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Model-Based Remaining-Useful-Life Prognostics for Aircraft Cooling Units

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Abstract

In this paper we develop model-based RUL prognostics for aircraft Cooling Units using operational data recorded during the flights of several aircraft. We estimate the distribution of the RUL of aircraft Cooling Units using a particle filtering algorithm with an exponential degradation model. The obtained RUL prognostics are assessed once a Cooling Unit is diagnosed as unhealthy, and just before failure. The results show that our proposed methodology is able to estimate well the RUL of the Cooling Units, both when a Cooling Unit crosses a prediction threshold and is expected to fail in the near-future, and just before failure. The choice of the prediction horizon is relevant from the point of view of the planning of aircraft maintenance. In practice, regular maintenance checks are scheduled at short time intervals of a few weeks. Having accurate RUL prognostics over such time horizons enables maintenance planners to efficiently plan maintenance tasks. In addition, the fact that we estimate the uncertainty associated with the RUL prognostics enables the maintenance planners to prioritize the maintenance of aircraft components.

1. Introduction

Global aircraft Maintenance, Repair and Operations (MRO) costs in 2018 represent 9% of the total airlines operational costs (IATA, 2019). To reduce the costs of aircraft maintenance, and, in particular, to reduce the costs with unscheduled maintenance due to unexpected failures, MROs are striving to conduct predictive maintenance by making use of continuously recorded data on the health of aircraft systems and components. As such, prognostics of the Remaining-Useful-Life (RUL) of aircraft components are crucial to support effective predictive aircraft maintenance planning.

In general, the RUL prediction methods can be classified as data-driven methods, model-based methods, and hybrid models. Data-driven methods make use of machine learning algorithms to identify degradation patterns in the measurements recorded for systems/components with a focus on neural networks (Atiya, El-Shoura, Shaheen, & El-Sherif, 1999; Liang & Liang, 2006), such as neural fuzzy networks and recurrent neural networks (Liu, Wang, Ma, Yang, & Yang, 2012).

Model-based methods propose degradation models, usually using stochastic processes such as Markov processes (Dui, Si, Zuo, & Sun, 2015; Cui, Xu, & Zhao, 2010), Wiener processes (Zhang, Si, Hu, & Lei, 2018; Si, Wang, Chen, Hu, & Zhou, 2013), Gaussian mixture models (Yu, 2013) and Gamma processes (Lee & Mitici, 2020). In some studies, these mathematical models have a direct physical interpretations (Lei et al., 2016; Guérin, Barreau, Cloupet, Hersant, & Hambli, 2010). In (Lei et al., 2016) the authors assume a Paris-Erdogan law for the degradation of machineries caused by micro fatigue cracks. In (Guérin et al., 2010) a physical model (Archard law) for disc brake wear is compared against a Bayesian estimation of the parameters of a Wiener degradation process for the brakes. Regarding the types of systems/components considered, model-based methods for RUL estimation have been applied for white-light LEDs (Huang, Xu, Wang, & Sun, 2015), bearings and rotating machinery (Li, Lei, Lin, & Ding, 2015; Lei et al., 2016), axial piston pumps (Wang, Lin, Wang, He, & Zhang, 2016), disc brake wear (Guérin et al., 2010), electric motors (Çağlar, İkizoğlu, & Şeker, 2014) and inertial navigation systems (Si et al., 2013).

One of the main challenges for model-based RUL prediction methods is to approximate the functional form of the degradation model and to estimate the model parameters using recorded degradation measurements. Here, many studies assume a generic functional form for a Wiener process (Zhang et al., 2018) or an exponential process (Park & Padgett, 2006; Gebraeel, Lawley, Li, & Ryan, 2005; Elwany, Gebraeel, & Maillart, 2011; Chen & Tsui, 2013), often also taking into account expert knowledge. Together with a given functional form of the degradation process, particle filtering is often employed to estimate the degradation state of the sys-

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tems/components and predict the future development of this degradation state, based on recorded degradation measurements and model parameters updates.

From a practical point of view of MROs, which provide and plan maintenance for large fleets of aircraft, it is also important that such prognostics can be integrated in their maintenance planning algorithms. Usually, maintenance planners aim to have RUL prognostics available on a prediction horizon of a few weeks, which allows the preparation of the necessary tools and equipment. The flight schedules, and thus, the actual availability of aircraft for maintenance is also known across a planning horizon of a couple of weeks.

In this paper, we address the challenges mentioned above as follows. We propose a model-based methodology to estimate the RUL of aircraft Cooling Units. In doing so, we consider sensor measurements which were recorded while the aircraft were in operation. We next apply a particle filtering algorithm and estimate RUL of the component considered using an exponential functional form of the degradation process for the components. With this, we estimate the RUL for the components. Overall, our results are expected to support MROs in their efforts for predictive aircraft maintenance planning.

The remainder of the paper is organized as follows. In Section 2 we introduce a particle filtering algorithm which is used to obtain RUL prognostics. In Section 3 we illustrate our methodology for aircraft Cooling Units. In Section 5 we provide conclusions and discuss future research directions.

2. Remaining-Useful-Life prognostics using particle filtering

In this section we briefly introduce a particle filtering algorithm, which is used to estimate the distribution of the RUL of aircraft components.

