Improved Time-Based Maintenance in Aeronautics with Regressive Support Vector Machines

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Abstract

In modern preventive maintenance, time-based management is still the mainstream approach. This strategy continues to be the preferred choice to manage the risk of equipment failure when other alternatives, such as condition-based management, are technically or economically unfeasible. In this paper we propose a novel approach to time-based maintenance based on (linear) regressive Support Vector Machines (SVM). In the proposed model, expected lifetime is estimated based on the equipment past failure times combined with the maintenance history of similar components. Time series analysis combined with outlier detection techniques and concepts from technical analysis, such as resistance and support levels, are used to establish the SVM model prediction bounds. The proposed SVM model is compared with the traditional approach to time-based maintenance – life usage modeling – and the autoregressive moving average (ARMA) forecasting method. Results are shown on an industrial case study of data describing the maintenance life-cycle of a critical component of the aircraft bleed air system. Results suggest that the SVM model can outperform the other tested approaches both in regards to the squared, percentage and absolute errors.

1. Introduction

Time-based maintenance (TBM), also termed periodic-based maintenance, is a traditional technique used in maintenance and repair operations (MRO). In TBM, maintenance decisions (e.g., preventive hard time intervals) are determined based on the analysis of past failure times (Ahmad & Kamaruddin, 2012). In this kind of approach, usually termed life usage (LU), the expected lifetime, T, of the equipment is estimated based on reliability data. Estimates of T are derived by fitting the data to a statistical distribution of failure rate over time. Here, the distribution of Exponential and Weibull tend to be the preferred choices.

Despite its widespread use, the strategy of TBM is often seen as a not so effective means of identifying when components will require a corrective intervention (Ahmad & Kamaruddin, 2012). Since this methodology determines MRO hard intervals based on the analysis of the statistics probability alone, TBM tends to disregard several aspects of maintenance, such as the specificity of the individual system – the within-component pattern of failure, as well as other relevant patterns related to the equipment lifecycle evolution, such as the assumption of mean reversion or jump probability (Xu & Perron, 2014).

In view of TBM limitations and as noted by Wang (2012), time-based maintenance could make use of more advanced models and methodologies. These, based on equipment usage and failure times, could more accurately predict and manage asset lifetime requirements compared to traditional life usage (LU) methods. More accurate models could be of use in diverse situations. First, a higher level of reliability is needed when it is necessary to recommend repair interventions based on past failure times alone, such as when information collected though condition monitoring is not yet available or too difficult/ impracticable to obtain. Also, time-based methods can be combined with advanced techniques and sensory real-time information to optimize condition-based maintenance (CBM), that is, maintenance based on the real-time assessment of the equipment health status (Brotherton, Jahns, Jacobs, & Wroblewski, 2000).

Data-driven techniques have recently become a popular approach to aircraft prognostics due to their ease of use and predictive power (Schwabacher, 2005). These techniques consist in the use of non-parametric modeling methods, which rely on past data and advanced statistics to derive estimates on the reliability of mechanical components. This paper proposes a data-driven approach to time-based maintenance based on (linear) regressive Support Vector Machines (SVM). This data-driven technique was considered suitable given its several advantages, such as its generalization ability and its guaranteeing of global minima for given training data (Widodo & Yang, 2007).

The SVM approach is tested on a real industrial case involving a two-valve system of the aircraft bleed air system. Air bleed valves are a critical component of the aircraft as they regulate bleed air exiting the engine pylon for use throughout the aircraft. The well functioning of these kind of components is key to prevent unexpected and unwanted operational anomalies.

Relevant literature on the past use of the SVM approach to this type of problem includes the work of de Pádua Moreira and Nascimento (2012). In this study, a SVM classification algorithm is proposed to estimate the remaining useful life of an aircraft bleed valve based on maintenance and condition-based data.

In our comparative study, the baseline model used is a Weibull life usage (LU) estimated using Maximum Likelihood Estimation (MLE). In addition to the LU, the proposed model is also compared with the autoregressive moving average (ARMA) forecasting approach. The novelty of our work is the application of regressive Support Vector Machines (SVM) to a (novel) forecasting parameter that combines time series statistical analysis, unsupervised techniques of outlier detection, and concepts from technical analysis such as support and resistance levels.

The remaining of the paper is organized as follows. Section 2 reviews the theoretical background of this study. Section 3 describe the data set, methodology and modeling approaches. Section 4 presents and discusses the results. To conclude, Section 5 summarizes the paper and outlines future research directions.

