Health-aware predictive maintenance planning for complex systems

Health Aware and Safe Control Learning & Design for Dynamic Systems 2024

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About me

- Assistant Professor - Algorithmic Data Analysis group, Utrecht University, Netherlands

- **Previously**:

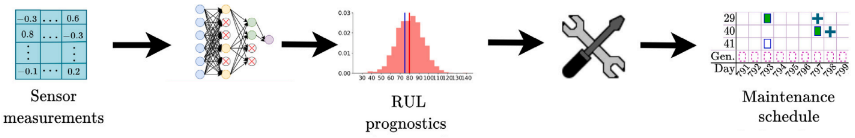
  - Assistant Urofessor at TU Delft, Aerospace Engineering (2016-2022)

  - PhD in Stochastic Operations Research - University of Twente

  - MSc in Operations Research - University of Amsterdam

Research focus

- Integration of data-driven prognostics into dynamic maintenance planning → **predictive maintenance.**

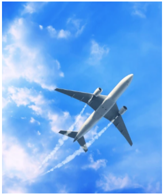


Agenda

- Predictive maintenance planning - a control problem
- Model-based approaches (batteries, wind turbines)
- Model-free approaches (aircraft engines)
- Open questions

Predictive maintenance nowadays

Large volumes of data as a result of continuous monitoring of cyber-physical assets.



- For a A350, 50,000 sensors collect 2.5 terabytes of data per day*.
- Supervisory Control and Data Acquisition (SCADA) systems record hundreds of parameters every second for one wind turbine.

*Data revolution in aviation, 2020. airbus.com

Opportunities

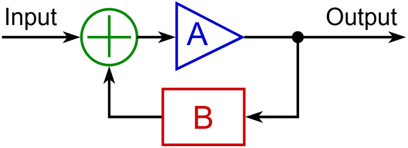
Continuous monitoring enables data acquisition and processing for knowledge acquisitions, forecasting and planning.

Sensor measurements enable:

- monitoring of the health of the components
- identification of abnormal behavior
- anticipation of failure times
- decision-making for maintenance planning.

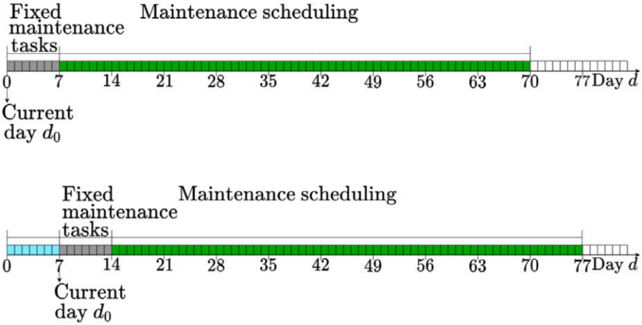
Goals: reduce costs, ensure safety, etc.

Predictive maintenance planning - a control problem



- **Input**: control policies π, measurements $\mathbf{x}_t$, operating constraints $\mathbf{c}_t$.
- **A**: prognostics $p(\mathbf{x}_t)$ of Remaining-Useful-Life(RUL) / State-of-Health(SOH) and maintenance planning decisions $\mathbf{y}_t(p(\mathbf{x}_t), \mathbf{c}_t)$.
- **Output**: optimal timing of maintenance (t^*). *Tension* between continuing operation while risking failure - preventive replacement of asset and wasting life.
- **B**: feedback on optimal maintenance timing vs current moment and reaction time, uncertainty of prognostics, consistency of maintenance decisions.

Maintenance planning - a dynamic process



- **B**: feedback on optimal maintenance timing vs current moment ($d_0 \in \{0, 7\}$) and reaction time (7 days), uncertainty of prognostics (variance of estimated RUL distribution), consistent "Do nothing"/"Immediate action".

Adaptation

Given measurements $\mathbf{x}_t$, operating constraints $\mathbf{c}_t$ and *periodically updated* RUL prognostics $p(\mathbf{x}_t)$:

- *adjust* maintenance timing t^* such that an asset failure is avoided (high cost), while the wasted life of the asset due to preventive replacements (decreasing cost) is minimized.

Today

Examples of predictive maintenance planning for:

- RUL prognostics of Lithium-ion batteries and maintenance - feedback: the shape of the estimated RUL distribution; tension risk of failure vs. wasted life
- RUL prognostics and maintenance for wind turbines - feedback: the consistency of the maintenance decision
- RUL prognostics and maintenance for aircraft engines - feedback: shape RUL distribution, optimal timing vs. current moment

[1] Mihaela, M., Leo, J., Zhiguo, Z., & David, C. (2024). Predictive Maintenance Planning For Batteries Of Electric Take-Off And Landing (eVTOL) Aircraft Using State-of-Health Prognostics. In the 34th European Safety and Reliability Conference (p. 117).

