A Study of Online Inspection for Multi-level Prognostics

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Abstract:
A system's degradation behavior is often correlated with internal and external covariates which are usually difficult to access owing to expensive measurement cost. This paper presents a Particle Filtering based multi-level prognostics approach to predict the Remaining Useful Life of a system based on its State of Health degradation estimation with online inspections of covariates. A degrading system is simulated with covariates at different level. By investigating the covariate online, the degradation estimation shows a better prediction and lower cost than the estimation without inspection.

Keywords: Multi-level prognostics, online inspection, Prognostics and Health Management (PHM), Particle Filtering (PF), Remaining Useful Life (RUL)

1. INTRODUCTION

To achieve successful commercialization, products must meet three important criteria: minimum cost, adequate performance and demonstrable durability. Durability assessment directly addresses all these three segments (Carlsson et al., 2004). A recent dynamic approach to manage the life duration of a system is Prognostics and Health Management (PHM). It enables the reliability evaluation of a system in its current condition (diagnostics) and determine the advent of failure (prognostics) and mitigate the risk (maintenance) (Ly et al., 2009). An accurate prediction of Remaining Useful Life (RUL) has become increasingly important in order to make an appropriate End of Life (EOL) decision for products or components (Hua et al., 2015).

Several PHM techniques have been applied on various systems. Different PHM tools for critical components of mechanical systems are summarized in Lee et al. (2014). Zhang and Lee (2011) reviewed various aspects of research and development works in Li-ion battery PHM. Jouin et al. (2013) drew a state of the art on PHM for a type of fuel cell systems. The presented work focuses on prognostics and is mainly devoted to the prediction of the future evolution of the degradation process.

Due to the broad nature of the problem, some characteristics of prognostics approaches would be required in practice (Zio, 2012). The degradation processes in general change with time, as do the functioning of the system due to changes in deterioration covariates, i.e. external operating conditions (e.g. environmental causes, input profiles, ...) or internal causes (e.g. modification of a system parameter, ...). A prognostic tool should be able to adapt and to accommodate such changes. The main obstacles to this adaptation are that the covariates effects might not be directly accessible from the current degradation indicator and that the link between the degradation process and covariates may differ in different cases. If there is a possibility to gather information on the hidden or "deep" covariates, it might be interesting to inspect them from time to time to improve the state of knowledge on the system for a better prognostics, even though the inspections are very costly. Understanding how performance parameters are affected by external covariates (*e.g.* by time-to-fail analysis) allows improved design for manufacturers and advanced maintenance for users. The mitigation in the impacts of known degradation covariates can help to improve the precision in durability assessment. The aim of this paper is to propose a multi-level prognostics approach for systems whose degradation covariates at different levels are accessible.

Section 2 presents the assumptions and the problem formulation. The multi-level estimation and prognosis approach involving covariates inspection is developped Section 3. Section 4 presents and discusses the numerical results of the proposed method on simulated data.

2. PROBLEM FORMULATION

The degradation evolution of a system under operation may not be well estimated because either external conditions or internal modifications can modify the degradation behavior: if these deterioration covariates are unknown, it can be difficult to identify their effect from the observation of the deterioration alone. Classic Bayesian estimation-based prognostic methods lack the ability to accommodate the unexpected changes in degradation evolution. A possible solution to this issue could be to investigate the deterioration covariate through indicators gathered at other levels of the system and to update the degradation parameters to adapt the changes in degradation evolution for a better estimation.

2.1 General Modeling Assumptions

Consider a new system subject to degradation under operation untill its end of life. Its performance level is constantly monitored to reveal the degradation of its State of Health (SOH) ($0 \leq$ SOH $\leq 100\%$). Assume that the evolution of this deterioration (SOH decrease) follows a process, which can be described by a discrete-time state transition model :

$$x_k = f_k(x_{k-1}, \omega_k, \Theta_k) \tag{1}$$

where k is the time step index, x is the system state representing the system performance, f is the state transition function (degradation model, *e.g.* the evolution of the degradation paths in Fig.1), ω is a Gaussian zero-mean process noise (variance σ_ω^2) and Θ is the vector of the model parameters ($\Theta = [\theta_1, \theta_2, ...]$). The measurement is given by $z_k = x_k + \nu_k$ where ν_k is a zero-mean Gaussian noise (variance σ_ν^2).