2. THEORETICAL BACKGROUND

2.1. Life Usage (LU) Model

Reliability theory tends to recommend that, unless strong evidence of failure times following another distribution, the Weibull distribution should be used as the preferred method to model technical failure, especially for samples with less than 20 observations (Liu, 1997). Here, removals are fit and modeled to a statistical distribution such as exponential, Weibull or lognormal.

Weibull distributions come in two and three-parameter variants. The three parameter Weibull Probability Density Function (PDF) and Cumulative Distribution Function (CDF) and the Failure Rate Function (FRF) are defined as:

$$f_T(t) = \begin{cases} \frac{\beta}{\alpha}\left(\frac{t-\gamma}{\alpha}\right)^{\beta-1} e^{-\left(\frac{t-\gamma}{\alpha}\right)^{\beta}} & t \geq 0, \\ 0 & t < 0, \end{cases} \tag{1}$$

$$F_T(t) = \begin{cases} 1 - e^{-\left(\frac{t-\gamma}{\alpha}\right)^{\beta}} & t \geq 0, \\ 0 & t < 0, \end{cases} \tag{2}$$

$$h_T(t) = \frac{\beta}{\alpha}\left(\frac{t}{\alpha}\right)^{\beta-1} \tag{3}$$

where β is the shape parameter (or slope), α is the scale parameter (or characteristic life) and γ is the location parameter (or failure free time). The two parameter Weibull distribution is obtained when γ is set to zero. In most cases, this two parameter description is sufficient.

Weibull is a flexible distribution as by changing the shape parameter, β, it can approximate the form of other probability distributions such as the exponential ($\beta = 1$) or the Rayleigh distribution ($\beta = 2$ and $\alpha = \sqrt{2}\sigma$). Figure 1 illustrates examples of Weibull distributions with distinct shape parameters.

As indicated in the plots of Figure 1, Weibull distributions with $\beta < 1$ have a failure rate that decreases with time, also known as *infantile* or *early-life* failures. Weibull distributions with β close to or equal to 1 have a fairly constant failure rate, indicative of the useful life with random failures. Weibull distributions with $\beta > 1$ have a failure rate that increases with time, also known as *wear-out* failures. These comprise the three sections of the classic "bathtub curve" (see Figure 2).

The Weibull scale parameter is another important parameter, as it determines the device *characteristic life*, that is, the age at which 63.2 [%] of the equipment will have probably already failed. A larger scale parameter is desirable as an indicative of a better durability for the device.

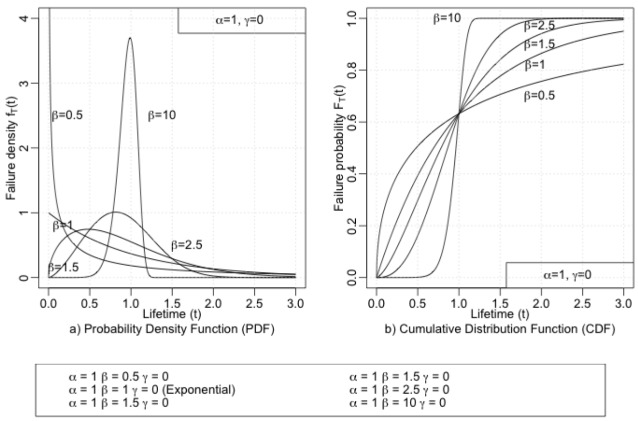

Figure 1. Weibull distribution functions for distinct shape parameters (β). By changing the shape parameter, the Weibull function can approximate the form of distributions such as the Exponential ($\beta = 1$) or Normal ($\beta = 10, \beta = 2.5$).

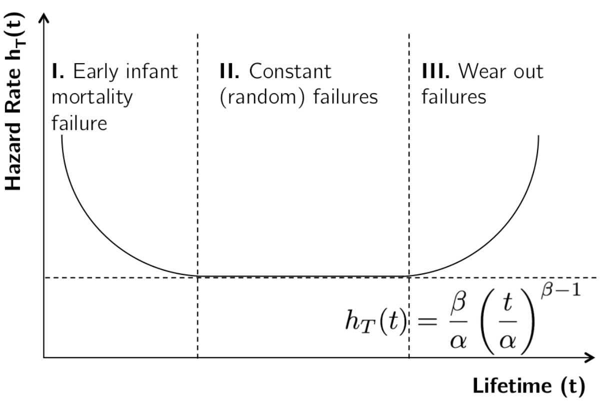

Figure 2. Typical failure curve (bathtub curve). The 'bathtub curve' hazard function is a combination of a stage of early failure (I), a constant stage of random failure (II) and a stage of wear-out failure (III).

