - To simulate failure process, maybe more simulation models are needed:
    - FEM model <- For mechanical failures like fatigue
    - Thermal model (CFD) <- When temperature is the failure inducing stress, e.g., thermal fatigue of solder joint.
- Given the observed patterns of the health indicators, which failure mode happens? (Inversed problem, fault diagnosis)
- RUL prediction + maintenance planning.

The platform – Next steps

Production line level

- Construct the digital twin model.
- Hierarchical digital twin modeling.
- Decision-making problems:
  - Collaboration between the two robots.
  - Resilience of production line.

Key questions:

- How DT can assist AI-driven decision making?
- What's the benefit of introducing DT compared to traditional approaches?

Together, let’s make a more reliable world!

Thank you for your attention!

Questions?