Aircraft On-Condition Reliability Assessment based on Data-Intensive Analytics

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Abstract—**The implementation of condition-based maintenance continues to face several challenges especially in the aeronautics field. While it is true that time-based maintenance dominates the industry today, it is believed that condition monitoring could yield promising results with a better compromise on cost over effectiveness in the long run. The aim of condition-based monitoring in aeronautics is, based on the available system data (e.g., flight, event and maintenance data), to evaluate the current health state of an aircraft component and to estimate its remaining useful life. Several approaches have been studied in condition-based maintenance with the most promising being data-driven modeling. This paper proposes a comparison of a set of data-driven modeling techniques to perform prognostics on a critical component of the jet engine bleed system. The novelty of our work is twofold. First, we perform this comparative study on a real case study of a critical valve of the aircraft bleed system. Fielded data from different data sources are used in the models. To our knowledge, this is the first case study that merges data from the computer central maintenance system (fault messages), maintenance data, and flight data on a prognostics system. Second, a variety of data-driven techniques are compared from neural nets to regression support machines. The models are compared using the standard metrics of absolute, mean, and squared errors. A regressive accuracy curve is also used to compare the models along different prediction window sizes. The results show the best model comprised information from all data sources. The data that most contributed to the performance improvement was the maintenance, flight and fault data, in this order. This result comes to reinforce the notion that it is more difficult to extract quantitative information from fault events than flight data with data-driven regressive methods.**

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1. INTRODUCTION

Damage prognostics is concerned with predicting the residual life of an asset or the time until the next failure is expected [1]. Prognostics is key to perform condition-based maintenance (CBM). The concept here is to track the system degradation from on-line monitoring instruments and to minimize the system downtime by balancing the risk of failure and achievable profits [2].

As with diagnostics, prognostics methods are typically categorized as either model-based or data-driven [3]. Model-based approaches usually employ mathematical models to describe the physical processes that have a direct or indirect influence on the structural health of the system. These models are usually developed by domain experts based on their practical and theoretical knowledge of the failure mechanisms that are likely to cause degradation. Despite the ability of these models to incorporate a physical understanding of the system working, their main disadvantages are their reliance on technical expertise and the need for large sets of data to validate the model parameters.

In contrast with model-based methods, data-driven approaches do not rely on a physical description of degradation phenomena [4]. Instead, these techniques use monitored operational data related to the system health to derive estimates of the system remaining useful life (RUL) and end of life (EOL) predictions. Data-driven methods are appropriate when the understanding of the first principles is not comprehensive or when the system complexity does not warrant the development costs of a model-based approach.

An effective CBM requires a good understanding of failure degradation. Understanding what to monitor for a given asset requires obtaining useful reliability data, eventually from multiple sources. In this paper we propose to address the influence of diagnostics data (fault messages) and other important data, such as sensory and environmental conditions, on data-driven on-condition models. We use the comparative research method to test our main hypothesis:

H1: The combination of data-intensive parametric and non-parametric data about the maintenance past history, environment conditions, structural health monitoring signals and fault events can significantly lead to significant performance enhancements of structural prognostics models.

The novelty of our work consists in the use and combination of parametric and non-parametric data to assess aircraft performance. The paper proposes a data-driven prognostics framework that uses supervised machine learning methods, the auto-regressive moving average methodology, stepwise model selection, and principal component analysis (PCA) for remaining useful life estimation.

As a case study, we consider a bleed valve from the aircraft air management system. We run a comprehensive set of prognostics experiments to demonstrate distinct data-driven approaches and establish that prognostics may be performed for air bleed valves using different data sets. We also compare the framework results to a model-based life usage model. Experimental results from real aircraft data are presented.

The paper is organized as follows. Section 2 formally defines the prognostics problem and describes the computational architecture. Section 3 presents the modeling methodology and describes the case study involving the air bleed valve. Section 4 discusses the damage estimation approach using particle filters, and Section 5 provides the prediction algorithm. Section 4 presents experiment results and the demonstration of the approach on real data. Section 5 discusses and concludes the paper. Future work is also discussed.

2. BACKGROUND

Experience-based, life usage or failure rate models are considered the most widely used and accepted form of prognostics in aviation [5]. They are often considered the most suitable alternative when the the failure risk of the equipment is low, or when the equipment exhibits a linear or constant failure event rate [6].

There are a number of published studies in modeling the maintenance prognostics using life usage methods – they work by fitting probability distribution functions to the past histories of repair events. This approach had been used extensively in reliability theory and a number of distribution functions are available. The most commonly used parametric distribution is the Weibull, given its flexibility to model all the range of the bathtub curve. For example, jet engine deterioration is modeled using the Weibull process in [7]. The authors found that the Weibull process yielded a good fit to represent maintenance policies. The authors also found that the Weibull had difficulties to forecast the maintenance pattern of an airline that had several "hard-time" repair events. The authors argued that in this latter case, the mandated removals resulted in a premature overhaul due to a cycle limited part.

Other authors used the Weibull process to model equipment reliability. In [8], engine reliability is determined by combining individual component distributions, approximated by the Weibull function. Here, the whole-engine reliability is a function of the individual reliabilities of the most critical modules of the engine. A finite mixture model was used to capture the combination of the individual reliabilities. A finite mixture model is a convex combination of two or more probability density functions. By combining the properties of the individual probability density functions, mixture models are capable of approximating any arbitrary distribution [9]. The authors found that such model could help not only to describe the engine reliability but also to investigate the interdependent effects among the disruption modes.

A finite mixture model is also used to describe jet engine failure modes in [10]. The mixed Weibull distribution is estimated from a large data set comprised of 325 jet engines. The estimation is subject to censoring at various times. Parametric uncertainty is derived analytically from the inverse Fisher information matrix and is mapped visually onto the functions of use in reliability theory such as the hazard function and survival function.