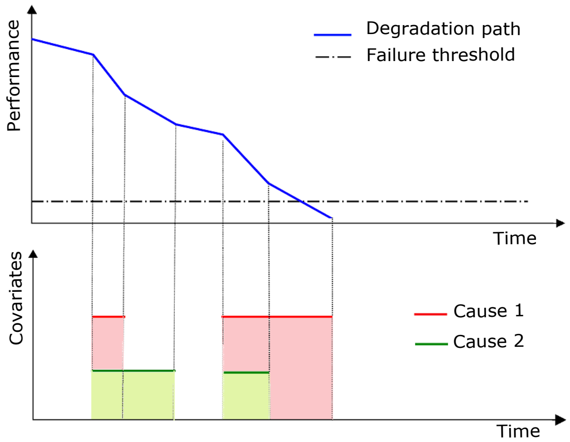

Fig. 1. Degradation path and covariates.

2.2 Effect of the Covariates on the Deterioration

The degradation in the SOH of the system can be due to its intrinsic imperfection and also, to the effect of both external or internal degradation covariates. Here we assume that some covariates, denoted c, can impact the degradation behavior by affecting the model parameters:

$$\Theta_k = g_k(c_k) \tag{2}$$

where g is the function describing the effect of the degradation covariates on the deterioration model parameters. Fig.1) shows a typical deterioration path, with the effect of effect of the covariates.

A classical PF-based prognosis method does not take into account directly those unexpected impacts when estimating the deterioration state and predicting the RUL. This is thus the aim of the multi-level prognosis approach proposed in the next section.

3. MULTI-LEVEL PROGNOSIS APPROACH

It has been proven that Bayesian estimation techniques provide a framework which can deal with high uncertainties in degradation processes (Vachtsevanos et al., 2006). Bayesian estimation with particle filters is not limited by either linearity or Gaussian noise assumption. PF-based approaches are more and more employed for prognostics purposes, and are chosen for the degradation path estimation in this study. For a comprehensive description, the reader is referred to a recent review on PF-based prognostics in (Jouin et al., 2016).

3.1 Particle Filtering Algorithm

In a PF framework (Arulampalam et al., 2002), the estimation of the degradation state is based on its prior Probability Density Function (PDF) and the degradation model parameters. The Bayesian update is processed in a sequential way by propagating particles carrying probabilistic information on the unknown states and model parameters (SIR filter):

(1) Draw and propagate N particles representing the system state probability density function (PDF) from x_{k-1} to x_k by state transition model.
(2) Update the particles weights by calculating the likelihood of the online measurement z_k given x_k^i, which quantifies the degree of matching between the estimation and the online measurement
(3) Re-sample the particles (Li et al., 2015) to remove the particles with small weights compared to a chosen weight limit, the ones with great weights are duplicated which represent the estimated posterior PDF of the system state.
(4) From the estimated posterior PDF, the corresponding model parameters are updated as well.
(5) The posterior PDF built in step (4) is used as the prior back into step (1). This will be performed until the online measurement is no longer available.

In the prediction phase, the posterior PDF of the state and model parameters are used for the estimation of the future degradation evolution. The RUL PDF can be obtained when the particles of system state reach the preset failure threshold by extrapolating the estimated degradation evolution.

3.2 Inspection of the Covariates

Assuming that the covariates impacts on the degradation level can be quantified and modeled, two covariates inspection policies are considered : periodic or online triggered. The estimated degradation model parameters can be updated after inspection, knowing the value of the covariate returned by inspection.

