Cranfield University

MARIE CURIE ACTIONS
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A Hybrid Prognostic Methodology for Aircraft Systems

Felix Fu
Marie Curie Researcher

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A Hybrid Prognostic Methodology for Aircraft Systems

ESR6 will develop a novel hybrid prognostic methodology focusing on the assessment of the state of the health of a system. The methodology will integrate **physics-based and data-driven prognostics models** in order to enhance the prognostic accuracy, robustness and applicability. Dedicated experimental test rigs such as **a clogged filter, a machinery fault simulator and a linear actuator failure simulator** will be used to obtain reproducible datasets under different operating conditions. Finally, the performance of the developed technique will be evaluated based on the most recent prognostic evaluation metrics.

Innovative aspects: Development of hybrid prognostic technologies

Objectives:

- Development of a novel hybrid prognostic methodology for aircraft systems
- Evaluation of the method based on prognostics evaluation metrics

Expected Results:

Tool for prognostics of aircraft systems

Planned secondment(s):

- **IKERLAN, 2/3 months, 2023, Spain**
  - Training on model-based condition monitoring tools
- **Tetra Pak, 3 months, 2023/24, Italy**
  - Industrial sector exposure, Application of developed methodologies on engineering systems

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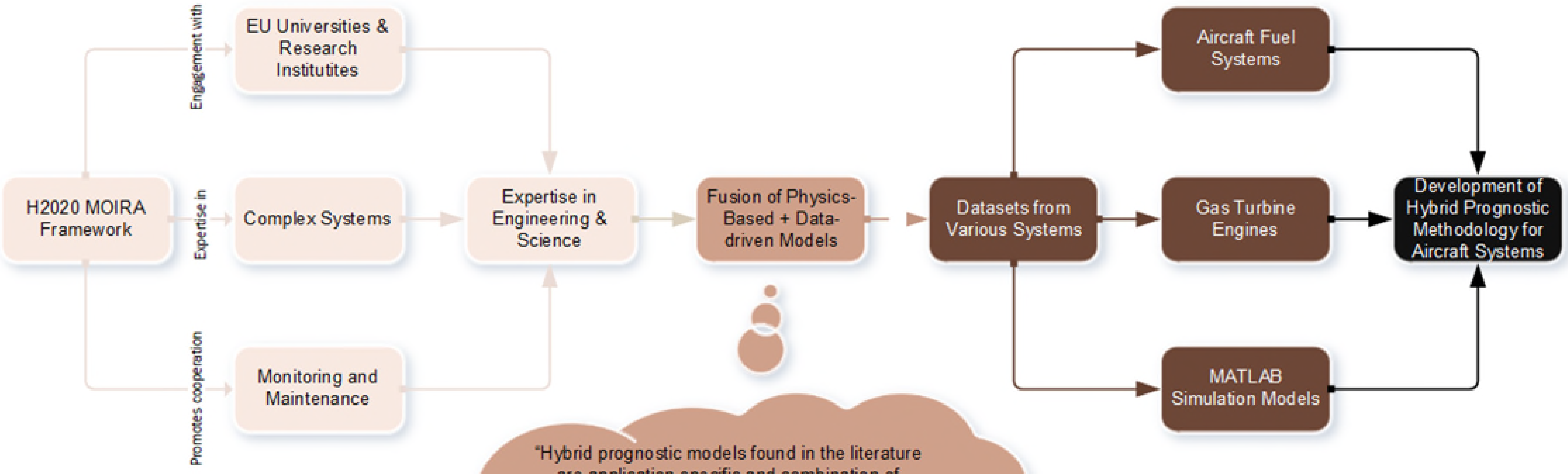
Context and Research gap



