Control reconfiguration strategies for Remaining Useful Life extension

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Abstract: Extending the Remaining Useful Life (RUL) of dynamic systems functioning in closed loop in accordance with damage progression dynamics is a challenging task. Such target combines the challenges emanating from the domain of Prognostic Health Management (PHM) and engineering of the control theory. The main contribution of the paper consists in the synthesis and the analysis of two control reconfiguration strategies in order to achieve such objective.
This paper presents two control strategies, one reconfigures the controls input and the other reconfigures the setpoint. The first structure modifies the controls input sent to the system using a modulation parameter. The second structure proposes a modification to the operational setpoint of the system's control loop. These modulations are obtained from an optimization algorithm making it possible to achieve a trade-off between the dynamic performance requirement and the RUL criteria.
The optimization algorithm is based on the prediction of the RUL and on the estimation of the deterioration. A numerical example illustrates the use of each of these two strategies, through the results of estimating the deterioration, predicting RUL, and obtaining the modulation parameter from the optimization. The RUL extension and its impact on performance trade-off are illustrated to evaluate the performances of both strategies.

Keywords: Failure Prognostic, Optimization and Control, Remaining Useful Life, Degradation.

1. INTRODUCTION

The extension of Remaining Useful Life (RUL) based on prognosis results is an emerging topic in maintenance activities. Today the number of complex systems is increasingly important; among these, the extension of their remaining lifetime during their operation by maintenance actions cannot always be conducted due to non-accessibility or non-availability (the mission of the system cannot be interrupted). Extending the RUL of these systems can then only be achieved with the help of a change in the mode of operation. Moreover, damage to the actuators that are directly related to the control inputs applied to the system, require special attention. To extend the RUL, a general solution lies in the modulation of the operating point to slow down the rate of degradation.

Indeed, the growth in the complexity of industrial systems and associated maintenance task lead to the increasing use of the prognostics strategies on maintenance activities. Among these, there are model-based strategies using knowledge of the system model, data-based strategies driven including historical data, and hybrid strategies which use both the data and system model.

Model-based strategies use the physical formalism or stochastic or deterministic degradation model. We can highlight in particular the work of (Luo et al., 2003) and (Swanson, 2001) on the subject.

Data-based strategies concatenate a large set of observation data such as system output measurements and operating mode. Works on given-based strategies include (Roemer et al., 2001) and (Pecht, 2008).

Hybrid strategies combine model-based and data-based strategies. They take advantage of the robustness given by the system model and the precision provided by the historical data. Among these works, publications are using a Kalman filter ((Kan et al., 2015), (Bressel et al., 2016) and (Pour et al., 2021)), or a particle filter ((Zio and Peloni, 2011), (Jha et al., 2016a) and (Jha et al., 2016b)) for example.

There are several approaches in the literature, reliability based wherein reliability is used as indicator of system degradation incorporated into the control loop structure ((Khelassi et al., 2011a) and (Khelassi et al., 2011b)), RUL based fault tolerant control and fault compensation

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inspired strategies((Rodriguez et al., 2018) and (Obando et al., 2021)). In the latter works, the choice of control loop structure would have deserved to be justified. This work, on the other hand, investigates two plausible control strategies inspired from optimization control based reliability framework and justifies their use for the extension of RUL.

The main contribution of this paper is to provide a real-time prognostic tool, combining optimization, RUL prediction and control input regulation. An optimization criteria is created between predicted RUL and an objective defined sensitive to RUL, allowing an extension of RUL in accordance with control modulation.

Section 2 is dedicated to the problem statement and RUL prediction. Section 3 will be devoted to the synthesis of the compensation structure and the associated optimization in the context of compensation on the control signal. Similarly, the synthesis of a second structure, whose compensation is performed on the setpoint.

Section 4 focuses on the robustness of these methodologies. An analysis of the impact of uncertainties on the prognostics and the optimization is carried out, completed with a numerical example by considering a forced uncertainty on the degradation injected into the prognostics of RUL. Finally, conclusions are presented and the perspectives are given.

