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Impact of control gain design on Remaining Useful Life for a Liquid Propellant Reusable Engine

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Abstract
The context of the liquid propellant reusable rocket engines brings new technological and scientific challenges for control, diagnostic and prognostic aspects. Much progress has been made independently on each facet, however, the combination of these is less discussed. The main contribution of the paper consists in the analysis of the remaining useful life estimated using a hybrid method as a function of variant control parameters. The degradation effect (link to input) on remaining useful life for closed loop and open loop in the case of a liquid propellant reusable engine is evaluated. An analysis of the controller parameters effects on the remaining useful life and the performance for a single input single output system case is presented. Numerical results concerning the variation of controller parameters on a liquid propellant reusable engine simulation platform are shown.

1. Introduction

The context of reusable cryogenic liquid rocket engines brings new technological and scientific challenges for control and prognostic aspects. Much progress has been made independently on each facet ([1], [2], and [3]), however, the combination of these is less discussed. To maximize the Remaining Useful Life (RUL) of a rocket engine under degradation, the link between the controller parameter and the RUL estimate using hybrid prognostic methods is investigated in this paper. The solicitations coming from the input commands of the system affecting the RUL are presented.

The case of a fictive LPRE LOX-LH2 engine of 10KN (show Figure 1) thrust subjected to degradation ([5] and [6]) has been studied in the literature. Degradation represents the appearance of cracks in the combustion chamber leading to fuel leakage from the regenerative circuit into the combustion chamber. The leakage of the regenerative circuit will cause a loss of combustion efficiency (degradation of η_{C*}).

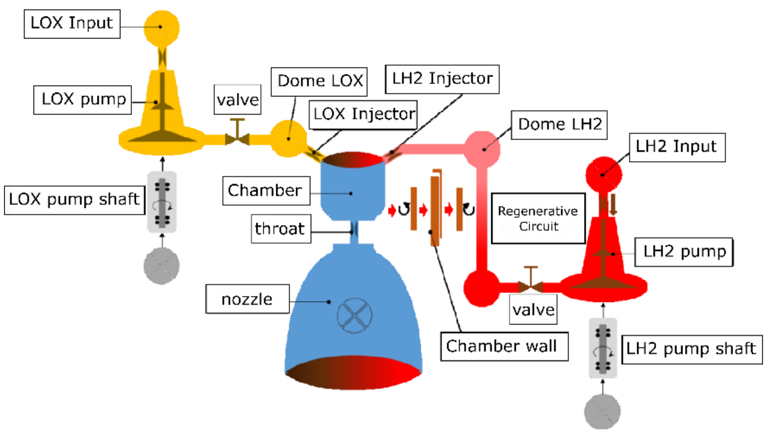

Figure 1: Reusable cryogenic liquid rocket engine's structure

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In the literature, prognostics strategies for maintenance activities can be sorted into three categories. First, model-based strategies use the physical form or deterministic or stochastic degradation model. We can cite articles [7] and [8] on the topic. Data-based strategies deal with a large set of observation data (system input, output and operating mode). Works on given-based strategies include [9] and [10]. Finally, hybrid strategies associate data-based and model-based strategies. The advantage of the robustness given by the system model and the precision provided by the historical data is used. Among these works, publications are using a Kalman filter ([11], [12] and [13]), or a particle filter ([14] and [15]) for example.

In the case of the LPRE, the authors [16] present a hybrid prognostics procedure with the formulation of the RUL prediction method using the Extended Kalman Filter (EKF). Estimation of the State of Health (SOH) and the degradation parameters has been performed.

The main contribution of the paper is made of the analysis of the RUL estimated using the hybrid method [4] as a function of varying gain of the control loop. Also, optimal parameters to ensure a balance between performance and RUL are obtained. The paper is divided into three sections. The comparison of the effects between closed loop and open loop on the estimate RUL based (on CNES CARINS Simulator tool). The analysis of the effects of the control parameters (variation of proportional parameter P and integral parameter I) on the RUL and the performance in the case of a SISO (Single Input Single Output) academic test case are presented in the second section. Finally, the last part focus on the results concerning the variation of the controller parameters on an Liquid Propellant Reusable Engine (LPRE) simulated on CNES Simulator tool. Also, their effect on the prognostics for the degradation level and degradation parameter is presented.

