REPLACEMENT INTERVAL OPTIMIZATION FOR AIRCRAFT MAINTENANCE

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SUMMARY

This paper deals with possible approaches to optimization of maintenance strategy of complex systems. It is based on the experience with Aircraft systems and their elements, but the methodology can be applied to any industry.

It is well known that Preventive Maintenance applied instead of (or in addition to) Corrective Maintenance may increase Reliability yet influencing expenses: cost of maintenance and downtime losses. Optimization of Preventive Maintenance Plan can lead to considerable savings and improve profitability of equipment users.

Two main approaches based on available data for system elements are used for the optimization of the Preventive Maintenance:

- Traditional statistical approach, based on the reliability characteristics of the population of items,
- PHM approach, based on measureable parameters of the individual items.

The paper considers both approaches, their advantages and disadvantages, and proposes improvements to them.

According to the traditional statistical approach, cost and efficiency of Preventive Maintenance depend on the Inspection/Replacement Intervals (IRI). Shorter IRI means higher reliability and less downtime penalties, but higher maintenance cost. Consequently, the task of selection of the optimal value of IRI taking into account trade-offs between two components of the Total Operational Cost: maintenance cost and operational penalties/losses, is of great interest. This paper suggests a model and a numerical method to evaluate Reliability distribution parameters of Aircraft items and a way of using these parameters for further optimal selection of IRI value.

The optimization uses a loss function of a special type which takes into account asymmetry of losses due to premature and late replacement, non-linearity of the Target Function, etc.

PHM approach is based on estimation of Remaining Useful Life (RUL) of Aircraft items, by means of advanced Prognostic Methodology resulting in Optimization of Preventive Maintenance. Most traditional models of PHM do not take into account specific characteristics of a loss function. A unique model of PHM has been developed, implementing Critical Zone Recognition to see whether Remaining Useful Life (RUL) of the item exceeds predefined critical value, i.e. entering the predefined critical zone (instead of traditional RUL calculation using regression). The model is based on the Support Vector Classification (SVC) approach, adjusted to the proposed loss function.

1 INTRODUCTION

Service and maintenance cost for every product-in-use is one of the major contributors and significant appraising factors of warranty charges and service budget. On the other hand, maintenance cost is closely related to the product reliability. Ability to control the behavior of the reliability function and consequently - the capability of ILS elements optimization (spare parts, test and support equipment, manpower, training, etc.), depends in its turn upon appropriate forecast of probable reliability deterioration and is crucial for a the product cost-effectiveness and competitiveness.

From the contractual point of view, incompliance with a guaranteed availability/dispatch reliability targets may invoke contractual penalties and even loss of future business.

Airplane consists of a great number of subsystems and components, all being a subject to fail; therefore a typical task for such a System of Systems development is Reliability, Maintainability and Availability Analysis performed in order to decide about an efficient maintenance policy, especially the relationship between proactive, preventive and reactive activities.

Preventive Maintenance (PM) is known to be efficient only for equipment which is subject to deterioration, i.e. with increasing failure rate, and can be inspected periodically. So the question is how to choose an optimal value of inspection interval and the right time for performing a specially defined PM with suitable accuracy and consistency.

Every Maintenance Action (MA) can be categorized as one of the following three types:

- Inspection (Inn). Is used to identify the equipment conditions of hidden failures. After an Inn, based on a system's condition, either preventive maintenance is performed, or no action is taken.
- Corrective Maintenance (CM). Is used to restore a system after a failure to initial status and so it does not depend on inspections.
- Preventive Maintenance (PM). Is used to restore a system to initial state before failure, according to inspection result.

For various systems, two alternatives are possible:

- Current operating state of a system can be identified by measureable critical parameters. The deterioration status, when the parameter exceeds the predefined control limit, is interpreted as a critical violation (failure). We use the term "critical", as we consider violations causing the necessity of an item's overhaul or replacement. Critical parameters can be measured during inspections. An example could be a tire protector depth. Preventive maintenance is replacement of the tire, if this depth is too low. Such tasks are known as PHM (Prognostics and Health Management) and they are considered in many articles (see, e.g., [1–3, 11-13]).

There is no critical parameter, or values of this parameter cannot be measured. Under this assumption we have to suppose, that following an inspection, restoration is performed, if needed. Such a repair, adjustment or replacement is done simultaneously with inspection. In this case, the task is only to select optimal value of Inspection (adjustment/repair/replacement) interval.