Despite the popularity of life usage models, most modern day maintenance programs in aeronautics are starting to be based on the on-condition concept. In this approach, maintenance activities occur when the equipment condition demands it. Here, the idea is that if equipment can be evaluated while still in service, the maintenance can be scheduled and planned and the overall cost of maintenance goes down. On-condition maintenance reduces the need for life usage "hard-time" intervals but requires routine monitoring of performance parameters of the equipment such as temperature, pressure, vibration, fuel flow, oil consumption, and rotor speed. Changes in any of these parameters beyond specified limits can warrant a removal of an aircraft system or component for maintenance.

A side effect of the on-condition maintenance paradigm is greater reliance on statistical data-driven analysis to predict the frequency and timing of maintenance events and their corresponding costs [11]. This approach uses statistical and artificial intelligence techniques on large sets of performance and degradation data to forecast the engine future state. In data-driven reliability models, degradation is estimated using only the data provided by the monitoring system, disregarding the analytic model of the system and its physical parameters.

Data-driven methods range from multivariate statistical methods to neural networks and Markovian processes. Artificial neural networks (ANN) are perhaps the most popular approach in remaining useful life (RUL) estimation. For example, [12] apply ANN methods to forecast the remaining useful life (RUL) of pump bearings. Their ANN model used age and condition monitoring data as inputs and the bearings life percentage as output. The proposed approach was validated using real-world vibration monitoring data. Other more sophisticated ANN approaches have been used for RUL forecasting. For example, a self-organizing map (SOM) and back propagation neural network using vibration signals was used to predict the remaining useful life of a ball bearing [13].

Even though ANNs are good at mapping non-linear information, much of the practical data for describing repair events is ambiguous or approximate. Thus, neuro-fuzzy systems have been proposed for RUL forecasting. An interesting example of a neuro-fuzzy approach is the work of [14] to predict the health state of a pinion.

Another popular data-driven approaches to RUL estimation are Kalman filters. The validity of this technique has been demonstrated in steel bands [15] and other applications. An alternative to Kalman filters and other space-state approaches are integrated autoregressive/moving average (ARIMA) models [16]. In [17] linear regression methods and autoregressive integrated moving average (ARIMA) are used to forecast jet engine removals. There has been a number of studies comparing these two approaches [18]. Overall, compared to ARIMA, state-space models allow the modeling of more complex processes, and can more easily handle data irregularities. Nevertheless, ARIMA alternatives are easier to parameterize and have less complex implementations.

Another statistical approach used to estimate the underlying RUL are Hidden Markov models (HMMs). In [19] HMMs are used to model bearing degradation. The authors considered degradation as a stochastic process with several states. In their model, each state represents a health state of the bearing. These states are learned by using vibration data. Once the current state is identified, together with its stay duration, the remaining useful life (RUL) of the bearing is predicted.

Other techniques from artificial intelligence and machine learning field have started to be applied to RUL estimation. For instance, some authors argue that support vector machines represent a promising approach [20]. Other authors propose ensemble approaches such as the one in [21] which combines multiple member algorithms with a weighted-sum formulation.

Despite the different models and techniques that have been proposed, few studies compare the different approaches on real case studies. An exception to this is the work in [22] that compares 13 forecasting methods for the management of spare parts in the aviation industry. The authors found that exponentially weighted moving average and Croston's methods outperformed the other forecasting methods. Nevertheless, the mean absolute percentage errors (MAPE) of the considered methods were greater than 80%, above what the authors considered the acceptable level for the case.

Another comparison study on data-driven techniques is the work in [23]. The authors compare a wide range of binary classifiers to predict the probability of servicing a jet engine component at a major shop visit. The techniques are discussed according to their ability to capture better or worse different perspectives of the data. The authors consider that ensemble models based on trees (random forests and boosted trees) present the best compromise between performance and interpretability while neural nets offer the best absolute performance.

3. METHODOLOGY

A) Problem Formulation

The problem of engineering prognostics is predicting the end of life (EOL) and/or the remaining useful life (RUL) of a technical system or component. In this section, we first formally define the data-driven prognostics. We assume the system can be described by

$$\mathbf{y}(t) = f(t, \mathbf{x}(t), \theta(t)) \tag{1}$$

where $t \in \mathbb{R}$ is the continuous time variable, $\mathbf{x}(t) \in \mathbb{R}^{\mathrm{n}}$ is the input vector, $\theta(t) \in \mathbb{R}^{\mathrm{n}}$ is the parameter vector, f is the output function, and $\mathbf{y}(t) \in \mathbb{R}^{\mathrm{n}}$ is the output vector. This representation considers a general nonlinear data-driven model with no restrictions on the functional forms of f.

The goal of the model is to predict the remaining useful life (RUL) at a given time point t_i using the discrete sequence of observations up to time t_i , defined as $\mathbf{x}_{0:t_i}$. Remaining useful life here is defined as the remaining time to a maintenance event: it marks the end of the life (EOL) of the component, that is, the point where it no longer meets one of a set of functional requirements (e.g., the valve no longer complies with the threshold limits of its leakage class). In general, we may express this as a function of the system state, $T_{EOL}(\mathbf{x}(t))$, which determines whether the system has failed, that is $T_{EOL}(\mathbf{x}(t), \theta(t)) = 1$. Seemingly, the remaining useful life (RUL) can be defined with

$$RUL(t_i) = t_f - t_i, t_f \in \mathbb{R} : t_f \geq t_i \wedge T_{EOL}(\mathbf{x}(t_f)) = 1 \tag{2}$$

where t_i is the actual time, t_f is the time of failure and T_{EOL} is a function which determines whether the system has reached the EOL.

We adopt a data-driven approach, meaning the model f does not depend on a physical description of how the faults evolve in time. Instead, it is a learning approach that estimates the behavior of the system from a time series of inputs and outputs $-$ it enables the extraction of general and abstract rules governing degradation processes from a large amount of data.

