The Aramis Challenge:

Prognostics and Health Management in Evolving Environments

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I. Introduction

A recurrent difficulty for the effective application of Prognostics and Health Management (PHM) tools in practice is related to the "evolving environment" in which industrial components typically operate, due to deterioration of components and sensors, maintenance activities, upgrading plans involving new components and system architectures, and the change in the operational and environmental conditions. The issue becomes even more complicated in case of multi-component systems, due to the (stochastic) dependence of the components degradation processes [1, 2]: the degradation of one component can accelerate the degradation processes of the other components, thus modifying their lifetime distributions and the statistical properties of the monitored signals over time. For example, the degradation of hydrodynamic bearings in wind turbines may lead to increasing the looseness of primary transmission shafts, which in turn increase the vibration levels in the gearbox and accelerate the degradation of the gears [1].

In an effort to convey research towards the solution of this key practical hurdle for PHM application in evolving environments, we propose a realistic case study in which the behavior of a system of components is simulated, considering the degradation of the components, their interactions and the presence of variable operating and ambient conditions. The availability of the ground-truth model allows fairly assessing the proposed PHM solutions.

II. Framework

The industrial system of interest is made up of $J = 4$ interconnected identical components, with mission times $T \in \mathbb{R}_+$, in arbitrary time units (atu). A number M of four component systems are installed in M different plants. The degradation of the j^{th} component, $j = 1, .., 4$, in the $m^{th}, m = 1, \dots, M$, system is modelled as a time-continuous stochastic process $\boldsymbol{D}^{j,m} = \left\{D_t^{j,m}\right\}_{t\geq 0}$ defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$. A component enters the abnormal condition when $D_t^{j,m}$ exceeds a threshold d_f. This abnormal condition state does not correspond to the component failure, but makes the operating conditions of the system harsher. The system failure occurs at time T_f, when all four components start operating in abnormal conditions. The degradation paths of the four components of all M systems have been simulated up to either the mission time T or the times of system failures, whichever comes first.

The level of degradation of the components can be estimated through $K = 10$ sensors installed on each component. The sensor signals, $s_t^{j,m,1}, \dots, s_t^{j,m,K}$, are influenced by both the degradation levels $D_t^{j,m}$, $j = 1, \dots, 4$, and the operating condition E_t^m. The measurements are taken at a fixed frequency $f_s = 1$ atu^{-1}.

An example of the evolutions of the K signals of a component in a given system is shown in Figure 1.

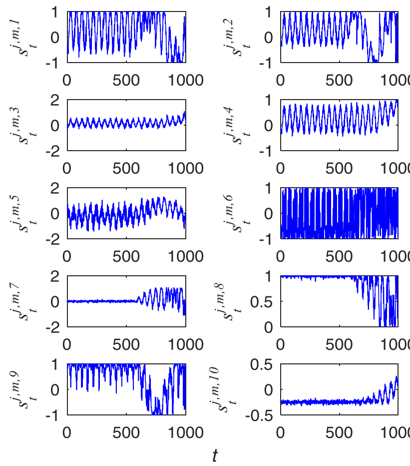

Figure 1. Evolution of the 10 monitoring signals during a component life

III. Problem statement

Let $\boldsymbol{x}_t^{j,m} = [s_t^{j,m,1}, \dots, s_t^{j,m,K}] \in \mathbb{R}^K$ be the vector of the K measurements taken from the j^{th} component of the m^{th} system at time t and $y_t^{j,m} \in \{0,1\}$ the label of the component with 0 indicating normal conditions and 1 indicating abnormal conditions at time t. Let $\tau^{j,m} \in \mathbb{R}^+$ be the time of the first entry into an abnormal state, i.e., $y_t^{j,m} = 0$ when $t < \tau^{j,m}$ and $y_t^{j,m} = 1$ when $t \geq \tau^{j,m}$. Notice that it can occur that $\tau^{j,m} > T$.

Given a training set of degradation trajectories

$$D_{train} = \{[\boldsymbol{x}_t^{1,m}, \dots, \boldsymbol{x}_t^{J,m}], [y_t^{1,m}, \dots, y_t^{J,m}], t = 0, \dots, T_{life}^m\}, m = 1, \dots, M \tag{1}$$

where

$$T_{life}^m = \min(T, T_f^m), m = 1, \dots, M \tag{2}$$

the objective of this challenge is to develop a model to identify the onset of the abnormal condition of all J components in a test system $D_{test} = \{[\boldsymbol{x}_t^{1,test}, \dots, \boldsymbol{x}_t^{J,test}], t = 0, \dots, T_{life}^{test}\}$.

To these aim the degradation trajectories of 250 four-component systems have been simulated. The obtained dataset has been randomly partitioned into a labelled training set containing the degradation trajectories of $M = 200$ systems for the development of a model for the identification of the onset of abnormal conditions and an unlabeled test set of $M_{test} = 50$ systems to validate the performance of the developed model.

IV. Performance metric

The test set containing the degradation trajectories of $M_{test} = 50$ four-component systems is considered. The following quantities are introduced:

- T_{life}^{m}: lifetime of the m^{th} system, defined by Eq. (2);
- $\tau^{j,m}$: ground truth time of the first entry of the j^{th} component of the m^{th} system into an abnormal state. In the case in which the component does not enter into an abnormal state within the time horizon T_{life}^{m}, $\tau^{j,m}$ is set to NaN (Not A Number).

