Prognostics Aware Control Design for Extended Remaining Useful Life: Application to Liquid Propellant Reusable Rocket Engine

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ABSTRACT

As most of the safety critical industrial systems remain sensitive to functional degradation and operate under closed loop, it becomes imperative to take into account the state of health (SOH) of systems within the control design process. To that end, an effective assessment as well as extension of the Remaining Useful Life (RUL) of is a standing challenge that seeks novel solutions at the cross-overs of Prognostics and Health Management (PHM) domain as well as automatic control. This paper considers a dynamical system subjected to functional degradation and proposes a novel prognostics aware control design strategy that takes into account the SOH estimate as well as RUL prediction within the control design procedure. The degradation model is considered unknown but input-dependent. The control design is formulated as an optimization problem and an optimal tradoff is searched between the performance and desired RUL of the system through the proposed optimization procedure. The main contribution of the paper remains in proposal of set-point modulation based approach wherein the control input at a given present time stage is modulated in such way that futuristic health of the system over a long time horizon is extended whilst assuring acceptable performance. The effectiveness of the proposed strategy is assessed in simulation using a numerical example as well as liquid propellant rocket engine case.

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ABBREVIATIONS

PHM	Prognostics and Health Management
SOH	State of Health
RUL	Remanining Useful Life
HAC	Health Aware Control
LPRE	Liquid Propellant Rocket Engines
EKF	Extended kalman Filter
ub	upper bound (on ω)
lb	lower bound (on ω)
LOX	Liquid oxygen
LH2	Liquid Hydrogen
PI	Proportional Integral

1. INTRODUCTION

Prognostics and health monitoring (PHM) domain calls for effective assessment of the state of health (SOH) of system(s) or sub-systems and development of efficient approaches for prediction of Remaining Useful Life (RUL) (Xia et al., 2018), (Jha, Dauphin-Tanguy, & Ould-Bouamama, 2016), (Jha, Bressel, Ould-Bouamama, & Dauphin-Tanguy, 2016). While most of the existing works in PHM domain focus upon the prognostics problem in open loop, those in automatic control community target control design without taking into account prognostics based information. However, as most of the safety critical industrial systems remain sensitive to functional degradation and operate under closed loop, it becomes imperative to take into account the SOH assessment within the control design process (Obando, Martinez, & Berenguer, 2021).
On the other hand, few works have also investigated RUL extension through mission re-planning. For example, (Camci, Medjaher, Atamuradov, & Berdinyazov, 2019) presents a mathematical formulation for integrated maintenance and mission planning for a fleet of high-value assets, using their current and forecast health information., (Bellani, Compare, Baraldi, & Zio, 2019) investigates the importance of considering the

dynamic management of equipment and its influence on future degradation when predicting RUL. It should be noted that this work does not focus on mission re-planning strategy based approaches but envisages control input reconfiguration "on the fly". The latter becomes particularly important for mission critical systems, as the extension of their remaining lifetime during their operation by maintenance actions cannot always be conducted due to non-accessibility to resources on fly or non-availability of such resources during the mission.

In fact, the rate of degradation of most industrial components is mostly system input dependant. For example, degradation of a rolling bearing depends on the rotating speed and exerted force (Wang, Tsui, & Miao, 2018), degradation of an electro-mechanical actuator depends on thermal temperature which in turn depends on the current within the solenoid coils (Brown et al., 2009) etc. When such systems operate in closed loop, the degradation speed invariably depends upon the control input as well as reference trajectories. An effective assessment and extension of the remaining useful life of complex systems is a standing challenge that seeks novel solutions at the cross-over of PHM domain as well as automatic control (Pour, Theilliol, Puig, & Cembrano, 2021; Jha, Weber, Theilliol, Ponsart, & Maquin, 2019). In the aerospace domain, very few investigations have been done in the past on these lines (Ray, Wu, Dai, Carpino, & LORENZO, 1993; Holmes, Tangirala, & Ray, 1997). They explored the concept of damage-mitigating control for reusable rocket engines and propose an optimal control policy that incorporates a functional cost based on the control effort and state error. The main objective of such a control policy being achieving a balance between the performance of the engine and the effort exerted on the engine's thrust. The use of a functional cost allows for the formulation of an optimization problem that seeks to minimize the cost while satisfying certain constraints. This optimization problem aims to find the optimal control inputs that achieve the desired balance between performance and effort. This enables real-time adaptation and optimization of the control actions during the operation of the reusable rocket engine. Although these studies highlight well the importance of implementing damage-mitigating control strategies in the design and operation of reusable rocket engines, and they do not take into account the SOH of the system and RUL predictions (prognostics) within the control design strategy.

Within the literature, there are broadly three types of prognostics approaches. Model-based methods (Swanson, 2001; Luo et al., 2003) that rely on accurate knowledge of degradation progression dynamics. However, in the context of most safety critical systems such as Liquid Propellant Rocket Engines (LPRE), the system's behavioral dynamics and degradation progression models are predominantly nonlinear and not precisely known, which limits the use of pure model-based approaches. Data-driven approaches (Roemer, Kacprzynski, & Orsagh, 2001; Pecht, 2013) on the other hand, primarily rely on failure data obtained during accelerated degradation tests as well as actual operational failures. In the presence of limited data-sets, such approaches remain quite ineffective for RUL prediction. On the other hand, hybrid prognostics (Jha, Bressel, et al., 2016) aim to combine the advantages of model-based and data-driven methods. These approaches involve fusing an approximately correct degradation model with information obtained from real sensor measurements in a suitable manner (Chelouati, Jha, Galeotta, & Theilliol, 2021). This fusion allows for a more effective prediction of RUL. However, up until now, there have been no existing work on applying hybrid approaches to the prognostics of LPREs and their suitable inclusion within control design.

Recently, there has been an extensive surge of endeavours within the framework of Health Aware Control (HAC) wherein control design approaches are being developed by aggregating theories of estimation, prognostics, reliability and learning schemes (Jha, Theilliol, Biswas, & Weber, 2019) leading to energy saving and optimal performance (Hu, Zou, Tang, Liu, & Hu, 2020; Ure, Chowdhary, How, Vavrina, & Vian, 2013) and optimal tracking of desired value of RUL (Jha, Weber, et al., 2019).

An accurate estimation of SOH and RUL makes it possible to monitor system health as well as carry out the maintenance actions proactively, thereby reducing the replacement/incurring costs and increasing the confidence in the functional operation. In this context, some previous works include (Commault, Dion, & Perez, 1991; Huang & Xue, 2014) that target life extension of propulsion systems without taking into account prognostics within control design. Further, there are some works that propose control design incorporating the reliability of the system (M. Khelassi, Jiang, Theilliol, Weber, & Zhang, 2011; A. Khelassi, Theilliol, Weber, & Ponsart, 2011) as well as RUL (Rodriguez, Martinez, & Berenguer, 2018; Obando et al., 2021). These latter works, however, propose reference modulation through design of a signal filter. Few works in HAC area include those based on model predictive control (Salazar, Weber, Nejjari, Sarrate, & Theilliol, 2017) as well as other model based approaches (M. Khelassi et al., 2011; A. Khelassi et al., 2011; Rodriguez et al., 2018; Obando et al., 2021) . However, none of the approaches develop hybrid prognostics within the control design framework in a comprehensive manner. Moreover, most existing work do not consider system input based degradation model which is much closer to the reality.