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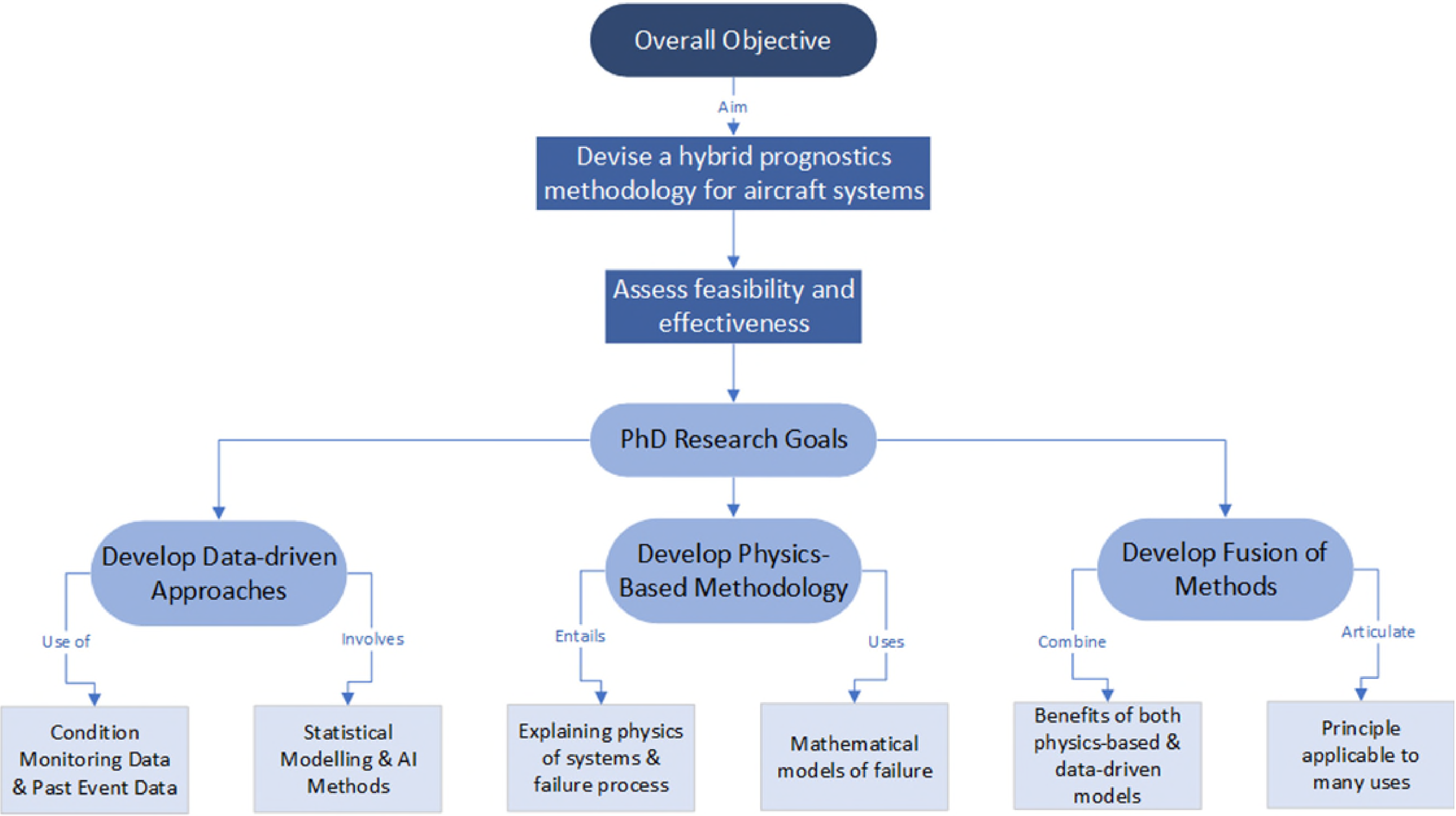
Overall Aim and Objectives



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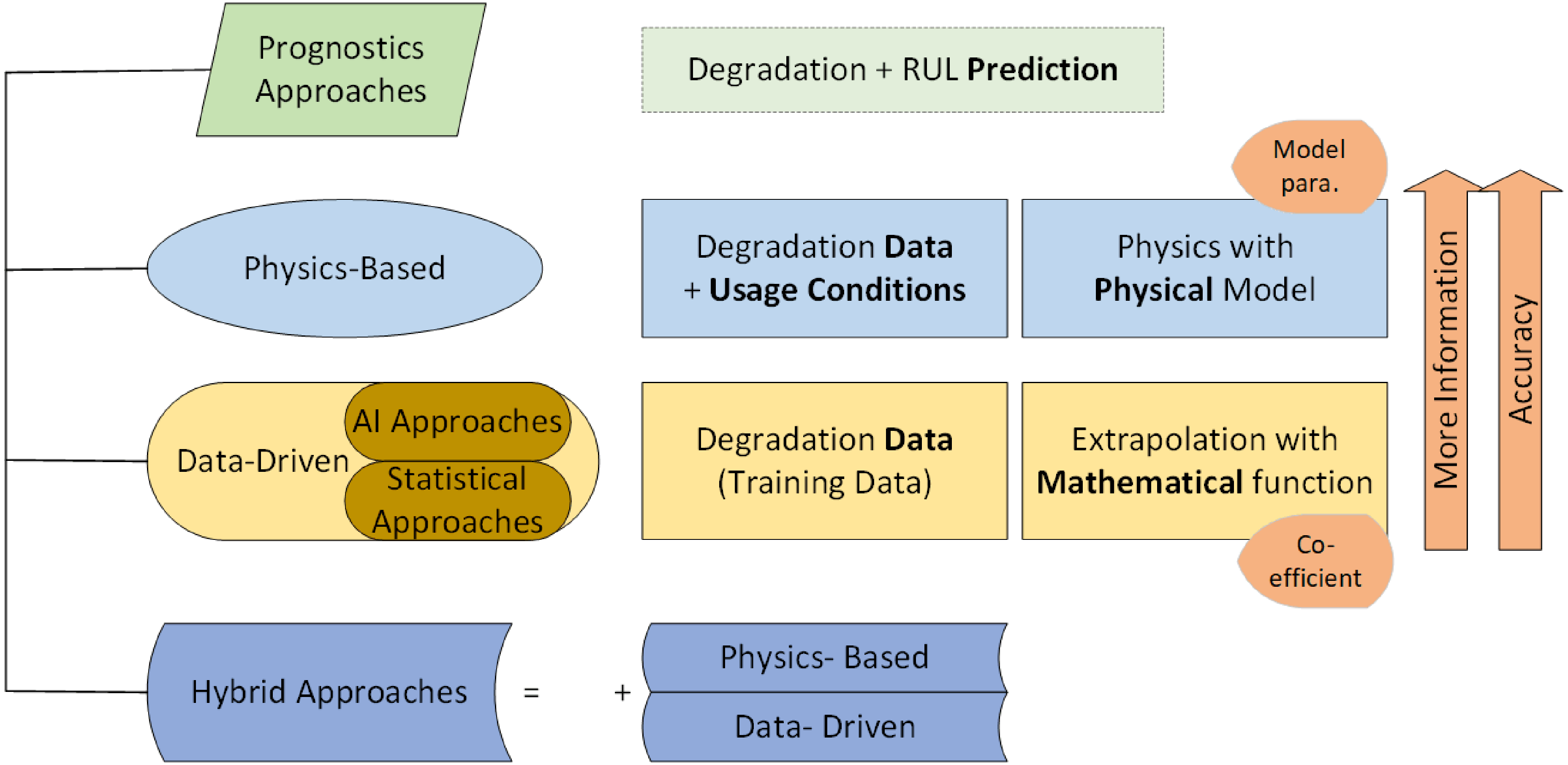