In discrete time i, we estimate $\mathbf{y}(t_i) = RUL(t_i)$, based on a set of training data $\mathbf{x}(t)$ and corresponding output data $\mathbf{y}(t)$. Accordingly, our solution to the prognostics problem takes the perspective of a supervised learning estimation.

The prognostics architecture is in Figure 1. The model proceeds in two steps. In the first step the system is provided with inputs $\mathbf{x}(t)$ and corresponding measured outputs $\mathbf{y}(t)$. With this data and the parameter vector $\theta(t)$ the system is able to estimate function f. After this, prognostics may begin at $i = 0$, with the prognostics module determining estimates of RUL, represented as $\hat{y}(t_i)$. 10-fold cross-validation is used to estimate and validate the model.

In the remainder of this section, we apply this modeling framework to an aircraft bleed valve, which serves as the case study for this paper.

B) Data Modeling

We develop a data-driven model of the system based on four classes of data:

$$\mathbf{x}(t) = [\mathbf{x}_m(t) \quad \mathbf{x}_f(t) \quad \mathbf{x}_h(t) \quad \mathbf{x}_a(t)]^T \tag{3}$$

where each $\mathbf{x}_m(t)$, $\mathbf{x}_f(t)$, $\mathbf{x}_h(t)$ and $\mathbf{x}_a(t)$ represents a vector of characteristics from four distinct data sources: a) maintenance logs, b) fault messages generated during flight by the aircraft central maintenance computer, c) health monitoring signals collected during flight by the aircraft sensor network and d) environmental parameters. Table 1 describes the variables considered.

Vector $\mathbf{x}_m(t)$ comprises 12 variables related to the past history of maintenance actions. Statistical distribution functions are used to estimate the parameters of this vector, such as the interquartile range, kurtosis or skewness. The idea here is to have a set of descriptors that capture the central tendency and variation of the maintenance interval times. Two traditional measures from reliability theory, operational time and time since last failure are also considered.

Also included in vector $\mathbf{x}_m(t)$ are the predictions of an autoregressive moving average model ($\hat{y}_{\text{ARMA}}$). This inclusion allows to capture the past series of maintenance events not only as a function of its values but also as a moving average (unevenly weighted) of past noise or residual values. In other words, the autoregressive moving average model includes lagged terms on the time series itself (auto-regressive AR parameters) and lagged terms on the noise or residuals (moving average MA parameters). The ARMA(p,q) model is given

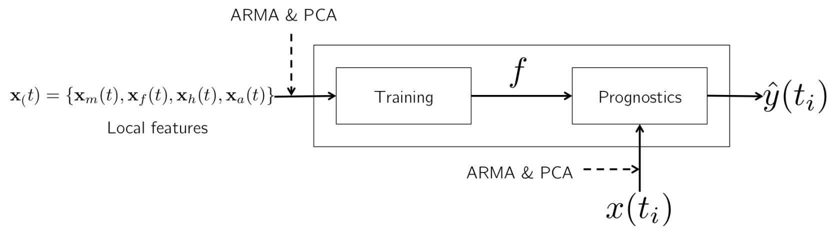


Figure 1: **Prognostics architecture.**

Table 1: **Input vector: categorical and numerical variables.**

	Symbol	Description
$\mathbf{x}_m(t)$	$t_f - t$	Time since failure
	Inf(t)	Min time between failures
	Sup(t)	Max time between failures
	$\mu(t)$	Mean time between failures
	$\tilde{\mu}(t)$	Median time between failures
	$Q1(t)$	1st quartile of time between failures
	$Q3(t)$	3rd quartile of time between failures
	$\sigma(t)$	Standard deviation of time between failures
	$\beta_2(t)$	Kurtosis of distribution of time between failures
	$\gamma_1(t)$	Skewness of distribution of time between failures
	$\hat{y}_{\text{ARMA}}(t)$	Auto-regressive moving average (ARMA) prediction
$\mathbf{x}_f(t)$	csum(t)	Cumulative sum of fault events
	csum$_c(t)$	Cumulative sum of fault events of same code
	csum$^w(t)$	Windowed cumulative sum of fault events
	csum$^w_c(t)$	Windowed cumulative sum of fault events of same code
	$t - t_{FC}$	Time since last fault event
	$t - t_{FC_c}$	Time since last fault event of same code
$\mathbf{x}_h(t)$	h_1 to h_7	7 continuous health monitoring parameters
	h_1^T to h_7^T	7 categorical health monitoring parameters
$\mathbf{x}_h(t)$	a_1 to a_7	7 continuous environmental parameters

by:

$$(1 - \sum_{j=1}^{p} \alpha_j L^j) t_i = (1 + \sum_{j=1}^{q} \theta_j L^j) \varepsilon_i \tag{4}$$

where L is the lag operator, the α_j are the AR parameters, the θ_j are the MA parameters and the ε_i are error terms. Please note that p and q refers to the number of AR and MA terms, respectively. To estimate the parameters of the ARMA we fit the model to the univariate time series of maintenance events by least squares estimation (LSE).

Vector $\mathbf{x}_f(t)$ comprises 9 variables related to the past history of fault events. Fault events result from the processing of parametric sensory data and aim to enhance their diagnostics usefulness. The processing involved in transforming health monitoring signals into fault events include outlier removal, noise reduction, and transformation into other domains, among others. Here, a fault event is described by a timestamp and a fault categorical code. To convert the non-parametric information of fault events into parametric data (see Table 1) we first construct a fault code matrix for each individual component:

$$\begin{array}{cc} & \text{Fault codes} \\ FC(t,j) = & \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{t1} & x_{t2} & x_{t3} & \dots & x_{tn} \end{bmatrix} \text{Time} \end{array} \tag{5}$$

where each cell of the matrix indicates if a fault code has occurred. Each row of the fault code matrix represents a timestamp and each column represents a fault code.