The rest of the article is organized as follows: Various techniques to define deterioration parameters are considered in Chapter 2. In Chapter 3, we present how the Cross-Entropy method can be applied to search required Weibull parameters. The task of selection of the optimal value of replacement interval is considered in Chapter 4. In Chapter 5 we illustrate the proposed technique using some numerical examples. Chapter 6 describes the PHM approach to the problem. Then, short conclusions are presented in Chapter 7.

2 DEFINITION OF DISTRIBUTION PARAMETERS

We consider a replaceable item of an aircraft and assume that the future operating and environmental conditions will remain the same. Both corrective and preventive maintenance bring the system to an "as good as new" state. During inspection a replacement is performed.

Simple but typical example of this situation is checking the tire pressure in a car. Usually some restoration (in our example - adding some pressure to keep it at defined level) is performed simultaneously with checking.

Let's consider a system with failure rate that follows a Weibull Distribution with parameters θ and β, i.e. the probability, that failure time is less than t, is distributed according to Weibull Cumulative Distribution Function:

$$F(t) = 1 - e^{-\left(\frac{t}{\theta}\right)^{\beta}} \tag{1}$$

where θ is scale parameter and β is shape parameter. The corresponding Probability Density Function is:

$$f(t) = \beta \cdot t^{\beta-1} \cdot \theta^{-\beta} \cdot e^{-(\frac{t}{\theta})^{\beta}} \tag{2}$$

Periodically the system is removed from operation for inspection/replacement. Replacement Interval (time between replacements) is a Control Parameter and it may be obtained by means of optimization. The Optimization Criterion is Total Cost. So, the first task is to define Weibull parameters by means of processing the available statistics. If statistics contain only the times of failures, the appropriate method is Least Squares applied to so called Weibull probability paper.

Since data are often inaccurate, it is important to try and extract any information we can from poorer data. Failure events may be grouped, so an exact time of a failure is unknown, rather a failure interval is given, or components may be "suspended" so that they are removed from service at a certain time although they did not fail. This information, if used in conjunction with accurate data, is very helpful in improving our estimates of the failure distribution parameters and verifying the shape of the distribution.

Typically the Maximum Likelihood Estimate (MLE) is used when we have mixed data including inaccurate failure times. The MLE uses a proposed distribution to model both failures at known times and failures over an interval. It models suspended components using the probability that they have not failed at the suspension time. In this way it is possible to make use of all the data, even if the number of accurate data points is small. Expressions for Negative Logarithmic Likelihood (NLL), depending of the type of data, are as follows:

- For single failure i with failure time of TFi we get $NLL_i = - \ln(f(TF_i))$;
- For single censored event i with censored time of TCi we get $NLL_i = - \ln(1 - F(TC_i))$;
- For single interval data i with interval times of $\{TL_i \ldots TH_i\}$ we get $NLL_i = - \ln(F(TH_i - F(TL_i))$;
- For grouped data of amount q the $NLL = q \cdot NLL_i$

Full Negative Logarithmic Likelihood is the sum of NLL of single and grouped data. Our goal is to search for values of parameters θ and β for which Full Negative Logarithmic Likelihood will be minimal.

3 CROSS-ENTROPY ALGORITHM FOR GLOBAL OPTIMIZATION

Global Optimization of non-linear function is a common task of many practical problems. For these numerous cases we have to look for parameters by means of non-linear and non-convex, global optimization. Our task is to find the value of Z that provides min G(Z) under constraints

$$Low_j \Leftarrow z[j] \Leftarrow High_j\,, \quad j = 1 \ldots. K,_{+} \tag{3}$$

where:

- Z = {z[1],…,z[j],…z[K]} is a set (vector) of parameters
- K is amount of parameters
- Low_j is Low Boundary of Parameter j value (j = 1…K)
- $High_j$ is High Boundary of Parameter j value (j = 1…K)
- G is a Target Function (analytical-form or, perhaps, table or even algorithm-calculated-form), dependent of vector Z.