2. Problem Statement

The nature of the degradation of LPRE is often associated with the thermal and mechanical gradients to which the chamber is subjected during its functioning (cracks on the internal wall). Degradation causes a leak of fuel from the regenerative circuit in the combustion chamber leading to a loss of thermal flux on the surface areas concerned by the cracks and an overall decrease of the combustion efficiency of the chamber.
The performances (Characteristic velocity and Specific Impulse) of a chamber affected by this degradation are impacted.

Reusable cryogenic liquid rocket engines bring two behaviors as reusability and varying set-point at their maximum. These behaviors involve strong solicitation, in the short term (varying set-point) and in the long term (reuse). Moreover, the solicitations applied to the LPRE are related to the dynamics of the degradation

In this context, the States of Health (SOH) estimation and degradation parameters of the LPRE are obtained in an open loop and closed loop to observe effect of solicitation via the command. RUL prediction is performed from these estimations.

A closed loop of the LPRE is composed of a pre-established nominal input (function of the operating point) associated with a PID Controller. To achieve this objective, we generate data by simulating the closed loop and open loop functioning of the LPRE via the CNES tool CARINS, then the prognostic method presented in [16] is applied. The chosen SOH is defined as the characteristic speed efficiency, which is composed of a quotient between the real and the theoretical characteristic speed. The RUL projection algorithms consider a constant input during prediction.

Figure 2 presents the evolutions of the States of Health (SOH) and the RUL in the case of a closed loop and an open loop LPRE. Time unit evolution is denoted in seconds. At time 3800s, the SOH begin to change drastically, demonstrating the beginning of the degradation. The slope of SOH is different in function of the control strategy. It increases faster in the case of the closed loop, this reflects a more sustained degradation.

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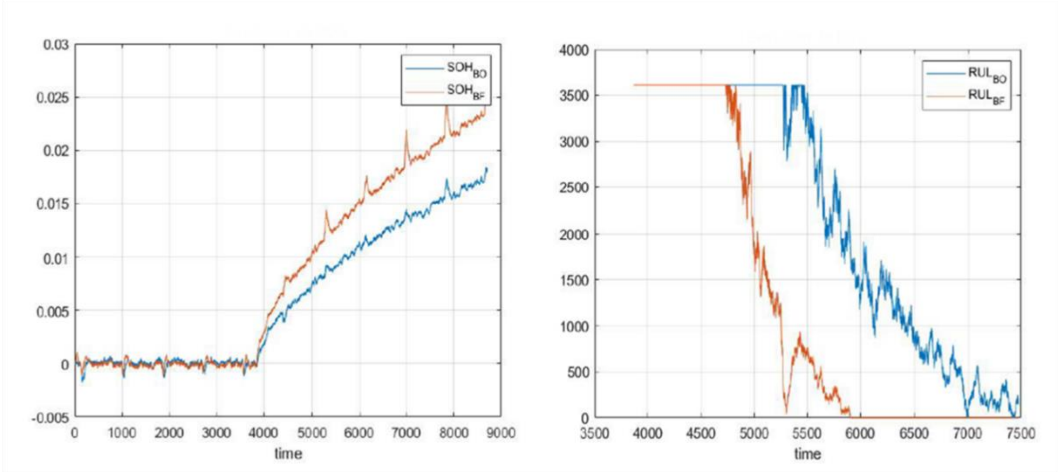

Figure 2: SOH and RUL evolution - close loop and open loop

Also, the RUL in the context of the closed loop reaches the value of zero more quickly, reflecting an earlier End of Life (EOL) of the system during its operation.

Results obtained for the RUL behaviour in the open loop and closed loop show the relation between a degradation link to the input and the control structure. In addition, the evolution of the degradation is indirectly link to the engine set-point. This suggests the interest in the development of new control strategies, to guarantee the classic criteria of robustness (ensuring stability and performance dynamics) as well as, to prolong the life of the LRPE system.

The next section will focus on the relation between the controller parameter, the degradation and the RUL for a SISO system.

3. Effect of regulation parameters on RUL and Performance – SISO system

Analysis of the effects of the control parameters (variation of proportional parameter P and integral parameter I) on the RUL and the Performance in the case of a SISO (Single Input Single Output) system (academic test case) is presented in this section in a first step.

3.1 System structure and degradation

The choice of an academic system is motivated by a large number of simulations and data required, to generate at a preliminary stage an analysis.