We first introduce the following definitions. Let a stochastic process $\{X_t, t \geq 0\}$ be the degradation of a component over time, where $X_t = x$ is the degradation level of this component at time t. Let $D > 0$ be a failure threshold. Let the history of the monitoring time and corresponding measurements be $\{t_0, \ldots, t_i\}$ and $\{X_{t_0}, \ldots, X_{t_i}\}$, respectively, i.e., at the k^{th} measurement at time t_k, the degradation equals X_{t_k}. .

Definition 1 (Component failure) *For a component that degrades according to $\{X_t, t \geq 0\}$, we say that this component has failed if $X_t \geq D$, $t > 0$.*

Definition 2 (Component RUL) *Given a current time t_i, the RUL of a component is defined as follows:*

$$RUL = \inf\{\tau : X_{\tau+t_i} \geq D | X_{t_0}, \ldots, X_{t_i}\}.$$

Let m_{t_k} denote the sensor measurement of a component taken at time t_k. where these measurements are a function of the degradation at time t_k:

$$m_{t_k} = g(X_{t_k}, v_k), \tag{1}$$

with $g(\cdot)$ a function and with v_k i.i.d. Gaussian variables.

Particle filtering (Djuric et al., 2003) is a sequential Monte Carlo method which recursively computes probability distributions by means of importance sampling and approximations of probability distributions.

Let us consider the following recurrence function:

$$X_{t_k} = f(X_{t_{k-1}}, \omega_k), \tag{2}$$

where $X_{t_{k-1}}$ is the degradation level of a component at time t_{k-1} and ω_k are i.i.d. Gaussian variables.

To obtain RUL prognostics, the particle filtering algorithm has four steps: i) prediction, i) updating, iii) resampling, and iv) prognostic.

i) The prediction step

We are interested in the conditional probabilities:

$$p_{X_{t_k}|X_{t_{k-1}}}(X_{t_k}|X_{t_{k-1}}) \tag{3}$$

$$p_{X_{t_{k-1}}|m_{t_{k-1}},m_{t_{k-2}},\ldots,m_{t_1}}(X_{t_{k-1}}|m_{t_{k-1}}, m_{t_{k-2}}, \ldots, m_{t_1}) \tag{4}$$

where eq. (4) is the conditional probability density function of the degradation level of the component at time t_{k-1}, given the measurements $m_{t_{k-1}}, m_{t_{k-2}}, \ldots, m_{t_1}$, whereas eq. (3) is the transition probability density function to reach future degradation state X_{t_k}, given the current degradation $X_{t_{k-1}}$.

Using the Chapman-Kolmogorov equation, we have the following probability density function for the state degradation at time t_k:

$$\begin{aligned} &p_{X_{t_k}|m_{t_{k-1}},m_{t_{k-2}},\ldots,m_{t_1}}(x_{t_k}|m_{t_{k-1}}, m_{t_{k-2}}, \ldots, m_{t_1}) \\ &= \int p_{X_{t_k}|X_{t_{k-1}}}(X_{t_k}|X_{t_{k-1}}) \\ &\cdot p_{X_{t_{k-1}}|m_{t_{k-1}},\ldots,m_{t_1}}(X_{t_{k-1}}|m_{t_{k-1}}, \ldots, m_{t_1}) dX_{t_{k-1}}. \end{aligned} \tag{5}$$