Finally, the authors are have conducted preliminary studies (Thuillier, Galeotta, Jha, & Theilliol, 2022; Thuillier, Jha, Galeotta, & Theilliol, 2022) wherein controller design is proposed sensitive to the RUL such that the useful life of such systems is extended. This work builds upon the previous work, presents detailed analysis and formalises the proposed approach with the hybrid prognostics framework. Moreover, the proposed strategy employs an approximately correct degradation model that is usually built using already available degradation data using some off-line data pre-processing. However, such aspects are not elaborated in this work but addressed in previous works (Chelouati et al., 2021; Kanso, Jha, Galeotta, & Theilliol, 2022).

To bridge this scientific gap, this paper develops a hybrid prognostics aware control design framework that enables fusion of an approximately known degradation model with available sensor measurements to obtain estimations of the state of health and hidden parameters leading to efficient RUL predictions. Then, as a novelty, the control problem is cast as an optimization problem taking into account system performance as well as desired levels of RUL, such that the reference trajectory is modified leading to extended useful life of the system at the expense of system performance. Extended Kalman Filter (EKF) is employed to preform SOH estimations and RUL predictions leading to effective hybrid prognostics. The main contribution of the paper remains in the proposition of hybrid prognostics enabled optimization based reference modification strategy for controller design.

This section is followed by problem statement formulation (section II), proposition of the novel control design strategy (section III), analysis in simulation (section IV) and conclusions (section V).

2. PROBLEM STATEMENT

2.1. Global system (Process model)

Consider a linear system in a closed-loop tracking defined as:

$$\begin{cases} x(k+1) = Ax(k) + Bu(k) + w_s(k) \\ z(k) = Cx(k) + v(k) \end{cases} \tag{1}$$

with

$$\begin{cases} y(k) = Dx(k) \\ u(k) = -K_1 x(k) + K_2(y_{ref}(k) - y(k)) \end{cases} \tag{2}$$

where $x \in R^n$ is the fully observable state vector, $u \in R^1$ is the control input vector, $z \in R^m$ the output measurement vector, $y \in R^1$ the output tracked, $y_{ref} \in R^1$ is the set-point, A, B, C, D are respectively the system matrix, control matrix, measurement matrix and tracking output matrix of appropriate dimensions. Also, $w_s \in R^n$ is the state noise vector considered Gaussian $w_s(k) \sim \mathcal{N}(0, \sigma_{\omega_s})$, $v \in R^n$ is the measurement noise considered Gaussian $v(k) \sim \mathcal{N}(0, \sigma_v)$. Finally, K_1 and K_2 are control gains with appropriate dimensions.

2.2. Unknown nonlinear degradation model

In general, the degradation models are rarely known in a precise manner. They must be identified or estimated offline using accelerated degradation test or otherwise. Moreover, most degradation mechanisms are nonlinear. In this paper, functional degradation is quantified by an auxiliary state called degradation state $d \in \mathrm{R}^1$ considered to evolve in a plausible nonlinear manner, remaining sensitive to system states x, input u and an unknown scalar parameter $\theta \in \mathrm{R}^1$, as:

$$d(k) = \phi(x(k), u(k), \theta(k)) \tag{3}$$

where $\phi(\cdot)$ is a nonlinear degradation function.

2.3. RUL dynamics

In general, it is very difficult if not impossible, to obtain dynamics RUL prediction function in a closed analytical form, as it remains highly nonlinear and depends on present as well as futuristic values of degradation states and system inputs. RUL prediction function denoted as $\widehat{RUL}$ can be considered as a plausible nonlinear function $\Phi(\cdot)$ sensitive to estimate of $\hat{d}$ and the system control input u such as:

$$\widehat{RUL}(k) = \Phi(\hat{d}(k), u(k)) \tag{4}$$

However, under tracking closed loop, the controller provides a controlled input by taking into account the difference between the desired reference trajectory (set-point) $y_{ref}(k)$ and system output $y(k)$. The RUL dynamics then depends upon the controller action that in turn minimises the difference between the former two. As such, predicted RUL can be expressed as:

$$\widehat{RUL}(k) = \Phi(\hat{d}(k), (y_{ref}(k) - y(k)) \tag{5}$$

Then, the main problem is formulated as development of a control reconfiguration strategy that takes into account the state of health of estimate as well as RUL predictions such that desired levels of RUL as well as system performance is satisfied leading to the extension of the useful life of the system and deceleration of the degradation speed.

2.4. Assumptions

Following assumptions are made in this work.

- Only a component undergoes functional degradation thereby affecting the global system. Moreover, it is assumed that this component is known beforehand (plausibly through some risk assessment analysis done *a priori* such as Failure Mode, Effects Criticality Analysis).
- The degradation state is assumed to be implicitly related to the control input. The value where the SOH attains the failure state is considered known *a priori*, based upon

which a failure threshold can be pre-fixed by the users.

- The desired RUL value is assumed to be known before hand, at the start of the system functioning to the user, based on some offline component level degradation tests adhering to user specifications. This desired RUL value is then used to generate a linear profile of desired RUL reference trajectory RUL_{ref}. Additionally, it is assumed that such there exists control input values corresponding to such a desired RUL value (that is, RUL is a reachable state).
- A nominal system reference trajectory y_{ref} is considered available to the user based on nominal system functioning profile.

3. HYBRID PROGNOSTICS ENABLED SET POINT MODULATION STRATEGY

The control reconfiguration design proposed in this paper blends the hybrid prognostics approach with a set-point modulation strategy as shown in Fig. 1. To this end, following aspects are developed:

- *Extended Kalman Filter (EKF) based hybrid prognostics*: An approximately correct degradation model sensitive to control input is proposed and EKF based state-parameter estimation technique is employed to assess estimations of SOH, hidden degradation parameters and RUL predictions. Such data are fed to an optimization module to control the RUL dynamics.
- *Set-point modulation*: Based on the assumption that the degradation rate is linked to the system solicitation (input), an optimization procedure modulates the reference trajectory to a predefined RUL target. To that end, a modulation parameter ω is introduced in tracking control setup, between set-point and system output $y_{ref}(k) - y(k)$ as $y_{ref}(k) - \omega(k) - y(k)$. The optimal value ω^* of the modulation parameter is obtained as the solution of a minimization problem with respect to an objective function sensitive to distance between RUL prediction (from EKF based hybrid prognostics) at instant k and the pre-fixed desired value of RUL.

The proposed prognostics-aware reconfiguration strategy is depicted in Fig. 1.

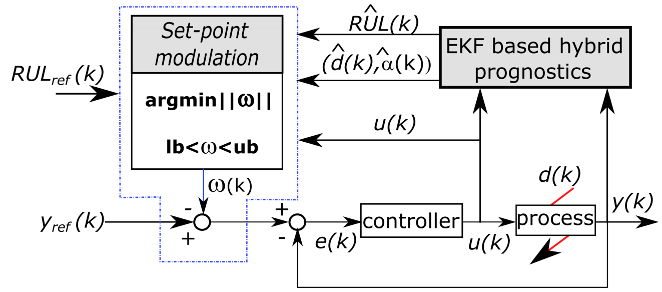

Figure 1. Proposed prognostics aware control reconfiguration strategy

In what follows, each block of the schematic in Fig. 1 is detailed.

