Remaining Useful Life Prediction for Liquid Propulsion Rocket Engine Combustion Chamber

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Abstract: The reusability of a liquid propulsion rocket engine (LPRE) has gained tremendous attention in the recent years. The present paper deals with an automatic estimation of the Remaining Useful Life of a LPRE combustion chamber with the cracking of the internal wall due to the thermo-mechanical stress considered as one of the major degradation modes. The study is performed using simulated data generated by a fictive LPRE engine model and the approach developed in this work is based on the Extended Kalman Filter. A hybrid approach is proposed for the failure prognostics by fusing the knowledge brought in by an approximately correct degradation model with actual sensor measurements. The RUL prediction is made with respect to a failure threshold set by the user. The study considers two kinds of missions: flight and ground missions. The results indicate the effectiveness of the approach under single as well as variable operating condition for LPREs.

Keywords: remaining useful life, liquid propulsion rocket, prediction

I. INTRODUCTION

In recent years, the reusability of a liquid propulsion rocket engine (LPRE) has gained tremendous attention. Efficient methods call for incorporation of current health state as well as prediction of future degradation levels within the life cycle analysis of LPRE [1]. LPRE constitutes as a very critical and dominating subsystem of a reusable vehicle with respect to reliability, maintenance cost, readiness, and safety factors calling for optimal maintenance operations and quick turnaround time [2]. Traditional methods based on routine inspections/assessment in disassembly, remain limited in terms of their efficiency for predictive/pro-active maintenance strategies [1]. To achieve radical reductions in maintenance costs, minimize the turnaround time require advanced prognostics and health management (PHM) methods based on efficient condition monitoring techniques of in-situ measurements of LPREs. This calls for development and deployment of advanced prognostics and recovery systems on LPREs.

To that end, Remining useful life (RUL) prediction plays critical role for efficient prognostics [3] and has significant impact on real health monitoring as well as maintenance strategy between successive operational cycles (flight or ground testing). PHM methods based on condition measurement information are divide into following large categories: model based [3] and data-driven techniques [4] and hybrid approaches [5]. Model based methods require accurate knowledge of degradation progression dynamics. Particularly in LPRE context, the behavioral dynamics of system and degradation progression models mostly nonlinear and plausibly, not known in an accurate manner. This renders the utility of pure model-based methods very limited. On the other hand, pure data-driven methods remain limited in feasibility due to shortage of failure data during actual operation. Hybrid approaches combine the advantages of model based and data-driven approaches in that approximately correct degradation model is fused with information brought by real sensor measurements in an appropriate manner [5]. However, hybrid approaches have so far evaded prognostics of LPREs and as such, there are no existing works on this axis.

To bridge the existing scientific gap, this paper presents a hybrid prognostics approach for health assessment and prediction of RUL of a LPRE combustion chamber. The major degradation mode for this equipment is assumed as the cracking of the internal wall due to the thermo-mechanical stress at each engine functioning cycle at each long duration boost of the engine [6]. Due to the absence in CRAN of experimental data showing the insurgency of this fault, this study has been performed on simulated data generated by a "fictive" LPRE engine model. The fault degradation has been simulated in accordance with the physical comprehension of the phenomena and a set of measures have been reconstructed according to a hypothetical engine measurement plan. The RUL estimator is based on the degradation of the combustion efficiency of the chamber, quantified via the characteristic velocity efficiency ηC^*, that needs to be reconstructed via the available measures from the engine (pressures and temperatures). The approach developed in this work is based on Extended Kalman Filter [7]. As the first step, raw sensor data is considered to obtain the estimation of the combustion efficiency. At second step this estimation information is used to generate a prediction of the RUL by considering a minimum threshold value over acceptable combustion efficiency. The RUL prediction is generated at every observation time step which leads to RUL predictions in an online manner.

Following this section, description of the LPRE system is provided in Section II, Section III describes the hybrid RUL prediction methodology proposed in this work, Section IV presents the application of the method over two datasets generated under different conditions and finally, Section V draws the conclusions and presents perspectives.

II. SYSTEM DESCRIPTION AND DEGRADATION INJECTION

The LPRE model involved in this work is a "fictive" engine model developed at CNES, of 10 kN thrust with a supply of liquid oxygen-liquid hydrogen propellants (LOX-LH2) in the chamber via two electric pumps. The combustion chamber is cooled via a regenerative circuit (RC, which is supplied by liquid hydrogen) and disposes of a divergent that provide the required thrust of 10kN.

