# A Prognostic Approach Based on Particle Filtering and Optimized Tuning Kernel Smoothing

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## Abstract

This paper proposes a novel approach based on a Particle Filtering technique and an Optimized Tuning Kernel Smoothing method for the prediction on the Remaining Useful Life (RUL) of a degrading component. We consider a case in which a model describing the degradation process is available, but the exact values of the model parameters are unknown and observations of historical degradation trajectories in similar components are unavailable. A numerical application concerning the prediction of the RUL of degrading Lithium-ion batteries is considered. The obtained results show that the proposed method can provide a satisfactory RUL prediction as well as the parameters estimation.

## 1. Introduction

Model-based prognostic methods resort to a mathematical representations of the degradation process (Orchard & Vachtsevanos, 2009; Sankavaram et al., 2009). They typically demand the knowledge of the values of the model parameters, which can be estimated considering the results of experimental tests or by observing the real degradation behaviors of similar components.

However, in some practical situations, e.g. for some safety-critical and high-value components (nuclear, aerospace, military, oil and gas fields), it is not feasible to perform run-to failure experimental tests on the component degradation process and observations performed on similar components in the field are not available. Thus, in these cases, the estimation of the degradation model parameters and the prediction of the component RUL can resort only to a sequence of online measurements performed on the operating component as it undergoes degradation.

In this work, this problem has been addressed by developing a Particle Filtering (PF) approach based on the definition of a "joint state" encoding the degradation state and the model parameters (D. An, J. H. Choi, & N. H. Kim, 2012; Daigle & Goebel, 2013). However, the direct application of the PF framework to the problem of parameter estimation typically provides unsatisfactory results due to particle impoverishment, especially in cases of several unknown parameters and very poor knowledge on their prior probability distribution functions (PDF). Some researches solve this problem by adding artificial noise on the particle model parameter values, but the variance of the artificial noise is a parameter difficult to set if complete degradation trajectories are not available. Another solution is to use the Kernel Smoothing (KS) technique whose key idea is to perform a shrinkage of the particle model parameter values (Hu, Baraldi, Maio, & Zio, 2013). The KS method has been shown to solve the particle impoverishment problem without the side effect of increasing the variance of the posterior PDF. However, the application of this algorithm requires the a-priori setting of the smoothing parameter which determines the amplitude of the particle shrinkage. Too large value of this parameter can cause an extra shrinkage and perturbation of the particles, which will result in a bias of the model parameter estimates. On the other side, too small values of the shrinkage parameter can result in the impoverishment of the population of particles. Notice that the proper setting of the smoothing parameter is a very critical problem in the case addressed in this work where historical trajectories describing the component degradation from its onset until failure are not available and, thus, a trial and error approach cannot be followed.

In this work, we adopt a scheme proposed in a different context in (Tulsyan, Huang, Bhushan Gopaluni, & Fraser Forbes, 2013) for setting the proper value of the smoothing parameter. The idea is to optimize the smoothing parameter by finding the minimized Kullback–Leibler (KL) divergence between the predicted and posterior PDFs. This method employs only the information of online degradation measurements, which is very suitable for the problem in this paper. A numerical case study concerning the prediction of Lithium-ion battery RUL is considered to verify the performance of the proposed prognostic approach.

The paper is formed by the following sections: section 2 makes a brief description of the problem addressed in this work; in section 3, the combined state and parameter estimation method and optimized turning kernel smoothing is proposed; an application study of Li-on battery is taken in section 4; section 5 summarizes this paper.

## 2. PROBLEM STATEMENT

We assume to know the physical model describing the degradation process formulated as a first order Markov Process:

$$d_t = g(d_{t-1}, \mathbf{p}_{t-1}, \gamma) \tag{2.1}$$

where $g(d, \mathbf{p}, \gamma)$ is the recursive transition function, $d_t$ is an indicator of the equipment degradation state at time $t$, $\mathbf{p}_t$ is the vector of the model parameters, whose true values are unknown, $\gamma$ is the process noise which represents the degradation process uncertainty.