As observed in Fig. 1, a controller drives the system output to follow the reference trajectory y_{ref}. Among others, a classical PI controller has been chosen. Thus, the input can be considered as:

$$C(z) = k_p + \frac{k_i.T_s.z}{z-1} \tag{6}$$

with k_p and k_i as the PI controller parameters and T_s as the sample time.

3.1. Degradation model sensitive to system input

Functional degradation mechanisms across various domains exhibit certain characteristics such as irreversible nature and monotonic. Such a set of characteristics can be efficiently captured mathematically by exponential functions. The exponential behavior in degradation models can be attributed to various factors such as wear and tear, aging, fatigue, or other underlying physical or chemical processes. These processes often exhibit a cumulative effect, resulting in an accelerated degradation pattern. For instance, Arrhenius model that has been used to model a variety of failure mechanisms that depend on chemical reactions, diffusion processes or migration processes, is exponential in nature (Rocco et al., 2004) ; Coffin-Manson model typically applied model to mechanical failure, material fatigue or material deformation is also exponential in nature (Li, Xie, Cheng, & Tian, 2020); Paris model often employed for crack propagation based prognostics remains exponential in nature (Paris & Erdogan, 1963). Motivated by these observations and similar trends in practice (Saxena, Goebel, Simon, & Eklund, 2008; Kumar, Kalra, & Jha, 2022), a general exponential degradation model is proposed that incorporates the cumulative effect of the system control input u as:

$$d(k) = e^{(\sum_{i=1}^{k} u(i).\alpha(i-1).T_s)} + w_d(k) \tag{7}$$

under the assumption that the value of u is constant between two sample times, and where $d(k)$ is the system SOH, and $\alpha(k)$ is a slowly varying unknown degradation rate parameter. $\omega_d \in R^1$ is the degradation process noise vector considered Gaussian $\omega_d(k) \sim \mathcal{N}(0, \sigma_{\omega_d})$. Sample time is denoted as T_s. In order to obtain the recursive version of Eq. (7), considering the fact that $\alpha(k)$ is a slowly varying parameter, following mathematical manipulation is done:

$$\begin{cases} d(k+1) = & e^{(\sum_{i=1}^{k+1} u(i).\alpha(i-1).T_s)} + w_d(k+1) \\ & = e^{(\sum_{i=1}^{k} u(i).\alpha(i-1).T_s)} \times e^{(u(k+1).\alpha(k).T_s)} \\ & \quad + w_d(k+1) \\ & = d(k)e^{(u(k+1).\alpha(k).T_s)} + w_d(k+1) \\ \\ \alpha(k+1) = \alpha(k) + w_\alpha(k+1) \end{cases} \tag{8}$$

Then, using a series expansion to order 1 for the exponential term in Eq. (8) ($exp(X) = 1 + X + o(X)$), the recursive form is obtained as:

$$\begin{cases} d(k+1) = d(k)(1 + u(k+1).\alpha(k).T_s) + w_d(k+1) \\ \alpha(k+1) = \alpha(k) + w_\alpha(k+1) \end{cases} \tag{9}$$

wherein the evolution of α is modelled as a slow random walk process and $\omega_\alpha \in R^1$ as the random walk process noise considered Gaussian $\omega_\alpha(k) \sim \mathcal{N}(0, \sigma_{\omega_\alpha})$.

3.2. EKF based hybrid prognostics

The hybrid prognostics is accomplished by fusing the degradation model Eq. (9) with the real measurements of system using an EKF leading to estimations of $d(k), \alpha(k)$ and corresponding RUL predictions.

3.2.1. Degradation estimation

EKF based joint state-parameter estimation approach is employed to estimate the degradation state or the SOH of the system. The augmented state-parameter vector of the system is considered as:

$$\begin{aligned} \begin{pmatrix} x(k+1) \\ x_d(k+1) \end{pmatrix} &= \begin{pmatrix} A & 0_{n,2} \\ 0_{2,n} & A_d(k) \end{pmatrix} \begin{pmatrix} x(k) \\ x_d(k) \end{pmatrix} + Bu(k) + w_S(k) \\ \begin{pmatrix} z(k) \\ z_d(k) \end{pmatrix} &= \begin{pmatrix} C \\ C_d \end{pmatrix} \begin{pmatrix} x(k) \\ x_d(k) \end{pmatrix} + v(k) \end{aligned} \tag{10}$$

with the degradation state vector $x_d(k) = \begin{bmatrix} d(k) & \alpha(k) \end{bmatrix}^T$, the system state vector $x(k)$ and the matrices:

$$A_d(k) = \begin{pmatrix} 1 + (\alpha(k).u(k).T_s & u(k).T_s) \\ 0 & 1 \end{pmatrix}, C_d = \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix},$$
$$v(k) = \begin{pmatrix} v_z(k) \\ v_d(k) \end{pmatrix}, w_S(k) = \begin{pmatrix} w_s(k) \\ w_d(k) \\ w_\alpha(k) \end{pmatrix}.$$

The EKF algorithm for estimation is described in Algorithm 1. The Jacobian matrix for the predicted state is defined as $J(k)$, the measurement model matrix H, the measurement model matrix with respect to the noise as G. The matrices Q and R correspond to respectively the process and measurement noise covariance matrices.

Algorithm 1 Algorithm for degradation estimation using EKF

Input: $z_{d_k}, P_{k|k}, u_k$
Output: $\hat{x}_{d_{k+1|k+1}}$
Initialisation : $z_{d_0}, \hat{x}_{0|0}, P_{0|0}$
if ($i \neq 0$) **then**
  $\hat{x}_{d_{k+1|k}} = A_d(k) x_{d_{k|k}}$
  $P_{k+1|k} = J(k) P_{k|k} J(k) + Q$
  $z_{d_{k+1|k}} = C_d x_{d_{k+1|k}}$
  $S_{k+1} = H_{k+1} P_{k+1|k} H_{k+1}^T + G R_{k+1} G^T$
  $K_{k+1} = P_{k+1|k} H_{k+1}^T S_{k+1}^{-1}$
  $\hat{x}_{d_{k+1|k+1}} = \hat{x}_{k+1|k} + K_{k+1|k}(z_{d_{k+1}} - z_{dk+1|k})$
  $P_{k+1|k+1} = P_{k+1|k} - K_{k+1} S_{k+1} K_{k+1}^T$
  $z_{d_{k+1|k+1}} = C_d \hat{x}_{d_{k+1|k+1}}$
end if
return $\hat{x}_{d_{k+1|k+1}}$

3.2.2. RUL predictions

A failure threshold (noted D_{fail}) indicates the limit on the SOH value corresponding to a system in failure. RUL is given by the equation below with k as the instant of prediction and n_{fail} as the instant of failure:

$$RUL(k) = (n_{fail} - k).T_s \tag{11}$$

The SOH progresses in time and as the fault value increases, the SOH attains the failure level D_{fail} known *a priori*. The RUL prediction at any discrete time instant k can be obtained using L-step ahead prediction. This is done by projecting the estimated SOH in the future along the estimated degradation model (state model) in Algorithm 1 (see Eq. (10)).