[2] Manna, D., Mitici, M., & Dalla Vedova, M. D. L. (2024). System-level Probabilistic Remaining Useful Life Prognostics and Predictive Inspection Planning for Wind Turbines. In PHM Society European Conference (Vol. 8).

[3] Lee, J., & Mitici, M. (2023). Deep reinforcement learning for predictive aircraft maintenance using probabilistic remaining-useful-life prognostics. Reliability Engineering & System Safety, 230, 108908.

Example1: Predictive maintenance - Lithium-ion batteries

eVTOL aircraft

- Electric Vertical Takeoff and Landing (eVTOL) aircraft [1]:
  - short ranges (50-100km), average speed 200km/hr
  - payload up to 500-800kg, 1-5 persons
  - urban traffic, remote areas.
- Battery management - critical for safe operations, but should also not waste its life due to costly replacement.

BBC

Home News Sport Business Innovation Culture Arts Travel Earth Video Live

"The biggest problem area when it comes to the cost of operation is the pilot and the batteries. You need to change the batteries a couple of times per year "

BBC News, 14th November 2024

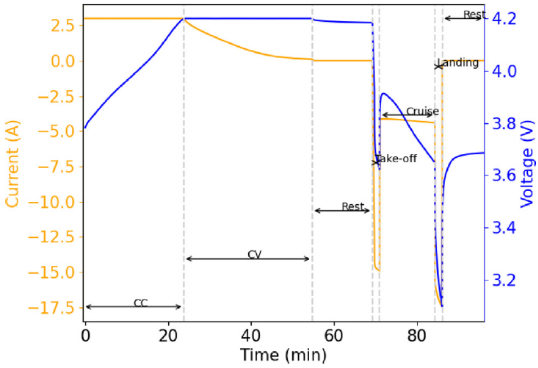
[4] Polaczyk, N., Enzo, T., Wei, P., Mitici, M. 2019. A review of current technology and research in urban on-demand air mobility applications. 8th Biennial Autonomous VTOL meeting & 6th Annual Electric VTOL Symposium, 333-343

[5] Mitici, M., Hennink, B., Pavel, M., & Dong, J. (2023). Prognostics for Lithium-ion batteries for electric Vertical Take-off and Landing aircraft using data-driven machine learning. Energy and AI, 12, 100233.

Missions

- A sequence of **missions** for each eVTOL:
  Constant Current (CC) battery Charging, Constant Voltage (CV) battery Charging, Rest period, Takeoff at given power, Cruise at given duration & power, Landing at given power.

Example of a single mission - eVTOL VAH01



Measurements

- Measurements every second:
  - cell voltage (V), cell current (mA), energy supplied to the cell during charge (Wh), charge supplied to the cell during charge (mAh), energy extracted from the cell during discharge (Wh), charge extracted from the battery cell during discharge (mAh), cell surface temperature (°C), cycle number (-) and cycle segment (-).

Mission profiles

Mission profiles (a total of 22)

- Baseline
  - CC battery charging phase: 1C-rate
  - CV battery charging phase: 4.2 V
  - Rest until cell temperature 35 °C.
  - Takeoff: 75s, 5C-rate; Cruise: 800s, 1.48C-rate; Landing: 105s, 5C-rate.
- Perturbed parameters: duration cruise , power during take-off, cruise, and landing, CC current, CV voltage, temperature.

Prognostics for battery RUL

End-of-Life (EOL): battery reaches EOL as soon as its capacity reaches 85% of the initially measured battery capacity.

Goal: estimate the distribution of the Remaining-Useful-Life (RUL).

$$RUL_{t_c} = T_{EOL} - T_c,$$

with T_{EOL} the cycle number when the battery capacity drops for the first time below the EOL-threshold, and T_c the current cycle number.