2. PROBLEM STATEMENT

In this paper, the effect of component degradation is studied. Closed loop systems in accordance with damage progression dynamics are highly influenced by controllers. In addition, the RUL is then significantly impacted by the control loop structure. The effect of the closed loop and the degradation on the RUL can be generalized by:

$$RUL(k) = f(d(k), u(k)) \tag{1}$$

with $u(k)$ the input produced by the closed loop controller and $d(k)$ the actuator degradation with damage progression dynamics.

2.1 Closed loop system

Considering a Single Input Single Output (SISO) discrete linear system noted P:

$$P(z) = \frac{Y(x)}{U(x)} \tag{2}$$

A controller noted C is considered to drive the system along the reference trajectory.

The tracking error is defined as: $e(k) = y(k) - r(k)$, and $y(k)$ corresponds to the system output and $r(k)$ is the reference output trajectory.

2.2 Degradation

The degradation noted $d(k)$ is defined as:

$$d(k) = d(k-1).(1 + u(k)^2.\alpha) \tag{3}$$

with α the degradation rate. Choice of the degradation's model is motivated by a sequential damage progression in function of the system's input (such as actuator degradation) (Letot and Dehombreux, 2009).

The degradation signal $d(k)$ and its interaction with the control signal from controller $u(k)$ are depicted in Fig. 1.

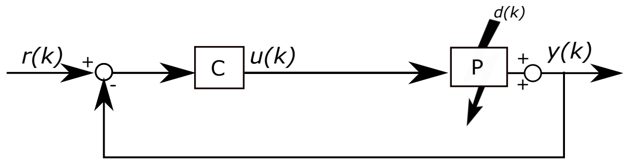

Fig. 1. System with degradation.

2.3 RUL prediction

From degradation dynamics, the degradation at an instant n from a previous instant k (if $n > k$) can be described as:

$$d(n) = d(k).(1 + u(k)^2.\alpha)^{n-k} \tag{4}$$

with the assumption that the input is considered constant during the prediction phase *i.e.* $\forall i \in [k+1, k+2, ..., n]$, $u(i) = u(k)$.

The instant of failure (n_f) corresponds to the time instant when the degradation magnitude exceeds a pre-defined threshold S.

$$d(n_f) = d(k).(1 + u(k)^2.\alpha)^{n_f - k} \geq S \tag{5}$$

Taking a trivial logarithm in (5), we obtained:

$$n_f \geq log_{(1+u(k)^2.\alpha)}\left(\frac{S}{d(k)}\right) + k \tag{6}$$

become as follows with a log_{10} base:

$$n_f \geq \frac{log_{10}\left(\frac{S}{d(k)}\right)}{log_{10}\left(1 + u(k)^2.\alpha\right)} + k \tag{7}$$

Taking the smallest integer value of n_f that satisfies the inequality:

$$n_f = \left\lceil \frac{log_{10}\left(\frac{S}{d(k)}\right)}{log_{10}\left(1 + u(k)^2.\alpha\right)} + k \right\rceil \tag{8}$$

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

Generally, RUL is defined as the estimated time in reserve for a system between the instant of estimation and the instant of failure. Considering (8), the instant of failure n_f is computable from an instant k. Substitute the instant of prediction k of the instant of failure n_f allows us to obtain the RUL (noted $RUL(k)$):

$$RUL(k) = n_f - k \tag{9}$$

explicitly as:

$$RUL(k) = \left\lceil \frac{log_{10}\left(\frac{S}{d(k)}\right)}{log_{10}\left(1 + u(k)^2.\alpha\right)} \right\rceil \tag{10}$$

In the case of a known degradation model, we can determine analytically the RUL. As shown in Lall et al. (2012), Singleton et al. (2014) and Lim and Mba (2015), health state and degradation parameters can be estimated using a stochastic signal estimators such as Kalman Filter/particle filter.

As depicted in (10), RUL is impacted by d and u leading to the objective to find a optimal trade-off between performance and RUL.

3. PROPOSED STRATEGIES

Two structures are proposed to extend the RUL of the system. These structures modulate the input signal or the setpoint signal. This modulation is provided by an optimization based on RUL criteria and performance. The following subsections will develop the two methodologies.