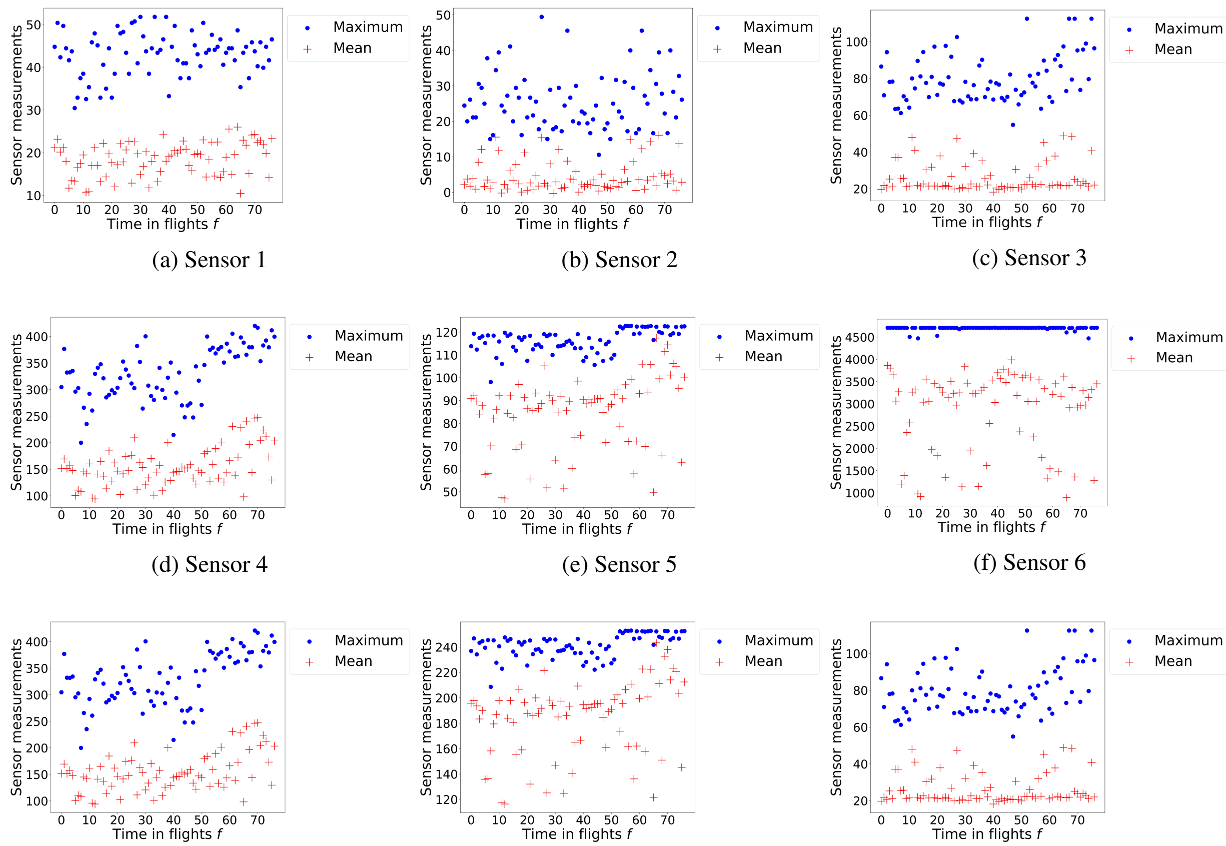
ii) The updating step

As soon as new measurements are available, the state probability density function is updated, using Bayes' theorem, as follows:

$$p_{X_{t_k}|m_{t_k},m_{t_{k-1}},\ldots,m_{t_1}}(X_{t_k}|m_{t_k}, m_{t_{k-1}}, \ldots, m_{t_1}) = \frac{p_{m_{t_k}|X_{t_k}}(m_{t_k}|X_{t_k}) p_{X_{t_k}|m_{t_{k-1}},\ldots,m_{t_1}}(X_{t_k}|m_{t_{k-1}}, \ldots, m_{t_1})}{p_{m_{t_k}|m_{t_{k-1}},\ldots,m_{t_1}}(m_{t_k}|m_{t_{k-1}}, m_{t_{k-2}}, \ldots, m_{t_1})}.$$

iii) The resampling step

We approximate eq. (5) numerically using Importance Sam-



(a) Sensor 1 (b) Sensor 2 (c) Sensor 3

(d) Sensor 4 (e) Sensor 5 (f) Sensor 6

(g) Sensor 7 (h) Sensor 8 (i) Sensor 9

Figure 1. Mean and maximum sensor measurement per flight for a CU for all nine available sensors. This CU fails at flight 77.

pling as follows. First, we sample M particles from a pdf $\tilde{p}_{X_{t_k}|X_{t_{k-1}},m_{t_k},\dots,m_{t_1}}(X_{t_k}|X_{t_{k-1}},m_{t_k},\dots,m_{t_1})$.

Then the probability density function of the degradation state of the component at some time t_k is approximated as:

$$p_{X_{t_k}|m_{t_{k-1}},m_{t_{k-2}},\dots,m_{t_1}}(X_{t_k}|m_{t_{k-1}},m_{t_{k-2}},\dots,m_{t_1}) \qquad (6)$$
$$\sim \sum_{i=1}^{M} w_{t_k}^{i} \cdot \delta(X_{t_k} - X_{t_k}^{i}),$$

where δ is a Dirac function . Also, $w_{t_k}^{i}$ is the weight of the ith particle, $i \in \{1, 2, \dots, M\}$, at time t_k, which is updated and normalized as follows:

$$\hat{w}_{t_k}^{(i)} = w_{t_{k-1}}^{(i)} \frac{p_{m_{t_k}|X_{t_k}^{(i)}}(m_k|x_{t_k}^{(i)}) \cdot p_{X_{t_k}^{(i)}|X_{t_{k-1}}^{(i)}}(X_{t_k}^{(i)}|X_{t_{k-1}}^{(i)})}{\tilde{p}_{X_{t_k}^{(i)}|X_{t_{k-1}}^{(i)},m_{t_k},\dots,m_{t_1}}(X_{t_k}^{(i)}|X_{t_{k-1}}^{(i)},m_{t_k},\dots,m_{t_1})} \qquad (7)$$

$$w_{t_k}^{(i)} = \frac{\hat{w}_{t_k}^{(i)}}{\sum_{i=1}^{M} \hat{w}_{t_k}^{(i)}}. \qquad (8)$$

In every re-sampling cycle, particles with higher weights are re-sampled proportionally to their weight. As the number of iterations increases, the particles with small weight are eliminated, while the particles with large weights are re-sampled, i.e., a new particle set $\{x^{(j)t_k}\}, i \in \{1, 2, \dots, M\}$ is generated by re-sampling M new particles, where the probability to be resampled is proportional to the weight.

iv) The prognostic

Lastly, we consider a threshold $D > 0$ and define the following stopping time T:

$$T = \inf\{t : X_t \geq D\}. \qquad (9)$$

3. Model-based RUL prognostics for Cooling Units of an Aircraft

In this section we estimate the distribution of the RUL of Cooling Units (CUs) of wide-body aircraft. The CU is a vapor cycle refrigeration unit consisting of a compressor, a condenser, an evaporator, a filter and a flash tank (see Figure 2). After some time of usage, the filter of the CU is clogged with burned oil, moist and sludge from the compressor, accelerating the compressor wear. Long time exposure to these conditions negatively affects the condition of the CU, which, in time, leads to a failure.