For Global Optimization Task, we propose to use one of the RANDOM SEARCH oriented methods – Cross-Entropy Optimization [4, 5]. It is a relatively new random-search oriented approach (for example, in comparison with Genetic Algorithm, implemented as Toolbox on Matlab), but it provides very good results for several similar tasks [6, 12, 13]. The method derives its name from the cross-entropy (or Kullback-Leibler) distance - a well-known measure of "information", which has been successfully employed in diverse fields of engineering and science, and in particular in neural computation, for about half a century. Initially the Cross-Entropy method was developed for discrete optimization, but later it was successfully extended for continuous optimization [4]. The Cross-Entropy method is an iterative method, which involves the following two phases:

- Generation of a sample of random data. Size of this data is 500 - 5000 random vectors on each algorithm step, amount of steps is 50 - 100. Generation is performed according to a specified random mechanism.
- Updating the parameters of the random mechanism, on the basis of the data, in order to produce a 'better" sample in the next iteration. Choice of these parameters is performed by means of maximization of Cross-Entropy function. This optimization is performed on each algorithm step, but differently from global optimization, this optimization is usually performed VERY EASILY and QUICKLY, because Cross-Entropy function is convex.

In the first phase we generate sample $Z_1 \ldots Z_V \ldots Z_N$, which is the size of N different parameter sets. This generation is performed according to common Probability Density Function F(Z) for parameter vector Z, which was calculated on the previous step of the algorithm.

For each v from N (v = 1,…,N) generated parameter vectors the value of Target Function is calculated. Then best N_{EL} (N_{EL} = 10,…,50) parameter vectors Z from all N generated are selected from full sample – it is named ELITE part. This selection is performed according to Target Function values, i.e. parameter vector with number 1 will have minimum value of Target Function, parameter vector with number 2 will have second value of Target Function, and parameter vector with number N_{EL} will have N_{EL} ordered value of Target Function.

After this, the algorithm calculates new values of the Probability Density Function F(Z) – it is the second phase of each algorithm step.

The aim of the use of the new function F(Z) is to maximize Cross-Entropy Function. In the general case the Cross-Entropy Function is the following:

$$\sum_{v=1}^{N_{EL}} \ln\{F(Z_V)\}, \tag{4}$$

which is Kullback-Leibler probability measure of distance between different Probability Density Functions. In this formula Z_V – value of generated parameter vector on the v-th set of Elite part of current sample.

So, first we have to choose a type of PDF to generate random parameter vectors Z. For continuous optimization we can use the following types of PDF:

- Beta PDF.
- Normal PDF.Double-Exponential PDF, etc.

Using Normal PDF F(Z) is advantageous, since in contrast to Beta and Double-Exponential PDFs, the Normal PDF allows analytical solution. Other types of PDF require numerical solution. Parameters of Normal PDF (Mean and Covariance Matrix) of function F(Z) can be calculated analytically:

$$\text{Mean}\,[j] = \sum_{v=1}^{N_{EL}} \frac{Z_V[j]}{N_{EL}} \tag{5}$$

$$\text{Covariance}\,[i,j] = \sum_{v=1}^{N_{EL}} \left(Z_V[i] - \text{Mean}\,[i]\right) \frac{\left(Z_V[j] - \text{Mean}\,[j]\right)}{N_{EL}} \ \ldots\, i, j = 1 \ldots K \tag{6}$$

We have to prevent too early occurrences of the PDF parameter, because in this case optimization is stopped wrongly (PDF will be simply Dirak function!). For this purpose, instead of a simple choice by means of independent current step result analysis, we will use smoothed updating procedure:

- $\text{Mean}[j](t) = \alpha\, \text{Mean}_{prel}[j](t) + (1 - \alpha)\text{Mean}[j](t-1)$ (7)

where:

$\text{Mean}_{prel}[j](t)$ – preliminary value of Mean[j], which we had got on current step t, i.e. before smoothed updating,

Mean[j](t) – final value of Mean[j], which we had got on current step t, i.e. after smoothed updating,

Mean[j] (t-1) – final value of Mean[j], which we had got on previously step (t-1),

α – smoothing parameter for Mean updating,

t – step number

- $\text{Cov}[i,j](t) = \zeta(t)\text{Covprel}\,[i,j](t) + (1-\zeta(t))\text{Cov}[i,j](t-1)$, (8)
- $\zeta(t) = \zeta - \zeta(\,(1 - 1/t)\gamma$, (9)

where:

$\text{Cov}_{prel}[i, j](t)$ – preliminary value of Covariance[i, j], which we had got on the current step t, i.e. before smoothed updating,

Cov[i, j](t) – final value of Covariance[i, j], which we had got on the current step t, i.e. after smoothed updating,

Cov[i, j](t-1) – final value of Covariance[i, j], which we had got on previous step (t-1),

ζ and γ – smoothing parameters for Covariance updating.