Feature engineering

Based on the measurements available - 32 features:

- Charging-related features: duration CC/CV charging phase (Δ^{CC}, Δ^{CV}), duration Rest after charging (Δ^{Rest})
- Discharge-related features: max, min, mean, variance of voltage/discharge capacity during flight segments take-off, cruise, landing ($V_{max}^{segment}$, $V_{min}^{segment}$, $V_{mean}^{segment}$, $V_{var}^{segment}$, $Qdis_{max}^{segment}$, $Qdis_{min}^{segment}$, $Qdis_{mean}^{segment}$, $Qdis_{var}^{segment}$), duration discharge $\Delta^{segment}$.
- Temperature-related features: max temperature during segment take-off, cruise, landing ($T_{max}^{segment}$)

Feature selection

Feature	Importance	Feature	Importance
$V^{take-off}_{min}$	**95.4**	$Qdis^{cruise}_{max}$	45.9
$V^{take-off}_{mean}$	**94.7**	T^{cruise}_{max}	45.4
$C^{measure}$	**93.4**	$T^{landing}_{max}$	41.1
$V^{take-off}_{var}$	**92.4**	$T^{take-off}_{max}$	38.8
V^{cruise}_{max}	**87.8**	Δ^{rest}	36.5
$Qcrg$	**87.1**	$V^{landing}_{max}$	35.5
Δ^{CV}	**86.5**	$\Delta^{take-off}$	23.4
V^{cruise}_{min}	**78.8**	Δ^{cruise}	19.7
V^{cruise}_{mean}	**63.8**	$\Delta^{landing}$	19.4
$V^{landing}_{var}$	**59.3**	Δ^{CC}	12.9
$V^{landing}_{mean}$	**57.4**	$Qdis^{cruise}_{var}$	3.5
$V^{take-off}_{max}$	**57.2**	$Qdis^{landing}_{max}$	2.4
$V^{landing}_{min}$	**51.6**	$Qdis^{cruise}_{mean}$	2.3
$Qdis^{take-off}_{var}$	**47.7**	V^{cruise}_{var}	2.2
$Qdis^{take-off}_{mean}$	**46.5**	$Qdis^{landing}_{var}$	1.4
$Qdis^{take-off}_{max}$	**45.9**	$Qdis^{landing}_{mean}$	1.2

Table: SHAP values (importance) for the 32 considered features; top 50% of the features are selected for RUL prognostics (in **bold**).

Prognostics for RUL - Mixed Density Networks

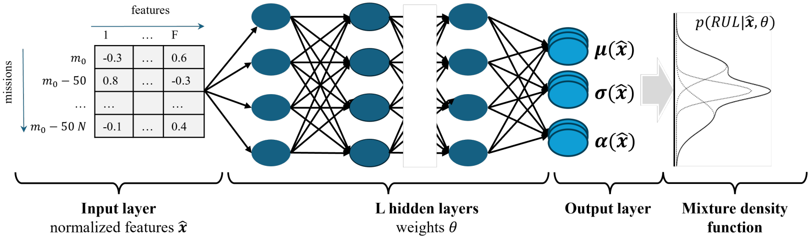


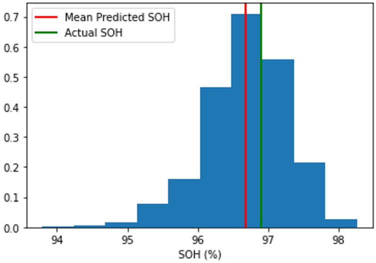
Figure: MDN neural network used to generate probabilistic RUL prognostics.

Results - RUL prognostics

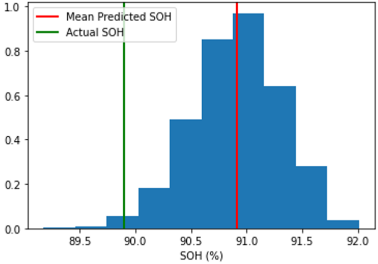
Fold 1				Fold 2				Fold 3			
VAH#	MAE	RMSE	CRPS	VAH#	MAE	RMSE	CRPS	VAH#	MAE	RMSE	CRPS
VAH01	63.69	68.15	47.29	VAH01	56.1	62.42	43.2	VAH10	10.4	12.33	7.18
VAH02	35.41	37.37	24.92	VAH05	29.4	37.0	19.65	VAH11	66.9	75.07	53.55
VAH13	17.06	20.81	13.02	VAH06	61.21	64.88	47.26	VAH17	34.45	38.83	24.11
VAH20	56.06	59.04	42.51	VAH13	32.78	36.06	22.36	VAH22	9.62	13.74	8.33
VAH28	22.01	25.47	18.12	VAH15	22.54	24.2	14.79	VAH23	98.7	125.89	72.87
VAH30	17.5	21.47	12.1	VAH16	20.32	22.34	14.41	VAH25	51.79	74.78	37.48
ALL	35.29	38.72	26.33	**ALL**	37.06	41.15	26.94	**ALL**	45.31	56.77	33.92