The engine has an operating range of thrust between 50% and 110% of the nominal thrust. The engine is throttle enabled, in closed loop with, as input variables, the power delivered to the motors of the electro-pumps. The fault candidate chosen for degradation injection are cracks generated on the combustion chamber internal wall leading to a leak of cold propellant from the regenerative circuit directly in the combustion chamber [6]. The CARINS software [8] allows to simulate this degradation and to see the impacts of such deviation on the engine performance (combustion efficiency, thrust, etc.,). The platform allows to simulate a cracking defect of the combustion chamber leading to a loss of combustion efficiency and consequently a global degradation of the engine performance. The cracking of the liner causes leak of hydrogen that circulates in the Regenerative Circuit (RC) in the combustion chamber which is modelled by shedding of the RC flow in combustion chamber i.e. simulated using appearance of a leak (singular pressure drop) with surface directly proportional to the number of cracks and area of a crack. Loss of combustion efficiency (due to inhomogeneous presence of the film cooling) is simulated by extracting from the chamber an additional heat flux directly proportional to the calculated leak rate. Degradation injection by considering the aforementioned aspects leads to loss of load in RC and more significantly, deterioration of characteristic velocity.

In this work, the characteristic-velocity-efficiency is chosen as the suitable state of health (SOH) indicator and represents the health of the LPRE combustion chamber. The characteristic velocity efficiency (SOH indicator) denoted as ηC^* is generated by the fictive model.

III. HYBRID PROGNOSTICS METHODOLOGY

This section presents the novel methodology developed for SOH estimation and RUL prediction.

A. Problem formulation

In reality, degradation processes are monotonic in nature (increasing or decreasing) and vary with time till the failure is reached [5]. As such, the unknown degradation dynamics can be described by an appropriate mathematical function that satisfies the properties: global monotonicity and time dependent variation. In this work, an exponential function in time $e^{\alpha t}$ is chosen to represent the unknown degradation model as:

$$x(k+1) = f_d(x_k, \alpha_k) + w_k \tag{1}$$

with $x_{k=0} = x_0$ where $x \in X$ denotes the unknown SOH, α denotes the unknown degradation progression parameter, $f_d(\cdot)$ denotes the transition function that determines the approximately known degradation evolution, w_k is the additive process noise assumed zero-mean Gaussian with variance Q. The degradation progression rate is generally considerably slow in comparison to the global system dynamics. Thus, it is reasonable to model the degradation rate evolution as a slowly evolving random-walk process [5]: $\alpha(t) = \alpha(t-1) + w_\alpha(t)$. Then, linearized system dynamics (degradation and measurement observation) can be described in discrete time as:

$$\begin{aligned} \boldsymbol{\chi}_{k+1} &= A_k \boldsymbol{\chi}_k + \boldsymbol{w}_k \\ y_k &= h(x_k, \alpha_k) + v_k \end{aligned} \tag{2}$$

where $\boldsymbol{\chi}_k = \begin{bmatrix} x_k \\ \alpha_k \end{bmatrix}; \boldsymbol{w}_k = \begin{bmatrix} w_{x,k} \\ w_{\alpha,k} \end{bmatrix}$, $A_k = \begin{bmatrix} 1+\alpha_k.Ts & -x_0.Ts \\ 0 & 1 \end{bmatrix}$ is the Jacobian matrix, Ts is the sampling time, $y_k \in Y$ is the measurement, $h(\cdot)$ describes the observation evolution function that is considered to depend upon x_k and α_k. Moreover, $w_{x,k} \sim N(0, \sigma_x)$ is the additive process noise, $w_{\alpha,k} \sim N(0, \sigma_\alpha)$ is the random walk noise and the associated variance matrix is Q with $Q = \begin{bmatrix} \sigma_x^2 & 0 \\ 0 & \sigma_\alpha^2 \end{bmatrix}$, $v_k \sim N(0, \sigma_v)$ is the measurement noise with variance where $R = \sigma_v^2$.

A. SOH estimation

The estimation problem of SOH is set as joint state-parameter estimation problem within the framework of Extended Kalman Filter (EKF) [9]. The major steps are presented as a pseudo-algorithm with $\mathrm{E}[\cdot] Var[\cdot]$ being the mean operator and $Var[\cdot]$ being the variance operator.