The cumulative conversion functions use the above matrix to estimate the prognostic parameter of csum(t), csum$_c(t)$ and their windowed versions (see Table 1):

$$\text{csum}(t) = \sum_{i=1}^{t} \sum_{j=1}^{n} FC(i,j) \tag{6}$$

$$\text{csum}_c(t) = \sum_{i=1}^{t} FC(i, j = c) \tag{7}$$

$$\text{csum}^w(t) = \sum_{i=t-w}^{t} \sum_{j=1}^{n} FC(i,j) \tag{8}$$

$$\text{csum}^w_c(t) = \sum_{i=t-w}^{t} FC(i, j = c) \tag{9}$$

These parameters allow measuring time as a function of the past number of fault events. In particular, the windowed cumulative sum functions of csum$^w(t)$ and csum$^w_c(t)$ allow measuring the rate of fault events at pre-defined window sizes. The selection of window size w was based on a criterion-based backward regression method (see Algorithm 1) using the root mean squared error (RMSE). Figure 2 illustrates the results of the method. As shown, the best

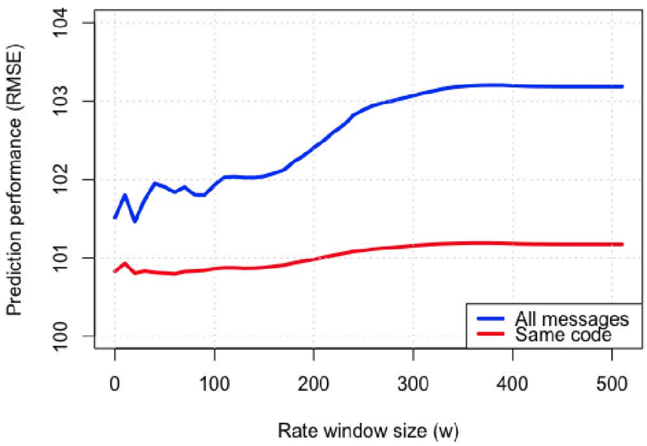


Figure 2: **Criterion-based selection of window size for cumulative mean computation.**

cumulative predictors correspond to the window sizes of 0, 10 and 80 days (1 - all messages and 2 - all messages of same code).

Other parameters related to fault codes include time since previous fault event $(t - t_{FC})$ and time since previous fault event with same code $(t - t_{FC_c})$.

Vector $\mathbf{x}_h(t)$ comprises 7 categorical and 7 numerical variables that are related to and are calculated from the continuous measurements on the different health monitoring signals. The numerical variables represent continuous measurements of different sensory signals such as temperature, vibration, pressure. The categorical variables are binary flags that indicate when a sensory signal goes above or below a given threshold.

Vector $\mathbf{x}_a(t)$ comprises 7 numerical variables related to the past history of environmental conditions.

Given the high number of variables considered (see Table 1) we use principal component analysis (PCA) [24] to reduce the dimension of the feature set.

C) Modeling Approaches

Two modeling approaches are compared: the baseline time-based approach and the data-driven on-condition approach described in Section IIIA. The time-based approach applies the two-parameter Weibull-Pareto distribution to the data set of removal times $\{t_i\}_{0:n}$. Cross-validation is used to evaluate the approach by dividing the original data set in $k = 10$ equal sized samples and using each sample of data as a testing fold. For each testing fold a Weibull distribution is fitted to the remaining data using maximum likelihood estimation (MLE) and the characteristic life α of this distribution is used to predict the next failure t_{i+1} and trigger the needed maintenance of the equipment.

D) Case Study

Air Management systems (AMS) can vary widely in design and operation from one aircraft to another, but they all perform the same basic group of functions. These critical systems ensure the tasks of monitoring and controlling the cabin temperature and air flow to the cockpit, passenger, and cargo areas as well as the secondary cooling of avionics. In addition to these functions, air bleed systems are responsible for managing the engine bleed air and providing ice protection for flight control surfaces. A schematic of the studied AMS is presented in Figure 3. As shown, the system consists of a complex structure of ducts, tapes, valves and regulators. The valve of interest is the bleed valve (EBV), a shutoff valve located near the aircraft engine.

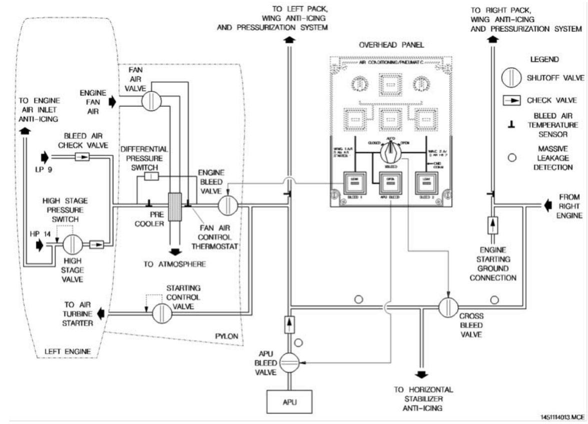


Figure 3: **Left-wing air management system and engine bleed valve.**

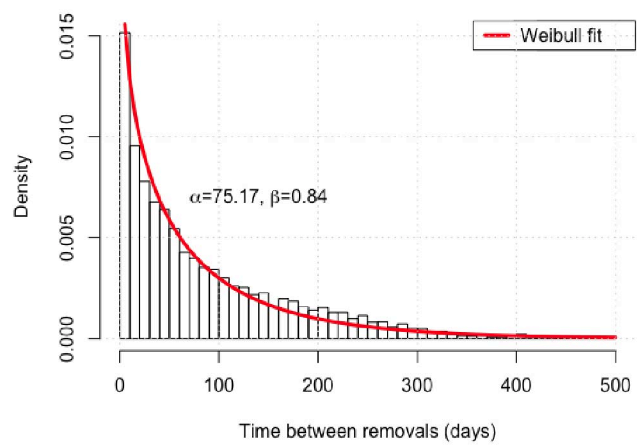


Figure 4: **Probability Density Function (PDF) of time between removals.**

Engine bleed valves are line-replaceable units (LRUs) – they are designed to be removed and replaced quickly in order to restore them to an operational condition. Our data set consists of 585 removals recorded between 2010 and 2015 of the bleed engine valves of 39 aircrafts from 3 airline companies. In the data set, the interval between two sucessive removals is a random variable with a probability density that resembles a Weibull distribution (see Figure 4).