Furthermore, the measurement equation linking the degradation state $d$ and its measurements, $z_t$, is known. It is typically represented by a possibly non-linear function $h$:

$$z_t = h(d_t, \sigma_n) \tag{2.2}$$

where $\sigma_n$ is the measurement noise. We assume a set of online measurements $z_t (t = 1, 2, ..., T)$ collected from the beginning life of component ($t$=1) to the present time ($t$=$T$) is available.

Furthermore, the failure threshold, $f$, i.e. a value of the degradation state such that if it is exceeded, the equipment is considered failed is assumed to be known and fixed.

## 3. MODEL-BASED PROGNOSTICS APPROACH

The description of the PF approach can be found in (Arulampalam, Maskell, Gordon, & Clapp, 2002; Orchard & Vachtsevanos, 2009), whereas its application to the problem of predicting the RUL of a degrading component can be found in (Hu et al., 2013; Zio & Peloni, 2011). In this section, we will discuss the use of the PF method for the problem of jointly estimating the degradation state and the model parameters' values.

### 3.1. Combined State and Parameter Estimation

The combined estimate of the equipment degradation state and model parameters can be performed by using an extended PF (D. An, J.-H. Choi, & N. H. Kim, 2012; Arulampalam et al., 2002; Ching, Beck, & Porter, 2006; Liu & West, 2001; Tulsyan et al., 2013). The idea is to consider the model parameters as elements of the state vector which is estimated by the PF. Thus, the generic augmented ***i***-th particle $k_t^i$, is represented by: $k_t^i = \{d_t^i, \mathbf{p}_t^i, w_t^i\}$, where $d_t^i$ represents the degradation state, $\mathbf{p}_t^i$ the model parameters at time $t$ and $w_t^i$ is the weight associated to the particle. Since we need to simultaneously estimate the degradation state and model parameter, we need to extend Eq.(2.1) in order to describe, not only the transition of the degradation state , but also that of the model parameters. Thus, Eq.(2.1) becomes a system of two equations, one describing the transition of the state ($g_1$) and the other the transition of the parameters ($g_2$):

$$\begin{aligned} d_t^i &= g_1(d_{t-1}^i, \mathbf{p}_{t-1}^i, \gamma) \\ \mathbf{p}_t^i &= g_2(\mathbf{p}_{t-1}^i) \end{aligned} \tag{3.1}$$

The transition function g, describing the degradation evolution, in Eq.(2.1) can be used for $g_1$, whereas there are different options to define $g_2$. In (Dawn An et al., 2012), the model parameters are kept unchanged during the prediction stage and $g_2$ is given by:

$$\mathbf{p}_t^i = g_2(\mathbf{p}_{t-1}^i) = \mathbf{p}_{t\text{-}1}^i \tag{3.2}$$

this strategy has been shown to suffer the problem of particle impoverishment when several model parameters need to be simultaneously estimated (Daum, 2005): only very few "strong" particles with an associated high weight will survive after the updating phase. This low variety of the model parameter values in the population of particles causes an imprecise estimation of the parameters.

The problem of the particle impoverishment has been addressed by adding an artificial noise to the particles parameters evolution equation (Corbetta, Sbarufatti, Manes, & Giglio, 2013; He, Williard, Osterman, & Pecht, 2011; Higuchi, 1997):

$$\mathbf{p}_{t+1}^i = g_2(\mathbf{p}_t^i) = \mathbf{p}_t^i + N(0, \sigma_{AN}^2) \tag{3.3}$$

where $\sigma_{AN}^2$ is the variance of the artificial noise. However, this method cannot be applied to our prognostic problem since it requires a proper setting of the value of $\sigma_{AN}^2$, which is difficult to achieve by trial and error attempts, due to the unavailability of complete examples of degradation trajectories in similar components. If too small values of $\sigma_{AN}^2$ are used, the convergence of the model parameter values $\mathbf{p}_t^i$ in the population of particles to the model parameter true values is too slow and the problem of particle impoverishment can still be encountered. Whereas, if large values of $\sigma_{AN}^2$ are used, the convergence to the parameters true values will never be achieved.