Fig. 1 Categorization and definition of prognostics methods

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Methodological Approach

Phase 1: Reseach Framework and Plan Development (Months 1-12)

Objective: Devise and implement the study framework and plan

Activities:
- Determine failure modes and their characteristics.
- Choose and validate the application.
- Review relevant literature on prognostic methods.
- Lead discussions with researchers and collaborators.
- Construct an outline of the research framework.

Deliverables:
- Specifications of degradation modes.
- Chosen application validation.
- Extensive literature review.
- Research framework outline.

Phase 2: Experimental Design and Data Collection (Months 13-24)

Objective: Conduct experimental design, data collection, analysis, and synthesis.

Activities:
- Obtain necessary apparatus and configure experimental system.
- Gather data for prognostic purposes.
- Analyse collected data and publicly available datasets.
- Investigate physics of failure using observed parameters.

Deliverables:
- Experimental system setup.
- Collected sensory data.
- Analysis of data for prognostic approaches.

Phase 3: Action Research and Dissemination (Months 25-36)

Objective: Develop and integrate prognostic methods, conduct capability and feasibility analyses, and disseminate findings.

Activities:
- Develop physics-based and data-driven prognostic methods.
- Conduct capability and feasibility analyses.
- Extract general principles for hybrid methods.
- Finalize reports for publication and distribution.

Deliverables:
- Developed prognostic methods.
- Capability and feasibility analyses.
- Final reports for publication and distribution.

Throughout the entire process, there's an emphasis on iterative refinement and parallel work, as deliverables from each phase inform subsequent research activities. The dissemination of findings to a broader audience, including industrial partners and public sectors, is also highlighted, indicating the importance of practical applicability and knowledge sharing. Overall, the approach combines theoretical investigation, empirical experimentation, and practical application, ensuring a comprehensive exploration of prognostic methods for the chosen application.

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Methodological Approach

1. Literature Review and Theory Comparison:
- Examine current research papers, articles, and technical documents about prognostics in aviation systems.
- Compare multiple prognostic methodologies used in the aviation sector. Comprehend their strengths, limits, and practicality.
- Identify relevant ideas or models that have been effectively used in comparable situations.

2. Data Collection and Pre-processing:
- Obtain historical data from flight records, maintenance logs, and other pertinent sources. The data should include details on the performance of the aircraft subsystems, the health of components, and any instances of failure.
- Clean and preprocess the data by eliminating noise, outliers, and inconsistencies. Methods like data normalisation, feature extraction, etc

3. Feature Engineering:
- Extract relevant characteristics from the original data. The characteristics may include fuel flow rates, pressure levels, temperature fluctuations, and system statuses.

4. Hybrid Model Selection:
A hybrid model selection involves combining physics-based models, which are derived from system dynamics and engineering principles, with data-driven models, such as machine learning or statistical approaches.

5. Feature Fusion and Integration
- Combine features from both kinds of models. This fusion improves the overall predictive accuracy.
- Utilise ensemble methods, weighted averaging, or Bayesian networks to merge predictions effectively.

6. Health Indicator Development:
- Develop health indicators specifically for fuel system components. The indicators measure the system's health condition.

7. Remaining Useful Life (RUL) Estimation:
- Estimate the RUL of vital aircraft subsystem components. This entails predicting the duration till a breakdown occurs.
- Use the hybrid model's results and health indicators to predict the RUL.

8. Validation and Performance Metrics:
- Split the dataset into training and validation sets using methods like random holdback, etc
- Evaluate the performance of the hybrid model by analysing parameters like as accuracy, precision, and RASE.
- Compare the findings with established literature or theoretical predictions.

