RUL Prognostics and Critical Zone Recognition for Suspended Time-Series

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Abstract **– Prognostic systems are expected to provide predictive information about the Remaining Useful Life (RUL) for equipment and components. During the last ten years, numerous RUL prediction models have been developed. These methods usually treat completed time-series only, i.e. full statistics before the item fails. Under actual operating conditions occasionally number of failed items is too small, and therefore application of uncompleted (suspended) time-series is necessary, and using Semi-Supervised methods instead of Supervised is required. In this paper, we propose an approach based on regression and classification models we have introduced in the past [1, 2]. These models consider monitoring data (time-series) as inputs and RUL estimation as output. Significant difference of this model is using suspended time-series to estimate optimal RUL for each suspended time-series, so they can be used for initial model training.**

This article describes the procedures that have been developed and applied successfully for Suspended Time-Series using. Several models based on modification of the SVR and SVC methods (Support Vector Regression and Support Vector Classification) are proposed for consideration. Number of uncompleted time-series used for training and cross-validation is proposed as additional control parameter. Suggested methodology and algorithms were verified on the NASA Aircraft Engine database http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic- data-repository/). Numerical examples based on this database have been also considered. Experimental result shows that the proposed model performs significantly better estimations than pure supervised learning based model.

Keywords – Cross-Entropy, Cross-Validation, Prognostics, Remaining Useful Life, RUL Estimation, Suspended, SVR, SVC, Time-Series.

I. INTRODUCTION

A lot of methods known as "Prognostics and Health Management" (PHM) have been recently developed. These methods may be used for diagnostics and prognostics; they could be data-driven (model-free) and model-based (physics-based).

Data-driven prognostic techniques are based on information obtained from historical/statistical data. Most of the RUL presiction models developed during the last 10 years are based on the Supervised Machine Learning methods and could be applicable only for direct RUL calculation. These methods usually treat completed time-series only, i.e. full statistics before the item fails.

Under actual operating conditions, number of failed items occasionally is too small, therefore application of uncompleted (suspended) time-series is necessary, and using Semi-Supervised methods instead of Supervised is required. Generally it is always possible to use suspended time-series. Classical Supervised Learning approach is intended to use completed time-series as Learning Data Set and suspended (uncompleted) time-series as test data set, which should be calculated to obtain the RUL values. Semi-Supervised Learning approach is intended to use time-series from the Test Data Set (suspended, non-completed time series) for learning. This is not necessary for large number of completed time-series, because influence of suspended time-series is negligible. It is critical only for small number of completed time-series (less than ten).

The "Missing Data" problem is not new, and usually it considers classic regression models in preference to the time-series [3]. In traditional reliability theory, statistics that includes only few failure times is a typical situation. In this case, suspended times should be also used to construct the likelihood function and to calculate parameters of some probability density function e.g., Weibull. Some aspects of the suspended time-series using for RUL prediction are considered in article [4], and below we compare our approach with approach proposed in this article.

It has to be mentioned, that problem of "Missing Data" consideration is very important on practice.

PHM Commander developed by A.L.D., supports RUL prediction for different Failure Modes, Operational Conditions, Smoothing tools, etc. Next version of A.L.D. PHM Commander shall support suspended time-series.

Remaining part of the paper is organized as follows:

II. RUL Calculation and Critical Zone Estimation Approaches – shortly describes the suggested prediction algorithms.

III. Experimental Data – describes the data sets analysis used as basis for the research.

IV. The Proposed Approach Utilizing Full and Suspended Time-Series – describes the developed approach for suspended time-series compared to the approaches suggested previously.

- V. Conclusions.

II. RUL CALCULATION AND CRITICAL ZONE ESITMATION APPROACHES

Different strategies are used for remaining useful life estimation (RUL) using data-driven methods. Proposed algorithms are based on the classical SVM approach (Support Vector Machine) [5]: SVR (Support Vector Regression) is used for direct RUL calculation and SVC (Support Vector Classification) is used for critical Zone Recognition [2]. Typical scheme of SVM applying is illustrated in Fig. 1.