2.2. Box-Jenkins Autoregressive Moving Average (ARMA) Models)

ARMA, or also called Box-Jenkins methodology, stands for Autoregressive Moving Average models. This methodology consists in projecting the future values of a univariate (single vector) time series based on its past history. It attempts to capture a time series using autoregressive (AR) and moving average (MA) parameters. Formal definition of ARMA follows.

Given a series of data points T_i where $i \in \mathbb{N}$ is the time index and $T_i \in \mathbb{R}$, then an ARMA(p,q) model is given by:

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

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.

2.3. (Regressive) Support Vector Machines (SVM)

Support Vector Machines (SVM) is a supervised learning technique developed at AT&T Bell Laboratories in the early nineties (Boser, Guyon, & Vapnik, 1992). As in other machine learning methods, the SVM assumes a set of training data $\{(\vec{x}_1, y_1), \ldots, (\vec{x}_l, y_l)\} \subset X \times \mathbb{R}$ where X denotes the space of input features, $\mathbb{R}^N$. The goal is to learn a model of how the target variable $y \subset \mathbb{R}$ changes with the inputs $\vec{x} \subset X$ in order to make accurate predictions of y based on the future values of $\vec{x}$. 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 linear SVM, this function takes the form:

$$f(\vec{x}; w) = \langle w, \vec{x} \rangle + b, b \in \mathbb{R} \quad (5)$$

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:

$$\text{minimize } \frac{1}{2}\|w\|^2$$
$$\text{subject to} \begin{cases} y_i - \langle w, x_i \rangle - b \leq \varepsilon \\ \langle w, x_i \rangle + b - y_i \leq \varepsilon \end{cases} \quad (6)$$

Figure 3 illustrates an example of a SVM linear regression. In the figure, the straight line depicts the fitted $f(\vec{x}, w) = mx + b$. The f function minimizes the error ε creating an epsilon margin around the linear function f.

Slack variables ξ_i, ξ_i^* are included in the above equations (6) when the optimization problem is unfeasible, that is, when the data is not (linearly) separable (Smola & Schölkopf, 2004). In this case, the slack variables help determine the penalty imposed on the observations that lie outside the epsilon margin (ε) and help to prevent model over-fitting. They control the trade-off between the flatness of the linear function and the deviations larger than ε.

In Figure 3, it can be seen how function f minimizes the error ε and penalizes the deviations, that is, the training data points shown as black star symbols, from this margin in a linear fashion creating a 'soft margin'. This soft margin concept is aimed at extending the SVM algorithm so that the hyperplane allows a few noisy data to exist.

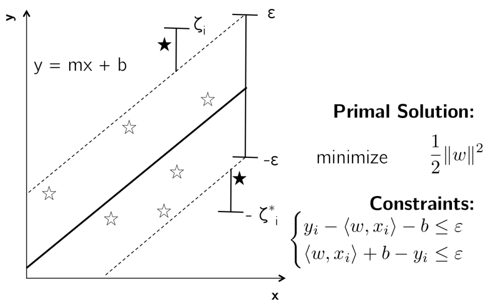

Figure 3. Convex optimization problem of support vector regression (primal formulation). Support Vector Machines can be applied not only to classification but also to regression problems. Still, this technique contains the main features that characterize a maximum margin algorithm.

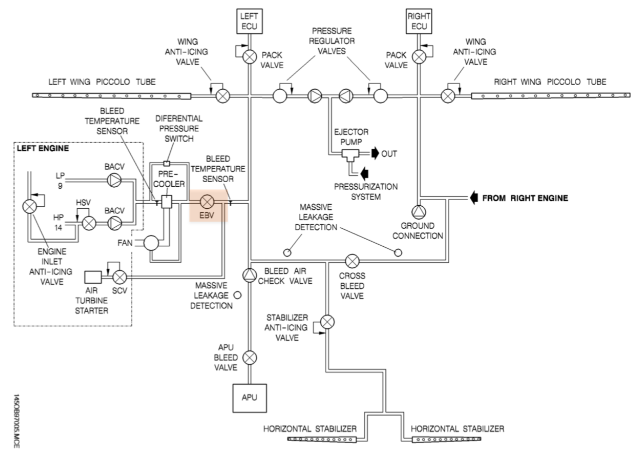

Figure 4. Schematics of the studied engine bleed system. The valve of interest is marked in light orange. The valve is located on the top of the thermostat bypass pipe/heater pipe assembly. To bleed, the valve is opened while the engine is running until all air has bled from the cooling system.

3. MODEL

In this section the data set used to evaluate the modeling approaches is described, as well as the implementation of each approach and methodology.

3.1. Aircraft Bleed Air System

Aircraft engine bleed-air system is of vital importance concerning flight safety and ground operations. The bleed system main functions include air conditioning and cabin pressurization. Its operation is carried out by a set of numerous air flow and temperature pneumatic or electrical switches and valves. Figure 4 illustrates the schematics of the bleed system studied in this work. In orange is the component of interest.