In order to overtake these difficulties, in this work we consider an alternative PF approach based on an Optimized Tuning Kernel Smoothing (OTKS) algorithm which will be object of the next Section 3.2.

### 3.2. Kernel smoothing approach

Kernel smoothing consists in two different procedures to the population of particles: shrinkage and perturbation. Shrinkage aims at reducing the variability in the particle population by moving the single particle $\mathbf{p}_t^i$ toward the current estimated values $\hat{\mathbf{p}}_t$, whereas perturbation adds a controlled noise on $\mathbf{p}_t^i$ in order to maintain the desired variance in the population (Chen, Morris, & Martin, 2005; Liu & West, 2001; Wan-ping, Sheng, & Ting-wen, 2009).

- Shrinkage

The particle shrinkage is performed by:

$$\tilde{\mathbf{p}}_t^i = \mathbf{p}_t^i \sqrt{1-h^2} + \hat{\mathbf{p}}_t \left(1-\sqrt{1-h^2}\right) \tag{3.4}$$

where the vector $\tilde{\mathbf{p}}_t^i$ contains the parameters values of the *i*-th particle after the shrinkage. The direction of shrinkage is the estimated value of the parameter $\hat{\mathbf{p}}_t$. The smoothing parameter, $h \in [0,1]$, determines the degree of shrinkage: higher is its value, deeper is the shrinkage. If $h = 1$, the model parameters completely shrink to the estimated values $\hat{\mathbf{p}}_t$; whereas if $h = 0$, no shrinkage is applied.

After shrinkage, the parameters variance in the population of particles will decrease from $V\left(\mathbf{p}_t^i\right)$ to $\left(1-h^2\right)V\left(\mathbf{p}_t^i\right)$. Then, Eq.(2.1) is used to predict $d_{t+1}^i$ based on $\tilde{\mathbf{p}}_t^i$:

$$d_{t+1}^i = g_1(d_t^i, \tilde{\mathbf{p}}_t^i, \gamma) \tag{3.5}$$

- Perturbation

Perturbation is used to maintain the variance of parameter particles by adding an artificial noise of variance $h^2 V\left(\mathbf{p}_t^i\right)$:

$$\mathbf{p}_{t+1}^i = g_2(\mathbf{p}_t^i) = \tilde{\mathbf{p}}_t^i + N\left(0, h^2 V\left(\mathbf{p}_t^i\right)\right) \tag{3.6}$$

### 3.3. Optimization of Smoothing Parameter *h*

The value of smoothing parameter *h* is very important for the performance of kernel smoothing. Some authors suggest to use the value $h = 0.1$, whereas other authors suggest optimizing the value of *h* using historical data (Chen et al., 2005; Liu & West, 2001). In our work, given that historical trajectories describing the component degradation from its onset until failure are not available, the value of *h* is continuously updated, considering the newest measurement of the degradation state, according to (Tulsyan et al., 2013). Since the main idea of this algorithm is to find the value of *h* which projects the prediction PDF in the high density region of the posterior PDF, it can be executed even when just one measurement of the degradation state is available.

The optimization of *h* is tactfully achieved by minimizing the KL divergence between prediction and posterior PDFs. In our case, the KL divergence is computed by:

$$KL\left(h_t\right) = \int_z \log\left(\frac{p(d_t \mid z_{1:t-1})}{p(d_t \mid z_{1:t})}\right) p(d_t \mid z_{1:t-1}) dd_t \tag{3.7}$$

where $p(d_t \mid z_{1:t-1})$ and $p(d_t \mid z_{1:t})$ are the prediction and posterior PDF, respectively. Using the Markov assumption and the Bayes theory, Eq.(3.7) can be rewritten as:

$$KL\left(h_t\right) = \int_z \log\left(\frac{\int_z p(z_t \mid d_t) p(d_t \mid z_{1:t-1}) dd_t}{p(z_t \mid d_t)}\right) p(d_t \mid z_{1:t-1}) dd_t \tag{3.8}$$

which is approximated by:

$$\begin{aligned} KL\left(h_t\right) &\approx \int_z \log\left(\frac{\int_z p(z_t \mid d_t) \sum_{i=1}^N w_{t-1} \delta\left(dd_t\right)}{p(z_t \mid d_t)}\right) \sum_{i=1}^N w_{t-1} \delta\left(dd_t\right) \\ &= \sum_{i=1}^N w_{t-1} \log\left(\frac{\sum_{i=1}^N w_{t-1} p(z_t \mid d_t^i)}{p(z_t \mid d_t^i)}\right) \end{aligned} \tag{3.9}$$

where $p(z_t \mid d_t^i)$ is the likelihood of particle *i*, given by Eq.(3.13). Thus, by substituting Eq.(3.13) into Eq.(3.9), one obtains:

$$KL\left(h_t\right) \approx -\sum_{i=1}^N w_{t-1}^i \log\left(w_t^i\right) \tag{3.10}$$

where $KL\left(h_t\right)$ is the KL divergence at time *t* using the smoothing parameter $h_t$, and $w_{t-1}^i$ is the weight of the *i*-th particle at time *t*-1 (which also depends on $h_t$). Finally, the optimal $h_t$ value, hereafter called $h_t^*$, is obtained by minimizing $KL(h_t)$:

$$h_t^* = \arg\min_{h_t \in [0,1]} \left[ KL(h_t) \right] \tag{3.11}$$

In order to perform the minimization, given the impossibility of using analytical methods due to the form of Eq.(3.10), we divide the interval [0,1] into 100 discrete values, namely 0.01,0.02,…,0.99,1. For each value, we calculate the corresponding *KL*(*h*) and search the one with minimum *KL*(*h*).

By substituting $h_t^*$ into Eq.(3.4), one obtains the new equation for the particle shrinkage:

$$\tilde{\mathbf{p}}_t^i = \mathbf{p}_t^i \sqrt{1-\left(h_{t+1}^*\right)^2} + \hat{\mathbf{p}}_t \left(1-\sqrt{1-\left(h_{t+1}^*\right)^2}\right) \tag{3.12}$$