Fold 4				Fold 5				Fold 6			
VAH#	MAE	RMSE	CRPS	VAH#	MAE	RMSE	CRPS	VAH#	MAE	RMSE	CRPS
VAH02	20.21	27.1	18.22	VAH05	23.88	28.56	16.24	VAH10	5.59	7.35	6.41
VAH06	29.36	33.22	19.54	VAH12	52.09	59.95	39.32	VAH12	61.23	66.06	48.09
VAH17	23.04	27.71	15.99	VAH15	11.31	13.89	8.25	VAH22	11.77	14.98	8.44
VAH20	57.5	59.24	42.48	VAH16	17.53	21.85	13.57	VAH24	20.93	25.28	14.27
VAH26	21.85	27.41	17.86	VAH24	11.84	16.03	9.8	VAH25	39.64	50.91	28.39
VAH30	7.59	9.46	7.85	VAH27	26.8	34.61	21.95	VAH27	36.84	40.62	24.11
ALL	26.59	30.69	20.32	**ALL**	23.91	29.15	18.19	**ALL**	29.33	34.2	21.62

Probabilistic RUL prognostics



(a) VAH09, Capacity test 1.



(b) VAH09, Capacity test 9.

Predictive maintenance planning

Based on the RUL prognostics, at current day d_0 decide whether to plan a battery replacement at some day d in the planning window $[d_0 + 1, d_0 + k]$, or to postpone the decision for the next window $[d_0 + 1 + l, d_0 + k + l]$.

Cost of replacing within $[d_0 + 1, d_0 + k]$

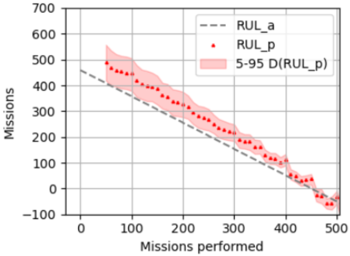
$$c_{vd} = c_{early}(d_v^* - d)^+ + c_{late}(d - d_v^*)^+. \qquad (1)$$

Cost of postponing to $[d_0 + 1 + l, d_0 + k + l]$:

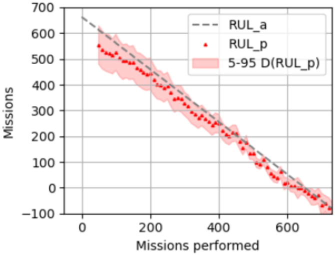
$$c_v^{postpone} = c_{late}(d_0 + k + l - d_v^*)^+, \qquad (2)$$

with d_v^* a function of the prognostic $\mathbb{P}[RUL_{d_0}^v \leq d]$.

Results

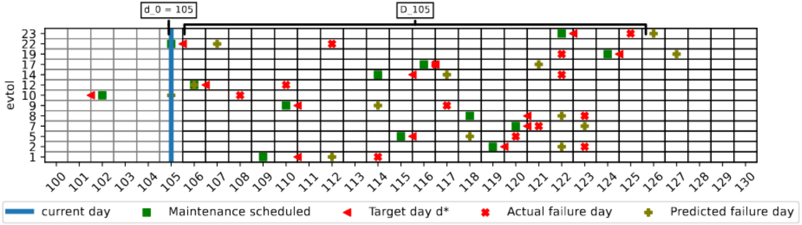


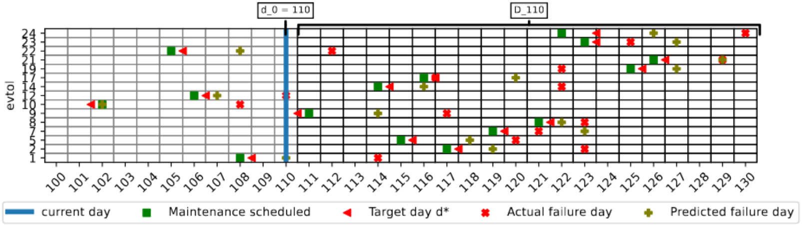
(a) VAH20, fold 1



(b) VAH13, fold 2

Results


d_0 = 105
D_105
evtol
23 22 19 17 14 12 10 9 8 7 5 2 1
100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130
current day
Maintenance scheduled
Target day d*
Actual failure day
Predicted failure day


d_0 = 110
D_110
evtol
24 23 22 21 19 17 14 12 10 9 8 7 5 2 1
100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130
current day
Maintenance scheduled
Target day d*
Actual failure day
Predicted failure day

Results

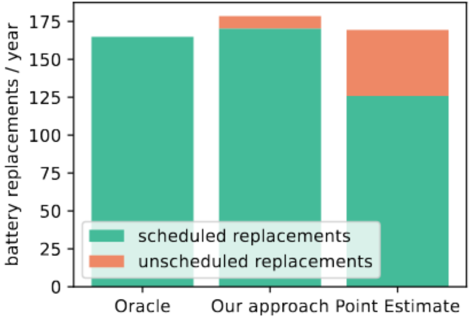


Figure: Average number of batteries used per year, given the Oracle, the RUL point estimate (RUL point) and Our (RUL distribution) planning - 10 years simulation, 50 eVTOLs, 10 missions/day/eVTOL.