The system considered is a seconder order, single input single output system, defined by the following transfer function *P(s)* dependant of the output *Y(s)* and the input U*(s)*:

$$\boldsymbol{P(s)} = \frac{\boldsymbol{Y(s)}}{\boldsymbol{U(s)}} \tag{1}$$

A PI controller is associated to the system in order to track the system trajectory (noted *y*) to follow a reference trajectory. The error between the reference trajectory and the system trajectory is noted ~~s~~ *e(t)*. The control law provided by the PI controller is described by the classical following equation:

$$\boldsymbol{u(t) = K_p e(t) + K_i \int_0^t e(t)\, dt} \tag{2}$$

The considered degradation d(t) is assumed to be dependent of the system's input *u* and a degradation rate noted α :

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$$\boldsymbol{d(t)} = \boldsymbol{f}(\boldsymbol{\alpha}(\mathbf{t}), \boldsymbol{u(t)}) \quad \textbf{(3)}$$

In our case, d is defined as: $d(k) = \left(u(k)^2.T_s.\alpha(k)\right)$ (choice related to the degradation dependent on the inputs of LPRE command as result in previous section). To simplify the prognostic part, the degradation is assumed to be well-known and can be monitored in simulation.

To analyse the effect of controller parameters, an experiment plan has been defined.

First, a reference system subject to degradation is defined and simulated with fixed parameters P and I. The output of the simulated system is noted Y_{REF}. The degradation dynamics is well known and monitored, a simple prognostic permits us to generates the associated RUL, noted RUL_{REF}.

Besides, the same system with degradation (same as in the reference system), named "varying system" is simulated for a various set of parameters P and I. Associated output and RUL are noted respectively Y_{VAR} and RUL_{VAR}, as presented in Figure 3.

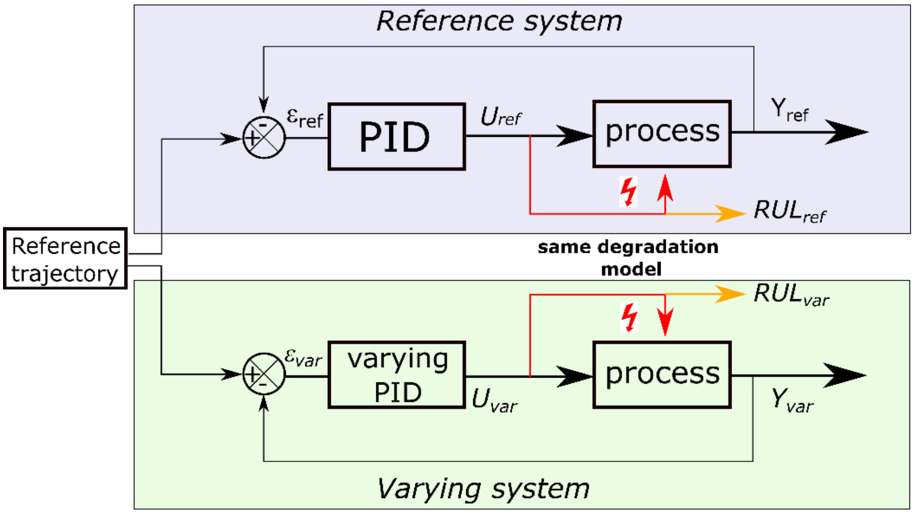

Figure 3: experiment structure

To be able to compare the effect of the variation of P and I parameters, two indicators have developed in the following subsection.

3.2 Proposed indicators

The two-indicators proposed concern the RUL and the dynamic performance.

RUL indicator:

A RUL indicator noted $RUL_{indicator}$ using RUL_{REF} and RUL_{VAR} is defined as:

$$\boldsymbol{RUL_{indicator}} = \sum_{t=0}^{t=t_{EOL}} \boldsymbol{\zeta(t).\gamma(t)} \quad \textbf{(4)}$$

$$\boldsymbol{\zeta(t)} = \boldsymbol{RUL_{var}} - \boldsymbol{RUL_{ref}} \quad \textbf{(5)}$$

The indicator is the error noted $\zeta(t)$ between the RUL of the reference system and the RUL of the variant system. For each error, a weight (noted $\gamma(t)$) is applied to balance the results. The higher t is, the bigger is the weight, in other words, the more we advance in the life of the system, the bigger the difference between the RUL are considered.