The bleed system is periodically maintained in order to insure safe and optimum system performance. Typical maintenance involves having the aircraft brought into a hangar and having the most critical components being subject to a removal. Here by *removal* we mean a maintenance and repair action where the equipment is removed from the aircraft and restored to its original condition or it is replaced by a new/repaired unit.

3.2. Data

The used data set reports on the removals of a set of two critical valves from the aircraft bleed air system. Please note that our original data set was submitted to a cleaning procedure: the techniques of Tukey's boxplot (Tukey, 1977) and Medcouple-based outlier detection method (Brys, Hubert, & Struyf, 2004) were used to detect outliers: removals with extremely long or short lasting times between repairs were considered outliers and removed from the sample. Also, components with a non-representative number of removals (< 10) were disregarded. After cleaning, the data set comprised information on 485 removals of 24 aircraft (average of 19.20 ± 6.51 removals per aircraft) $-$ removals recorded during six years, between January 2010 and June 2015[1].

3.3. Modeling Approaches

In this study three modeling approaches were analyzed: life usage (LU), auto-regressive moving average (ARMA) and (regressive) support vector machines (SVM). In this section we detail each of these. Please refer to Table 1 for a summary and comparison of these approaches.

The life usage (LU) approach consisted in applying the Weibull-Pareto distribution to the data set of N removal times $\{T_i\}_{i=1}^{N}$. To evaluate this approach, we used 10-fold cross-validation. Here, we divided the original data set $\{T_i\}_{i=1}^{N}$ with N observations in $k = 10$ equal sized samples. Of the 10 samples, a single sample of data was used as the testing set and the remaining 9 samples were used as training data.

The auto-regressive moving average (ARMA) approach consisted on an ARMA(p, q=0) model.We chose p to be the number of total past observations at time index i ($i-1$ observations). This way, the model was able to compute the next removal time as an function of past removal times. For simplicity, the moving average (MA) terms were not considered.

As the validation method for the ARMA approach we used the forecast evaluation with a rolling origin (Bergmeir & Benítez, 2012):

1. Suppose there are N independent observations, $T_1, \ldots, T_N$ for aircraft j.
2. Let observation T_i form the test set and fit the ARMA

[1]For a more detailed description on the data cleaning process please refer to (Baptista et al., 2016).

Table 1. Comparison of studied approaches: life usage modeling (LU), ARMA forecasting and regression support machines.

Dimension	Life Usage (LU)	ARMA	SVM	Description
Sample Size	$***$	$**$	$*$	SVM requires a considerable set of data while LU can provide good estimates for less than 20 observations. ARMA requires a considerable number of observations of same and similar component.
Generalization	$*$	$**$	$***$	As life usage (LU) is based on the characteristic life α of the Weibull distribution it has more difficulty in generalizing to unseen data points. The data-driven approach of SVM is well known for generalizing well to unseen data while the the ARMA by the use of mean and outlier detection methods also adapts fairly well to distinct patterns from the training set.
Performance	$***$	$**$	$*$	SVM has the worst performance of the three analyzed approaches. The solving of the optimization problem of SVM uses more time than the algorithm of ARMA or the simple solution of LU.
Simplicity	$***$	$**$	$*$	The data-driven SVM provides a less intuitive solution than the ARMA or the Weibull model. The hyper-plane provided by this solution is more difficult to understand than the point estimates of the ARMA model and the characteristic life measurement of LU.
Cost	$***$	$**$	$*$	The data-driven SVM and ARMA have high implementation costs compared to the LU model.

Note: we evaluate each studied approach − LU, ARMA and SVM, according to five criteria: sample size, generalization (ability to generalize to unseen data points), performance (processing time), implementation cost and simplicity. In regards to evaluation, $***$ stands for best performance and $*$ for worst performance on criteria.

model to the remaining $p = i - 1$ past values $T_1, \ldots, T_{i-1}$. Estimate the future $\hat{T}_i$ value.

3. Compute the residual $\hat{T}_i - T_i$. Apply statistics of Table 2. Repeat step 1 for aircraft $j = 1, \ldots, M$.

The SVM model consisted on an univariate (linear) regressive SVM (please see a description of the SVM technique in Section 2.3). We choose to construct a univariate instead of a multivariate model to reduce complexity and also processing time. A model with less features is faster to construct and hence easier to sophisticate, eventually with health monitoring variables. A univariate model is also easier to interpret.