Table 1: Pseudo code SOH estimation using EKF [9]

Algorithm1: SOH Estimation using EKF

Inputs: $\chi_{0|0}, Q, R, y_0$

Outputs: $\hat{\chi}$

Initialize: $\chi_{0|0} = \mathrm{E}[\chi_0], P_{0|0} = Var[\chi_0]$

prediction

$$\begin{aligned} \boldsymbol{\chi}_{k|k-1} &= A_k \boldsymbol{\chi}_{k-1|k-1} \\ P_{k|k-1} &= A_k P_{k-1|k-1} A_k^T + Q \end{aligned} \tag{3}$$

correction

$$\begin{aligned} \boldsymbol{\chi}_{k|k-1} &= A_k \boldsymbol{\chi}_{k-1|k-1} \\ K_k &= P_{k-1|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R)^{-1}; H_k = \partial h / \partial \boldsymbol{\chi}_k \\ P_{k|k} &= (I - K_k H_k) P_{k|k-1} \\ \boldsymbol{\chi}_{k|k} &= \boldsymbol{\chi}_{k|k-1} + K_k (y_k - h(x_k, \alpha_k)) \\ \hat{\boldsymbol{\chi}}_k &\leftarrow \boldsymbol{\chi}_{k|k} \end{aligned} \tag{4}$$

B. Prognostic using L-step ahead prediction of RUL

As shown in Figure 1, RUL is defined as the time difference between two instants as [3]:

$$RUL_k = t_{fail} - t_{pred} \tag{5}$$

where t_{pred} is the time instant when prediction is made and t_{fail} is the predicted time of failure.

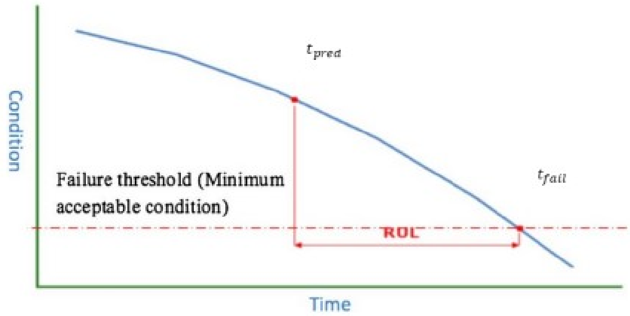

Figure 1 Illustration of RUL

The SOH progresses in time and as the fault value increases, the SOH attains the failure levels. Such a failure value x_{fail} is considered known *a priori,* based upon which a failure threshold is pre-fixed by the users. Then, the RUL at any discrete time instant *k* can be obtained using *l-step* ahead prediction. This is done by projecting the estimated SOH in (4) in the future along the estimated degradation model (state model) in (2). This projection is done recursively at each time step by simulating the SOH *l*-steps ahead into the future as:

$$\hat{x}(k+l) = (1 + \hat{\alpha}_k.Ts)\hat{x}(k+l-1) - x_0.Ts.\hat{\alpha}_k \tag{6}$$

For any discrete-time step, the simulation is stopped when estimated future state reaches x_{fail} and number of steps taken to reach the future equals the RUL (in discrete time) at *k*. The corresponding pseudo-algorithm is given below with *Ts* being the sampling time.

Table 2: Pseudo code for *L-step* ahead projection for RUL prediction [5]

Algorithm2: *L-step* ahead projection for RUL prediction at discrete time *k*

Inputs: $\hat{x}_k, \hat{\alpha}_k, x_{fail}$

Output: RUL_k

Initialize: *l=0*

while ($x_{k+l} \le x_{fail}$) **do**

$l \leftarrow l+1$

$x_{k+l} \leftarrow f_d(x_{k+l-1}, \alpha_{k+l-1})$

end while

$RUL_k \leftarrow l * Ts$

Remark 1: It is noted that RUL prediction is done only using the deterministic part of the degradation model.

Remark 2: In this work, RUL predictions do not consider the future values of the input.