As seen, for PDF parameter Mean we use fixed smoothing parameter α and for PDF parameter Covariance we use dynamic (dependent on step number) smoothing parameter $\zeta(t)$.

4 MODEL FOR REPLACEMENT INTERVAL SELECTION

To select optimal replacement interval, we should calculate Total Cost depending on the Replacement Interval value. Input data for this calculation are the following:

- v - Assigned Replacement Interval
- θ and β – Weibull distribution scale and shape parameters

for the analyzed aircraft item

- C_{pen} – Penalty per hour for the "replacement duration more than some predefined value" (for Corrective Maintenance only)
- P_{pen} – Probability of the "replacement duration more than some predefined value" (for Corrective Maintenance only)
- T_{pen} – Average delay for the "replacement duration more than some predefined value" (for Corrective Maintenance only)
- C_r – Labor and Material Cost per single replacement
- T – Operating Time

$$\text{Total Cost} = (P_{cm} \cdot A_r) \cdot (C_r + P_{pen} \cdot C_{pen} \cdot T_{pen}) + (P_{pm} \cdot A_r) \cdot C_r, \quad (10)$$

$$A_r = \frac{T}{P_{cm} \cdot W + P_{pm} \cdot v} \quad (11)$$

total amount of replacements during Operating Time

$$P_{cm} = 1 - e^{-(\frac{\theta}{v})^{\beta}} \quad (12)$$

Probability of Corrective Maintenance

$$P_{pm} = e^{-(\frac{\theta}{v})^{\beta}} \quad (13)$$

Probability of Preventive Maintenance

$$W = \int_0^v f(t)dt \quad (14)$$

Mean Working Time before Corrective Maintenance

The task is to select Optimal Replacement Interval (v) so that Total Cost will be minimum.

5 CASE STUDY

Consider one of the Aircraft Items with the following input parameters:

$$C_r = 22{,}000; \quad C_{pen} = 43{,}000;$$

Input statistics contain both Failure Times (59 events) and Suspended Times (180 events). The data have been analyzed and the parameters of the Weibull distribution have been estimated:

- β = 2.77; θ = 25,903 (hours) ;

Based on input statistics, also the following parameters were defined:

- P_{pen} = 20/59; T_{pen} = 125/60 (hours)

The following output results were obtained:

- Optimal Replacement Interval = 19,090 hours; Percentage replaced preventively = 65%

The graph below presents the Total Annual Cost for the analyzed item, including maintenance costs and downtime costs. This Total Annual Cost is a function of a replacement interval. The axes of the graphs are:

- Horizontal - Replacement interval (x10,000 hours)
- Vertical - Total Annual Cost