3.1 Strategy I

Similar to the principle of disturbance rejection (as in (Commault et al., 1991) and (Huang and Xue, 2014)) and fault compensation (Noura et al., 2009), a signal $w(k)$ is generated to modify the $u_{nom}(k)$ generated by the controller. $w(k)$ is obtained from an optimization procedure based on the extension of the RUL. The control structure is depicted in Fig. 2.

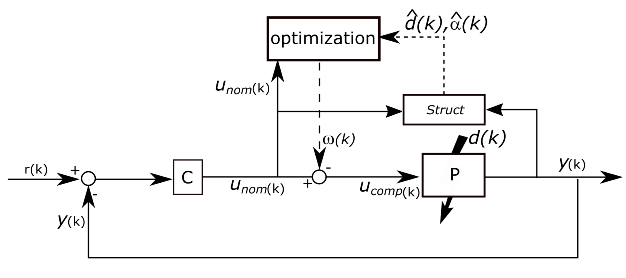

Fig. 2. Structure of strategy I.

The optimization block provides a signal $w(k)$ which is added to $u_{nom}(k)$ to obtain the $u_{comp}(k)$ as:

$$u_{comp}(k) = u_{nom}(k) + \omega(k) \tag{11}$$

with the cost function defined at each sample time k as:

$$J(k) = L_1.\omega(k) + L_2.\left(RUL_{Ref}(k) - R\hat{U}L(u_{pi}(k), \omega(t), \hat{d}(k))\right) \tag{12}$$

where $RUL_{Ref}(k)$ is the RUL objective at each sample time and $R\hat{U}L(u_{nom}(k), \omega(k), \hat{d}(k))$ the RUL prediction at time k.

ω^* is the minimizer of the cost function $J(u_{nom}(k), \omega(k))$ given as:

$$\omega^* = argmin \quad J(u_{nom}(k), \omega(k)) \tag{13}$$

Based from (13), (10) is revised as follow:

$$R\hat{U}L(k) = \left\lceil \frac{log_{10}\left(\frac{S}{\hat{d}(k)}\right)}{log_{10}\left(1 + \left(u_{nom}(k) + \omega(k)\right).\alpha\right)} \right\rceil \tag{14}$$

3.2 Strategy II

The principle of this strategy is to modify the trajectory of the system based on reference reconfiguration under fault occurrences (Blanke et al., 2006). The strategy is depicted in Fig. 3.

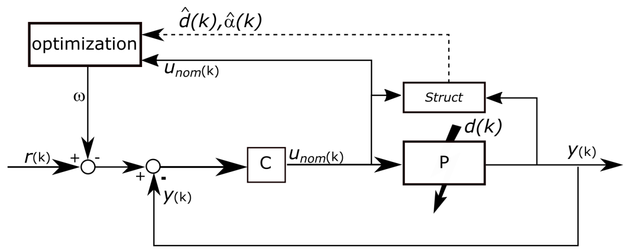

Fig. 3. Structure of strategy II.

In this case, the optimization provides a signal $\omega(k)$ which is added to $r(k)$ to obtain the $e(k)$:

$$e(k) = [r(k) + \omega(k)] - y(k) \tag{15}$$

Injecting (15) in controller formulation, we obtain the control input formulation:

$$u_{nom}(k) = F\left(r(k), \omega(k), y(k)\right) \tag{16}$$

As in previous subsection, ω^* is the minimizer of the cost function:

$$\omega^* = argmin \quad J(u_{nom}(k), \omega(k)) \tag{17}$$

with the cost function defined as:

$$J(k) = L_1.\omega(k) + L_2.\left(RUL_{Ref}(k) - R\hat{U}L(u_{nom}(k), \hat{d}(k))\right) \tag{18}$$

From optimization, RUL prediction becomes:

$$R\hat{U}L(k) = \left\lceil \frac{log_{10}\left(\frac{S}{\hat{d}(k)}\right)}{log_{10}\left(1 + u_{nom}^2.\alpha\right)} \right\rceil \tag{19}$$

4. NUMERICAL EXAMPLE

This section presents the simulation of a SISO transfer function system control with a PI controller. First, strategy I and strategy II under the assumption that degradation model is known, are simulated. Next, theses strategies in the case of an uncertain degradation are simulated.