Example2: System-level prognostics for Wind Turbines

Manna, D., Mitici, M., Dalla Vedova, M. (2024). *System-level Probabilistic Remaining Useful Life Prognostics for Wind Turbines*. European Conference of Prognostics and Health Management (PHMe) 2024.

Prognostics and Health Management for wind turbines

- Wind energy - crucial role in the energy transition.
- Goal: by 2030, no less than 20% of worldwide electricity demand satisfied by wind energy (Global Wind Energy Council).
- Wind energy - unreliable source of energy, also due to system malfunction and failures.
- High costs with maintenance, particularly for offshore wind turbines (remote areas).

Prognostics development

Monitoring a Wind Turbine at time step d (dth day), with available measurements:

$$x_d = \{x_{1,d}, x_{2,d}, \ldots, x_{m,d}\},$$

with m the total number of features, $x_{j,d}$s the measurement corresponding to feature $j, 1 \leq j \leq m$ recorded on day d.

Then, the actual system-level RUL of the WT at time d is:

$$RUL^a(WT) = \min\{\tau(c_1) - d, \tau(c_2) - d, \ldots, \tau(c_n) - d\},$$

with $\tau(c_j), 1 \leq j \leq n$ the time of failure of component c_j^i of WT i, n the total number of components of the WT.

Data Description

- 4 offshore Wind Turbines, 1st January 2017 - 31st December 2017.
- Supervisory Control and Data Acquisition (SCADA) measurements, meteorological recordings every 10min, and the logs of the WT component failures,
- SCADA measurements are recorded for: gearbox, gearbox bearing, generator, generator bearing, transformer, grid, rotor, blades, nacelle, controller, spinner, hydraulic group.

SCADA measurements:Max/Min/Average/STD Generator RPM (rpm), Max /Min/Average Rotor RPM (rpm), Average Temperature Generator Bearing (°C), Average Temperature Generator Phase 1/2/3 (°C), Average Temperature Hydraulic Group Oil (°C), Average Temperature Gearbox Oil (°C), Average Temperature Gearbox Bearing (°C), Average Temperature Nacelle (°C), Average Temperature High Volt Transformer Phase 1/2/3 (°C), Average Temperature Grid Inverter Phase1 (°C), Average Temperature Controller Top/Hub, VCP (°C), Average Temperature Generator Slip Ring (°C), Average Temperature Spinner (°C), Max/Min/Average/STD Blades Pitch Angle (degree), Average Temperature Controller VCP Chokcoil (°C), Average Temperature Grid Rotor Inverter Phase1/2/3 (°C), Average Temperature Controller Cooling Water (°C), Average Nacelle Direction (degree), Average Temperature Grid Busbar (°C), Average Temperature Generator Bearing (°C).

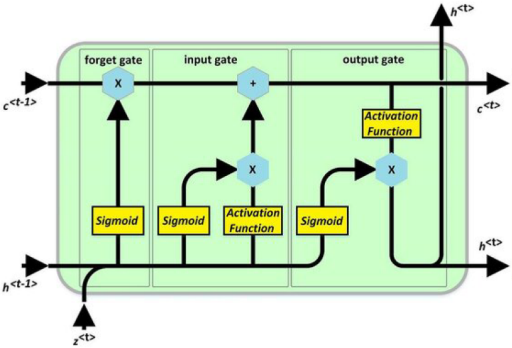
Cases

- Constructing training, testing and valisation sets - four case studies.

	Case 1	**Case 2**	**Case 3**	**Case 4**
Testing	**WT06**	**WT07**	**WT11**	**WT01**
Training	WT01, WT07	WT01, WT06	WT06, WT07	WT06, WT07
Validation	WT11	WT11	WT01	WT11
First fault	Hydraulic Group	Hydraulic Group	Hydraulic Group	Transformer
Actual Lifetime	8 months	6 months	4 months	8 months

Probabilistic RUL prognostics

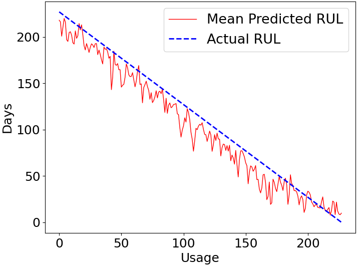
Long-short term memory (LSTM) with Monte Carlo dropout.