The (novel) SVM predictor d_{ij} for time index i and aircraft j is calculated as follows:

$$w_{ij} = \left(\left(\frac{1}{1 + exp(-p_{ij})} \right) * 2 - 1 \right) \tag{7}$$

$$\overline{T_{ij}} = \frac{\sum_{m=1}^{i-1} T_m}{i - 1} \tag{8}$$

$$d_{ij} = w_{ij} \overline{T_{ij}} + (1 - w_{ij}) (\sum_{m \neq j} \overline{T_{im}}) \tag{9}$$

where p_{ij} is the number of past removals of aircraft j at time index i. Here, $\overline{T_{ij}}$ stands for the mean of past removal times for aircraft j at time index i and w_{ij} is the weight associated to this factor. Seemingly, $\sum_{m \neq j} \overline{T_{im}}$ stands for the mean of past removal times for all aircraft except j at time index i. Seemingly, $1 - w_{ij}$ is the weight associated to this factor.

The SVM predictor d_{ij} weights the past removal times of aircraft component j at time index i against the removal times all the other similar equipment. Here, weight given to the aircraft removal history (w_{ij}) depends on the number of past removals ($i - 1$).

Figure 5 shows how the weight of past removals increases as

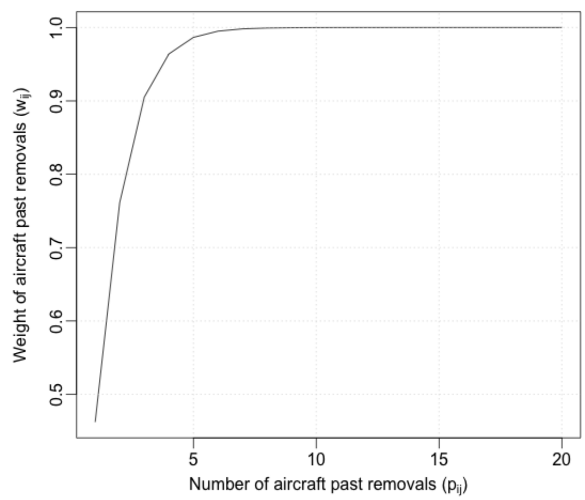

Figure 5. Weight function (7) of the (novel) univariate predictor of the SVM model. The weight function measures the importance of the component past removal times against that of other aircraft. To compute this function an exponential construction was used to capture the weight exponential rise.

the number of past removals grows (7). For $i - 1 = 1$, the same importance is given to the aircraft and to similar aircraft. For $i - 1 = 2$ this importance grows to around 0.7. From the 5 removals the most prevalent factor is the aircraft own history.

Please note that prior to the computation of factors $\overline{T_i}$ and $\sum_{m \neq j} \overline{T_{im}}$, an outlier detection algorithm was applied to each set of past removals. The goal here was to disregard abnormal past removal times from calculation: long or short removals were identified and ignored for each time index i. Outlier detection was based on the standard boxplot rule (Williamson, Parker, & Kendrick, 1989), taking into account only the nominal data range:

$$[Q1c * IQD, Q3 + c * IQD] \tag{10}$$

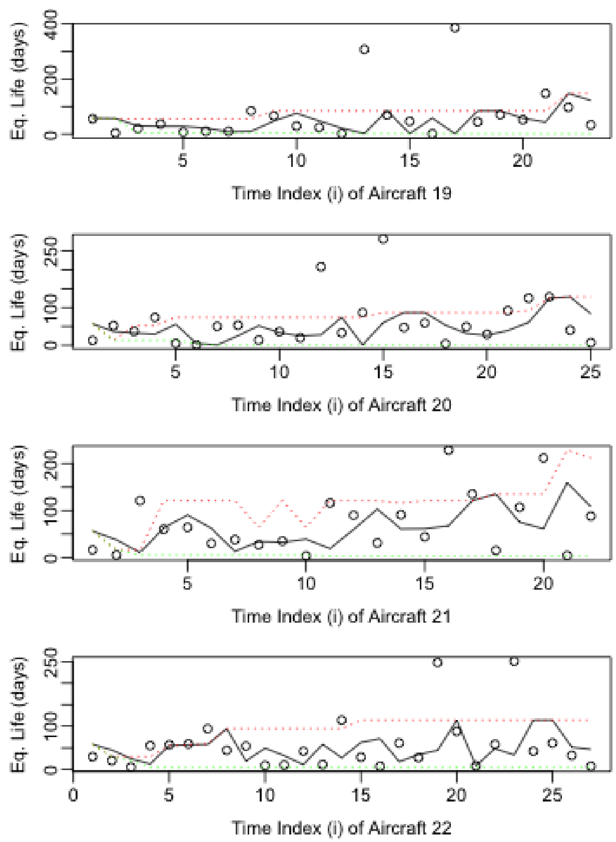

Figure 6. SVM predictor (d_{ij} (in black solid line) for different aircraft timelines. Support and resistance are shown as dashed lines (red and green lines). Dark circles represent removals with time index i on the x-axis and T_i on the y-axis.

where Q1 and Q3 represent the lower and upper quartiles, respectively, of the data distribution. $IQD = Q3 - Q1$ is the interquartile distance, a measure of the spread of the data similar to the standard deviation. The threshold parameter c used is set as the value most commonly used in this outlier detection rule ($c = 1.5$).