The linear (SISO) system used in the simulation is defined below:

$$P(s) = \frac{2}{s^2 + 10s + 20.02} \tag{20}$$

The system is associated to a PI controller with parameters $P = 47$ and $I = 17$ with simulation rate $T_s = 0.01s$.

The choice of a PI controller is motivated by its ability to reduce the steady-state error. Nevertheless, within the framework of our study on a SISO system, the PI controller is the chosen candidate owing to good overall performance. A PID isn't considered but results will be the same.

4.1 RUL and optimization - know degradation

In Fig. 4, the evolution of the reference trajectory ($r(k)$), the output of the system and the degradation evolution are shown. The reference trajectory switches between value 1.5 and value 2.5 for every 15 seconds. System control allow the system to track the desire trajectory correctly as shown. The system is considered in failure when the

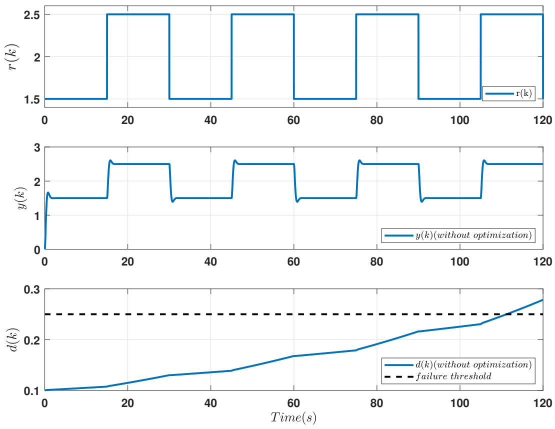

Fig. 4. Representation of trajectory, output and degradation of the system.

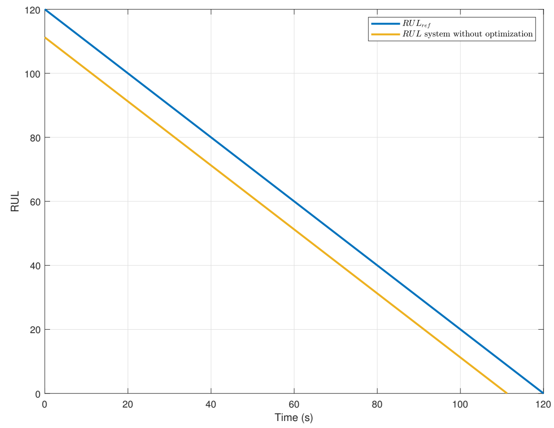

Fig. 5. RUL of the system and RUL_{Ref} evolution.

degradation exceeds a pre-established threshold set to the value 0.25. Degradation is increasing and the slope is function of time and setpoint (modification of the desired trajectory). At time $t = 110s$ the degradation exceeds the failure threshold, indicating a faulty system.

RUL of the system (in yellow) and RUL_{Ref} (in blue) are shown in Fig. 5. RUL_{Ref} objective extend the system RUL, corresponding to a system EOL at $120s$.

Strategy I:

Similar to Fig. 4, Fig. 6 contains also the output and the degradation of a system resulting from application of the strategy I.

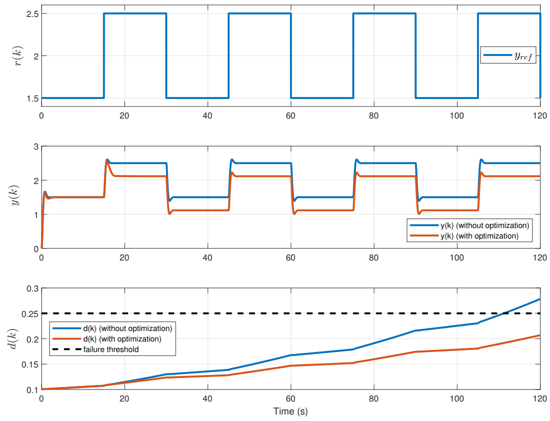

Fig. 6. Trajectory output and degradation of the system: Strategy I.