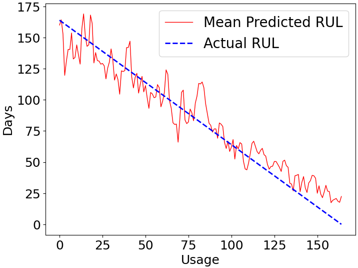
Results - Probabilistic RUL prognostics

	MAE	*RMSE*	*CRPS*	$CRPS^{W}$ $\beta = 1.9$
Case 1: WT06	12.72	15.52	9.98	2.51
Case 2: WT07	11.30	13.65	7.86	9.16
Case 3: WT11	9.40	11.08	6.93	6.88
Case 4: WT01	19.35	22.42	14.68	3.11

Prognostics over time

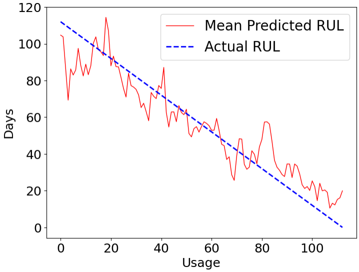


Case 1 - RUL estimation, WT06.

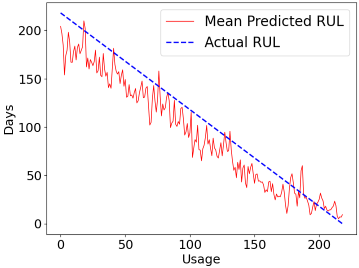


Case 2 - RUL estimation, WT07.

Prognostics over time

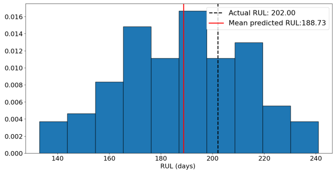


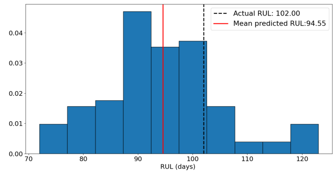
Case 3 - RUL estimation, WT11.

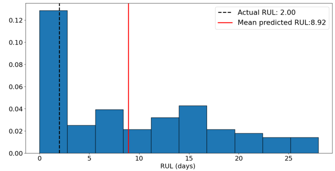


Case 4 - RUL estimation, WT01.

Probabilistic RUL prognostics over time - WT06







Optimal Replacement time

At current time k, interested in the optimal time to inspect t_k^*, i.e.,

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

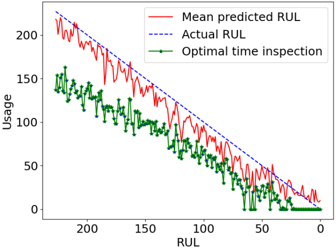
where

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

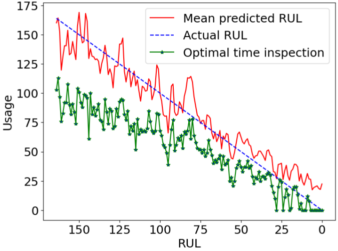
and

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

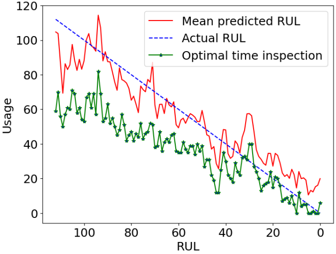
Results - Inspection Planning



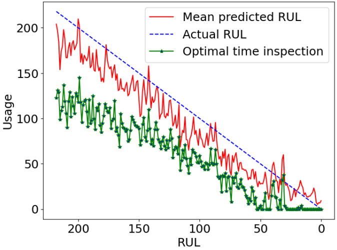
(a) WT06



(b) WT07



(c) WT11



(d) WT01

Results - Inspection planning

- Overall, conservative planning of inspections.
- The timing of the inspections reflects the insights obtained using $CRPS$ and $CRPS^W$ scores - WT for which the prognostics obtain low CRPS scores also have timely inspections planned (WT06, WT01), i.e. the failures of the WT are well anticipated.
- In the last phase of the life of the WT, the inspections are consistently planned within a short period of time.