Recursive approach
A recursive approach for RUL prediction within the hybrid prognostics context is well established in the literature (M. Daigle, Saha, & Goebel, 2012; M. J. Daigle & Goebel, 2012) and quite extensively employed in several domains in conjunction with wide range of estimators and their variants such as kalman filters, unscented kalman filters, particle filters (Reuben & Mba, 2014) etc. this approach is adopted here. The L-step ahead prediction procedure employed for RUL prediction is given in Algorithm 2. It should be noted that futuristic predictions are computed keeping the value of control input same, throughout the prediction process. To that end, a recursive algorithm is employed as shown in Algorithm 2 (Thuillier, Galeotta, et al., 2022).

Remark: Although, the recursive algorithm successfully generates RUL prediction estimates, the optimization based approach proposed in this work requires closed-forms of mathematical expression of RUL prediction. To this end, a closed

Algorithm 2 L-step ahead RUL prediction

Input: u_k
Output: $R\hat{U}L$
Initialisation : $L = 0$
1: $[\hat{d}(i), \hat{\alpha}(i)]$ =Algorithm 1$(z_{d_k}, P_{k|k}, u_k)$
2: $d_L(i) = \hat{d}(i)$
3: **while** $d_L(i) \leq D_{fail}$ **do**
4: $\quad d_L(i) = d_L(i).(1 + \hat{\alpha}(i).u(i).T_s))$
5: $\quad L = L + T_s$
6: **end while**
7: $R\hat{U}L = L$
8: **return** $R\hat{U}L$

form analytical expression is derived next.
The degradation expressed in Eq. (9) is expressed as function of the instant of system's failure n_{fail} and the SOH value at instant k.

$$d(n_{fail}) = d(k).(1 + \alpha(k).u(k).T_s)^{n_{fail}-k} \quad (12)$$

Defining L as the number of discrete time steps needed to SOH failure value, n_{fail} can be expressed as $n_{fail} = k + L$, so at instant k, L step prediction is necessary from k in future to reach the instant of failure n_{fail}:

$$d(n_{fail}) = d(k).(1 + \alpha(k).u(k).T_s)^{L} \quad (13)$$

Then, consider the situation when degradation value (SOH) exceeds a threshold D_{fail} at the instant n_{fail}:

$$d(n_f) < D_{fail} \quad (14)$$

From Eq. (13) and Eq. (14) one obtains:

$$d(k).(1 + \alpha(k).u(k).T_s)^{L} < D_{fail} \quad (15)$$

Taking logarithm on either sides, one obtains:

$$L.log\left(1 + \alpha(k).u(k).T_s\right) > log\left(\frac{D_{fail}}{d(k)}\right) \quad (16)$$

so that:

$$L > \frac{log\left(\frac{D_{fail}}{d(k)}\right)}{log\left(1 + \alpha(k).u(k).T_s\right)} \quad (17)$$

Then, consider the smallest integer value of L that satisfies the inequality :

$$L = \lceil \frac{log\left(\frac{D_{fail}}{d(k)}\right)}{log\left(1 + \alpha(k).u(k).T_s\right)} \rceil \quad (18)$$

where $\lceil x \rceil$ correspond to the ceiling of the value of x.

As this L steps are taken to reach the failure from the present instant k, RUL prediction value at time k $\widehat{RUL}(k)$ becomes:

$$\widehat{RUL}(k) = L \quad (19)$$

leading to closed-form expression of RUL prediction as:

$$\widehat{RUL}(k) = \lceil \frac{log\left(\frac{D_{fail}}{\hat{d}(k)}\right)}{log\left(1 + \hat{\alpha}(k).u(k).T_s\right)} \rceil \quad (20)$$

3.3. Set-point modulation

To optimize RUL evolution, a modulation parameter $\omega(k)$ is introduced in the tracking control between the set-point and the system output so that $y_{ref}(k) - y(k)$ becomes $y_{ref}(k) - \omega(k) - y(k)$. Then, Eq. (5) can be expressed as a function of the modulating parameter ω, i.e.

$$\widehat{RUL}(k) = \Phi(\hat{d}(k), ((y_{ref}(k) - \omega(k)) - y(k))) \quad (21)$$

The modulation parameter $w(k)$ is a design variable to slow down the degradation rate and directly modulate the reference trajectory $y_{ref}(k)$.
To that end, a cost function is proposed that penalizes the magnitude of the modulation parameter ω as well as the RUL based performance i.e. difference between the desired and actual RUL estimate. This is done to obtain a suitable trad-off between system performance and slow down the degradation rate leading to the desired RUL based performance of the system. Moreover, penalizing ω translates to the fact that modulation of control input reference is not very "aggressive" which is required for appropriate functioning of the system .
To that end, consider the cost function $J(k)$ defined as:

$$J(k) = \gamma.\omega(k)^2 + (1-\gamma).\left(RUL_{ref}(k) - \widehat{RUL}(k)\right)^2 \quad (22)$$

using $\widehat{RUL}(k)$ from Eq. (21) and $RUL_{ref}(k)$ is the RUL objective given. In terms of the computational aspect, $\widehat{RUL}(k)$ can be obtained from the closed form (Eq. (20)) or via recursive L-step ahead approach (Algorithm 2).
The objective function $J(k)$ can be seen as a result of a trade-off between the modulation of the reference trajectory (effort on the system) and the system's RUL value where γ is the weight parameter. Then the objective of the optimization is translated to finding an optimum $\omega^*(k)$ that minimizes the objective function, i.e.

$$\omega^*(k) = \text{argmin} \quad J(k) \quad (23)$$

where the constraints on the solution can be imposed as $lb \leq \omega(k) \leq ub$ wherein, by default, they can be set as $lb(k) = 0$

and $ub(k) = max(y_{ref})$, to prevent a complete breakdown of the system.

The procedure of the set-point modulation is presented in the Fig. 2 and details are summarised in Algorithm 3.

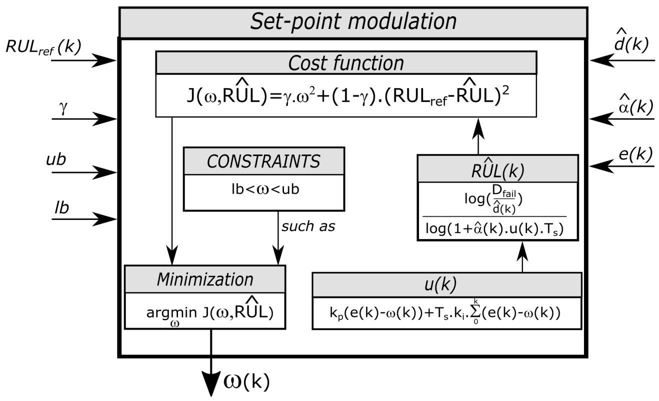

Figure 2. Set-point modulation

Algorithm 3 Set point modulation based reconfiguration strategy

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Input: $RUL_{ref}, y_{ref}, y, u_k,$
Output: ω^*
  $[\hat{d}(k), \alpha\hat{(}k)]$ =Algorithm $1(z_{d_k}, P_{k|k}, u_k)$
  if $R\hat{U}L(k) < RUL_{ref}(k)$ **then**
    $J(k) = \gamma.\omega(k)^2 + (1 - \gamma).(RUL_{ref}(k) -$ Algorithm $2(u(k))^2$
    such $lb \leq \omega \leq ub$
    $\omega^*(k) = \text{argmin}(J(k))$
  end if
  return $\omega^*(k)$

Remark: As the cost function penalises the modulation parameter and RUL based performance difference, it remains system/degradation mechanism agnostic in that it can be applied to dynamical systems in general, respecting the given set of hypotheses.