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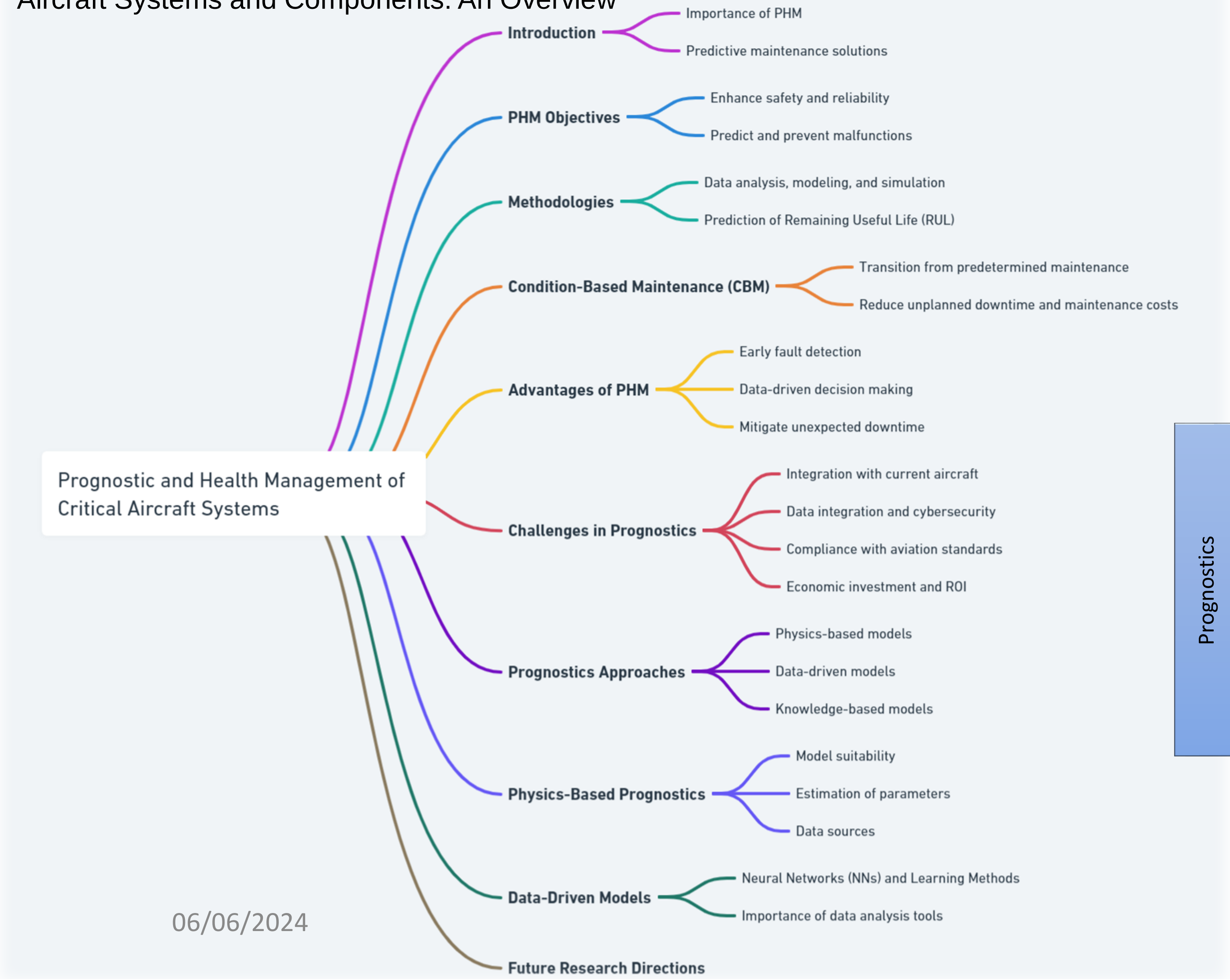
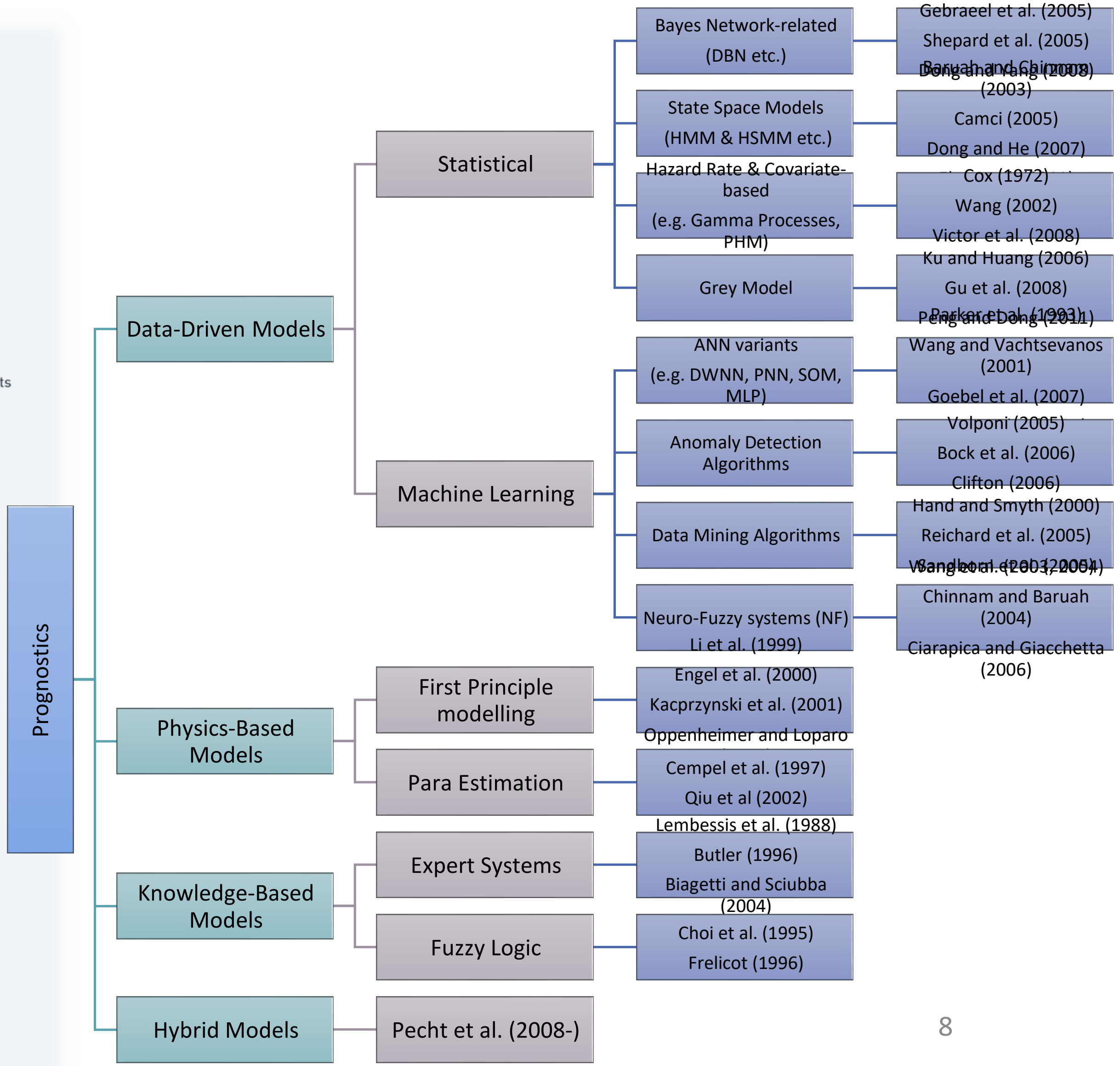
Key Findings to Date 1/4