IV. APPLICATION ON LPRE DATA

As discussed in Section II, $\eta C*$ generated by the LPRE simulator is considered as the principal SOH indicator measurement. As such, measurements at time *k*, $y_k = \eta C_k^*$. In practice, accurate estimate of process and noise variance is difficult to obtain, especially for varying systems. Therefore, Q, R are used as tuning parameters. Readers are referred to [10] for a methodology of tuning Q, R for parameter tracking. In this paper, x and α are considered un-correlated; random walk noise σ_α is injected artificially and tuned in a manner such that enough excitation is rendered to the state for convergence, diagonal terms of Q are set as the square of the typical variation of parameter on a sampling interval. Moreover, typical variation of measurement around its mean over an interval renders an approximate sense of the magnitude of σ_v and hence, *R*. in order to give a sense of the order, typical values of these parameters are $\sigma_x = 1.5\times10^{-5}$ $\sigma_\alpha = 2\times10^{-5}$ $\sigma_r = 10^{-3}$ $\sigma_x = 1.5\times10^{-5}$. In this work, two kinds of missions have been considered for the generation of degradation data from the fictive engine model. In what follows in this section, application on these two datasets is described.

A. Functioning Engine Data (FE)

The first dataset corresponds to the ageing of a "flight" engine. Such an engine undergoes to a quick ground acceptance firing test and then is used for several flight mission (at least 8). The engine is mainly used on its 100% functioning point but with short boost at 50% of thrust (reentry boost).

As such, the degradation mode remains the same throughout. Figure **2** shows the estimation performance (Algorithm 1). As it is clear, measured SOH indicator ηC^* degrades in time and exhibits a certain global trend (slope). The SOH is well estimated by the proposed degradation model in (1). Moreover, the unknown degradation progression parameter value is captured by $\hat{\alpha}$. It should be noted that artificial noise $w_{\alpha,k}$ is injected in the random walk process that facilitates the estimation of α. The value of the latter is tuned in such a manner so that convergence of $\hat{\alpha}$ is achieved fairly quickly and at the same time, the estimation is not “corrupted” with white noise (see [5] for more details on noise tuning). At each instant *k*, the estimation is followed by RUL prediction (Algorithm 2) till the pre-fixed failure threshold (shown in red in Figure **2**) is reached by the mean of the measurement ηC^*. The RUL prediction generated through the application of Algorithm 2 at each time step *k* is shown in Figure 3. The true RUL line is generated using the ground truth knowledge i.e., the time instant at which the mean of measured SOH indicator crosses designated threshold.

Remark 3: As seen in Figure 2, evolution of α reflected in its behavioral profile could be used to diagnosis a problem which occurs on LPRE For example, a trend analysis applied on α estimation can be developed to detect drift fault occurrence.

In presence of single degradation mode (single true value of α), the RUL_{real} helps in assessing the accuracy/quality of RUL predictions. It should be noted that in presence of real data, it is only the true *end of life* (time instant when true RUL is zero) which is known in real sense. Assuming that the degradation is influenced by only one degradation mode (mono operation condition), the RUL_{real} helps to validate the RUL predictions [7]. As seen in Figure 3, the RUL predictions remain quite close to the RUL_{real} profile globally. It is noted that RUL prediction procedure (Algorithm2) is started at around time step 5400s for FE i.e. RUL predications are generated only after this time instant to avoid computational complexities at the start of degradation.

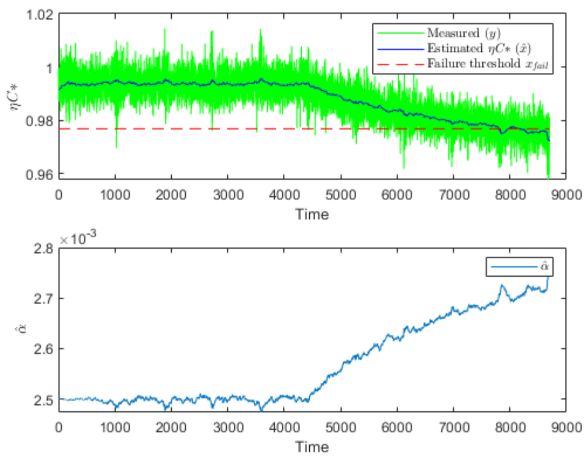

Figure 2 FE: Estimation of SOH

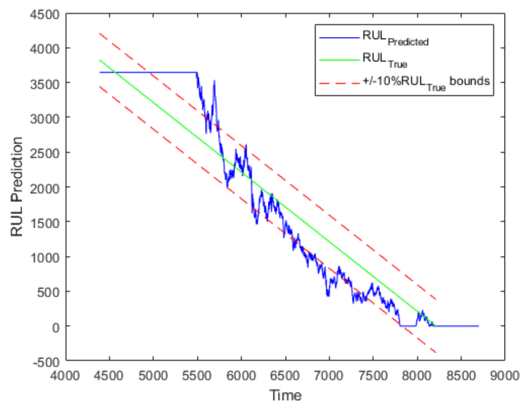

Figure 3 FE: RUL Prediction

B. Qualification Engine Data (QE)

The second dataset QE corresponds to the lifetime ageing of a "ground" engine (production support engine). Such an engine undergoes to a series of tests that sweep all the engine functioning domain. In particular, this second test case has been designed by CNES in order to mimic functioning under severe/extreme operational conditions. This test case is introduced to test the efficiency of the algorithm with respect to variable functional/operational changes in the engine. As such, the degradation data show the consequences on engine performances around several functioning points and does not exhibit a mono-trend.