4. SIMULATION STUDY

Simulation studies on two dynamical systems is presented to assess the effectiveness of the proposed approach.

4.1. Example 1

The system considered is a second-order linear state space system as:

$$\begin{cases} \begin{pmatrix} x_1(k+1) \\ x_2(k+1) \end{pmatrix} = \begin{pmatrix} -12 & -20.02 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} x_1(k) \\ x_2(k) \end{pmatrix} + \begin{pmatrix} 1 \\ 0 \end{pmatrix} u(k) + w_S(k) \\ z(k) = \begin{pmatrix} 0 & 2 \end{pmatrix} \begin{pmatrix} x_1(k) \\ x_2(k) \end{pmatrix} + v(k) \end{cases} \tag{24}$$

A PI controller described in Eq. (6) drives the system output to follow the reference trajectory with $k_p = 17$ and $k_i = 47$ and $w_S(k)$ and $v(k)$ represent the state noise and measurement noises respectively as described in (1). The damage propagation model is considered as a degradation of the actuator, affecting the input signal u as:

$$x(k+1) = A_d x(k) + B(u(k) - d(k)) + w_S(k) \tag{25}$$

with $d(k)$ being the cumulative degradation phenomena. As explained in Eq. (26), the degradation is an accumulation of $\Phi(k)$ based on the system's state x_1. The degradation is active on the system when $\Phi(k)$ exceeds a certain threshold noted K_{lim}:

$$d(k) = \begin{cases} 0 & \textbf{if} \Phi(k) < K_{lim} \\ (\Phi(k) - K_{lim})^{K_{exp}} & \textbf{if} \Phi(k) > K_{lim} \end{cases} \tag{26}$$

with $\Phi(k)$ defined as:

$$\Phi(k) = \sum_{k=1}^{N} x_1(k)$$

where N is the iteration number.

Numerical parameters are set as $K_{lim} = 1.5 \times 10^5$. The system is considered in failure when the degradation hits a failure threshold, which in our case is set as $d_{fail} = 0.65$. The optimization parameters are set as follows: $ub = 35$ and $\gamma = 0.99$ so that more importance weight can be attributed on the RUL control than the performance in the objective function, to better highlight the impact of the proposed reconfiguration strategy on the RUL.

Fig. 3 shows the profiles of degradation $d(k)$, the accumulation of the degradation Φ, the reference trajectory y_{ref}, the system trajectory y, and the system input u provided by the PI controller. It can be seen that the system output follows the reference trajectory (the controller has compensated for the degradation effects) in an appropriate manner.

At each discrete time step k, degradation estimation as well as RUL predictions are generated using an EKF and the L step prediction process respectively. The estimation and prediction $\hat{d}$, and $\widehat{RUL}$ obtained are shown in Fig. 4. It can be seen that the RUL predictions are well sensitive to the control input changes. With the given RUL_{ref}, it is observed that in the absence of a reconfiguration strategy, the RUL of the system does not follow the target RUL_{ref}.

Algorithm 3 (see also Fig. 2) is applied on the system at each time step k. The solution of the optimization ω and the value of the objective function are shown in Fig. 5. The value of ω increases over time with the RUL being modified through

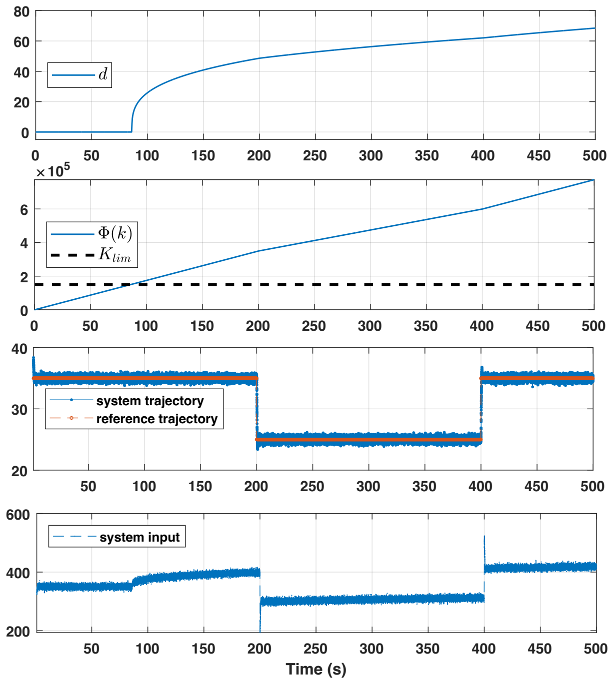

Figure 3. Evolution of the degradation level, degradation accumulation, reference, and system trajectory and system input

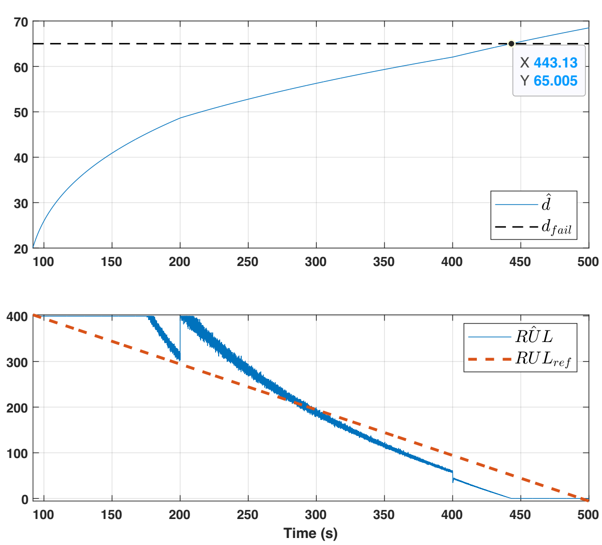

Figure 4. Degradation estimate and RUL prediction - using algorithm 1.

out the lifetime of the system. Moreover, with an injection of an abrupt change (step) at $400s$ in the set-point y_{ref}, it is observed that the algorithm takes into account this change to provide an adequate solution on ω. Upon the application of the proposed ω (Fig. 6), there is a certain reduction in the magnitude of the reference trajectory (in red) leading to de-