Prognostic and Health Management (PHM) of Critical Aircraft Systems and Components: An Overview





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Key Findings to Date 2/4

Data-driven Methodology for Aircraft Gas Turbines

The dataset contains eight datasets of run-to-failure trajectories for a fleet of 128 aircraft engines under different flight conditions. Failures can occur in either the flow(F) or efficiency (E) of different subsystems: Fan, Low Pressure Compressor (LPC), High Pressure Compressor (HPC), High pressure Turbine (HPT), and Low-Pressure Turbine (LPT), as indicated in the table below.

Table 1. NASA PoE Dataset

Name	# Units	Flight Classes	Failure Modes	Fan		LPC		HPC		HPT		LPT		Size
				E	F	E	F	E	F	E	F	E	F	
DS01	10	1, 2, 3	1							✓				7.6 M
DS02	9	1, 2, 3	2							✓		✓	✓	6.5 M
DS03	15	1, 2, 3	1							✓		✓	✓	9.8 M
DS04	10	2, 3	1	✓	✓									10.0 M
DS05	10	1, 2, 3	1					✓	✓					6.9 M
DS06	10	1, 2, 3	1			✓	✓	✓	✓					6.8 M
DS07	10	1, 2, 3	1									✓	✓	7.2 M
DS08	54	1, 2, 3	1	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	35.6 M

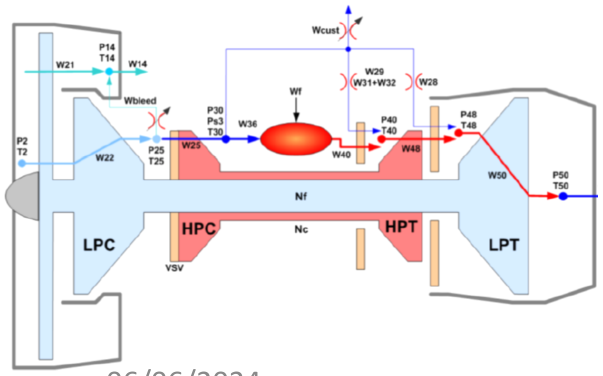

Figure 2. Simplified Engine Structure

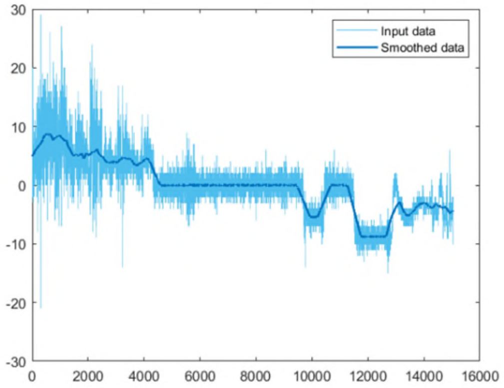

Figure 3. Smoothed Flight Phase

Table 2. Prognostic Results (A) Training. (B) Validation

(A) TRAINING RESULTS

Measures	Value
RSquare	0.9943186
RASE	1.6864235
Mean Abs Dev	1.2315266
Loglikelihood	6813165.7
SSE	9980079.4

(B) VALIDATION RESULTS

Measures	Value
RSquare	0.9943197
RASE	1.6860187
Mean Abs Dev	1.2314788
Loglikelihood	3405651.1
SSE	4986896.9

(A) TRAINING RESULTS

Measures	Value
RSquare	0.9923164
RASE	1.9609583
Mean Abs Dev	1.3880437
Loglikelihood	7342425.6
SSE	13493897

(B) VALIDATION RESULTS

Measures	Value
RSquare	0.9923078
RASE	1.9624767
Mean Abs Dev	1.3879187
Loglikelihood	3672020.3
SSE	6756388.2