Table 1. Overview of considered health indicators. For each sensor, the correlation coefficient between the health indicator and the time to failure is given. The highest absolute correlation coefficient is given in bold.

Health-indicator	Sensors								
	1	2	3	4	5	6	7	8	9
$\text{RMS}_f = \sqrt{\frac{1}{B^i_f}\sum_{b=1}^{B^i_f}(\hat{y}^{i,s}_{f,b})^2}$	-0.02	-0.10	0.27	0.45	**0.47**	-0.11	0.43	**0.47**	0.27
$\Delta\text{RMS}_f = \text{RMS}_f - \text{RMS}_{f-1}$	0.01	0.02	0.01	**0.03**	0.00	0.02	0.02	0.00	0.01
$\text{Peak-to-peak}_f = \max_{b\in 1,\dots,B^i_f}(\hat{y}^{i,s}_{f,b}) - \min_{b\in 1,\dots,B^i_f}(\hat{y}^{i,s}_{f,b})$	-0.24	0.12	0.25	**0.44**	0.36	-0.21	0.43	0.36	0.25
$\text{Crest Factor}_f = \frac{\max_{b\in 1,\dots,B^i_f}(\hat{y}^{i,s}_{f,b})}{\text{RMS}_f}$	-0.16	0.09	0.14	-0.10	-0.14	0.05	-0.10	-0.14	**0.19**
Kurtosis_f	-0.05	0.16	0.10	-0.11	0.16	**0.21**	-0.11	0.16	00.10
Skewness_f	**-0.28**	0.03	0.10	-0.22	-0.16	-0.09	-0.22	-0.16	0.10

Each aircraft is equipped with a Cooling System consisting of four Cooling Units. According to the Minimum Equipment List (MEL, (EASA, 2018)), an aircraft is allowed to fly if at least three out of these four Cooling Units are operational (de Pater & Mitici, 2021).

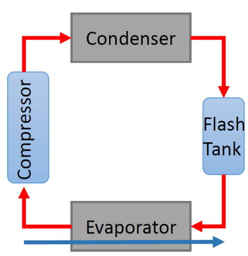


Figure 2. Schematic representation of a Cooling Unit

3.1. Health indicator for CU

We consider a set of J CUs. For each CU, run-to-failure measurements are considered, available after some initial usage of the component. Each CU is monitored using nine sensors $S = \{1, 2, \dots, 9\}$, each generating a measurement every 10 seconds during each flight. For the purpose of our analysis, the data sets are anonymized, and the type of measurement each sensor generates is thus unknown. Figure 1 shows the mean and maximum sensor measurement per flight until the moment of failure for a CU and the nine available sensors.

Let $y^{i,s}_{f,b}$ denote the b^{th} measurement during flight f for CU i generated by sensor s, and let B^i_f denote the total number of measurement for CU i generated during flight f. We first normalize the sensor measurements as follows:

$$\hat{y}^{i,s}_{f,b} = \frac{y^{i,s}_{f,b} - \min_s}{\max_s - \max_{b\in 1,\dots,B^i_f}(y^{i,s}_{f,b})}, \; s \in \{1, 2, \dots, 9\}, \tag{10}$$

with $\min_s$ and $\max_s$ the available minimum and maximum measurement generated by sensor s for the set J of CUs, respectively. For the sensor measurements for CU i, we only consider the measurements up to flight f.

The normalization is performed to be able to combine the measurements from multiple sensors, each with different measurement ranges. Moreover, the proposed normalization is aimed to capture the increase in the maximum sensor measurements per flight towards failure (see Figure 1).

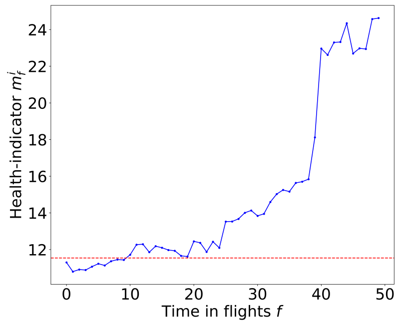
We consider several health indicators, as discussed in (Zhu, Nostrand, Spiegel, & Morton, 2014). Table 1 shows an overview of the considered health indicators and the corresponding correlation coefficient. The highest correlation coefficients are obtained for the Root Mean Square (RMS) health indicator. We thus construct a health indicator based on the Root Mean Square (RMS) of the normalized measurements (Zhu et al., 2014). Let B^i_f denote the total number of measurements recorded during flight f for component i. Then the RMS of sensor s of CU i during flight f is:

$$RMS^{i,s}_f = \sqrt{\frac{1}{B^i_f}\sum_{b=1}^{B^i_f}(\hat{y}^{i,s}_{f,b})^2}. \tag{11}$$