Example 3: Deep reinforcement learning for maintenance

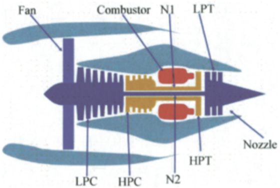
What if the maintenance planning of engines does not follow the renewal theory?
More general optimisation frameworks are needed → Reinforcement Learning

Deep Reinforcement Learning for Predictive Aircraft Maintenance using Probabilistic Remaining-Useful-Life Prognostics. J. Lee, M. Mitici. Reliability Engineering & Safety Systems, 108908, 2023

Measurements

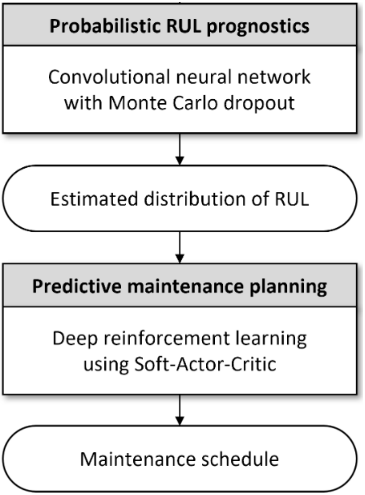
Aircraft turbofan engines - the degradation of engines is simulated using the Commercial Modular Aero-Propulsion System Simulation (C-MAPSS) program developed by NASA.

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	--



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

Reinforcement learning for maintenance planning



Assumptions

- Maintenance schedule updated every $D \geq 1$ flight cycles.
- Need to decide to replace/ not an engine during the next D cycles (a decision step).
- At start of decision epoch t, available prognostic

$$p_{k,t} = P(R_t \leq k \mid x_t), \text{ for } k \in \{1, ..., D\},$$

with x_t measurements available at decision step t.

RL formulation

- State:
$$s_t = \left[p_{1,t} \quad , \quad ... \quad , \quad p_{D,t}\right],$$
with $p_{k,t}$ the probability that the RUL is less than k cycles.
- Action:
$$a_t = \begin{cases} k, & 0 < k \leq D \quad \text{Schedule replacement at cycle } k, \\ M, & M > D \quad \text{Do nothing} \end{cases}.$$

RL formulation

- Reward:

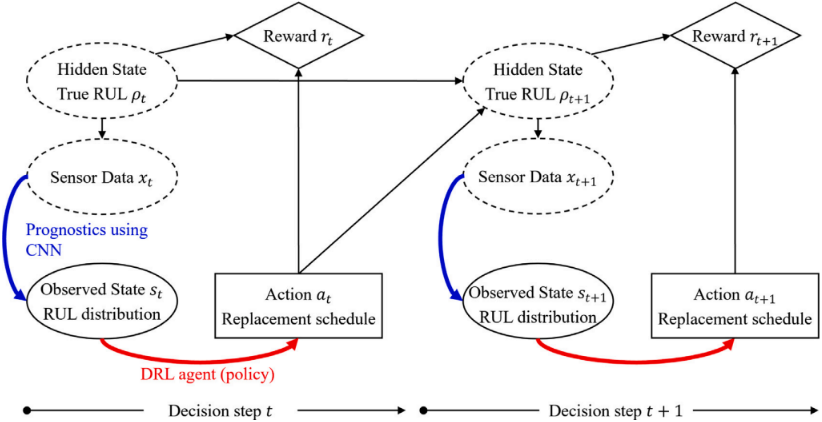
$$r_t = \begin{cases} -c_{\mathrm{sch}}(k) & \text{if } (k-1) < a_t \leq k \text{ and } \rho_t > k \\ -c_{\mathrm{uns}} & \text{if } (k-1) < a_t \leq k \text{ and } \rho_t \leq k \\ -c_{\mathrm{uns}} & \text{if } a_t > D \text{ and } \rho_t \leq D \\ 0 & \text{if } a_t > D \text{ and } \rho_t > D \end{cases},$$

where

$$c_{\mathrm{sch}}(k) = c_0 - c_1 k, \tag{3}$$

with c_0 a fixed cost of replacement ($c_0 > 0$), c_1 a penalty for an early replacement ($c_1 > 0$), ρ_t the hidden state, i.e., the true RUL.

RL formulation



DRL approach

DRL agent chooses action a_t (maintenance decision) given state s_t (estimated distribution of RUL) based on a *policy* $\pi(a_t|s_t) : \mathcal{S} \times \mathcal{A} \to [0, 1]$.