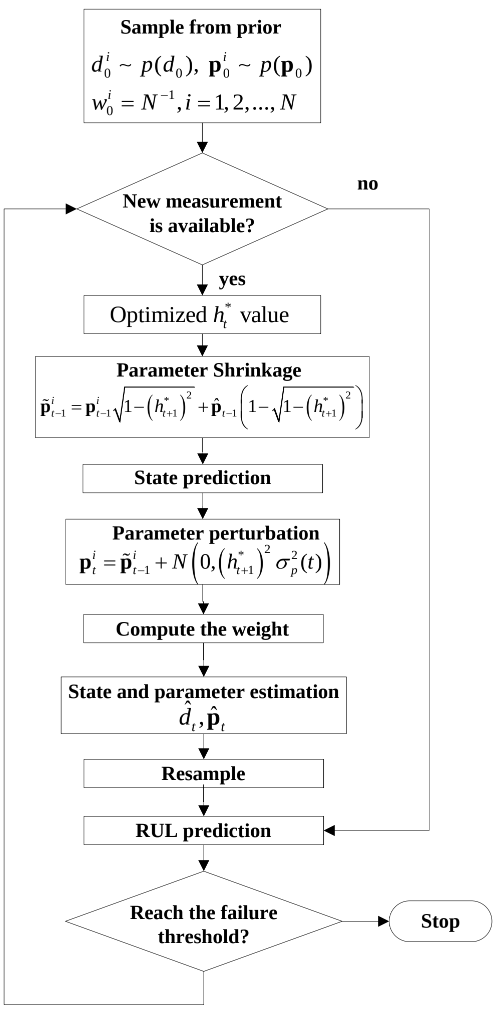


Figure 1 Flow chart of PF-OTKS

Notice that the execution of the shrinkage at time *t* requires the knowledge of $h_{t+1}^*$, which is based on the knowledge of the measurement $z_{t+1}$. In practice, at time *t*, once the measurement $z_t$ becomes available, we firstly calculate $h_t^*$ and perform the kernel smoothing of the particle parameter at time *t*-1, $\mathbf{p}_{t-1}^i$ and, then, we can apply the PF procedure to estimate the degradation state and parameters, as well as the RUL prediction, at time *t*.

Figure 1 shows the flow chart of execution.

In practice, the procedure is based on the repetition, at each time *t*, of the following steps:

1) Sample the particles $k_0^i = \{d_0^i, \mathbf{p}_0^i, w_0^i\}$ from their prior PDFs. At time *t*=1, the prior PDFs of the degradation state and parameter values are defined according to expert knowledge based on the specific applications.

2) At time *t*, using the newest measurement $z_t$ to figure out the optimal $h_t^*$ value using Eq.(3.11)

3) Shrink the parameters particles with $h_t^*$ (based on Eq.(3.12)) , and get $\tilde{\mathbf{p}}_{t-1}^i$

4) Make the prediction using $\tilde{\mathbf{p}}_{t-1}^i$ (based on Eq.(3.5)) and get the particles of degradation state $d_t^i$

5) Perform the particle perturbation using $h_t^*$ (based on Eq.(3.6), and get $\mathbf{p}_t^i$

6) Compute the weight $w_t^i$:

$$w_t^i = w_{t-1}^i \frac{P(z_t \mid d_t^i)}{\sum_{i=1}^{n} P(z_t \mid d_t^i)} \tag{3.13}$$

where $P(z_t \mid d_t^i)$ is the likelihood of particle *i*.

7) Compute the estimates of the parameters and state $\hat{d}_t, \hat{\mathbf{p}}_t$ as well as their posterior PDFs:

$$\hat{d}_t = \sum_{i=1}^{N} w_t^i \times d_t^i \tag{3.14}$$

$$\hat{\mathbf{p}}_t = \sum_{i=1}^{N} w_t^i \times \mathbf{p}_t^i \tag{3.15}$$

8) Perform particle resampling using the systematic resampling method whose description can be found in (Arulampalam et al., 2002; Douc & Cappé, 2005)

9) Perform the RUL prediction using $d_t^i$, $\mathbf{p}_t^i$ and $w_t^i$ (based on Eq.(2.1))

10) Predict the prior PDFs for $d_t^i$ and $\mathbf{p}_t^i$ at next cycle (using Eq.(2.1)).

11) Set $t$=$t$+1, repeat from 2)

## 4. NUMERICAL APPLICATION

In this Section, we apply the proposal approach on the RUL prediction of a Lithium-ion battery. A detailed explanation of the battery degradation mechanism can be found in (He et al., 2011; Marcicki, Todeschini, Onori, & Canova, 2012; Saha, Goebel, Poll, & Christophersen, 2009; Zhang & Lee, 2011). The quantity which is frequently used to indicate the battery degradation state is the battery capacity $q(t)$. The degradation is mainly represented by a first phase during which the battery capacity slowly decreases, followed by a second phase characterized by a fast decreasing process. These two phases can be described by a double exponential model:

$$q(t) = p_1 \exp(p_2 \cdot t) + p_3 \exp(p_4 \cdot t) + N\left(0, \sigma_p^2\right) \quad (4.1)$$

where $p_1, p_2, p_3$ and $p_4$ are the four model parameters ( $p_1, p_3$ determine the initial state and $p_2, p_4$ the degradation rate), $\sigma_p^2$ is the process noise and $t$ is the number of charge/discharge cycles experienced by the battery. The measurement equation is:

$$Q(t) = q(t) + N(0, \sigma_m^2) \quad (4.2)$$

where $Q(t)$ is the measurement at the $t$-th charge/discharge cycle and $\sigma_m^2$ is the measurement noise. The failure threshold of $q(t)$ is set according to expert knowledge.