In addition to removal events, our data set also comprises around 100 thousand fault events for the 39 jets. These data consists of all the automatic fault messages exchanged between the aircraft central maintenance computer (CMC) and ground facilities between 2010 and 2015. For each fault message, we have the following information: (1) time of message transmission and (2) indication of the processing code. Eleven crew-alerting system (CAS) codes were considered. It is important to note that the recorded fault events do not provide direct information on the condition of the aircraft EBVs. Instead, the message codes convey information about the overall health of the AMS, such as when the system overall temperature goes beyond a given threshold.

Our data set also comprised structural health monitoring (SHM) data and information about the environmental conditions during flight. Data exploration is described in more detail in [25].

4. RESULTS

To investigate hypothesis H1 we performed a number of experiments with distinct data-driven techniques using the prognostics framework of Section IIIA.

H1: The combination of data-intensive parametric and non-parametric data about the maintenance past history, environment conditions, structural health monitoring signals and fault events can significantly lead to significant performance enhancements of prognostics models.

The models used in the experiments are described in Table 2. Estimation was evaluated based on the predictions of the remaining time to a removal. Estimation accuracy was computed using the median absolute error (MdAE) and the root mean squared error (RMSE). The prognostics performance is summarized in Table 3. All times are given in days. The performance metrics are defined in the Appendix. We also include a brief description of each technique in the Appendix.

In Table 3 the results of the baseline model (Weibull model) are compared to the results of data-driven models of type I, that is, the models which are based solely on the data set of removal times ($\mathbf{x}_m(t)$). As shown, regarding the mean error (ME), the best data-driven models were the generalized linear model (glmStepAIC), nearest neighbors (kknn) and decision trees (rf). These models had comparable results to the baseline Weibull model on this metric. On the contrary, the neural nets (nnet) and the regressive support vector machines (svmLinear) exhibited poor performance with negative errors indicating underestimation bias, that is, these forecasts tended on average to be smaller than the forecasted values.

In regards to model accuracy, as measured by the median absolute error (MdAE), the data-driven approach based on removal times ($\mathbf{x}_m(t)$) was able to outperform the baseline. Concretely, the generalized linear model (glmStepAIC I) and the regressive support machines (svmLinear I) exhibited positive results. In particular, the regressive support machines (svmLinear) had a MdAE of 67 days compared to the MdAE of 76 days ($\uparrow 12\%$) of the baseline.

The root mean squared error (RMSE) allowed to compare the accuracy of the data-driven models of type I and the baseline. Here, all models of type I had similar results to the baseline not showing a significant difference, with the exception of the neural networks (nnets) which had a considerably lower performance and the support vector machines (svmLinear) model which had a slightly worse performance.

Overall, in the class of data-driven models of type I the regressive support vector machines (svmLinear) exhibited the best accuracy in regards to the median absolute error (MdAE). However, the random forests model exhibited the best compromise between the considered metrics. The model had a MdAE, ME and RMSE comparable to the baseline and the longest mean time between failures (MTBF) of its class.

The comparison between the baseline and the models of class I comes in line with the results reported in [26]. The main finding here is that for certain goals, such as when a low MdAE is needed, it may be useful to employ a data-driven technique on the data set of removal times rather than a life usage model.

It is also possible to compare the results of the baseline model (Weibull model) to the results of data-driven models of type II from Table 3. The models of type II are based on the data set of removal times ($\mathbf{x}_m(t)$) and on the data set of fault messages ($\mathbf{x}_f(t)$). The intention here was to analyze the influence of the fault events on prognostics.

As shown, the data-driven approach of type II, with the support vector machines technique (svmLinear), was able to outperform the baseline (and the techniques of type I) on median absolute error (MdAE), root mean squared error (RMSE) and mean error (ME). Also, the random forests technique showed better results to the baseline and to approach I, on MdAE and RMSE. On the downside, the technique exhibited a large mean error (ME).

The generalized linear model (glmStepAIC) and nearest neighbor (kknn) model also registered a better performance than baseline and I version on the MdAE and RMSE metrics. Overall, these results suggest that the use of data-intensive analytics both on the maintenance history and fault events can lead to a better understanding of the equipment future reliability.

To test the influence of the health monitoring and environmental variables we used the data-driven models of type III. These models were based both on maintenance data ($\mathbf{x}_m(t)$) and on health monitoring ($\mathbf{x}_h(t)$) and environmental variables ($\mathbf{x}_a(t)$). From Table 3 it is possible to compare the results of these models to the baseline. Here, the performance of some models was significantly better than their type II version in MdAE, ME and RMSE. Regarding the baseline, again the data-driven techniques has a significantly better performance. This comes to show that not only the technique but also the data set is important to obtain reliable structural prognostics. Particularly, it also shows that some data-driven techniques may work better with certain types of data than others. For instance, a technique that showed a performance decrease from its I version was the nearest neighbors (kknn) technique. Despite the technique having a performance similar to the baseline, its MdAE and RMSE were larger than for the group of models of type II. These results suggest that the inclusion of new data may not always be well captured by a given data-driven technique. These findings suggest that some data-driven techniques may work better with certain types of data than others and that parametric data is easier to analyze with regression techniques.