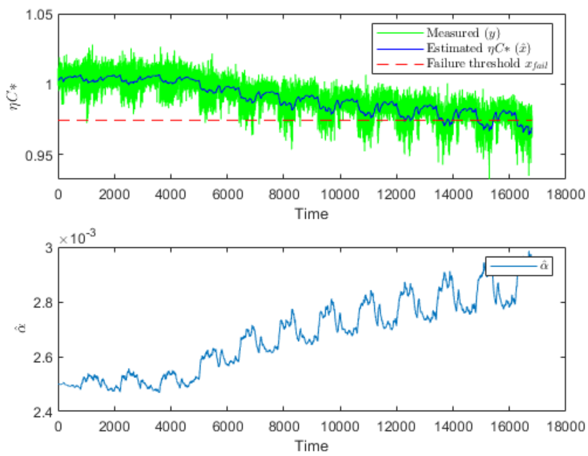

Figure 4 QE: Estimation of SOH

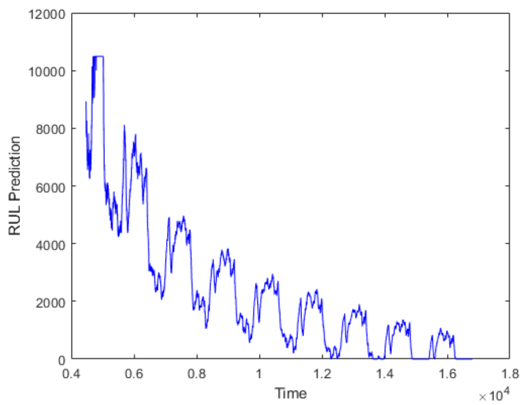

Figure 5 QE: RUL Prediction

Figure 4 shows the estimation performance (Algorithm 1). The measured SOH indicator ηC^* degrades globally in a monotonic manner. However, locally the degradation profile remains sensitive to several severely changing operating conditions. The SOH is well estimated by the proposed degradation model in (1). Moreover, the unknown rate of degradation progression is captured by $\hat{\alpha}$ in accordance with the measured SOH indicator. The RUL prediction (Figure 5) is generated through the application of Algorithm 2 at each time step k.

Contrary to the previous case, functioning of the system under multiple operational conditions leads to manifestation of multiple degradation rates. As such, presence of single true value of α cannot be assured for mission throughout. Thus, in absence of the knowledge of true values of α at each time step, a RUL_{real} profile cannot be generated and be used to validate the quality of RUL predictions at each instant of time. In such cases, as discussed in [11], only the true *end of life* can be used as a measure to assess the RUL predictions. For example, if the RUL prediction is indeed zero at the true *end of life* time step, then the RUL prediction scheme is qualitatively producing reasonably accurate predictions. Such is the case here as shown in Figure 5, RUL prediction at true *end of life* around approx. $1.62e^4$ s is indeed zero.

V. CONCLUSION

This paper proposed a hybrid prognostics method for LPRE combustion chambers wherein the knowledge brought-in by an approximately correct degradation model is blended with real information from sensor measurements for SOH estimation and RUL predictions in an online manner. The results obtained demonstrate the limitation and the performance a good capability of the algorithm to predict the RUL of the chamber for engines functioning under nominal as well as variable conditions. However, the degradation model does not incorporate the future inputs or input(s) profile for SOH estimation as well as RUL predictions which remains a potential perspective. Future works will consider incorporation of system inputs variations for futuristic RUL generations as proposed in [12]. Moreover, taking into account variance of SOH distribution for generation of RUL prediction distribution is another potential perspective towards development of health aware control framework in this domain[13], [14].

ACKNOWLEDGEMENT

The authors are thankful to Centre National d'Etudes Spatiales (CNES) for financial support, technical support and availability of simulated degradation data.

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