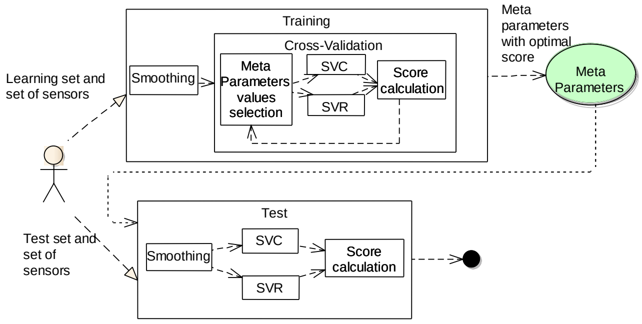

Figure 1. RUL Calculation and Critical Zone Recognition diagram

As can be seen in Fig. 2, experimental data is contaminated with large amount of measurement noise. So, the first task is to suppress the noise from input statistics in order to get monotonic function as improved performance of device degradation process.

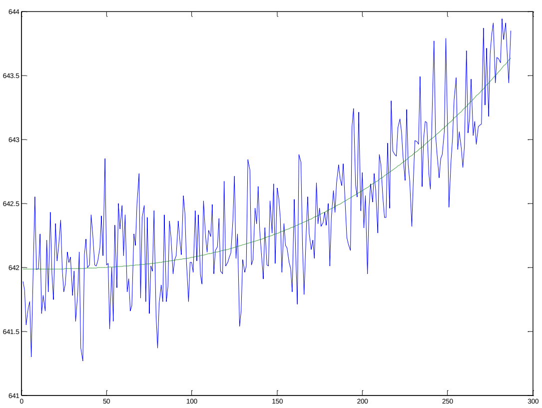

Figure 2. Typical plot of trendability parameter behavior – before and after smoothing

Monotonic Fitting is performed by non-linear regression methods, which may use different types of smoothed functions such as polynomial, exponential, etc. For polynomial smoothing, the following function is used to fit the measurement series:

$$F(t) = A + Bt^C .$$

For exponential smoothing, the following function is used:

$$F(t) = A + Be^{Ct} ,$$

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

Thus the smoothed function has 3 parameters, which may be determined using least-square method based on actual measurement time-series. In this work, we determine these parameters using Cross-Entropy Algorithm [6] to find the optimal values.

We have tested both the polynomial and exponential functions on many time-series collected from the Aircraft Engines NASA Data Repository [7], and found that both types of smoothing could not guarantee permanent stability. Therefore, new type of "combined" smoothing has been proposed: for each pair of unit and sensor we select type of smoothing (polynomial or exponential) to minimize the goal function value used in least-square method.

For each time-series of the pair (item, sensor) from Test Data Set we have done smoothing at the last measurement cycle. According to the data from Table I number of cycles they may vary from 31 to 303!).

Consider the data after smoothing: at time per cycle t, the input for RUL calculation or critical zone recognition (both for SVR and SVC methods) are L sets for S sensors with a space interval D, where:

- L is a length of used pre-history measurements
- D is a depth of used pre-history measurements
- S is number of sensors

The Training is followed by Quadratic Programming Task solving. For example, for classification we consider set $\{X_i, y_i\}$ as training data, which defines the correct classification using SVC, by dividing on hyper-plane, which follow the form:

$$y(\mathbf{X}) = \sum_{i=1}^{n} a_i y_i K(\boldsymbol{X}, \boldsymbol{X}_i) + b , \qquad (1)$$

where y_i is a label of vector $\boldsymbol{X}_i$, $K(\boldsymbol{X}, \boldsymbol{X}_i)$ is a kernel function, b is a bias, vector $\boldsymbol{X}$ has dimension S∗L and Training Set has dimension *n*. Binary variable y_i either "1" or "−1" is a label that denotes the class point $\boldsymbol{X}_i$ belongs to. Label "1" means that for point $\boldsymbol{X}_i$, the RUL is below or equal to the pre-defined Critical Value. Label "-1" means that for point X_i the RUL is above the pre-defined Critical Value.

The goal of the SVC method is to find and minimize the values: $a_1,...,a_n$:

$$\sum_{i=1}^{n}\sum_{p=1}^{n} a_i a_p y_i y_p K(X_i, X_p) - 2\sum_{i=1}^{n} a_i \ ,$$

$$\text{so that} \quad 0 \le a_i \le C_i, \sum_{i=1}^{n} a_i y_i = 0 \ .$$

For each new vector x, SVC goal function is calculated according to (1).

The following functions may be used as Kernel function: Linear, Polynomial, RBF (Radial Basis Function), etc. Kernel parameters (Kernel type, polynomial Kernel degree, RBF Delta, etc.) and penalty parameters C_i are the meta-parameters and defined as control parameters L, D and S using tuning methods based on Cross-Validation.