The neural networks had an MTBF of 1 day across the models (see Table 3). The technique attempted to capture the high percentage of short removals (see Figure 4), by prescribing a maintenance action every day (MTBF = 1.00 days, σ = 0). Despite the acceptable performance results, this is not

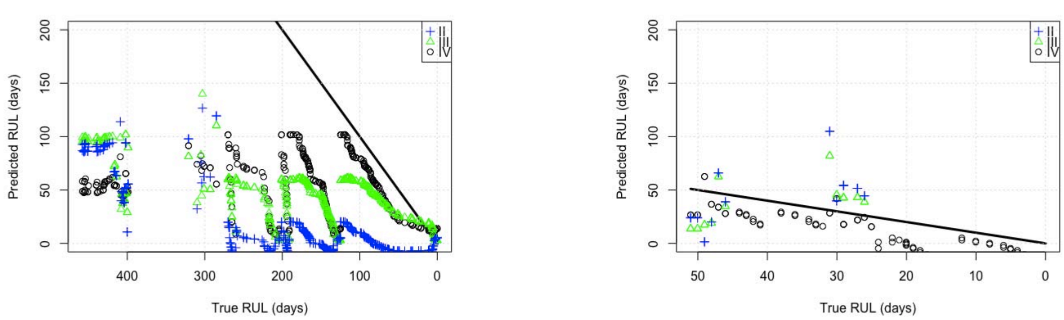
Table 2: **Evaluated approaches.**

	Baseline	Data-driven Techniques			
	Life Usage	Data-driven I	Data-driven II	Data-driven III	Data-driven IV
Maintenance data ($\{\mathrm{x}\}_m(t)$)	×	×	×	×	×
Fault events ($\{\mathrm{x}\}_f(t)$)			×		×
Health monitoring signals ($\{\mathrm{x}\}_h(t)$)				×	×
Ambient variables ($\{\mathrm{x}\}_a(t)$)				×	×

Table 3: **Prognostics performance results.**

		Error Measures			
	Data	ME	MdAE	RMSE	MTBF
Weibull (Baseline)	$\{\mathbf{x}_m(t)\}$	7.66	76.21	101.45	90.79
Data-driven I	$\{\mathbf{x}_m(t)\}$				
glmStepAIC		-0.14	73.39	101.86	82.99
kknn		-1.28	77.64	108.97	81.85
nnet		-82.13	82.28	136.39	1.00
svmLinear		-36.01	66.72	111.63	47.12
rf		3.75	76.09	104.63	86.88
Data-driven II	$\{\mathbf{x}_m(t), \mathbf{x}_f(t)\}$				
glmStepAIC		62.31	67.8	70.54	85.77
kknn		2.34	74.54	101.83	53.09
nnet		-61.06	61.13	83.39	1.00
svmLinear		5.22	62.64	78.77	49.99
rf		24.81	67.86	89.26	67.55
Data-driven III	$\{\mathbf{x}_m(t), \mathbf{x}_h(t), \mathbf{x}_a(t)\}$				
glmStepAIC		54.64	60.98	63.99	80.3
kknn		23.37	78.09	108	68.86
nnet		-59.38	59.45	80.1	1.00
svmLinear		9.12	51.93	64.98	52.7
rf		63.76	66.4	68.23	87.59
Data-driven IV	$\{\mathbf{x}_m(t), \mathbf{x}_h(t), \mathbf{x}_a(t), \mathbf{x}_f(t)\}$				
glmStepAIC		61.33	64.34	67.1	85.38
kknn		22.42	72.2	100.91	66.24
nnet		-59.38	59.45	80.1	1.00
svmLinear		16.44	44.98	53.41	55.25
rf		59.01	59.86	65.27	81.18

* ME stands for Mean Error (days) where ME = mean(simulated - observed), MdAE for Median Absolute Error (days), MTBF for Mean Time Between Failures (days) and RMSE for Root Squared Mean Error.

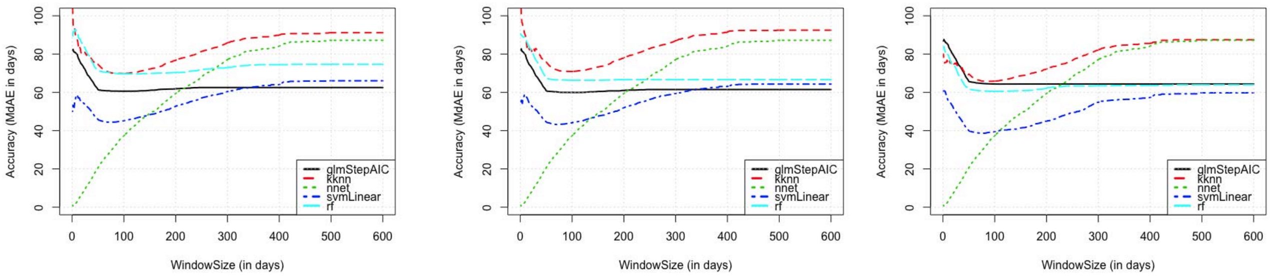


(a) **Removal I**

(b) **Removal II**

Figure 5: **Estimation results for different removals.**

a feasible solution in aeronautics due to the high maintenance costs involved. Please note that an unscheduled removal is not a catastrophic incident that must be avoided at all costs since there is a certain level of redundancy in the bleed system. Alternative solutions could include a customized parameterization of the technique or the use of a different neural network architecture for this class of models.



(a) **Data-driven II** (b) **Data-driven III** (c) **Data-driven IV**

Figure 6: **Accuracy vs Window size.**

Finally, the most balanced results were obtained by the models of type IV (svmLinear). In this class of models, data about the removal times ($\mathbf{x}_m(t)$), fault events ($\mathbf{x}_f(t)$) and the environmental ($\mathbf{x}_a(t)$) and sensor variables ($\mathbf{x}_h(t)$) were used to predict the remaining useful life (RUL) of the valves. In this set, and as shown in Table 3, the majority of the techniques had a better performance than models of type II or type III. Our results hence provide enough evidence to support the hypothesis that the combination of data on fault events, health monitoring signals, environmental conditions and maintenance records can provide enhanced prognostics performance.