The predictor d_{ij} attempts to capture the removal trend. Figure 6 shows this index tends to provide moderately good estimates: each plot in the Figure shows the successive removals of an aircraft as white circles. Time index i is presented on the x-axis while the observed removal time value T_{ij} is on the y-axis.

In Figure 6, two dashed lines are also shown. These lower and upper lines correspond to the support (s_{ij}) and resistance levels (r_{ij}), that is the minimum past removal time and the maximum past removal time seen to date. These concepts borrowed from technical analysis and stock trade (Edwards, Magee, & Bassetti, 2007) allow us to set reasonable boundaries for the d_{ij} values.

Using the boundary values of support and resistance levels it is assumed the removal time d_{ij} does not go above maximum removal time (resistance) or below minimum removal time (support). Please note that in the computation of these thresholds we also use the boxplot outlier detection method.

3.4. Methodology

In this study we used the comparative research method to test our main hypothesis:

> H1: Predictive time-based Support Vector Machines (SVM) models can outperform traditional prognostics models based on statistical techniques (Weibull analysis) and forecasting techniques (ARMA model).

To test this hypothesis, the three modeling approaches previously described were compared:

- Life Usage (LU) (*baseline*): the calculation of the life of the equipment is based on a Weibull distribution.
- Auto-regressive Moving Average (ARMA): an ARMA model is used to predict the future life of the equipment based on past reliability time series (removal history).
- Support Vector Machine (SVM): a linear SVM model is constructed from a degradation index. This approach is distinct from the previous as it is data-driven (Schwabacher, 2005), meaning it is mostly focused on the information (data) making no a-priori assumptions on the data relations (Si, Wang, Hu, & Zhou, 2011).

In this study the target variable was the future life of the equipment at time index i (T_i). Model accuracy was evaluated and compared in terms of mean absolute error (MAE), mean-square (MSE), mean absolute percentage error (MAPE), root-mean-square (RMSE), and mean error (ME) which is also designated mean bias. Table 2 details the used metrics.

4. RESULTS

The accuracy and performance results of the comparative research study are shown in Table 3. Here, the absolute (MAE), mean (ME) square errors (RMSE) are important metrics as they report how much the model predictions deviated from reality in absolute terms.

The mean error (ME) of the Life Usage (LU), ARMA and SVM models indicate the forecasts do not tend to be inherently biased – i.e., they are not (on average) disproportionately positive or negative. This can also be observed in the third column of Figure 7. Here, for each approach, the residuals of each aircraft are shown. As illustrated, the residuals of the SVM approach do not exhibit substantial bias even tough there is a tendency towards towards over-prediction (ME=31.85 days).