### 4.1. Generation of Online measurements

Motivated to have a test of the performance of the proposed method, one complete battery degradation trajectory has been simulated using Eq.(4.2). The values of the parameters $p_1, p_2, p_3$ and $p_4$ have been as set in Table 1, the value of process and measurement noises $\sigma_p, \sigma_m$ have been both equal to 0.001, and the threshold value equal to 0.7172. These parameters values, as well as the obtained degradation state $q$ and the failure time will be referred to as the "true" values of the battery trajectory.

### 4.2. Results

The experiment is performed assuming that the true values of $p_1, p_2, p_3$ and $p_4$ are unknown, and the measurements performed on the battery of which we want to predict the RUL are available from cycle 1 to the present cycle. The prior PDFs for parameters $p_1, p_2, p_3$ and $p_4$ are $U$(0.85,1.2), $U$ (-0.001,0), $U$ (-0.001,0) and $U$ (0.03,0.13), respectively. Notice that the prior PDFs of $p_1, p_2, p_3$ and $p_4$ are remarkably more dispersed than those used for the simulation of the true values of these parameters (in Table 1). Furthermore, the true of the four parameters are located in the tail of the prior PDFs. This setting has been chosen in order to assess whether the method can work even if the parameter prior PDFs are very uncertain and shifted.

Table 1 True values of the parameters in the considered battery degradation trajectory

| Parameter | $p_1$ | $p_2$ | $p_3$ | $p_4$ | life cycle |
|---|---|---|---|---|---|
| Value | 0.917 | -8.19e-4 | -2.93e-4 | 0.0523 | 115 |

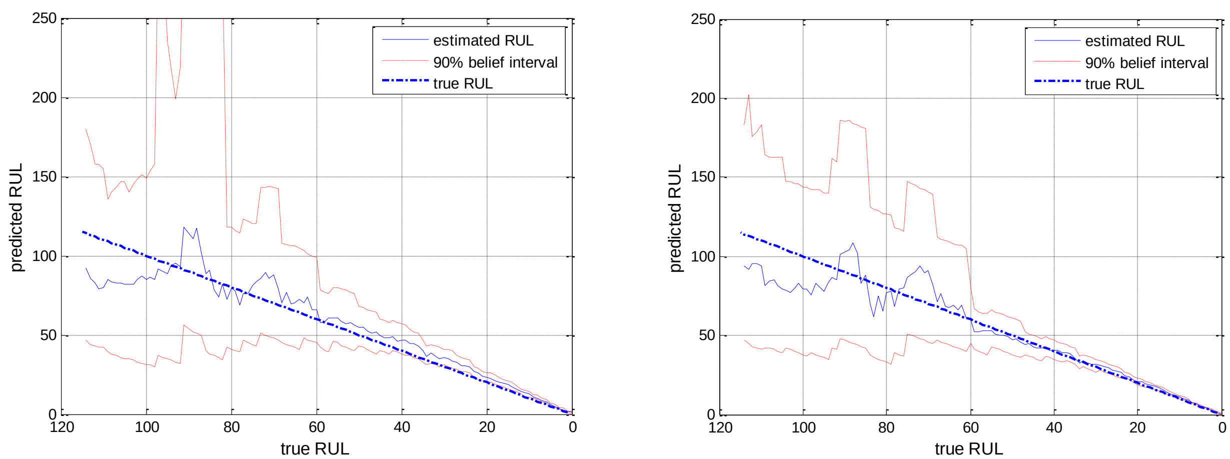


Figure 2 RUL prediction using PF-KS (left) and PF-OTKS (right)