Performance indicator:
The first indicator noted $Performance_{indicator}$ is defined as:

$$\boldsymbol{Performance_{indicator}} = \left(\sum_{t=0}^{t_{end}} |\boldsymbol{Y_{VAR}(t)} - \boldsymbol{Y_{REF}(t)}|^2\right)^{\frac{1}{2}} = \left(\sum_{t=0}^{t_{end}} \left|\left(\boldsymbol{Y_{VAR}(t)} - \boldsymbol{ref_{traj}}\right) - \left(\boldsymbol{Y_{REF}(t)} - \boldsymbol{ref_{traj}}\right)\right|^2\right)^{\frac{1}{2}} \quad \textbf{(6)}$$

The more the value of the indicator is close to 0, the more the performance of the varying system follows the reference system (error between the output of the reference system and the varying system).

The next section is composed of a numerical simulation and the analysis of the results obtained.

3.3 Numerical simulations

A SISO transfer function is defined as:

$$\boldsymbol{P(s)} = \frac{\mathbf{2}}{\boldsymbol{s^2+12s+20.02}} \quad \textbf{(7)}$$

The proportional and integral parameters of the PI controller are defined as “optimal” for P=17 and I=47.

As shown in Figure 4, evolution of the RUL indicator in the function of a set of P and I parameters (P, I) for a pulse reference trajectory of magnitude 3. Also, an improvement limited zone is traced to highlight improvement on the RUL. RUL is improved for some sets (P, I).

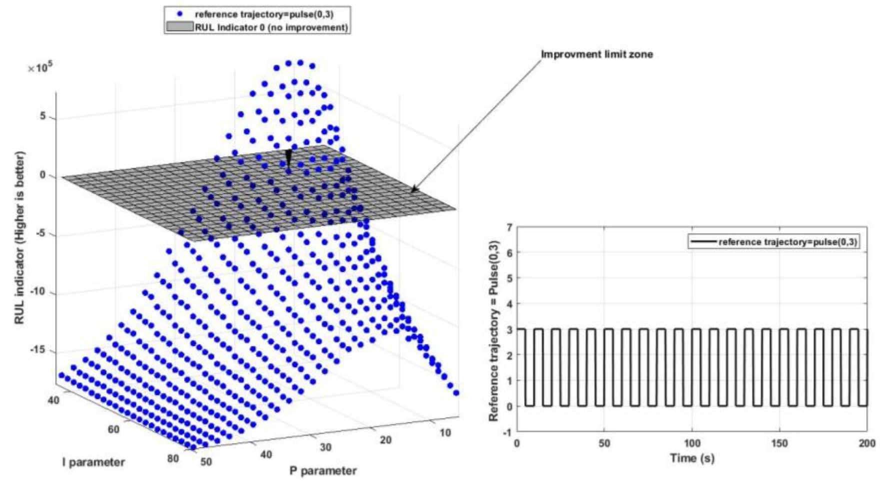

Figure 4: RUL indicator in the function of P and I parameters

RUL is clearly function of the parameter P and I of the controller. More parameter’s values P and I are high, more the RUL is decreased. Smaller value parameters for the controller improves the RUL. this is explained by the fact that these parameters induce less solicitation of the system and therefore a lower rate of degradation.

As presented in Figure 4, Figure 5 shows the RUL indicator evolution for different (P, I) set, for different reference trajectory (magnitude solicitation).

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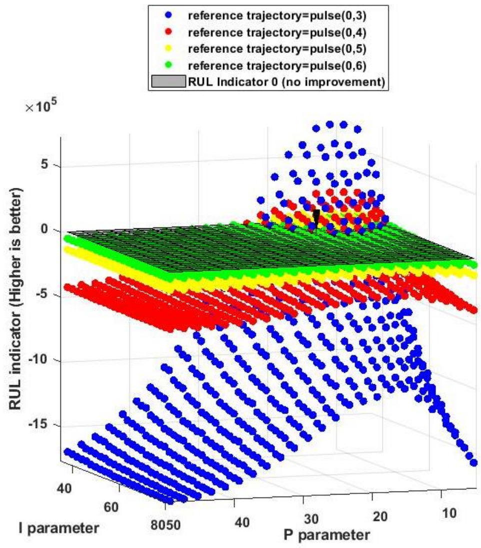

Figure 5: RUL indicators in the function of P and I parameters for a different trajectory

As shown, more the demand solicitation on the system is important, less controller's parameters affect the RUL.

Figure 6 has illustrated the RUL indicator (axe z) and performance indicator (colormap) in the function of a set of (P, I) for different reference trajectories. A trade-off between performance and RUL indicator is observable and confirms the necessity to develop a control strategy considering RUL prediction to extend the EOL of the system.