The participants to this challenge are required to provide an estimate $\hat{\tau}^{j,m}$ of $\tau^{j,m}$ for any $m = 1, \dots, M_{test}$ and $j = 1, \dots, J$. If no entry into an abnormal state is detected, $\hat{\tau}^{j,m}$ should be set to NaN.

The error that one makes in estimating the time $\tau^{j,m}$ with $\hat{\tau}^{j,m}$ is defined by:

$$\Delta^{j,m} = \begin{cases} \tau^{j,m} - \hat{\tau}^{j,m} & \tau^{j,m} \neq \text{NaN}, \hat{\tau}^{j,m} \neq \text{NaN} \\ 0 & \tau^{j,m} = \text{NaN}, \hat{\tau}^{j,m} = \text{NaN} \\ k_{false} & \tau^{j,m} = \text{NaN}, \hat{\tau}^{j,m} \neq \text{NaN} \\ -k_{missed} & \tau^{j,m} \neq \text{NaN}, \hat{\tau}^{j,m} = \text{NaN} \end{cases} \quad j = 1, .., J; m = 1, \dots, M \tag{3}$$

Notice that an error equal to $k_{false} > T$ is assigned in case of false alarms (i.e., $\tau^{j,m} = \text{NaN}, \hat{\tau}^{j,m} \neq \text{NaN}$) and an error of $k_{missed} > T$ is assigned in case of missed alarms (i.e., $\tau^{l} \neq \text{NaN}, \hat{\tau}^{l} = \text{NaN}$).

The following metric is used to quantify the average error of the solution provided by the challenge participant on all test components

$$A = \frac{1}{4M_{test}} \sum_{m=1}^{M_{test}} \sum_{j=1}^{4} \varphi\left(\Delta^{j,m}\right) \in [0,1] \tag{4}$$

$$\varphi\left(\Delta^{j,m}\right) = \begin{cases} 1 & \Delta^{j,m} < -T \\ \left(1 - e^{\Delta^{j,m}/a_1}\right) b_1 & -T \leq \Delta^{j,m} < 0 \\ \left(1 - e^{-\Delta^{j,m}/a_2}\right) b_2 & 0 \leq \Delta^{j,m} \leq T \\ 1 & \Delta^{j,m} > T \end{cases} \quad j = 1, .., J; m = 1, \dots, M \tag{5}$$

$$\begin{aligned} b_1 &= 1/\left(1 - e^{-T/a_1}\right) \\ b_2 &= 1/\left(1 - e^{-T/a_2}\right) \end{aligned} \tag{6}$$

Parameters b_1 and b_2 are set to obtain $\varphi(T) = 1$ and $\varphi(-T) = 1$, respectively. Parameters a_1 and a_2 are set equal to 13 and 10, respectively, in such a way that delayed estimates are more penalized than anticipated estimates [3].

The proposed metric A is a variant of the timeliness metric [3] that has been used in the PHM08 data challenge[4, 5] to sort participants' algorithm. Finally, we observe that this metric is desired to be as small as possible (ideally close to 0).

V. Participation

The methods developed and analysis performed in response to this challenge will be part of a dedicated session of the ESREL 2020-PSAM 15 conference (*https://www.esrel2020-psam15.org/*) to be held in Venice, Italy, from June 21st to June 26, 2020.

To confirm the intention to participate to the challenge, each research group must first preliminary register by sending an email to PHMchallenge@aramis3d.com by December 2nd, 2019. The names and work email addresses of all the members of the group participating to the challenge must be provided. All interactions with the challenge hosts must be made by an indicated corresponding member of the group using the email address PHMchallenge@aramis3d.com. For the sake of fairness, we request each team to work independently from the other teams. Therefore, no exchanges of information between teams is allowed and a member of a registered group cannot be part of any other groups.

In your work, please use the notation introduced in the challenge presentation of Sections II and III above, justify the methods chosen and developed, and comment also on those that did not work. The results should be submitted by February 15, 2020 following the procedure available on the Aramis website (*www.aramis3d.com*). Correspondingly, an abstract or a full paper describing the team work should be submitted for presentation to the ESREL2020-PSAM15 conference by February 15, 2020 according to the guidelines given in *https://www.esrel2020-psam15.org/authors.html.*

Abstract and/or full papers will be evaluated by peer review based on their technical merit, adherence to the challenge's goals and clarity. Accepted full papers will be published in indexed proceedings of ESREL2020-PSAM15 and referenced by SCOPUS, EI COMPENDEX and THOMSON REUTERS (ISI Web Knowledge, Conference proceedings) citation indexes.

VI. Research reproducibility

We would encourage that the obtained and published research results be made reproducible for model in future research works. This would allow reducing unintentional errors when comparing models with those developed by others. For this, participants to this challenge are encouraged (it is not compulsory) to provide the developed codes together with the final paper version. The provided code will not be used to validate the results provided by the group and will be available on the conference site. Any commercial use of the codes is forbidden.

References

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