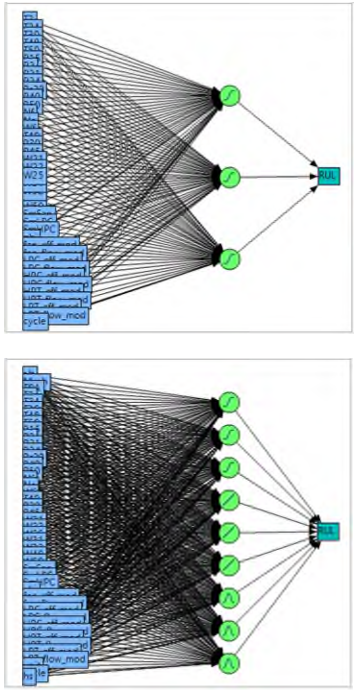

Figure 5. NN Structures

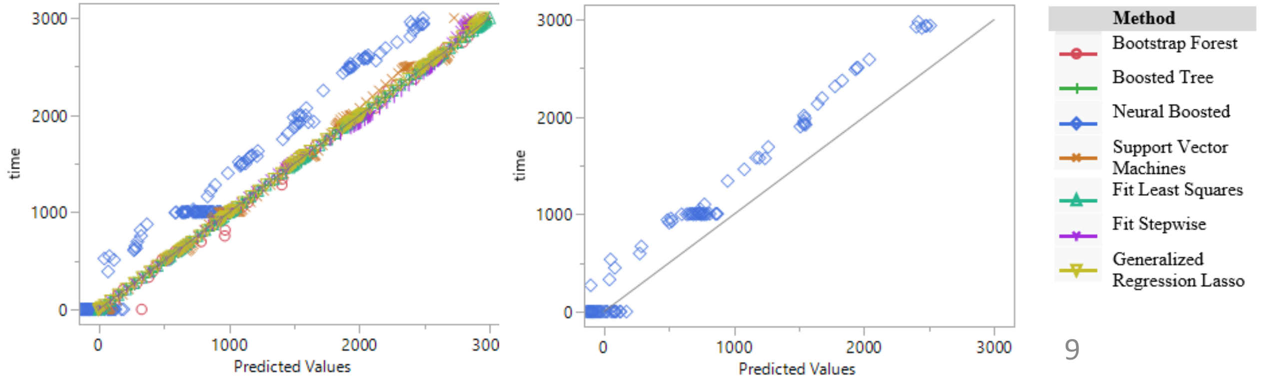

Figure 4. RUL Prediction Results. (Left) Training. (Right) Validation

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Key Findings to Date 3/4

Physics-based Approach development and its fuel rigs

Table 3. Fuel Rig Experimental Plan

Category	Name	Range	Interval	Number of level	Activated component on the fuel rig	Condition of activated component
Working condition	Pump speed	200-600rpm	100rpm	5	Gear pump	200-600rpm
Degradation	Pump external leakage	0-40%	10%	5	DPV1	0-40% open
	Pump internal leakage	0-40%	10%	5	DPV2	0-40% open
	FOHE blockage	0-40%	10%	5	DPV3	100-60% open
	FOHE leakage	0-60%	15%	5	DPV4	0-60% open
	Nozzle blockage	0-40%	10%	5	DPV5	100-60% open

Table 4. Fuel Rig Initial Health Condition

Failure mode	DPVs	Healthy condition
Pump ext leakage	DPV1	Close
Pump int leakage	DPV2	Close
FOHE blockage	DPV3	100% Open
FOHE leakage	DPV4	Close
Nozzle blockage	DPV5	100% Open