We were also interested in studying how the different models changed its performance along the prognostics window. Figure 5 compares the support vector machines (svmLinear) across approaches II (fault events), III (HM + ambient) and IV (fault events + HM + ambient). Please note that this was the technique with the lowest median absolute error (MdAE) of all the models. Two removals are shown comparing the true RUL with the predicted RUL. We show the evolution of the predictions between two consecutive valve removals, starting immediately after the first removal. Even far from the next removal models are still converging, especially for the removal in Figure 5a, which is the longest. Afterwards, the error of the prediction starts to decrease. Close to the end of life, RUL is predicted with reasonable accuracy, with moderately confident predictions for all model types. Accordingly, this example shows that the SVM models take time to converge but can provide good estimates near the end of life of the equipment.

Figure 5 compares the models of type IV, III and II in how they were able to estimate the remaining useful life of the valve for different time horizons. On the x-axis we have the time horizon and on the y-axis we show the accuracy of the prognostics model measured by the median absolute error (MdAE). The lower the MdAE the more accurate the model performs its predictions. As shown, the support vector machines (svmLinear) yielded the best results for the different classes of models. Also, the models of type IV tend to show a better performance than models of type II and I.

5. CONCLUSION

In recent years, airlines have steadily started to adopt on-condition data-driven policies to reduce costs and optimize their fleet performance [5]. Introducing on-condition maintenance leads to new challenges and opportunities within maintenance engineering. On one hand, CBM offers potential benefits such as increased system reliability and availability as well as more effective maintenance actions. On the other hand, the success of CBM relies on multiple factors from design of sensors to the sophistication of the used techniques.

In this paper, we developed a condition-based prognostics framework using data-driven methods, auto-regressive moving average methodology, stepwise model selection, and principal component analysis (PCA) for remaining useful life estimation. We applied the framework to a bleed air valve, performing a series of experiments that included different predictor variables as well as distinct data-driven techniques. The results demonstrated the effectiveness of the data-driven approach, and gave insight into the way parametric and non-parametric data can be combined and used to enhance structural prognostics.

The goal of this work was two-fold: (1) to compare the use of data intensive analytics on different types of parametric and non-parametric variables and (2) to compare five regression techniques. Here, we have shown that our proposed prognostics framework can outperform the baseline approach of the life usage model in regards to mean, absolute and squared errors.

We studied the influence of maintenance, fault and flight/ambient data on prognostics. We have shown that while data-driven algorithms can learn the evolution of a degradation process considerably well, the RUL estimates depend significantly on the predictor variables. Our results suggest that it is possible to obtain reliable prognostics estimates from fault events and from traditional health monitoring variables (e.g. temperature, vibration, pressure) as well as from a combination of these two types of data. Most importantly, the main finding of this paper is that the combination of these data sources can yield better overall performance than the single use of each of these sources, confirming the overall hypothesis of this study.

We have also shown that RUL estimates depend not only on the chosen data predictors but also on the technique used. Interestingly, we have shown that the inclusion of new data may yield positive results on some techniques but not on others. For instance, the generalized linear model technique had a considerable decrease of performance from model III (flight data) to model IV (flight + fault data). This was despite all the other techniques having registered a significant performance increase from approach III to IV. We hypothesize that this was due to the generalized linear model not being able to discern significance in the new predictors, fitting to noise and resulting in increased variance of the prediction. In future work, we may work on strategies against overfitting such as complexity reduction and early stopping [27].

The results showed how the different techniques tended to converge to the end of life: accuracy of RUL estimations improved closer to failure. The rate of the convergence again varied from models II to IV: the models of type IV (flight + fault data) were more likely to converge than models of type III (flight) and II (fault data). This result is promising for the aeronautics field. Please note that nowadays, the prognostics of these valves is performed on a daily basis by maintenance and repairing operations experts. To be able to know in advance that there is going to be a failure for a larger time interval can significantly improve maintenance operations.

The regressive support vector machine distinguished itself as the most promising data-driven technique. Using this method we were able to reach a considerably low absolute and squared error. Random forests also exhibited a good performance. In the future, it might be worthwhile to understand why some models, such as the support vector machines, were better able to capture the dynamics of the data sets than other models. It might also be interesting to study how to combine the models using combination methods such as bootstrap aggregating, boosting or stacking [28]. Applying the framework to additional data sets is also part of future work.

APPENDICES

A. PERFORMANCE EVALUATION

Estimation performance of our proposed framework and baseline is evaluated based on the estimate of the remaining useful life (RUL). In this section we describe the metrics used to assess reliability performance.

The window size w of the windowed cumulative sum was computed using the root mean squared error (RMSE) criterion:

$$\text{RMSE} = \sqrt{\text{Mean}_i\left[\left(\hat{y_i} - y_i\right)^2\right]} \tag{10}$$

where $\hat{y_i}$ denotes the estimated RUL at time t, y_i denotes the true RUL at t, and Mean_i denotes the mean over all values of t.

Estimation accuracy is estimated based on the above RMSE metric. To estimate performance accuracy we also use the median absolute error (MdAE), which takes the absolute value of forecast errors and averages them over the entirety of the forecast time periods.

$$\text{MdAE} = \text{Median}_i\Big(|\hat{y_i} - y_i|\Big) \tag{11}$$

Estimation bias is estimated from the mean error (ME):

$$\text{ME} = \text{Mean}_i\left[\left(\hat{y_i} - y_i\right)\right] \tag{12}$$

The mean error measures the bias of the forecasts. A positive error indicates that, on average, the forecast tends to be larger than the outcome (overestimation bias) while a negative error indicates forecasts tends to be smaller than the outcome (underestimation bias).

B. DATA-DRIVEN TECHNIQUES

Our framework features a number of statistical regression techniques, such as generalized linear model, nearest neighbors, neural networks, regressive support vector machines, and decision trees. A brief explanation of these techniques is given in the following subsections.