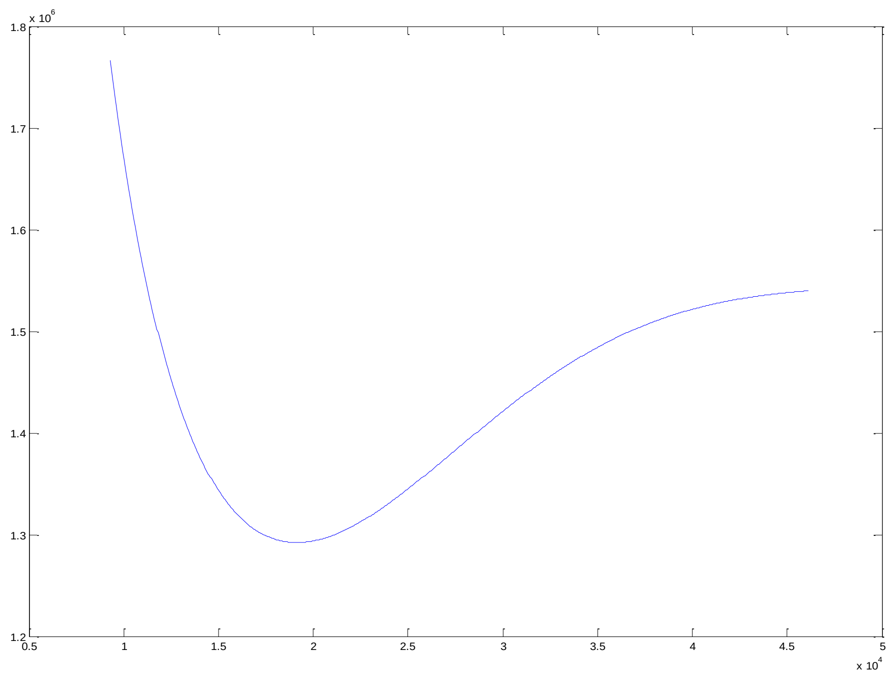

Figure 1. Total Cost VS Replacement Interval

The graphs above demonstrate high sensitivity to replacement interval length in the area of the optimum value.

6 PHM APPROACH

As mentioned in Chapter 1, two alternatives are possible for Preventive Maintenance planning – Traditional approach and PHM approach.

Traditional approach is described above for one practical case, assuming Weibull distribution for the whole PUO FAMILY - family of the products under observation (PUO) - and optimizing the Replacement Interval after the Weibull distribution parameters estimation.

PHM approach is dealing with every individual PUO separately taking into account its critical characteristics measurements.

It is evident that PHM approach may be more effective, because it supposes tailoring of the individual maintenance procedure for each PUO. But it is not always possible. Two conditions are necessary for using PHM approach:

- Devices should have some parameters (or at least one parameter), which can describe aging or deterioration of the device;
- A sensor(s) should exist in order to measure and investigate the trend of the parameter(s) over time.

For example, for aircraft items like a “window” the PHM approach is hardly applicable, because for a window such critical parameter(s) probably does not exist.

On the other hand, for the aircraft item "engine" PHM is completely applicable, see [9, 10] where a set of the 24 aircraft engine indicators was applied, which allows to consider aging of one separately taken single item.

The basic tasks of the PHM are Failure Prognostics (performed before a failure occurs) and Failure Diagnostics (performed after failure occurs). Prognostic systems are expected to provide predictive information about the Remaining Useful Life (RUL) of the PUO. For the purpose of PM optimization, the traditional prognostics’ goal of the RUL value calculation (prediction), based on historical data, is very appropriate. A lot of methods, based on “supervised learning” were proposed in recent years for more accurate RUL prediction and prognostic of time-to-failure. Different strategies, used for RUL estimation, including Similarity-based Prognostics [1], Artificial Neural Networks [2, 3] and others, have been explored extensively for equipment fault prognostics. These methods take into account possible real life loss functions (scores, penalties, output criteria) for the prediction inaccuracy (see, e.g., [7-8, 1, 3, 12-13]). These Loss functions may be different in shape and amplitude, with symmetrical or asymmetrical profile, etc., approximating the losses which may happen in reality. For example, in the IEEE PHM 2012 Prognostic Challenge [13], the score of the single item RUL prediction was defined as exponential penalty to the relative prediction error and the score of an algorithm was defined as the overall score for all Products under Observation RUL prediction. As written in [13], "Underestimates and overestimates have not be considered in the same manner: good performance of estimates related to early predictions of RUL, with deduction to early removal, and more severe deductions for RUL estimates that exceeded actual component RUL". Nevertheless, in the PHM-2008 Prognostics Data Challenge [7-8, 1] the score of the single RUL prediction was defined as exponential penalty regarded to the absolute prediction error.

Thus, for the prognostic determination of the optimal Inspection interval for each individual Item, based on the RUL calculation (based on regression), the well-known approach for the stated Loss function (score) should be used and the optimal value should be chosen, minimizing the overall losses.

As seen on the Figure 2, usually the experimental data are contaminated with significant measurement noise.