- Periodic covariates inspections are performed every τ time steps;
- Online covariates inspections are triggered online by the estimation error: the covariates can thus be inspected only when it is necessary, i.e. when the deterioration estimation accuracy is no longer satisfactory. At each timestep k, the estimation error is calculated online:

$$\hat{\epsilon}_k = \frac{\sum_{l=k-L}^{l=k} \|z_l - \hat{x}_l\|}{L} \tag{3}$$

where z_l is the online measurement, $\hat{x}_l$ is the estimated state and $\hat{\epsilon}_k$ is the current estimation error with a time window of size L. An inspection is triggered whenever $\hat{\epsilon}_k$ reaches preset error threshold ET : $\hat{\epsilon}_k \geq ET \quad \rightarrow \quad inspection$

Integrating the inspection procedure into the PF prognosis algorithm gives (at step k):

(1) Draw particles $x_k^i, (i = 1, \ldots, N)$ from the prior density $p(x_k|x_{k-1}^i)$ (integrating the state transition model)
(2) Calculate the corresponding weight of each particle: $w_k^i = \mathcal{L}(z_k|x_k^i)$ and then normalize the weights: $w_k^i = w_k^i / \sum_{i=1}^{N} w_k^i$
(3) Re-sampling (Multinomial, Li et al. (2015)):
  (a) Calculate the cumulative sum of normalized weights: $\{Q_k^j\}_{j=1}^N = CumulativeSum\left[\{w_k^i\}_{i=1}^N\right]$
  (b) For i=1,N
    - Draw a random value u from the uniform distribution $\mathcal{U}(0, 1]$
      · j=1;
      · while $Q_k^j < u$; $j = j + 1$; end
    - Assign particles $x_k^{i*} = x_k^j$, $\Theta_k^{i*} = \Theta_k^j$
  (c) End (for)
(4) State and parameters estimation:
$\hat{x}_k = MedianValue\left[\{x_k^{i*}\}_{i=1}^N\right]$
$\hat{\Theta}_k = MedianValue\left[\{\Theta_k^{i*}\}_{i=1}^N\right]$
(5) Calculate $\hat{\epsilon}_k$
if $\hat{\epsilon}_k \geq ET$, inspect $\Theta_k = g_k(c_k)$ and update the parameters if necessary
(6) Go back to step (1)

3.3 Decision Variables for the Inspections Policies

The covariates inspection policy can be optimally tuned using one of the decision variables (either the inter-inspection period τ or the error threshold ET) to ensure the best estimation accuracy and to minimize the overall estimation cost. The estimation cost J in this study is defined as the combination of two parts: the cost (or penalty) resulting from the estimation error $\hat{\epsilon}$, and the cost of inspections represented by the number of performed inspections:

$$J = \alpha \cdot \hat{\epsilon} + \beta \cdot \frac{EOL}{\tau} \tag{4}$$

Two weight coefficients α and β are assigned to each part. From the estimation accuracy's point of view, the more inspections are carried out, the better accuracy can be achieved. On the other hand, implementing too many inspections leads to higher costs. The objective here is to balance the quality of the deterioration estimation and the number of inspections.

4. APPLICATION & NUMERICAL EXPERIMENTS

4.1 Deterioration Simulation

The degradation paths are simulated using an exponential state transition function described in (An et al., 2013), with zero-mean Gaussian process noise (variance σ_ω^2):

$$x_k = x_{k-1} \cdot exp(-b(c_k) \cdot \Delta t) + \omega_k \tag{5}$$

The initial state value x_0 is equal to 100% of SOH. The presence of covariate c (Fig.1) impacts the degradation behavior, which is represented by the change in trend parameter b in (5):

$$b(c_k) = \begin{cases} b_0, & if \quad c_k = 0 \\ b_0 \cdot (1 + 3c_k), & else \end{cases} \tag{6}$$

The covariate c is generated by a 2-level Markov process: $c = 0$ and $c = 1$ (Fig.2). The initial value is $b_0 = 10^{-3}$. The form and values in (6) are set to locate the degradation path (Fig.3) in a specific scale (y-axis: SOH from 0% to 100%; x-axis: time from 0h to 1000h). An additive zero-mean Gaussian measurement noise is added to x_k to give z_k.