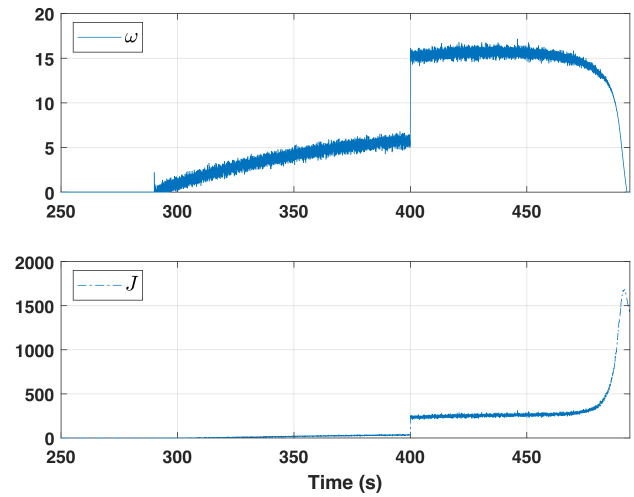

Figure 5. Optimization solution and cost Function

celeration of the degradation rate, which in turn allows the system's RUL to follow RUL_{ref} (in black).
Now, the pre-defined EOL of the system RUL_{ref} is set at 500 seconds. The proposed approach extends the EOL of the system from 442 seconds (without the proposed strategy) to 494 seconds. Indeed, the parameters γ and ub chosen in this case attribute higher relative importance to the RUL than the system performance.
Next, to asses the relative performance associated with and without the proposed approach, certain indicators of health and performance are defined that facilitate the study the parameters' impacts on the results obtained from the proposed approach.

4.1.1. Indicator definition

The performance indicator (noted I_P) and the health indicator (noted I_H) are defined below as a function of a given set of parameters (γ,ub):

$$I_H(\gamma, ub) = \frac{EOL_{WithStrategy}}{EOL_{WithoutStrategy}} \times 100 \qquad (27)$$

$$I_P(\gamma, ub) = \frac{1}{N}\left(\sum_{i=1}^{N} \frac{y_{ref}(i) + \omega(i)}{y_{ref}(i)}\right) \times 100 \qquad (28)$$

with y_{ref} and y corresponding respectively to the reference trajectory and the system output trajectory.
These indicators illustrate the impact of the trade-off between performance and health under the proposed strategy.

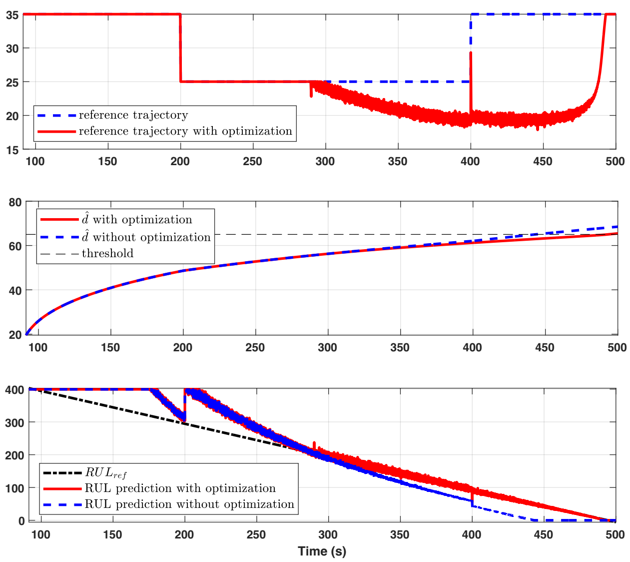

Figure 6. reference trajectory, degradation evolution and RUL with and without optimization

4.1.2. Results of different parameter ub

Different tests with different values of the parameter ub and a fixed value of γ have been performed ($\gamma = 0.1$) (see Table I).

Table 1. Test with different ub values

test	1	2	3	4	5	6	7	8
ub	1.5	3	4.5	6	7.5	9	10.5	12

The obtained reference trajectory, degradation, and RUL evolution for each test are shown on Fig. 7. The Indicator I_P and I_H results are shown Fig. 8.
With big values of ub, the range of the possible solutions ω becomes wider, which leads to a more significant reduction of the system performance indicator I_P and an increase in the system health indicator I_H. In fact, the basic requirements on system performance and system health, a value of ub must be properly chosen. Further, an appropriate choice of γ allows for suitable balance between the system performance and the RUL oriented performance of the system.

4.1.3. Results with different parameter γ

Different tests with different values of the parameter γ and a fixed value of ub ($ub = 4$) have been computed (see Table II).

Table 2. Test with different γ values

test	1	2	3	4	5	6	7	8
γ	0.001	0.01	0.1	0.25	0.5	0.75	0.9	0.99

A decreasing γ value leads to a higher value of the objective function with respect to "RUL tracking". This means that the

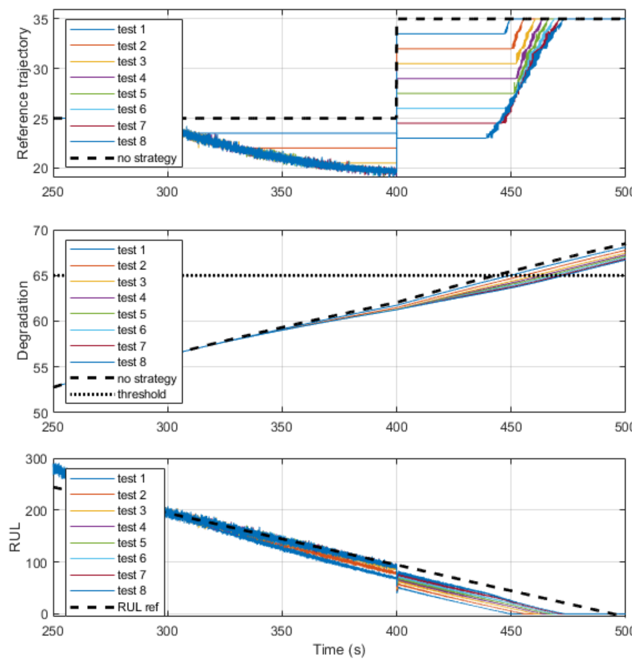

Figure 7. ub variation: reference trajectory, degradation evolution and RUL with and without optimization

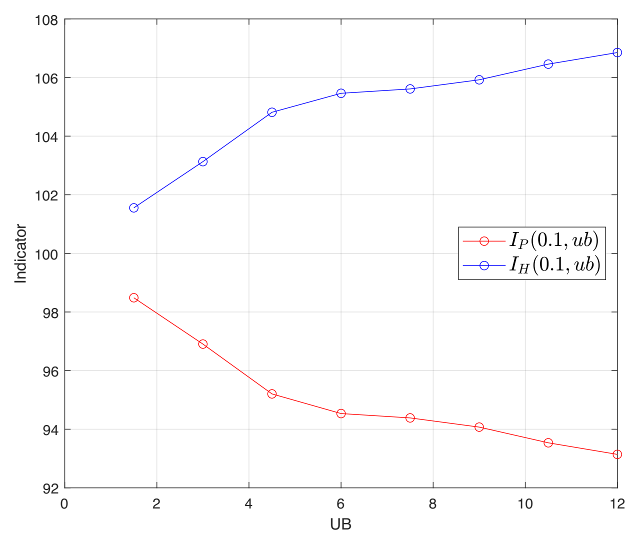

Figure 8. Indicators evolution for ub variations

control design prioritizes the remaining useful life of the system over its performance. With a higher value of solution ω obtained, the degradation rate reduces. On the contrary, when a higher value of γ is applied, we obtain a lower I_H and a bigger I_P. This means that the control design prioritizes the performance of the system over its remaining useful life. In order to balance between performance and remaining useful life, the value of γ must be properly defined. The final