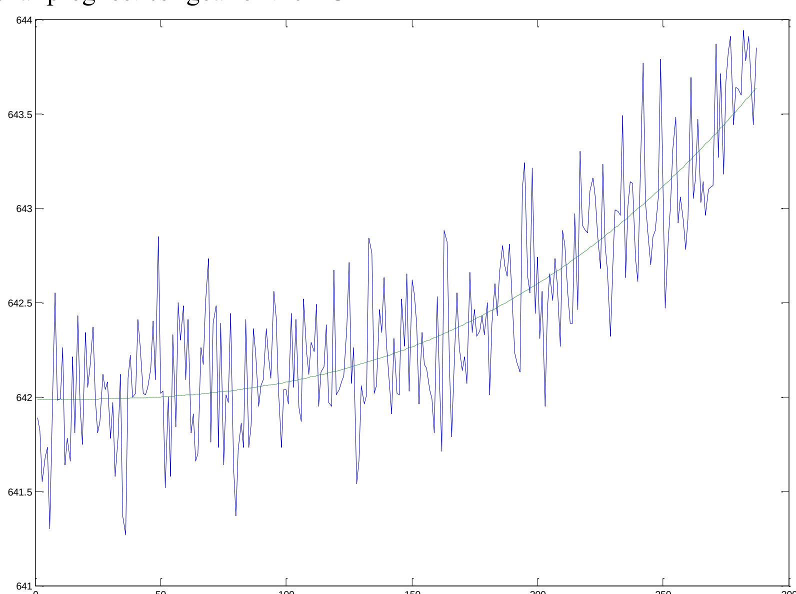

Figure 2. Typical plot of the trendable parameter behavior – before and after smoothing.

According to the behaviour of this parameter it is possible to produce a "fitting by monotone curve" and later on perform the multi-parameter analysis using smoothed data rather than the original.

So, the first task is de-noising of input statistics to get monotonic function as a better representation of device degradation process. Monotonic Fitting is performed by non-linear regression methods which use different types of smoothed functions, like: polynomial functions, exponential functions, etc. For polynomial smoothing the following function is used to fit the measurement series:

$$F(t)=A+Bt^{C}. \tag{15}$$

For exponential smoothing the following function is used:

$$F(t)=A+Be^{Ct}. \tag{16}$$

where t is the age of the unit, $F(t)$ is fitted measurement value.

Therefore, the smoothed function has 3 parameters. These parameters can be determined using least-square method based on the actual measurement time-series, or using relatively new random search-oriented approach - Cross-Entropy Algorithm [4, 5] - which provides very good results in getting the optimal values for those 3 parameters. Initially the Cross-Entropy method was developed for discrete optimization, but later was successfully extended for continuous optimization. Using the Cross-Entropy method, one can find the optimal prognostic value of the Inspection interval, minimizing possible losses.

But it seems that in PM planning case it is not necessary to estimate the “exact” moment of optimal PM performance, rather it is important to understand whether or not the current PUO (actually, its lifetime) achieved the critical zone? In other words, the question is not “how long is RUL of the PUO”, but “Is the RUL less that the pre-defined Critical Value (Critical RUL) or not”?

To solve this problem, the Classification Approach rather than Regression Approach was proposed [11]: to recognize entering the critical zone.

In general, Classification Approach is more applicable for recognition tasks. But on the other hand, Classification methods have very serious disadvantage: they provide a binary answer “yes/no” only (whether or not the current object belongs to the "positive" or to the "negative" class?) and do not consider more detailed information, such as real error magnitude, in our case - distance of the object from the Critical point. For Critical Zone Recognition it is impossible to use criteria, proposed in [7-8, 13], because there is no predicted RUL value - output will be only “the recognized class” (positive or negative in respect to critical zone). Traditional classification approach deals only with labels (binary or multi-values) and usually doesn't consider quantitative parameters, such as RUL. So, how one could take into account the Loss function such as in the chapters 4 and 5? Indeed, how could we take into account the asymmetry of penalty for underestimates and overestimates, distance from the real value of the failure time, so necessary for PM interval determination?

To solve this problem, a mixed, combined approach was developed – to use "classification-based methods" (and their advantages) concurrently with "regression-based criteria" (with their advantages) [11].

Recognition tasks usually use different criteria (Accuracy, Sensitivity, Specificity, Precision, Recall, F1 measure, etc.) based on primary output parameters:

- #TP (true positives) is amount of positive examples, correctly classified.
- #TN (true negatives) is amount of negative examples, correctly classified.
- #FP (false positives) is number of negative examples, incorrectly classified as positive; this is amount of Type_1 Errors to include "garbage" (determined as a positive instance when it is not).
- #FN (False Negatives) is number of positive examples incorrectly classified as negative; this is amount of Type_2 Errors, i.e. "loss" errors of really positive instances.