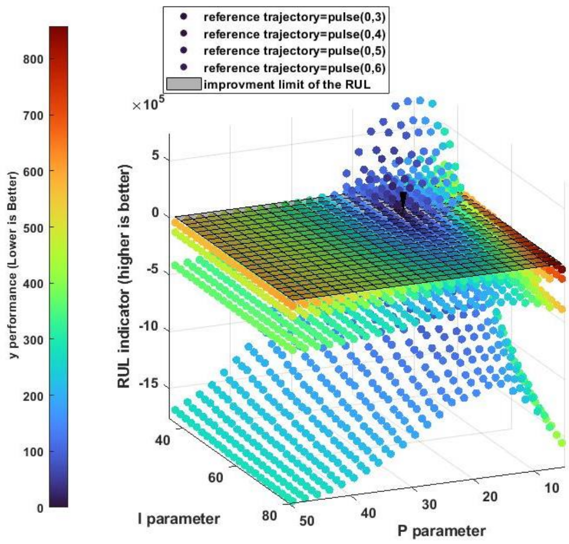

Figure 6: RUL and performance indicators in function of P and I parameters

4. Effect of controller parameters on RUL and Performance – LPRE system

This section presents the simulation of a closed-loop LPRE system on the CNES simulator. The generated command, denoted *u*, is defined as:

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$$u(t) = u_{nominal}(t) + u_{PID}(t) \quad (7)$$

The control law is based on the association of a nominal command and a correction command provided by a PID. The nominal command is pre-defined in a table and calculated according to operating point/reference trajectory. In this case, the contribution of u_{PID} is minor compared to $u_{nominal}$ as: $u_{PID} \ll u_{nominal}$. The variation on the parameters P and I, therefore, have a small effect on the degradation considering the profile of the reference trajectory.

To highlight the effects of the solicitation on the RUL we assumed in the study a simple proportional controller. In association with varying P parameters, $u_{nominal}$, will be varying as shown in Table 1.

Table 1: Test parameters table

	P	U_{nom}
Test: 1	**-30% nominal of P**	**-30% of Unom**
Test: 2	**-50% nominal of P**	**-50% of Unom**
Test: 3	**+30% nominal of P**	**+30% of Unom**
Test: 4	**+50% nominal of P**	**+50% of Unom**

Figure 7 presents the evolution of the SOH for the four tests described with various P values. SOH computed for a different levels of solicitation are sensible to this variation.

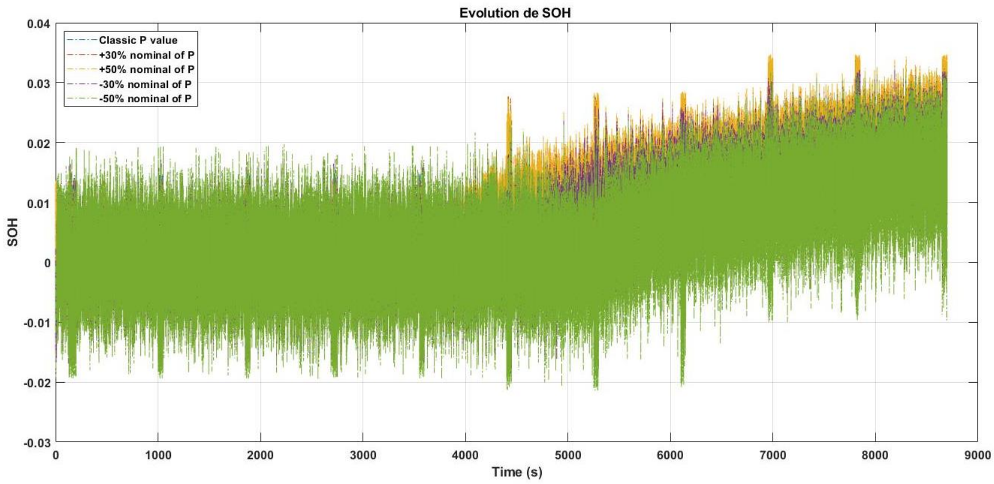

Figure 7: SOH for the different tests of a LPRE system

Estimation of the SOH, based on the Extended Kalman Filter is presented Figure 8. Kalman filtering permits us to observe more clearly an evolution of the SOH.