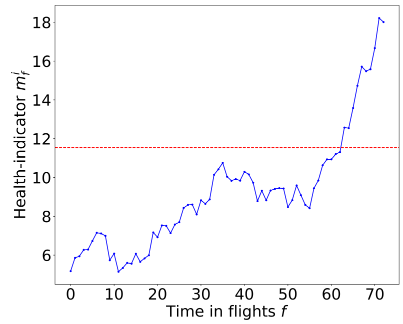
Now, a health indicator m^i_f for CU i during flight f is obtained as the moving average of the maximum RMS obtained by the sensors $s \in S'$, as follows:

$$m^i_f = \frac{1}{N}\left(\sum_{l=f-N}^{f}\left(\max_{s\in S'} RMS^{i,s}_l\right)\right), \tag{12}$$

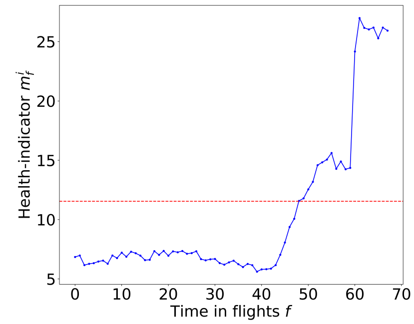
where $S' \subseteq S$ is the set of sensors for which the RMS of the measurements obtained in the last 50 flights before failure has an absolute correlation coefficient (also called trendability)



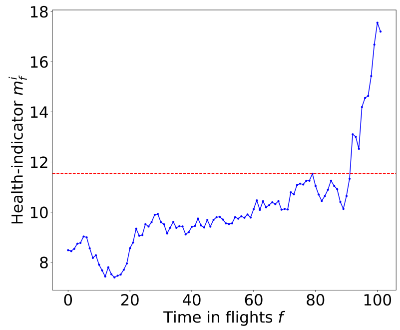
(a) Health-indicator for CU 1.



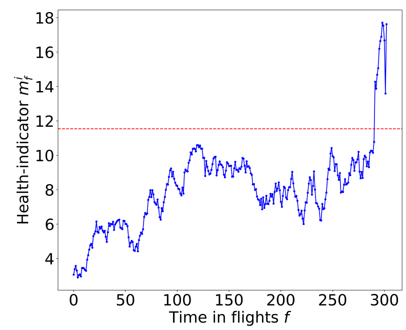
(b) Health-indicator for CU 2.



(c) Health-indicator for CU 3.



(d) Health-indicator for CU 4.



(e) Health-indicator for CU 5.

Figure 3. Health-indicator for CU $i \in \{1, 2, \ldots, 5\}$.

with the time of failure of at least 0.40 (Lei et al., 2018; Yang et al., 2016). Moreover, $N = 10$ is the number of flights over which the moving average is taken. This health-indicator is shown for CU $i \in \{1, 2, 3, 4, 5\}$ in Figure 3.

3.2. Model-based RUL prognostics

Based on the form of the health-indicators in Figure 3, we next consider the following exponential degradation model for the degradation:

$$X_t^i = \alpha^i + exp(\beta^i t) + \sigma^i B_t \tag{13}$$

where X_f^i is the degradation of component i at time t, α^i is the initial degradation, β^i and σ^i model parameters, and B_t a standard Brownian motion.

Taking the derivative,

$$dX_t^i = \beta^i e^{\beta^i t} dt + \sigma^i dB_t$$

Re-writing the above equation in the form of equations (2) and (1) with $t_k - t_{k-1} = 1$ flight, we obtain:

$$X_{t_k}^i = X_{t_{k-1}}^i + \beta_{t_k}^i (t_k - t_{k-1}) e^{\beta_{t_k}^i \cdot t_k} + \sigma_{t_k}^i \Delta B_{t_k}, \tag{14}$$