Generalized Linear Model

The generalized linear model (GLM) was proposed as a way of unifying various other statistical models, such as linear regression, logistic regression and Poisson regression [29]. This kind of model allows for the response variables to that have an error distribution other than a normal distribution. Formally, a generalized linear model can be described by the following assumptions [30]:

- There is a response y observed independently at fixed values of stimulus variables $x_1, \ldots, x_p$
- The stimulus variables influence the distribution of y through a linear function $\eta = \beta_1 x_1 + \ldots + \beta_p 1 x_p$
- The distribution of y has density of the form

$$f(y_i, \theta_i, \varphi) = exp[A_i\{y_i\theta_i - \gamma(\theta_i)\}/\varphi + \tau(y_i, \varphi/A_i)] \tag{13}$$

where φ is a scale parameter, A_i is a known prior weight and parameter θ_i depends on the linear predictor

- The mean μ is a smooth invertible function of the linear predictor:

$$\mu = m(\eta), \eta = m^{-1}(\mu) \tag{14}$$

The inverse function is called the link function. This function describes how the mean, E(y_i) depends on the linear predictor.

In this paper we use a generalized linear model with stepwise regression in which the choice of predictive variables is carried out by bidirectional selection.

K-Nearest Neighbours

The k-Nearest Neighbors (KNN) algorithm is one of the most fundamental and simple supervised methods in machine learning. The algorithm consists in finding the k closest training examples in the feature space, using a distance function such as the Euclidean distance function. With this function, the distance between sample $\mathbf{x}_i$ and $\mathbf{x}_j$ ($l = 1, 2, \ldots, l$) is defined as

$$d(\mathbf{x}_i, \mathbf{x}_j) = \sqrt{(x_{i1} - x_{j1})^2 + \ldots + (x_{ip} - x_{jp})^2} \tag{15}$$

where p is the total number of predictors and l is the total number of input samples. In k-NN regression, the output is the average of the values of its k nearest neighbors:

$$N_i = \{\mathbf{x} \in \mathbb{R}^p : d(\mathbf{x}, \mathbf{x}_i) \leq d(\mathbf{x}, \mathbf{x}_m), \forall i \neq m\} \tag{16}$$

Neural Networks

An artificial neural network (ANN) can be defined as a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs [31].

The architecture considered are layered feed-forward networks [32], that is, networks with one layer of input units, one layer of output units, and one or several layers of hidden units. We assume that there are T input patterns X_t ($1 \leq t \leq T$) and T corresponding target output patterns Y_t which are used to train the network. The error function is defined as $E = ||Y_t - F(x_t)||$ where F is the function implemented by the network. During the training stage, the weights, and hence F, are successively modified, according to one of several possible algorithms, such as backward propagation, in order to reduce the quadratic function error E.

Regressive Support Vector Machines

As other machine learning methods, the Support Vector Machines (SVM) [33] assume a set of training data $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_l, y_l)\} \subset X \times \mathbb{R}$. Accuracy here is defined as a function f that has at most an ε deviation from targets y_i in the training data. Prediction is based on a function $f(x) : X \to \mathbb{R}$ defined over the input space X where SVM learning is used to infer the parameters of this function. Generally, for a linear SVM, this function takes the form:

$$f(\vec{x}; w) = \langle w, \mathbf{x} \rangle + b, b \in \mathbb{R} \tag{17}$$

where $\langle \cdot, \cdot \rangle$ denotes the dot product and $w = (w_0, w_1, ..., w_N)^T$ is a weight vector.

This problem can be written as a convex optimization problem:

$$\begin{aligned} &\text{minimize } \frac{1}{2}\|w\|^2 \\ &\text{subject to } \begin{cases} y_i - \langle w, x_i \rangle - b \leq \varepsilon \\ \langle w, x_i \rangle + b - y_i \leq \varepsilon \end{cases} \end{aligned} \tag{18}$$

Random Forests

Random forests (RF) or random decision forests are an ensemble learning method for classification, and regression, which operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

Formally, a random forest is a predictor consisting of a collection of randomized base regression trees $\{r_n(x, \theta_m, D_n), m \geq 1\}$ where $\theta_1, \theta_2, \ldots$ are outputs of a randomizing variable θ. These random trees are combined to form the aggregated regression estimate

$$\overline{r_n}(x_i, D_n) = \mathbb{E}_\theta[x_i, \theta, D_n] \tag{19}$$

where $\mathbb{E}_\theta$ denotes expectation with respect to the random parameter, conditionally on x_i and the data set $D_n = \{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_l, y_l)\}$. The expectation function is evaluated by Monte Carlo, that is, by generating M random trees and taking the average of the individual outcomes.The randomizing variable θ is used to determine how the successive cuts are performed when building the individual trees, such as selection of the coordinate to split and position of the split.

NOMENCLATURE

ANN	=	Artificial Neural Network
ARIMA	=	Auto-regressive Integrated Moving Average
ARMA	=	Auto-regressive Moving Average
CMC	=	Central Mainenance Computer
EOL	=	End of Life
GLM	=	Generalized Linear Model
HM	=	Health Monitoring
KNN	=	K-Nearest Neighbours
LSE	=	Least Squares Estimation
MdAE	=	Median Absolute Error
ME	=	Mean Error
MTBF	=	Mean Time Between Failures
PCA	=	Principal Component Analysis
PRMSE	=	Percentage Root Mean Squared Error
RF	=	Random Forests
RMSE	=	Root Mean Squared Error
RUL	=	Remaining Useful Life
SVM	=	Support Vector Machines
t	=	Time (continuous)
t_i	=	Time of prediction
t_f	=	Time of failure
$\mathbf{x}$	=	State vector

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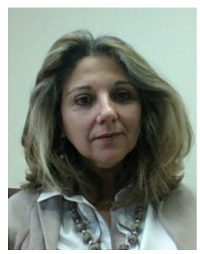

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