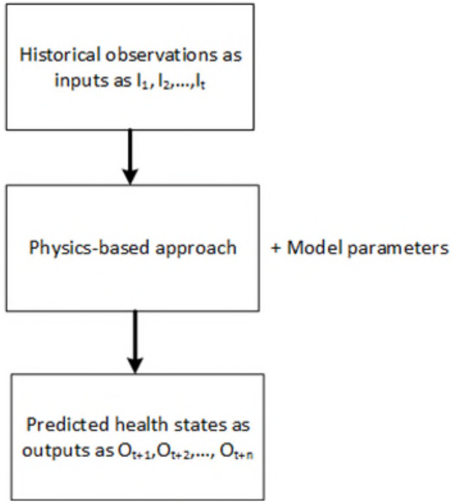

Figure 8. PbM prognostic process

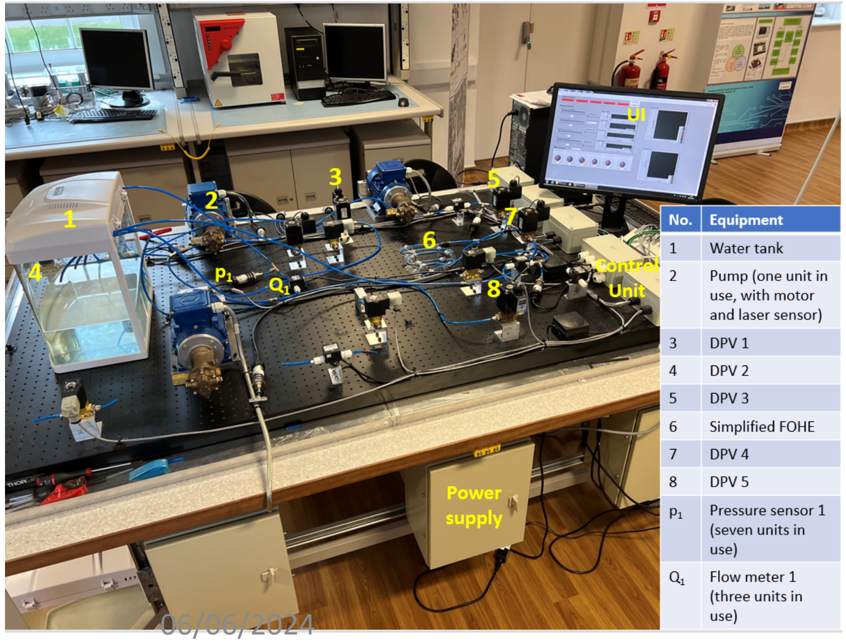

Figure 6. IVHM Centre Fuel Rig

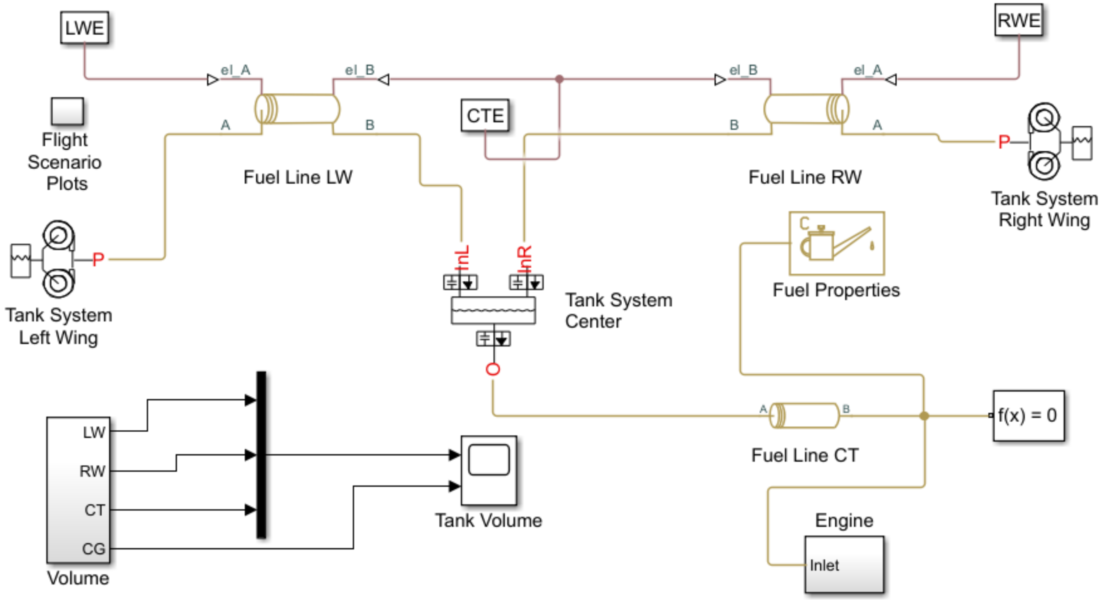

Figure 7. Aircraft Fuel System Simulation Model

1. principle of mass conservation

$$\frac{dV}{dt} = Q_{in} - Q_{out}$$

2. Bernoulli's equation

$$P + \frac{1}{2}\rho v^2 + \rho g h = constant$$

3. PID (Proportional-Integral-Derivative) control

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)\, d\tau + Kd \frac{de(t)}{dt}$$

4. Darcy-Weisbach equation

$$\Delta P = f \frac{L}{D} \frac{\rho v^2}{2}$$

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Key Findings to Date 4/4

Hybrid Prognostic Approach development and implementations for Aircraft Systems

Multivariate time-series of condition monitoring sensors readings $X_{s_i} = [x_{s_i}^{(1)},\ldots, x_{s_i}^{(m_i)}]^T$ are given and their corresponding RUL, i.e., $Y_i = [y_i^1, \ldots, y_i^{m_i}]^T$ from a fleet of N units (I = 1,…, N). Each observation $x_{s_i}^{(t)} \in R^s$. The length of the senso signal for the i-th unit is given by m_i, which differ from unit to unit. The total combined length of the available data set is $m = \sum_{i=1}^N m_i$. More compactly, it denotes the available dataset as $D = \{W_i, X_{s_i}, Y_i\}_{i=1}^N$. Given this set-up, the task is to obtain a predictive model G that provides a reliable RUL estimate $(\widehat{Y})$ on a test dataset of M units $D_{T_*} = \{X_{sj*}\}_{j=1}^M$, where $X_{sj*} = [x_{sj*}^1, \ldots, x_{sj*}^{k_j}]$ are multivariate time-series of sensors readings.

$$\mathrm{RUL}_t^u = \frac{\sum_{i=1}^N \left(s_i \mathrm{RUL}_{t_{i,s}}^i\right)}{\sum_{i=1}^N s_i}$$

RUL_t^o : Remaining Useful Life of the asset under observation (o) at time t

N : Number of previously degraded assets

s_i : Similarity of the health state progressions of the asset under observation and asset i

$\mathrm{RUL}_{t_s}^i$: Remaining useful life of asset i at time t_s

$t_{i,s}$: The time where the most similar segment of health progression of the asset i to the health progression of asset under observation starts

Similarity (s_i) is used as the main criteria for long term forecasting and is calculated based on the function given in

$$s_i = e^{-\frac{(d_i^{min})^2}{\lambda}}$$

λ : Gaussian variable of the similarity function

d_i^{min} : Minimum distance of the segments of health progression of asset i to the health progression of the asset under observation

The distance calculation between two segments with the same length is given in Eq.

$$d_{\alpha,T}^i = \sqrt{\sum_{j=0}^{n_0}\left\|z_{\alpha+j}^i - z_{t-n_0+j}^o\right\|^2 + \sum_{k=1}^{n_1}\left\|z_{\alpha+n_0+k}^i - z_{t+k}^o\right\|^2}$$