We can observe the beginning of the degradation is amplified by the magnitude of the solicitation (degradation start is based on an accumulation indirectly link to the command). Also, the degradation rate is modified.

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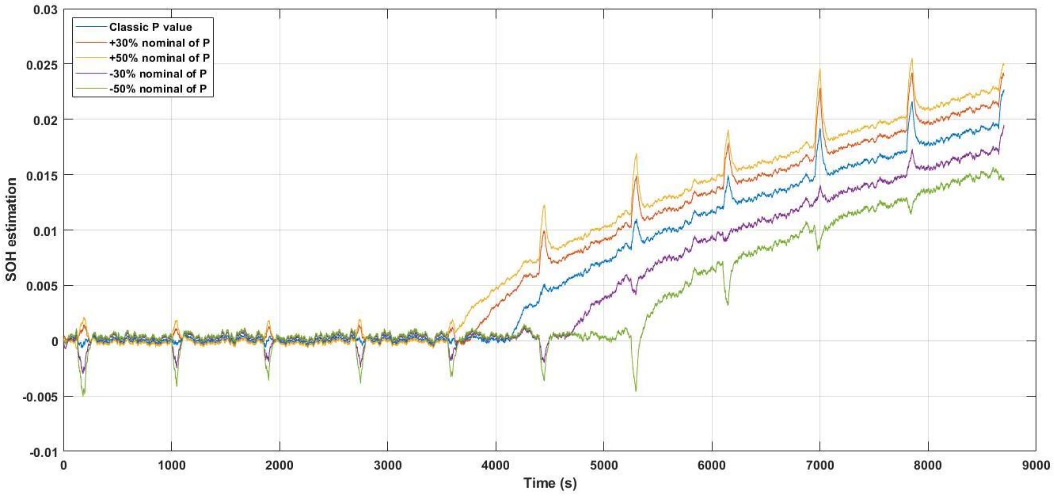

Figure 8: Estimation of the SOH for different tests of a LPRE system

Regarding the effect on the performance of the different configuration of the command (change of P and Unom). The lower the commands are, the less the system is degraded but the more the outputs deviate from the setpoint.

Associated RUL of SOH evolution present previously are shown in Figure 9 below. RUL decrease more quickly when solicitation of the system are high.

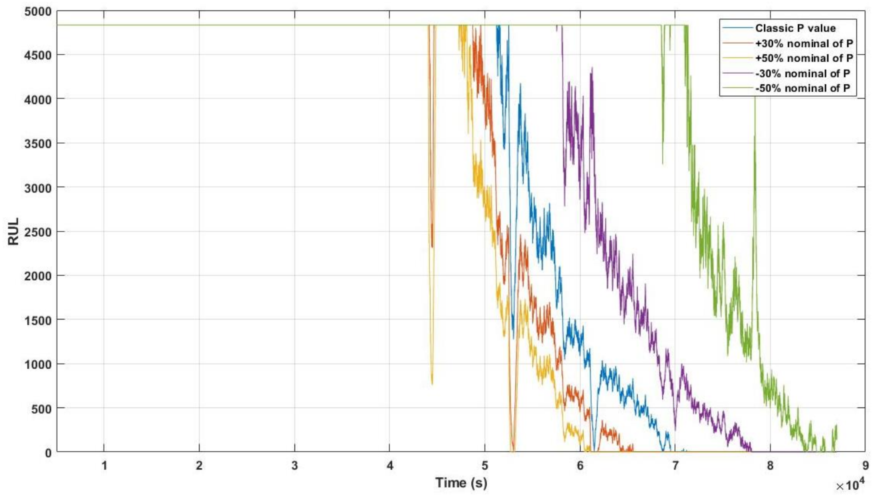

Figure 9: RUL for different tests of a LPRE system

So, the degradation of a LPRE system is affected by the command/solicitation applied. These results confirm the previously obtained in section 2 and section 3.

Conclusion

A LPRE system and an academic system have been used, to analyse the effect of controller parameters on a type of degradation linked to system's solicitation. Experiments have been highlighted the link between solicitation and command on the RUL in the case of degradation related to the input. A clear trade-off between the performance requirement and the RUL criteria has been shown in the numerical result. It expresses the necessity of providing a real-time prognostic tool, combining optimization, RUL prediction and control input regulation.

Further work will focus on the development of this type of tool and of an optimization criterion between predicted RUL and an objective defined sensitive to RUL, allowing an extension of RUL by control modulation.

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