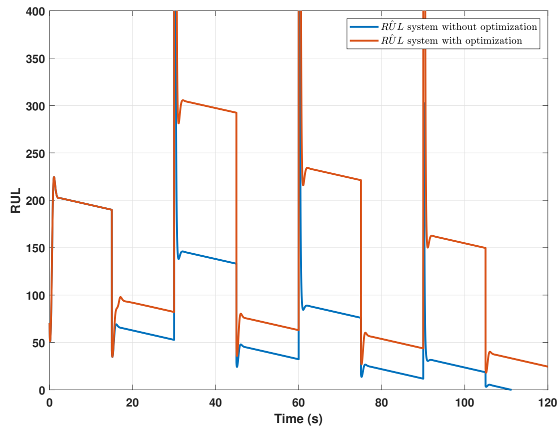

Fig. 7. $R\hat{U}L$ without optimization and $R\hat{U}L$ with strategy I.

The optimization leads to input generation sent to the system to reach the EOL objective. The strategy is resulting in a decrease on system's output to satisfy EOL. The degradation slope is reduced, in order to make the degradation not exceed the failure threshold at $t = 120s$.

RUL estimated, denoted as $R\hat{U}L$ is shown in Fig. 7. Final trajectory of estimated RUL satisfies RUL_{Ref} objective. The RMSE (Root Mean Square Error) between $r(k)$ and $y(k)$ is given: $RMSE = 0.4033$.

Strategy II:

The numerical application of strategy II is presented in this section. A PI controller is considered from 16, defined as:

$$u(k) = K_p.([r(k) - \omega(k)] - y(k)) + K_i.\sum_{j=1}^{k}([r(j) - \omega(j)] - y(j)) \tag{21}$$

RUL prediction becomes:

$$\hat{RUL}(k) = \left[\frac{log_{10}\left(\frac{S}{\hat{d}(k)}\right)}{log_{10}\left(1 + \left[K_p.e(k) + K_i.\sum_1^k e(k)\right]^2 .\alpha\right)} \right] \tag{22}$$

System trajectory, output and degradation are shown in Fig. 8 and $\hat{RUL}$ with and without optimization in Fig. 9.

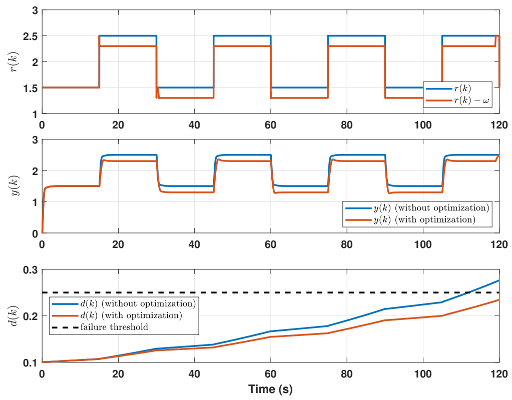

Fig. 8. Trajectory output and degradation of the system: Strategy II.

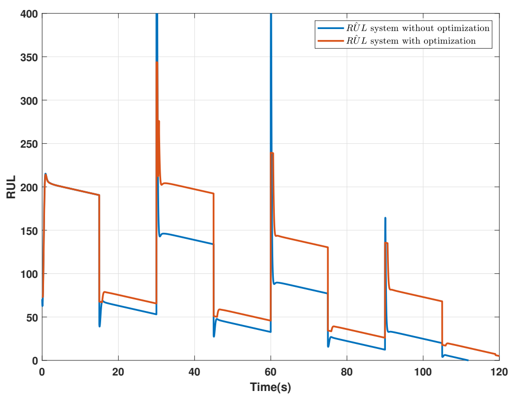

Fig. 9. $\hat{RUL}$ without optimization and $\hat{RUL}$ with Reference trajectory modification strategy.