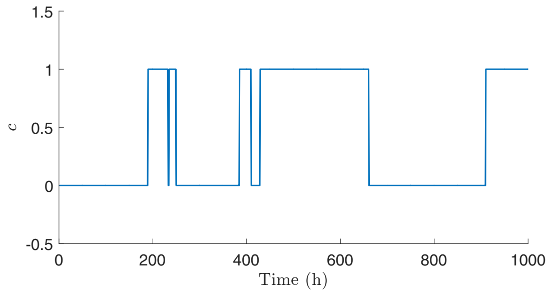

Fig. 2. 2-level Markov covariate evolution.

4.2 Estimation without Inspection

First, a PF estimation is applied without any inspection on covariate c.

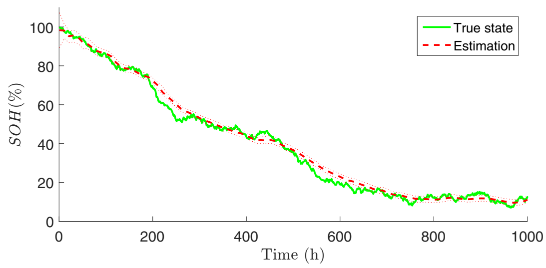

Fig. 3. Estimation without inspection.

Fig.3 shows the degradation estimation by a classic PF without inspection. The PF filter does not adapt rapidly to the sudden changes due to covariate changes. Fig.4 shows the average error corresponding to the estimation without inspection, that reaches a maximum around 10%.

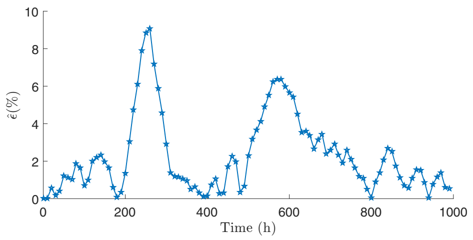

Fig. 4. Estimation error without inspection.

4.3 Estimation with Periodic Inspection of the Covariate

A deterioration estimation procedure with periodic inspection of the covariate is considered here. The inspection period τ is optimally tuned to minimize the criterion cost J combing the estimation accuracy and inspection costs introduced in Section 3.3. Assuming the cost of estimation (un-)accuracy is more important than the cost of inspection action, we chose for example $\alpha = 10€/\epsilon$, $\beta = 1€/inspection$ and $EOL = 1000h$ in Eq. (4). To determine the optimal inspection period, 50 different values of τ are tested from 10h to 500h.

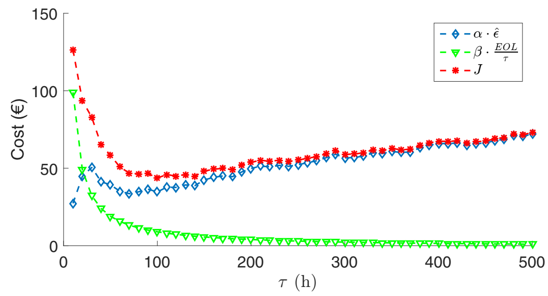

Fig. 5. Cost curve for estimation with periodic inspection.

Fig.5 shows the cost curve of different inspection periods τ and a minimum cost for $\tau^* \simeq 100h$.

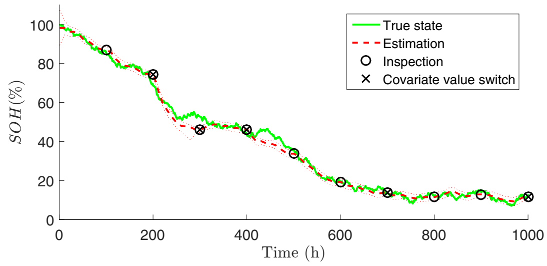

Fig. 6. Estimation with periodic covariate inspection.