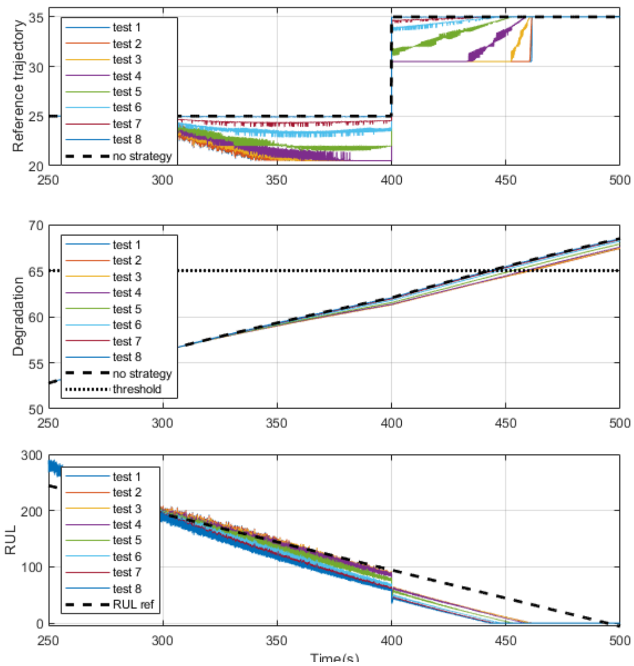

Figure 9. γ variations: reference trajectory, degradation evolution and RUL with and without optimization

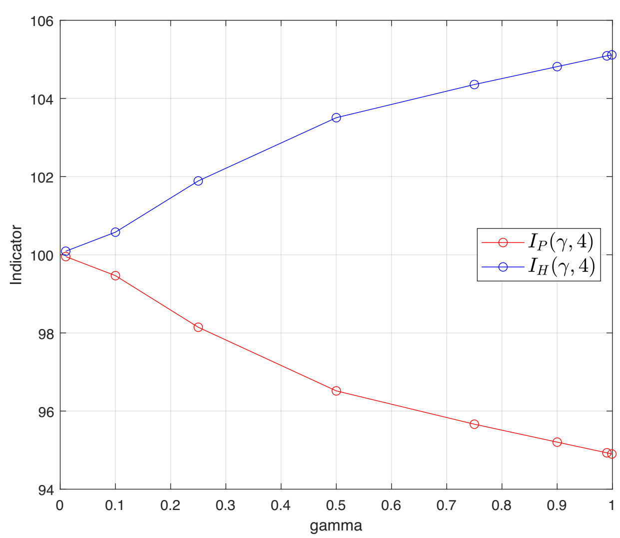

Figure 10. Indicators evolution for γ variations

parameter choices must take into account both indicators to achieve an optimal control design.

4.2. Application LPRE

The proposed strategy is applied on a fictive LPRE LOX-LH2 engine model of 10KN subjected to degradation shown in Fig. 11. The engine is composed of liquid rocket propellant pumps operated to allow circulation under high pressure

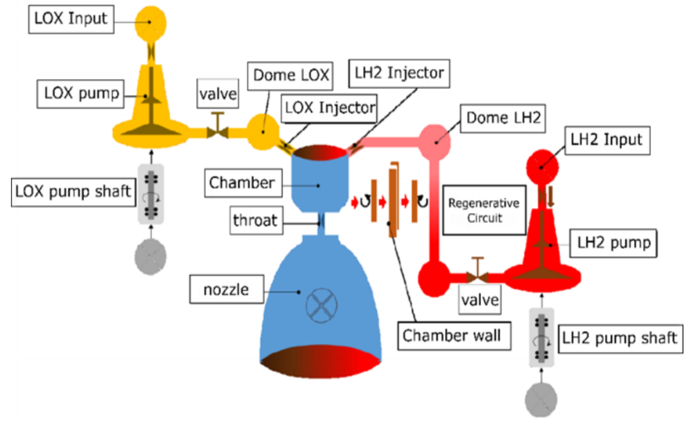

Figure 11. Liquid Propellant Rocket Engine - LH_2-LOx

through complex liquid circuits. Two control valves allow the mixture ratio balance of the engine to be adjusted according to the operating point. The reaction between the propellants is carried out within the combustion chamber with the ejection of the heat flow through the throat and the nozzle. Readers are referred to (Thuillier, Galeotta, et al., 2022; Thuillier, Jha, et al., 2022)) for details on the system.
Here, degradation refers to the appearance of cracks on the combustion chamber wall which can cause fuel leakage from the regenerative circuit into the combustion chamber and cause combustion efficiency loss (degradation of ηC^*). The degradation is modeled as leak in the regenerative circuit and a loss of flow in the combustion chamber. The SOH indicator denoted as SOH is defined as the normalized characteristic speed efficiency, which is the ratio (denoted ηC^*) between the real characteristic speed (C^*) and the theoretical characteristic speed ($C^*_{theoretical}$).

The efficiency is defined as:

$$\eta C^*(k) = \frac{C^*(k)}{C^*_{theoretical}} \tag{29}$$

and as such, the SOH can be expressed as:

$$SOH(k) = \frac{\eta C^*_{max} - \eta C^*(k)}{\eta C^*_{max} - \eta C^*_{min}} \tag{30}$$

with ηC^*_{max} and ηC^*_{min} the maximal and the minimum reachable values of ηC^*.

The exact degradation model is considered unknown due to the complexity of the LPRE physical model. An approximately correct degradation model based on general characteristics of degradation, previously described in Eq. (12), is considered for hybrid prognostics using an EKF. The proposed approximation model of the degradation is adapted to such a

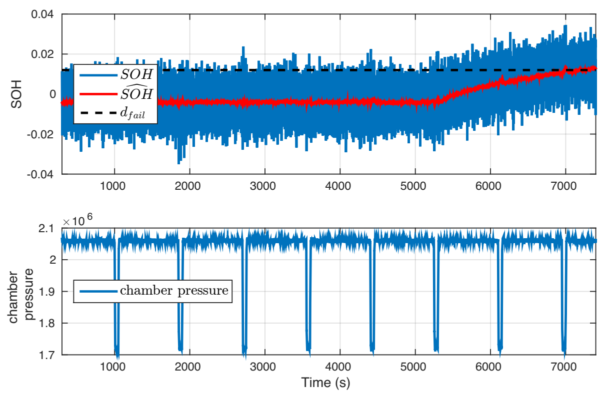

Figure 12. SOH, RUL and pressure chamber of the system without strategy

system followed by an estimation of the SOH and futuristic RUL for the chamber pressure chamber. SOH, $\widehat{SOH}$, and chamber pressure are shown in Fig. 12. The chamber pressure profile, oscillating between two values of pressure, can be identified as a stress bench in order to assess the quality of the motor. The SOH (in blue) is highly noisy. EKF (based on an approximate degradation model input dependant, see Eq. (12)) provides a good estimate of the SOH noted $\widehat{SOH}$ (in red).
Considering the LPRE case, the failure threshold d_{fail} is set to $d_{fail} = 0.012$. $\widehat{SOH}$ and RUL prediction are presented in Fig. 13. The SOH passes the failure threshold at time $6988s$ which leads to system failure. The system without the set-point modulation strategy doesn't achieve the set EOL target of $7300s$ given by the RUL_{ref} (in black).