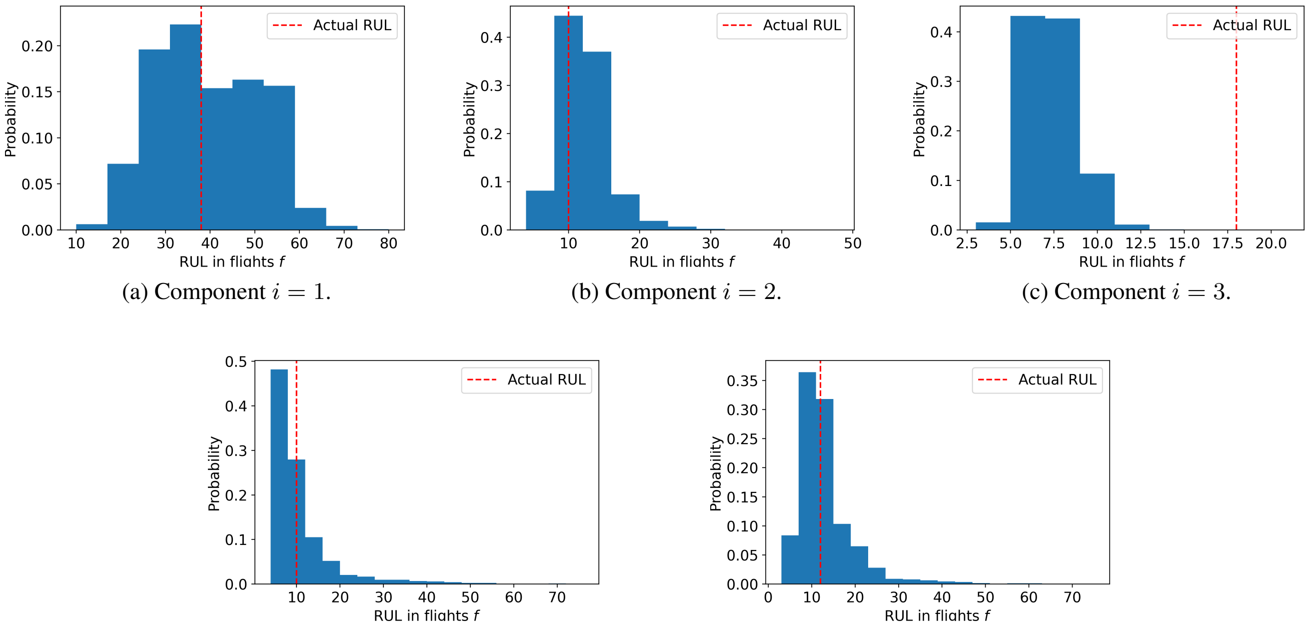
$$m_{t_k}^i = X_{t_k}^i + \nu_{t_k}^i \tag{15}$$

where $\nu_f^i \sim N(0, \sigma_{\nu_f^i})$ is the measurement noise at flight f_k. The distributions of the model parameters are initialized as $\beta_0^i \sim U(0.01, 0.1)$, $\sigma_0^i \sim U(0, 0.01)$ and $\sigma_{\nu_0^i} \sim U(1, 2)$.

The functional form in eq. (13) is assumed based on the fact that the cumulative damage in the component has an effect on the degradation rate (Si et al., 2013). It has been shown that an exponential type of degradation model is a good approximation for non-linear degradation processes such as corrosion, bearing degradation, deterioration of LED lighting (Elwany et al., 2011; Chen & Tsui, 2013). In fact, the CU can also be seen as subject to corrosion and accelerated wear accumulated over time.

Lastly, with the degradation models introduced above, we apply the particle filtering algorithm (see Section 2, Step 4) to estimtate the RUL of the CUs.

We start generating RUL prognostics as soon as the degradation of the CU exceeds a prediction threshold T defined by the Chebyshev's inequality (Shakya, Kulkarni, & Darpe, 2014), which specifies that for any probability distribution with a specified mean μ and standard deviation σ, at most $\frac{1}{k^2}$ percent of the values from this distribution fall outside the



(a) Component $i = 1$. (b) Component $i = 2$. (c) Component $i = 3$.

(d) Component $i = 4$. (e) Component $i = 5$.

Figure 4. Estimated distribution of RUL for components $i \in \{1, 2, \ldots, 5\}$ at the moment the health-indicator of the component exceeds a prediction threshold T.

$\mu \pm k\sigma$ interval, $k > 0$. This implies that

$$P(|m_f^i - \mu| \geq k\sigma) \leq \frac{1}{k^2}, \tag{16}$$

where μ is the mean and σ is the standard deviation of the health indicator while it is healthy. We approximate μ and σ using the measurements available for the first 5 flights (the beginning of the measurement series). We thus use the following prediction threshold T:

$$T = \mu + k\sigma. \tag{17}$$

We use $k = 2$ in our approach. The corresponding prediction threshold is denoted by the red, dotted line in Figure 3. Once the health-indicator of a component crosses this prediction threshold, we expect a near-future failure and we expect that reliable RUL predictions can be made.