The modified trajectory $(r(k)-\omega)$ obtained from optimization is shown Fig. 8. The output of the system is decreasing and is following the new trajectory given to the system $(r(k) - \omega)$. Also, objective of system's EOL is achieved. $\hat{RUL}$ with and without optimization is presented in Fig. 9. Corresponding RMSE (between $r(k)$ and $y(k)$) is given: $RMSE = 0.1820$.

Strategy II result in a better RMSE than the strategy I due to structure of the input reconfiguration. Proposed strategies are operating for all system with SISO process and controller.

4.2 RUL and optimization - uncertain degradation

In previous section, the degradation is considered well-known ($\hat{d}(k)$ and $\alpha(k)$). Supposing that, the estimated degradation given to the optimization block (used in RUL prediction $\hat{RUL}$) is uncertain and bounded. In this case three sets of simulation are chosen:

- case a: $\hat{\alpha} = \alpha$, is provided to the optimization block - RUL is estimated correctly: $\hat{RUL}(k) = RUL(k)$.
- case b: $\hat{\alpha} = \alpha + \Delta\alpha$, is provided to the optimization block - RUL is under-estimated: $\hat{RUL}(k) < RUL(k)$.
- case c: $\hat{\alpha} = \alpha - \Delta\alpha$, is provided to the optimization block - RUL is over-estimated: $\hat{RUL}(k) > RUL(k)$.

Degradation of the system is still defined as in (3).

Numerical results obtained from a, b and c sets of simulation are shown for strategy I in Fig. 10 and for strategy II in Fig. 11.

As expected for both strategies, if the RUL is under-estimated (case b) the EOL is not reached. If the RUL is over-estimated (case c), the EOL is reached, but the criteria are too conservative.

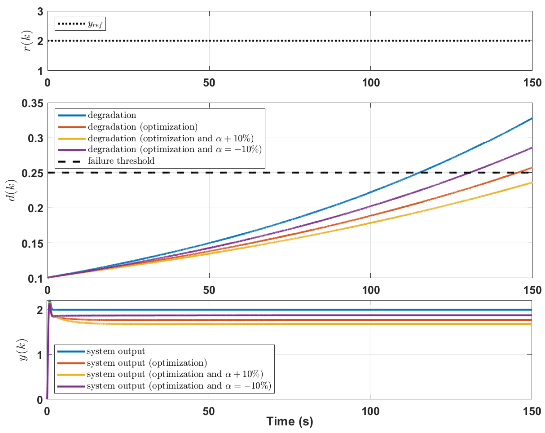

Fig. 10. Uncertainty: strategy I.

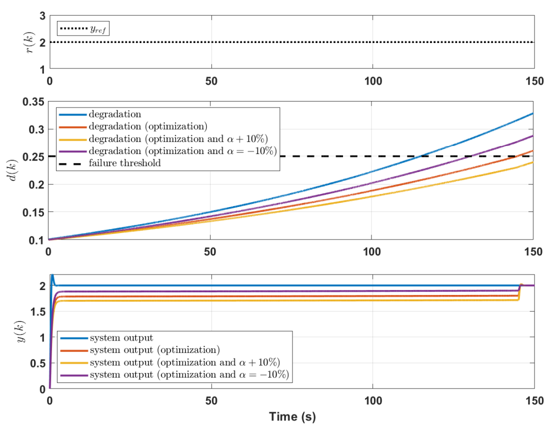

Fig. 11. Uncertainty: strategy II.

5. CONCLUSION

Two control strategies to extend RUL have been proposed. The formalism of theses strategies has been presented. The optimization algorithm has achieved a balance (Trade-off) between the performance requirement and the RUL criteria in the numerical result section. Also, uncertainty in the degradation model has also been studied. Both structures give satisfying results however in terms of implementation and integration, strategy II is more effective in terms of RMSE. The two structures are fully operational for system damage.

For a real system, the degradation model is often unknown, and RUL prediction is stochastic.This work will be extended to take into account the stochastic aspect in prognostic and optimization. Extension in MIMO process and controller is possible without difficulty.

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