On the other hand, the set-point modulation strategy (Algorithm 3), leads to the optimization Eq. (22) performed at each instant of time. To that end, the optimization parameters $\gamma = 0.1$ and the upper bound $ub = 0.6 \times 10^6$ are set in accordance to the real time on-field application constraints.
The target EOL is set to $7200s$. Implementation to LPRE implies modulation of the chamber pressure that invariably leads to change in dynamic behaviour of the LRPE.

Fig. 14 shows the evolution of SOH, RUL prediction and chamber pressure. Under the proposed approach, the optimization procedure results in progressive decrease in chamber pressure when the approach is activated. This is due to the modulation of the input in order to reach the desired RUL at each instant of time through a suitable comprise on the system performance leading to a certain "reduction" in the pressure value until the demanded comprise is reached through optimization. The modulation strategy enables changes (abrupt as well as oscillatory) within system variables such that predicted RUL matches the desired RUL. Against the system performance without the proposed strategy shown in Fig. 14,

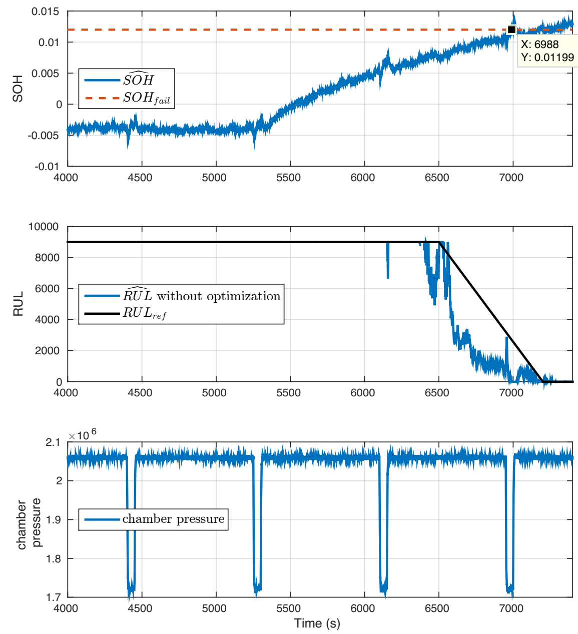

Figure 13. SOH, RUL and pressure chamber of the system without strategy

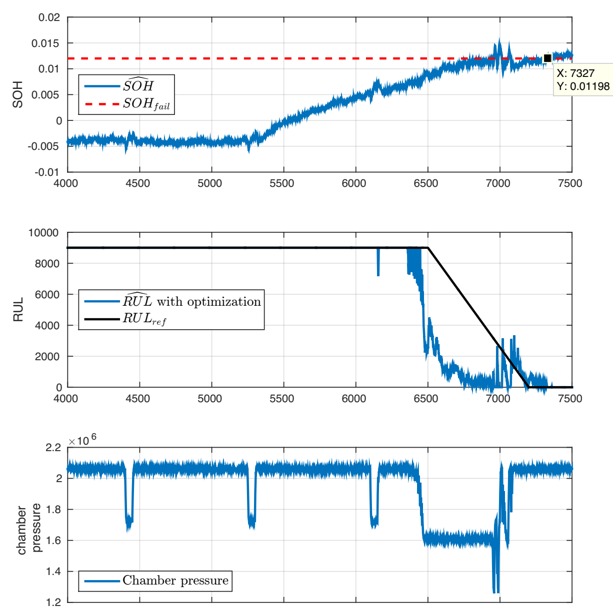

Figure 14. SOH, RUL and pressure chamber of the system with strategy

such changes are apparent and amplified as the EOL approaches (near 7000s) as shown in Fig. 14. The controller attempts to reduce further the chamber pressure (system performance) in order to gain RUL. As discussed before, various hyper-parameters prevent the controller from reducing the performance beyond a certain level. The set point modulation strategy is able deliver an extension of EOL to 7327s.

5. DISCUSSIONS

LPRE system is a complex nonlinear system wherein various components and sub-systems are mutually coupled dynamically. As such, degradation in a component raises the possibility of affecting the nominal functioning of other components and system as a whole. Thus, the compromise over performance of a component must be sought taking into account nominal functioning of other critical components not necessarily sensitive to degradation directly. This indeed reduces the scope for values of several hyper-parameters including γ within the optimization routine leading to plausible conservative behaviour. This is evident from predicted RUL profile in Fig.14 where the proposed strategy seems to "revive" the system near 7000s wherein EOL seems have been attained, followed by increase in RUL prediction through a subsequent action of controller. Although this demonstrates well the influence of proposed strategy over the system/RUL dynamics, the complex dynamics leaves the users with restricted choices leading to such a conservative behaviour which may be avoided through more sophisticated nonlinear control designs in future.

Further, the controller is primarily PI based and as such, with suitably selected controller gains, the controller with modulation conserves the basic properties of a PI controller such as stability of the system and robustness to perturbation. However, given that such properties of a PI controller is well established, this work does not study the controller performance in the classical sense.

6. CONCLUSION

This paper presents a novel control design strategy that takes into account the state of health and remaining useful life of a dynamical system subjected to functional degradation. The proposed strategy introduces a set-point modulation approach that adjusts the reference trajectory of the system based on the degradation state estimation and remaining useful life prediction. The modulation parameter within the optimization, not only modifies the reference trajectory, but also affects the performance of the system. The results show that the proposed strategy can effectively extend the remaining useful life of the system while maintaining acceptable performance. As novelty, an analytical closed form of RUL prediction equation is derived for computationally efficient generation of RUL predictions, contrasting with the typically employed $L-step$ ahead prediction procedures that require waiting for arrival of predictions before optimization leading to computations at different time scales. Moreover, presence of closed form facilitates the formulation of the optimization cost function. Although, the work considers exponential degradation mechanism which are quite ubiquitous, derivation of a closed form RUL prediction expression cannot always be guarenteed calling for further research in this direction. The proposed strategy assumes that the failure threshold value is known and prefixed, and the desired RUL trajectory or the desired EOL is known beforehand, which may not be true in all scenarios. A reachability analysis needs to be performed to ascertain if the desired RUL is attainable, that is, there is a control input that will lead to such a desired RUL/EOL value. Furthermore, in this work, uncertainty associated with RUL prediction as well as state-of-health (SOH) estimation have not been considered. Uncertainty quantification and inclusion of the latter within control design is a promising perspective for future research as initiated in (Kanso et al., 2022).

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