First we should perform the Cross-Validation to select the optimal values of control parameters, then based on the selected values, we can calculate output parameters for the Test Data Set.

III. Experimental Data

Proposed methodology for the RUL prediction and estimation is illustrated using Aircraft Engines real data set from the NASA Data Repository [7]. Data set comprises multiple multivariate time series (variables) from the different instances and is contaminated with measurement noise i.e. representing history of fault degradation process. In addition, information about engine condition and manufacturing parameters is not available. Data set includes information about 200 units: 100 units belong to the Learning Set, while 100 units belong to the Test Set. Unknown system has been run for a varied number of cycles on each unit data set (ground-air-ground) until the failure has been occurred. Table I summarizes statistics on the Learning and Test Data Sets.

TABLE I. INPUT STATISTICS CHARACTERISTICS

	Number of Cycles for Learning Data Set	*Number of Cycles for Test Data Set (Last Time of the Measurements)*	*RUL Values for the Last Cycle for Test Data Set*
Minimum	128	31	7
Maximum	341	303	145
Average	206	131	76
Standard Deviation	46	54	42

- 24 indicators are used in analyzed Data Set
- 3 indicators are described as “operational settings”
- 21 indicators are described as “sensor measurements”

As source data we use the time series of Cycle number vs Sensors (see Table II).

TABLE II. CYCLES VS SENSORS

Cycle / Sensor	1	5	19	22	30
Sensor 2	642.61	642.07	642.29	642.24	642.09
:					
Sensor 5	1395.48	1402.54	1397.51	1394.58	1396.49
:					
Sensor 8	554.76	554.64	554.26	554.63	554.78

IV. The Proposed Approach Applying Completed and Suspended Time-Series

Most of the RUL prediction methods ignore suspended time-series and use only completed time-series (before failure occurs). In article [4] it is suggested to use the following approach for suspended time-series (ANN stands for Artificial Neural Network):

"We can specify a failure time for a suspension history and train the ANN using the training set constructed based on that suspension history and all of the failure histories. For the suspension history, the optimal failure time is supposed to correspond to the trained ANN with the best training performance".

The principle of approach proposed in article [4] is following: for each suspended time-series, the RUL is selected so that average deviation of the actual RULs and calculated RULs is minimal for all completed time-series based on Cross-Validation including all completed time-series and single evaluated suspended time-series. According to the article [4], the RUL of suspended time-series is not calculated by means of the ANN model, but is simply selected based on large number of Cross-Validations.

From our point of view, this approach is applicable only for cases with a small number of the suspended time-series. In case study considered in article [4], the training data set consists of 2 full time-series and 4 suspended time-series. For cases with large number of suspended time-series using this approach is not effective. As shown above (Chapter 3), for experimental data comprising 3 completed time-series (Training Data Set) and 100 suspended time-series (Test Data set), accuracy of results based on this approach is unsatisfactory (see table III below). In our opinion, the reason for that is following: each RUL of the item from the Validation Data Set is calculated on very small number of time-series (2 completed time-series + 1 suspended time-series), but in fact it is possible to use significantly more time-series for RUL prediction: 2 completed time-series + 10…20 and more suspended time-series. Given the number of suspended time-series, we propose the following approach:

The first stage is to calculate the RUL for some of the Test Data Set suspended time-series based only on completed time-series from the Learning Data Set.

At the second stage, to calculate RULs for other suspended time-series from the Test Data Set based on completed time-series with exact measured RULs and suspended time-series with RULs calculated at the first stage.

Obviously, if we use small number of suspended time-series for RUL calculation, under-fitting of calculations occurs. Otherwise, if we use large number of earlier directly calculated suspended time-series, over-fitting of calculations occurs – influence of suspended time-series with approximate/calculated RULs values shall be significant, while influence of completed time-series with exact/measured values of RULs shall be insignificant. Thus there is some intermediate optimal number of suspended time-series for the direct calculations (first stage of calculations), which provides minimal error for RUL prediction. This optimal value is selected based on the Cross-Validation performing.