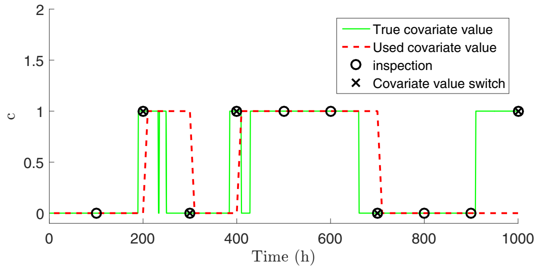

Fig. 7. Periodic inspection for covariates.

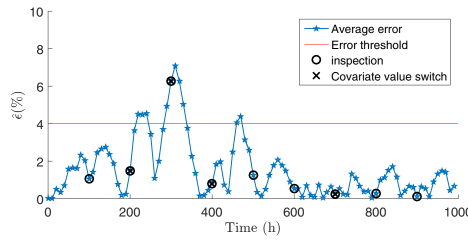

Fig. 8. Estimation error with periodic inspection.

Fig.6 shows the estimation for the optimal period. It can be seen from Fig.7 that the deterioration estimation procedure is able to integrate the covariate information delivered by inspections to adapt the degradation estimation as shown in Fig.6. It can be also noticed that the state model does not always need to be updated. The black circles (Fig.6 and Fig.7) without a central cross (covariate value switch) imply that these inspections are not necessary since the used covariate value is actually the same as the true one. Fig.8 shows the estimation error of periodic inspection which remains at a lower level thanks to the inspection every 100 hours. Nevertheless, to avoid unnecessary inspections, a decision has to to be made on wether to carry out or not the inspection.

4.4 Estimation with Online Triggered Covariate Inspection

Consider now the procedure for the deterioration estimation with online triggered covariate inspection. Three decision variables have to be tuned for this procedure: i) the time window size L to filter the estimation error; ii) the threshold ET on the estimation error to trigger the inspection; iii) the minimum waiting time τ_h between two inspections to avoid unnecessary inspections.

- Window size L: A preliminary sensitivity analysis on L in Eq. (3) has shown that a window size of $L \geq 50h$ does not alter the estimation accuracy nor the number of inspections. Thus L is set at $50h$.
- Error threshold ET: When the estimation error reaches the threshold ET, a covariate inspection is triggered to decide whether it is necessary to update the deterioration model parameters. The estimation error is calculated as in (3) as the average distance between estimated value and the observation on a moving window of size L. In the presented example, values of ET are tested from 1% to 15%.
- Waiting time τ_h: Different values of the minimum waiting time between two inspections τ_h are tested from 10h to 500h.

Fig.9 shows the cost surface for the estimation with online inspections of a 2-level covariate as a function of two decision variables, ET and τ_h. The minimum cost is found at $ET^* = 4\%$ and $\tau_h^* = 50h$.

Fig.10 shows the estimation for the optimally tuned decision variables. On Fig.12, when the estimation error reaches ET, inspections on covariate c are triggered and a correction, i.e. a covariate value switch, can be decided (Fig.11). The number of unnecessary inspections is reduced when compared with periodic inspection, which permits a lower cost as shown in Tab.1. The results are the average of 100 estimations.