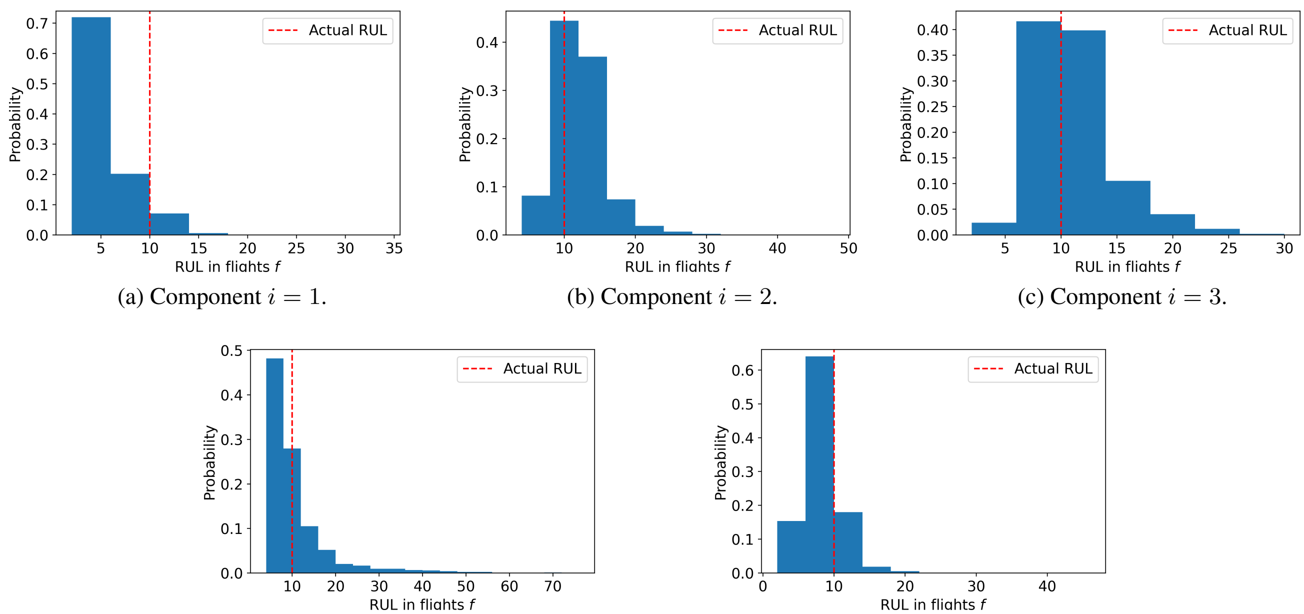
4. Results - RUL prognostics for Cooling Units

The results are obtained using a total amount of $M = 5.000$ particles for the particle filtering algorithm and a failure threshold of $D = 22$.

Tables 3 and 2 show the mean RUL and the actual RUL for components $i \in \{1, 2, \ldots, 5\}$ at the moment a prediction threshold T is exceeded (i.e., the CU is expected to fail in the near-future) and 10 flights before the actual failure time, respectively. Moreover, Figures 4 and 5 show the estimated probability density function of the RUL for component $i \in \{1, 2, \ldots, 5\}$ at the moment a degradation threshold T is exceeded and 10 flights before the actual failure time, respectively. From Figure 4c and Table 2, it is clear that the RUL of CU 3 is underestimated when the health-indicator of the CU crosses the prediction threshold. However, the prediction of the RUL for this CU improves when the data of more flights is gathered, as is clear from the RUL prediction 10 flights before failure (see Figure 5c and Table 3). In contrast, the RUL prediction of CU 1 at the moment it crosses the prediction threshold T is very well (see Figure 4a and Table 2), but the RUL is underestimated 10 flights before failure (see Figure 5a and Table 3). However, the results show that the RUL of most components is well estimated across the considered prediction horizons (at the moment when their degradation exceeds a prediction threshold T, as well as 10 flights before the actual failure).

Table 2. Actual and mean estimated RUL (in flights) of CUs $i \in \{1, 2, 3, 4, 5\}$ at the moment their health-indicator exceeds a prediction threshold T.

CU i	Actual RUL (flights)	Mean estimated RUL (flights)
1	38	39
2	10	12
3	18	7
4	10	10
5	12	13



(a) Component $i = 1$.

(b) Component $i = 2$.

(c) Component $i = 3$.

(d) Component $i = 4$.

(e) Component $i = 5$.

Figure 5. Estimated distribution of RUL for components $i \in \{1, 2, \ldots, 5\}$, using a prediction horizon of 10 flights before failure.

Quantifying the uncertainty associated with RUL prognostics enables maintenance planners to prioritize maintenance tasks. Moreover, the horizon of the predictions of 10 to 40 flights allows the planners to efficiently allocate the resources (man power, equipment and machines), while the availability of the aircraft for maintenance, relative to their flight schedule, is known.

Table 3. Actual and mean estimated RUL (in flights) of CUs $i \in \{1, 2, 3, 4, 5\}$ 10 flights before the actual failure.

CU i	Actual RUL $(flights)$	Mean estimated RUL $(flights)$
1	10	5
2	10	12
3	10	11
4	10	10
5	10	8

5. Conclusions

We have proposed a model-based RUL estimation method for aircraft components, which we illustrated for aircraft Cooling Units (CUs). For this RUL estimation, we applied a particle filtering algorithm to the sensor measurements of these CUs. In doing so, we assumed an exponential functional form for the degradation process of the components, which is representative for the degradation trend of the CUs. Furthermore, we defined a prediction threshold T after which we started to predict the RUL, thus ensuring reliable RUL estimates.

The results show that our proposed methodology is able to estimate well the RUL of the components for various prediction horizons. By using a particle filtering algorithm, we are also able to quantify the uncertainty associated with the RUL predictions. From a practical point of view, our RUL estimation results of 10 to 40 flights before failure have the potential to support aircraft maintenance planning with predictive, short-term maintenance task scheduling.

References

Atiya, A. F., El-Shoura, S. M., Shaheen, S. I., & El-Sherif, M. S. (1999). A comparison between neural-network forecasting techniques-case study: river flow forecasting. *IEEE Transactions on neural networks*, *10*(2), 402–409.

Çağlar, R., İkizoğlu, S., & Şeker, S. (2014). Statistical wiener process model for vibration signals in accelerated aging processes of electric motors. *Journal of Vibroengineering*, *16*(2), 800–807.