Notations:

- N_f – number of the units with completed time-series of measurements, corresponds to the size of Learning Data Set
- N_s – number of the units with suspended time-series of measurements, corresponds to the size of Test Data Set
- TL[i] – value of last time measurements of the i-th suspended time-series (i = 1… N_s)
- M_s – number of suspended time-series, for which their RUL values are calculated directly based on Nf completed time-series
- RUL_s[i] - corresponding RUL values of the i-th suspended time-series calculated directly based on N_f completed time-series (i = 1… Ms)

Variables N_f, N_s and TLi are the input parameters, variable Ms is the introduced optimized control parameter, variables RUL_s[i] are calculated parameters. We also use an additional control parameter – set of indexes of suspended time-series {j[1],…,j[i],…,j[Ms]}, for which their RUL values are calculated directly based on Nf completed time-series. To optimize this set using the Cross-Validation is impossible, because it requires a lot of computer time. Large time-series are more informative in comparison with small time-series, so we construct this set according to decreasing of the TL[i] values – so, we suppose that:

$$TL[1] \geq TL[2] \geq \ldots \geq TL[Ms] \geq \ldots \geq TL[Ns].$$

This assumption has been confirmed with experiments using NASA data set.

Detailed description of the proposed approach is following:

1. Select value for the M_s (M_s = 1… N_s)
2. Select the M_s suspended time-series according to TL[i] values decreasing, i = 1… N_s from Test Data Set
3. Calculate RULs of selected M_s suspended time-series (or calculate their labels – inside or outside the critical zone) by means of the SVR or SVC models described above (see Chapter 2) based on N_f completed time-series from Learning Data Set.
4. Construct Extended Learning Data Set by means of combining of N_f completed time-series from Learning Data set and selected M_s suspended time-series from Test Data Set with calculated RULs or their labels.
5. Perform Special Cross-Validation and calculate some output criteria on this Extended Learning Data Set (MRE – Mean Relative Error, or some complex Score, for example, considered in [2]).
   We could not randomly separate this data set into parts using classic Cross-Validation and use several times the same part as validation data set and other parts as training data set. We should use only completed time-series with known measured RULs for validation and suspended time series with un-measured but calculated RULs for training data set.
   For example, the Cross-Validation scheme LOO (Leave One Out) is following: N_f times to calculate RULs (or labels for the Critical Zone Recognition task) for one of the completed time-series from initial Learning Data Set by means of SVR or SVC model using for Data set of (N_f – 1) completed time-series with measured RULs + M_s suspended time-series with earlier calculated RULs.
6. Calculate Mean Relative Error (or some other score) for different Validation Sets for this concrete value of the M_s
7. Select optimal value of the M_s so that score of the Validation Sets shall be minimum
8. Calculate (N_s – M_s) remaining suspended time-series from Test Data Set by means of SVR or SVC model using for Data Set of N_f completed time-series with measured RULs + M_s suspended time-series with RULs calculated earlier.

To compare three approaches, we have used data described above in Experimental Data (Chapter III):

- Approach proposed in this article
- Approach from article [4]
- Classic Supervised-Learning approach used only for completed time-series training and ignores suspended time-series.

Comparison is based on 100 items from Test Data Set of the Data Base [3] and performed for different number of the completed time-series - Nf Learning Data Set size). The Test Data Set size (number of suspended time-series) is constant: Ns = 100. This NASA Data Base is most often used as a benchmark for different algorithm verification. Some results are summarized in Table III.

TABLE III. VALUES OF THE OUTPUT CRITERIA UNDER TEST DATA SET

Output Parameters	**Number of the completed time-series**				
	2	**3**	**4**	**5**	**10**
Optimal Value of M_s for Proposed Approach					
Mean Relative Error for Test Data Set (in %):					
Proposed Approach					
Approach from article [4]					
Classic Approach, i.e. M_s = 0 (ignoring suspended time-series)					

V. CONCLUSIONS

Accurate prediction of Remaining Useful Life (RUL) for units is critical for effective condition based maintenance. During the last ten years, a lot of RUL prediction methods have been developed, but most of them are applicable only for direct RUL calculation. The article describes the case of trendability statistics with large amount of units in learning data set and presents a suspended time series-based model of the data-driven prognostics methods. The paper explains how to obtain the optimal value of suspended time-series, which should be included to the Extended Learning Data Set.

The proposed approach for using suspended time-series was validated using the monitoring data collected by NASA. An experimental result shows that mixed, semi-supervised model produces better estimations as opposed to pure supervised learning based model. Obtained results also show that for some amounts of the completed time-series (below 10) it is not necessary to use the suspended time-series for learning, and using only completed time-series is sufficient enough.

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