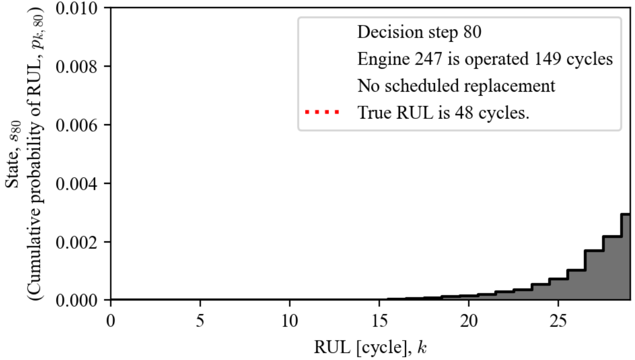
An optimal policy π^* maximizes:

$$J(\pi) = \sum_t \mathbb{E}_{(s_t, a_t) \sim \rho_\pi} \left[\gamma^t r_t(s_t, a_t) \right],$$

where ρ_π is the state–action trajectory distribution induced by a policy π.

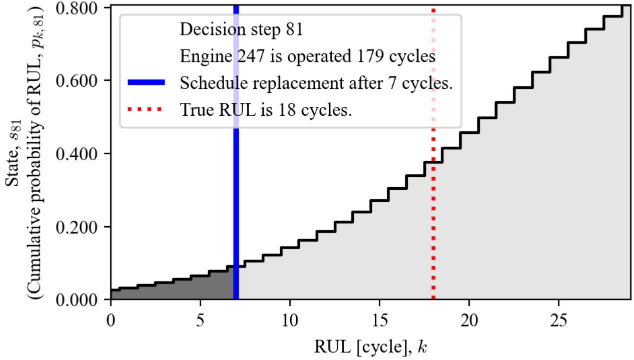
Results

RUL prognostics, every $D = 30$ flight cycles.



Decision step $t = 80$, replacement is not scheduled. At previous steps, consistently not scheduling a replacement.

Results



Decision step $t = 81$, replacement is scheduled after 7 cycles.
From this step, consistent decision to replace asset.

Results

	Total cost	Number of unscheduled replacements	Total number of replacements
DRL approach using distribution of RUL	17.84 (-36.3%)	0.62 (-95.6%)	14.89 (+6.4%)
Predictive maintenance at mean-estimated-RUL	25.23 (-9.8%)	10.87 (-22.3%)	14.00 (0.0%)
Corrective maintenance	27.99 (0.0%)	13.99 (0.0%)	13.99 (0.0%)
Ideal maintenance at true RUL	16.10 (-42.5%)	0.0 (-100.0%)	13.95 (-0.3%)

Conclusion & Outlook

- Prognostics successfully integrated into maintenance planning, leading to fewer failures, less wasted life of assets.
- Beneficial to use probabilistic RUL prognostics instead of a point/mean estimate of RUL, and dynamic assessment of maintenance decision.

Remaining challenges:

- Formulate degradation models that are reacting to control strategies while continuous measurement collection is enabled.
- Dynamic adaptation of the control strategies directly connected to the degradation models.
- Safety assessment framework that includes data-driven methods.

Thank you for the invitation!

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Open Positions

- **Postdoc** - Reinforcement Learning for energy strategies in the nexus of electric vehicles - photovoltaic panels - buildings.
- **PhD** - Optimisation models (linear programming) for energy usage balancing and battery degradation in low-voltage medium-voltage networks.

References

[1] Mitici Mihaela, Jenneskens Leo, Zeng Zhiguo, and Coit David. Predictive maintenance planning for batteries of electric take-off and landing (evtol) aircraft using state-of-health prognostics. In *the 34th European Safety and Reliability Conference*, page 117. Krzysztof Kołowrocki; Beata Magryta-Mut, 2024.

[2] Davide Manna, Mihaela Mitici, and Matteo Davide Lorenzo Dalla Vedova. System-level probabilistic remaining useful life prognostics and predictive inspection planning for wind turbines. In *PHM Society European Conference*, volume 8, pages 13–13, 2024.

[3] Juseong Lee and Mihaela Mitici. Deep reinforcement learning for predictive aircraft maintenance using probabilistic remaining-useful-life prognostics. *Reliability Engineering & System Safety*, 230:108908, 2023.

[4] Nicholas Polaczyk, Enzo Trombino, Peng Wei, and Mihaela Mitici. A review of current technology and research in urban on-demand air mobility applications. In *8th Biennial Autonomous VTOL technical meeting and 6th Annual electric VTOL Symposium*, pages 333–343. Vertical Flight Soc. Mea, Arizona, 2019.

[5] Mihaela Mitici, Birgitte Hennink, Marilena Pavel, and Jianning Dong. Prognostics for lithium-ion batteries for electric vertical take-off and landing aircraft using data-driven machine learning. *Energy and AI*, 12:100233, 2023.