Regarding the Mean Absolute Error (MAE), the SVM model

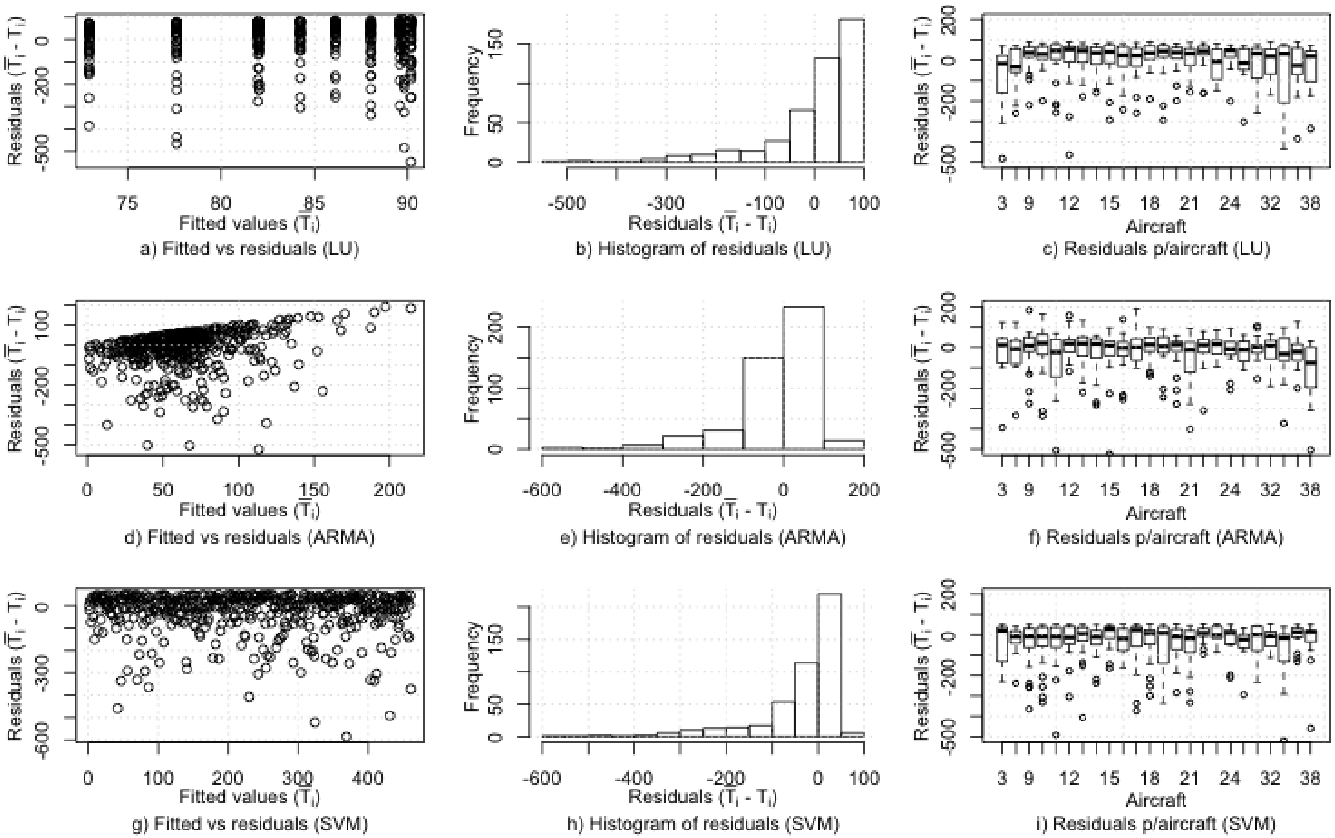

Figure 7. Model validation graphs. Top to bottom plots: comparison of Life Usage (LU), ARMA and SVM models. Left to right plots: a,d,g) Fitted values vs residuals (homoscedasticity), b,e,h) Histogram of the residuals (normality) and c,f,i) Boxplot of residuals per aircraft. The first set of plots examine how each of the approaches were able to generate homoscedastic residuals, that is, residuals are approximately equal for all predicted values. The second set of plots analyze residuals normality. Finally, the final plots exhibit residual distribution per aircraft.

Table 2. Performance metrics used in comparative study.

Metric	Abbr	Formula
Mean error	ME	$\frac{1}{N}\sum_{i=1}^{N}(\hat{T}_i - T_i)$
Mean squared error (days)	MSE	$\frac{1}{N}\sum_{i=1}^{N}\left(\hat{T}_i - T_i\right)^2$
Root mean squared error (days)	RMSE	$\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{T}_i - T_i\right)^2}$
Mean absolute percentage error (%)	MAPE	$\frac{1}{N}\sum_{t=1}^{N}\left\lvert\frac{\hat{T}_i - T_i}{T_i}\right\rvert$
Mean absolute error (days)	MAE	$\frac{1}{N}\sum_{i=1}^{N}\left\lvert\hat{T}_i - T_i\right\rvert$

Note: N stands for number of observations in testing set. For each observation T_i at time index i, the model outputs the $\hat{T}_i$ prediction. Here, variable T_i means equipment life or, the removal time value at time index i.

presented the best results with an error of 61.90 days against the results of 68.91 and 66.20 days of the LU and ARMA models. Please note that this difference of 7 (SVM vs LU) and 4 days (SVM vs ARMA) is significant in the context of (aeronautics) maintenance planning for the long run. In percentage terms, this result represented an improvement of around 10 and 6% in predictive accuracy. The Mean Percentage Error (MAPE) of the model also showed a considerable improvement compared to the other approaches.

Regarding the Root Mean Squared Error (RMSE), the three models had comparable results (third line of Table 3). As

Table 3. Accuracy and performance results.