Usually, the performance of a classifier is measured in terms of accuracy based on the comparison of the classifiers of the true prediction:

Accuracy = (#TP + #TN)/((#TP + #TN + #FP + #FN) (17)

But this and other traditional classification criteria do not take into account both asymmetric scoring functions (which are preferred for early prediction) and different penalty for different distance of real RUL value from critical zone. To take into account asymmetric scoring functions, it is possible to use the following simple measure:

Simple_Score = #FP +2* #FN (18)

We should modify regression criteria to consider features of recognition task, e.g. modified criteria from [7] to evaluate item number “i” as following:

$$Linear\_Score_i = \begin{cases} 0, if\ (TP_i = 1\ or\ TN_i = 1) \\ RUL_i - Critical\_Rul,\ if\ FP_i = 1 \\ 2(Critical\_Rul - RUL_i),\ if\ FN_i = 1 \end{cases}$$

$$Complex\_Score_i = \begin{cases} 0, if\ (TP_i = 1\ or\ TN_i = 1) \\ e^{\left(\frac{RUL_i - Critical\_Rul}{13}\right)},\ if\ FP_i = 1 \\ e^{\left(\frac{Critical\_Rul - RUL_i}{10}\right)},\ if\ FN_i = 1 \end{cases} \tag{20}$$

Full_Score is defined as $\sum(\mathrm{Linear\_Score}_i)$ or $\sum(\mathrm{Complex\_Score}_i)$. Using Cross-Validation instrument one should select values of control parameters to minimize Full_Score.

In [11] the case of trendability statistics with large amount of units in learning data set is described, and the classification-based model of the data-driven prognostics methods is compared with the regression-based model. The following table, constructed for the PHM application [11] experimental result using the NASA Ames Research Center engines data, shows that classification-based model produces better critical zone prediction estimations compared to regression-based model. To check stability of the conclusions, a comparison between SVR and SVS has been performed independently 3 times – according to criteria Simple Score, Linear Score and Complex Score. First, the 2-fold Cross-Validation was made independently for these criteria – to select optimal values of control parameters, and after this, based on the selected values, output parameters for the Test Data Set have been calculated. The output results are summarized on the Table I:

Output Parameters	**Type of Score**					
	Simple Score		***Linear Score***		***Complex Score***	
	SVR	***SVC***	***SVR***	***SVC***	***SVR***	***SVC***
#FP	1	1	1	1	1	1
#FN	5	4	5	5	5	4
Mean Relat. Error (%)	15.6	-	14.7	-	14.7	-
Accuracy (%)	-	95	-	94	-	95
SCORE	**11**	**9**	**15**	**7**	**1.00**	**0.19**

Table I.

The proposed approach to critical zone recognition was validated using the monitoring data, collected by NASA[8]. An experimental result shows that classification-based model produces better critical zone prediction estimations than a regression-based model.

7 CONCLUSION

In this paper, we analyzed replacement-based preventive maintenance in operational aircraft items, in which two types of maintenance are performed – Corrective Maintenance and Preventive Maintenance. The paper outlines the advantage of replacement-based maintenance over pure corrective maintenance. It is explained how to obtain the optimal value of replacement interval minimizing expected total cost for an assumed set of parameter values. Finally, it has been shown how to get the optimal decision about PM performance for every single individual item (PHM approach) using Classification Machine instead of Regression one.

Clearly, PHM approach and "Condition Based Maintenance" strategy, based on it, are much more efficient than the traditional approach to PM, applying the same maintenance interval to all products of the same type. Thus, if the monitoring of the physical condition of individual PUO is feasible, PHM approach will produce better results. If PHM approach is used, it is presented and recommended in this paper to use Classification methodology for recognition of entering the Critical Zone, instead of classical Regression approach.

If the monitoring of the physical condition of individual PUO is unfeasible (if there are no appropriate sensors or data collection means), the only remaining possibility is the traditional Preventive Maintenance approach with one (optimal) replacement/inspection interval for all devices of the same type. In this case one has to estimate the PUO Family time-to-failure distribution. The General multimodal optimization method "Cross Entropy" is presented, illustrated and recommended as a universal approach.

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