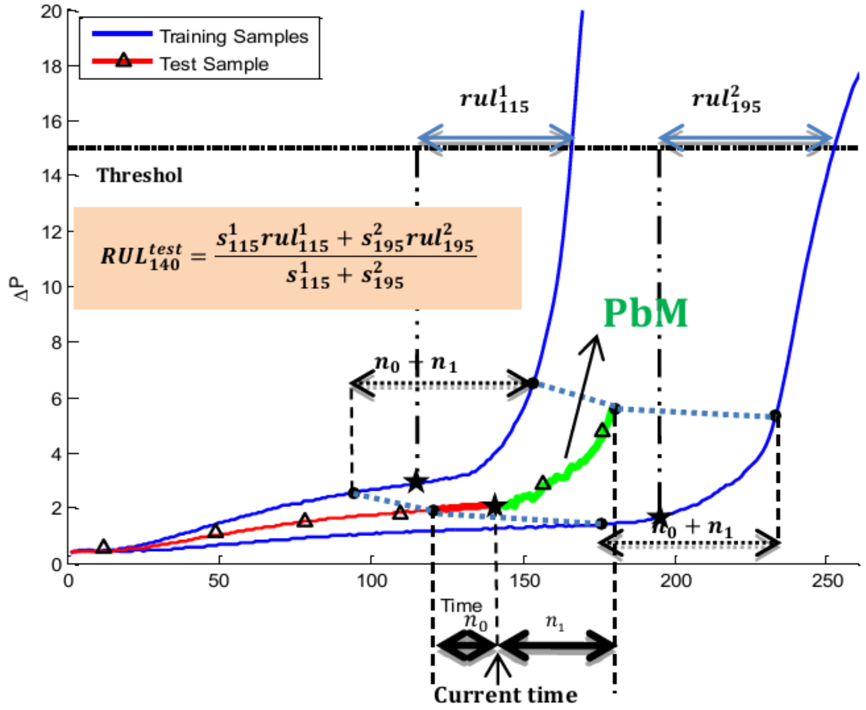

Figure 9. RUL Calculation

In the figure, the RUL calculation is performed for a test specimen at the 140th second, shown in a curve with triangle markers where the future measurements are not known. The other two solid run-to-failure trajectories represent the training samples. It is assumed that the sample is failed when it reaches the predefined threshold shown in the horizontal dashed line (ΔP=15). Thick line extension (starting from the current time) is the 'n1' number of time point predictions to the future, obtained from the physics-based model.

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Conclusions

- Prognostics methodologies typically revolve around physics-based or data-driven approaches. Both options provide benefits and drawbacks, but precise forecasting hinges on the availability of enough data. In industrial applications, it is infrequent for this scenario to occur, resulting in a significant decline in the performance of the selected method from its ideal state. Hence, a hybrid methodology has been devised, combining physics-based and data-driven approaches, and is documented in this research.
- In various stages of the prognostics process, such as state estimation and state forecasting, hybrid methods commonly use both physics-based and data-driven approaches. The proposed strategy combines two forecasting methodologies by integrating a physics-based model for short-term prediction and a similarity-based data-driven model for long-term projection. This integration allows for the estimation of the remaining useful life.
- Multiple engineering datasets were used to test the proposed hybrid prognostic methodology: one for aircraft turbines and the other for fuel systems. The efficacy of the methodology described will be assessed through a comparative analysis of the remaining useful life estimations derived from hybrid and individual prognostic models. The findings indicate that the methodology given in this study enhances accuracy, robustness, and application, particularly in situations where there is limited data available.

Publications

Journals:

1. Fu S, Avdelidis NP. Prognostic and Health Management of Critical Aircraft Systems and Components: An Overview. Sensors. 2023; 23(19):8124.
2. Fu S, Avdelidis NP. Novel Prognostic Methodology of Bootstrap Forest and Hyperbolic Tangent Boosted Neural Network for Aircraft System. Elsevier. Reliability Engineering & System Safety. In Press.

Conferences:

1. S. Fu, N. P. Avdelidis and I. K. Jennions, "A Prognostic Approach to Improve System Reliability for Aircraft System," 2023 7th International Conference on System Reliability and Safety (ICSRS), Bologna, Italy, 2023, pp. 259-264,
2. Fu, S., P. Avdelidis, N. ., Plastropoulos, A., & Fan, I.-S. (2023). Fusion and Comparison of Prognostic Models for Remaining Useful Life of Aircraft systems. Annual Conference of the PHM Society, 15(1).
3. Fu S, Avdelidis NP. Aeronautics Failure: A Prognostic Methodology Based on the Physics of Failure and Statistical Approaches for Predictive Maintenance. SPIE. In press.
4. Fu S, Avdelidis NP. Application of a Hybrid Prognostic Methodology to Predict Remaining Useful Life of Aircraft Systems. PHMe24. Under review.
5. Shuai Fu, Nicolas P. Avdelidis, "Aeronautics failure: a prognostic methodology based on the physics of failure and statistical approaches for predictive maintenance," Proc. SPIE 12952, NDE 4.0.

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Ongoing & To dos

Main Activities		Date est.
Action Research	Analyse the integration points of physics-based and data-driven models	15 Apr 2024
	Develop the hybrid prognostic approach	1 May 2024
	Extract general principle that can be used as a guideline for other systems	30 Jul 2024
Synthesis & Dissemination	Write thesis on the knowledge built from this research work	1 Mar 2024
	3 months placement at Tetra Pak in Italy, validate findings with collaborators and other academics, and application of developed methodologies on CBM	May – Aug/Sep 2024

Academic Activities	Title	Date
EWSHM2024/Journal of Nondestructive Testing	Structural Health Management in Aircraft Fuel Systems: A Hybrid Prognostic Perspective	10-13 Jun 2024
PHMe2024	Application of a Hybrid Prognostic Methodology to Predict Remaining Useful Life of Aircraft Systems	3-5 Jul 2024
2nd International Conference for CBM in Aerospace	Statistical Analysis and Simulation-Based Prognostic Approach of Aircraft Fuel System Failure	11-13 Sep 2024

THANK YOU

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