Metric	Life Usage (LU)	ARMA	SVM
MAE (days)	68.91	66.20	61.90
ME (days)	1.42	-18.86	31.85
MSE	9524.40	10279.02	9540.49
RMSE	97.59	101.39	97.67
MAPE	556.76	417.74	332.12
Time (s)	0.14	0.35	15.34

* Time stands for processing time (seconds), ME for Mean Error (days) where ME = mean(simulated - observed), MAPE for Mean Absolute Percentage Error (MAPE), MAE for Mean Absolute Error (days) and RMSE for Root Squared Mean Error.

a measure of the model error standard deviation, this result suggests the prediction errors of the tested models vary in the same magnitude.

Regarding computational performance, the life usage (LU) model exhibited the best results $-$ 0.14s vs the 0.35s of the ARMA model and the 15.34s of the Linear SVM model. However, overall, all models exhibited a reasonable performance given that these were time-based models processing N=485 removals.

We present a residual analysis for the three compared approaches in Figure 7. Here, the residuals of each prediction model are computed as the difference between the fitted values and the actual values: $e_i = \overline{T_i} - T_i$. In Figure 7, three plots are shown for each model with LU on top, ARMA middle and SVM in the bottom row.

From left to right, the first charts of Figure compare the model fitted values against the corresponding residuals. These plots should by definition, show no clear pattern $-$ if no pattern is observed, there is “homoscedasticity” in the residuals, meaning modeling errors are uncorrelated and uniform (Cook & Weisberg, 1982). An observation of the first column of Figure 7 shows that the best models in this dimension are the ARMA and SVM models. While residuals of the LU model are projected along the 10 vertical lines corresponding to the characteristic lives of the 10-fold Weibull distributions, the residuals of the ARMA and SVM model are more scattered along the x-y plane.

Even though it is not essential for forecasting that residuals are normally distributed (Cook & Weisberg, 1982), this is a positive trait, as it facilitates the calculation of prediction intervals. Here, the ARMA model provide stronger evidence to hold the assumption of normality than the LU model, as shown in the second-column charts of Figure 7.

All the studied models had residuals that seemed to be slightly negatively skewed, even though this tendency was more pronounced in the ARMA model. This is not surprising, as the ARMA model outputs predictions based on a data set of past removals which may include outlier data, that is, extremely long or short past removals. The SVM model in contrast, by its technical construction and due to its specific degradation index, can deal better with this kind of problem.

Comparing the SVM and the ARMA model in regards to residual distribution per aircraft (Figures 7f and 7i), both have comparable results in regards to their under-predictions (residuals below zero) even though the ARMA model appears to be slightly better. In contrast and in regards to over-prediction errors, the SVM model is better than ARMA.

In conclusion, and disregarding the inferior computational performance, the results obtained in this case study (show in Table 3) appear to suggest that the SVM model has a better accuracy performance than the contrasting LU and ARMA models. Accordingly, we conclude there is sufficient evidence to support hypothesis **H1** (Section 3.4).

5. CONCLUSION

For most industrial and commercial equipment, time-based maintenance continues to be a dominant maintenance policy, as it is a strategy easy to implement and the technology involved is not as costly as in condition-monitored policies. It is often the preferred solution for systems with a minimal variation in usage and when the associated degradation process varies proportionally with time.

In this paper, we proposed a new type of prognostics model for improved time-based maintenance. Based on a data set of cross-sectional time series of past maintenance actions, the model used several techniques to compose a degradation index that was then combined into a linear Support Vector Machines (SVM) model. The novelty of our work lies on the use of a new data-driven technique, not usually applied in time-based maintenance, and the construction of the degradation index using a set of techniques from statistics, technical analysis and outlier detection.

On this comparative case study, it was shown that the proposed SVM model could provide significantly better estimates for the next maintenance event than traditional time-based maintenance models. Also, the proposed model outperformed, in most metrics, an ARMA model, a traditional forecasting technique.

Overall, our results suggested time-based maintenance may be enhanced by the use of data-driven modeling. As future research, we intend to explore other data-driven techniques for time-based maintenance. Concretely, we are interested in the study of how to deal with prediction uncertainty in this kind of time-based models, using for instance, techniques such as Relevance Vector Machines (RVMs) and Bayesian Models (BM), that is, techniques which can provide probabilistic solutions for regressive prognostics.

NOMENCLATURE

Most relevant nomenclature used in paper follows.

T	Remaining time to removal
MRO	Maintenance and Repair Operations
HM	Health Monitoring
PHM	Prognostics and Health Monitoring
PDF	Probability Density Function
CDF	Cumulative Distribution Function
RUL	Remaining useful life
SVM	Support Vector Machines
MAE	Mean Absolute Error
$MAPE$	Mean Absolute Percentage Error
MSE	Mean Squared Error
$RMSE$	Root Mean Squared Error
ME	Mean Error (Standard Error)

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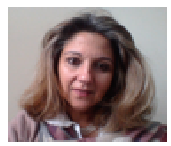

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