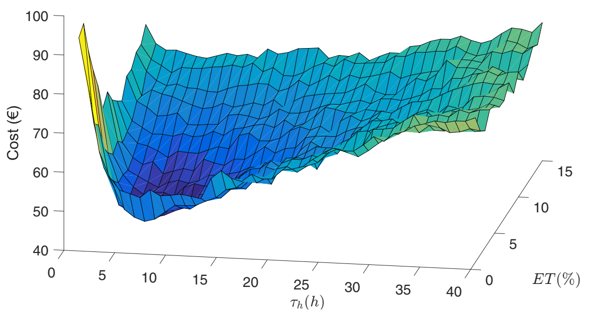

Fig. 9. Estimation cost surface for online triggered covariate inspection $J(ET, \tau_h)$

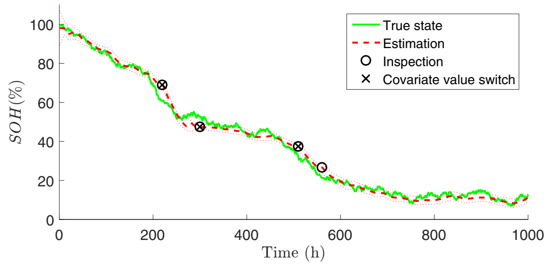

Fig. 10. Estimation with online triggered inspection

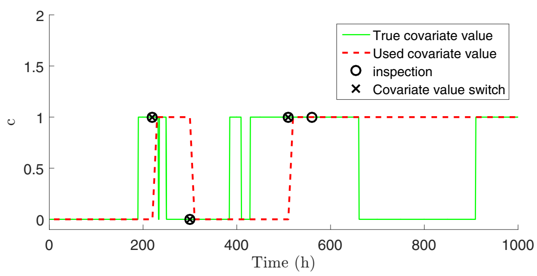

Fig. 11. Online inspection for covariates.

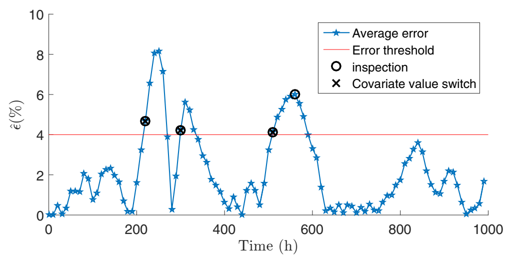

Fig. 12. Estimation error with online triggered covariate inspection.

Table 1. Estimation cost for different covariate inspection scheme

	Without	Periodic	Online
MAE(%)	5.91	3.47	3.51
Inspections	0	10	7
Cost (€)	59.07	44.69	42.27

4.5 RUL Prediction

The PF is used to train the state transition model during the estimation phase until prediction time t_p, then the particles are propagated through the estimated model, assuming the covariate remains at its last measured value. Fig.13 shows the RUL prediction example for $t_p = 600$ hours. The RUL histogram represents the time indexes distribution of all particles reaching a preset failure threshold.

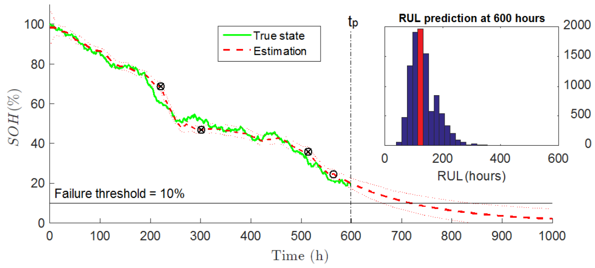

Fig. 13. Degradation estimation with online inspections and RUL prediction at $t_p = 600$ hours.

To evaluate the prognostic performance, several RUL predictions with different process noise levels are made and assessed using two metrics: Prognostic Horizon (PH) and α metric, (Saxena et al., 2010).

Prognostic Horizon (PH) The PH is the horizon between the end of life (EOL) and the first time index i when predictions satisfy $\pm\alpha$ bounds.

$$\begin{aligned} PH &= EOL - i \\ i &= min\{i | RUL_{true} - \alpha \cdot EOL \leq RUL(i) \\ &\leq RUL_{true} + \alpha \cdot EOL\} \end{aligned} \tag{7}$$

The choice of α value depends on the allowable error to take a corrective action. Here α =0.1 which meets most prognostic needs in industry fields. The longer is PH, the better is the score.