Chen, N., & Tsui, K. L. (2013). Condition monitoring and remaining useful life prediction using degradation signals: Revisited. *IiE Transactions*, *45*(9), 939–952.

Cui, L., Xu, Y., & Zhao, X. (2010). Developments and applications of the finite markov chain imbedding approach in reliability. *IEEE Transactions on Reliability*, *59*(4), 685–690.

de Pater, I., & Mitici, M. (2021). Predictive maintenance for multi-component systems of repairables with remaining-useful-life prognostics and a limited stock of spare components. *Reliability Engineering & System Safety*, *214*, 107761.

Djuric, P. M., Kotecha, J. H., Zhang, J., Huang, Y., Ghirmai, T., Bugallo, M. F., & Miguez, J. (2003). Particle filtering. *IEEE signal processing magazine*, *20*(5), 19–38.

Dui, H., Si, S., Zuo, M. J., & Sun, S. (2015). Semi-markov process-based integrated importance measure for multi-state systems. *IEEE Transactions on Reliability*, *64*(2), 754–765.

EASA. (2018). Easy access rules for master minimum equipment list (CS-MMEL). *European Aviation Safety Agency (EASA)*.

Elwany, A. H., Gebraeel, N. Z., & Maillart, L. M. (2011). Structured replacement policies for components with complex degradation processes and dedicated sensors. *Operations research*, *59*(3), 684–695.

Gebraeel, N. Z., Lawley, M. A., Li, R., & Ryan, J. K. (2005). Residual-life distributions from component degradation signals: A bayesian approach. *IiE Transactions*, *37*(6), 543–557.

Guérin, F., Barreau, M., Cloupet, S., Hersant, J., & Hambli, R. (2010). Bayesian estimation of degradation model defined by a wiener process-application on disc brake wear. *IFAC Proceedings Volumes*, *43*(3), 74–79.

Huang, Z., Xu, Z., Wang, W., & Sun, Y. (2015). Remaining useful life prediction for a nonlinear heterogeneous wiener process model with an adaptive drift. *IEEE Transactions on Reliability*, *64*(2), 687–700.

IATA. (2019). Airline maintenance cost executive commentary, an exclusive benchmark analysis (FY2018 data) by IATA's maintenance cost technical group. *MCTG December 2019*.

Lee, J., & Mitici, M. (2020). An integrated assessment of safety and efficiency of aircraft maintenance strategies using agent-based modelling and stochastic petri nets. *Reliability Engineering & System Safety*, *202*, 107052.

Lei, Y., Li, N., Gontarz, S., Lin, J., Radkowski, S., & Dybala, J. (2016). A model-based method for remaining useful life prediction of machinery. *IEEE Transactions on Reliability*, *65*(3), 1314–1326.

Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to rul prediction. *Mechanical systems and signal processing*, *104*, 799–834.

Li, N., Lei, Y., Lin, J., & Ding, S. X. (2015). An improved exponential model for predicting remaining useful life of rolling element bearings. *IEEE Transactions on Industrial Electronics*, *62*(12), 7762–7773.

Liang, Y., & Liang, X. (2006). Improving signal prediction performance of neural networks through multiresolution learning approach. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *36*(2), 341–352.

Liu, J., Wang, W., Ma, F., Yang, Y., & Yang, C. (2012). A data-model-fusion prognostic framework for dynamic system state forecasting. *Engineering Applications of Artificial Intelligence*, *25*(4), 814–823.

Park, C., & Padgett, W. J. (2006). Stochastic degradation models with several accelerating variables. *IEEE Transactions on Reliability*, *55*(2), 379–390.

Shakya, P., Kulkarni, M. S., & Darpe, A. K. (2014). A novel methodology for online detection of bearing health status for naturally progressing defect. *Journal of Sound and Vibration*, *333*(21), 5614–5629.

Si, X.-S., Wang, W., Chen, M.-Y., Hu, C.-H., & Zhou, D.-H. (2013). A degradation path-dependent approach for remaining useful life estimation with an exact and closed-form solution. *European Journal of Operational Research*, *226*(1), 53–66.

Wang, X., Lin, S., Wang, S., He, Z., & Zhang, C. (2016). Remaining useful life prediction based on the wiener process for an aviation axial piston pump. *Chinese Journal of Aeronautics*, *29*(3), 779–788.

Yang, F., Habibullah, M. S., Zhang, T., Xu, Z., Lim, P., & Nadarajan, S. (2016). Health index-based prognostics for remaining useful life predictions in electrical machines. *IEEE Transactions on Industrial Electronics*, *63*(4), 2633–2644.

Yu, J. (2013). A nonlinear probabilistic method and contribution analysis for machine condition monitoring. *Mechanical Systems and Signal Processing*, *37*(1-2), 293–314.

Zhang, Z., Si, X., Hu, C., & Lei, Y. (2018). Degradation data analysis and remaining useful life estimation: A review on wiener-process-based methods. *European Journal of Operational Research*, *271*(3), 775–796.

Zhu, J., Nostrand, T., Spiegel, C., & Morton, B. (2014). Survey of condition indicators for condition monitoring systems. In *Annu. conf. progn. heal. manag. soc* (Vol. 5, pp. 1–13).

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