α Metric The output of α metric is the percentage of predictions located in a $\pm\alpha$ accuracy zone.

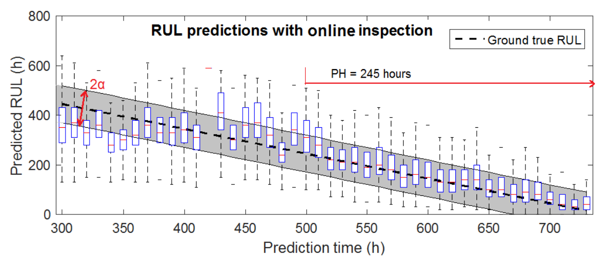

Fig. 14. RUL predictions with online inspections.

Fig.14 shows the predicted RULs with uncertainties at different prediction times t_p ranging from 300h to 740h, with a step of 10h (i.e. 44 predictions). The PH is calculated as the time index of first prediction located in the accuracy zone (grey bounded zone of 2α width). The performance for those three cases are listed in Tab.2.

Prediction with periodic inspection gives the best prognostics performance thanks to the information delivered by

Table 2. Prognostics performance ($\sigma_\omega = 1.2$)

	Without	Periodic	Online
PH (h)	40	335	245
α metric (%)	16	82	82

the inspections and associated the model update. Meanwhile, this incurs a higher cost. Online triggered inspections can provide better predictions than without inspection and incur a lower cost than periodic inspections.

In this study, it has been found that the estimation error decreases when the variance of process noise ω used in the PF filter (i.e. in the importance density $p(x_k|x_{k-1}^i)$) increases. With a smaller noise, the PF-based estimation is constrained thus the degradation trend cannot be followed which leads to a higher error. With a larger noise, the particles have more freedom to adapt the degradation changes which reduces the estimation error. From the estimation accuracy point of view, a better estimation can be achieved by increasing the process noise.

However, the prognostics approach is devoted to predicting RUL. Thus the necessity and benefit of inspection should be also discussed in the view of RUL prediction. In a numerical experiment, 100 estimations are made with different σ_ω. It is shown in Fig.15 that, with very small noise (around 0), the PF-based prognostic approach is not able to perform a RUL prediction. For a process noise with a large variance (for $\sigma_\omega \geq 4$ in Fig.15), both predictions without inspection and with online inspections are the same. It indicates that when the noise is large, the inspection is no longer activated. The model is thus not trained by the true state process but by its noise, which results in inaccurate predictions. On the other hand, prediction with periodic inspection continues to check periodically the covariates, which helps the model to learn the useful information and make predictions at higher accuracy although being impacted by the noise.

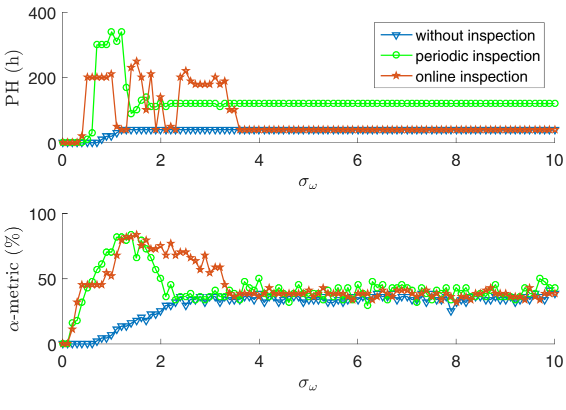

Fig. 15. Prognostic performances with different σ_ω.

Fig.15 shows that the best prediction performance for periodic inspection is obtained with $\sigma_\omega = 1.2$, and with $\sigma_\omega = 1.4$ for online inspection.

5. CONCLUSION

The proposed study on a simulated deteriorating system shows that the multi-level prognostics can be improved using online inspections. Covariates inspection allows the PF-based prognostics approach to give better predictions for RUL at a lower cost. The RUL estimation with multi-level prognostics for a real system with covariates identification will be the subject of future work.

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