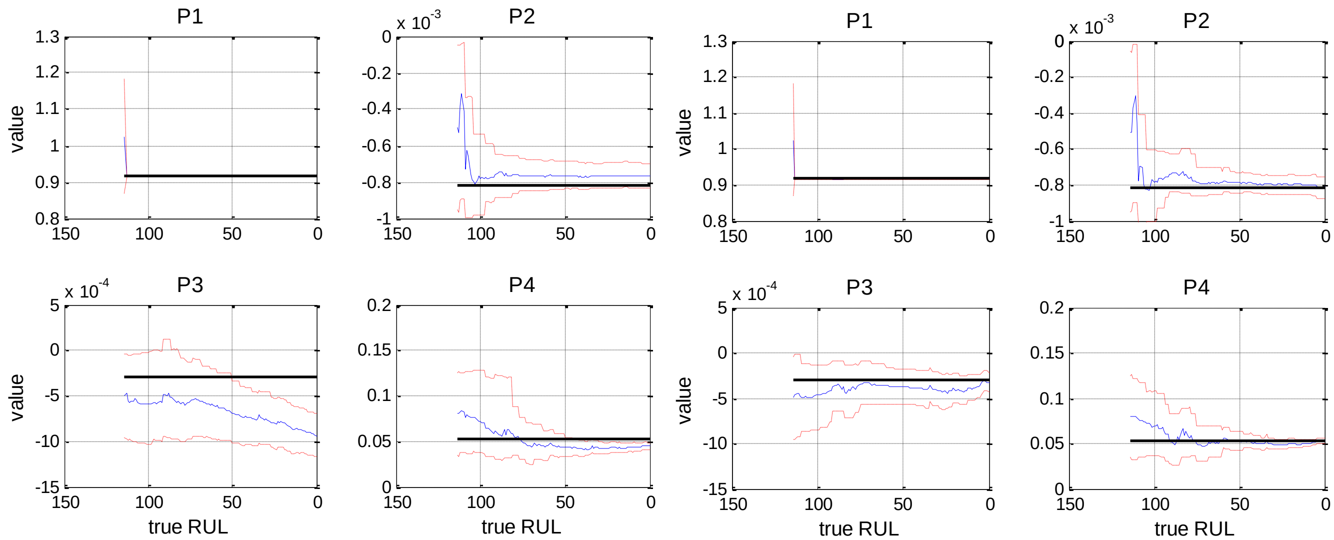


Figure 3 Parameter estimation using PF-KS (left) and PF-OTKS (right)

Figure 2 shows the RUL predictions obtained at different times, with the red lines representing the 90% confidence interval. Figure 3 shows the estimates of the expected values and 90% confidence intervals of the four parameters of the considered battery. The continue thick horizontal lines represents the true value, the thin continuous line represents the estimates of the parameters expected values and the red lines are the 90% confidence interval of the parameter posterior PDF.

From Figure 2, it can be observed that the RUL prediction given by PF-KS has more uncertainty than PF-OTKS. Furthermore, at the end of life of the battery, the PF-KS's RUL prediction drifts from the true value, due to the unsatisfied estimation of the four parametesrs (in Figure 3), while PF-OTKS does not suffer this problem.

For the parameter estimation, the PF-KS estimation of $p_3$ is significantly drifted from the true value. And $p_2, p_4$ have small bias, whereas PF-OTKS provides more satisfied estimates of the parameters. Figure 4 shows the optimal $h_t^*$ value provided by PF-OTKS. Notice that the value of 0.1, which is suggested by (Liu & West, 2001), appears to be too large in this application. Large *h* means deeper shrinkage, which causes the bias and drift of the parameter estimation in the PF-KS. It is also interesting to observe that the optimal *h* value tends to decrease as time passes. At the beginning, since the particles of $p_1, p_2, p_3$ and $p_4$ are far away from the true value, the optimal $h_t^*$ value is larger since deeper shrinkage and perturbations are needed to avoid particle impoverishment. On the other hand, at the end of the battery life, the particles are close to the true model parameter values, so the deep shrinkage and perturbation are not necessary.

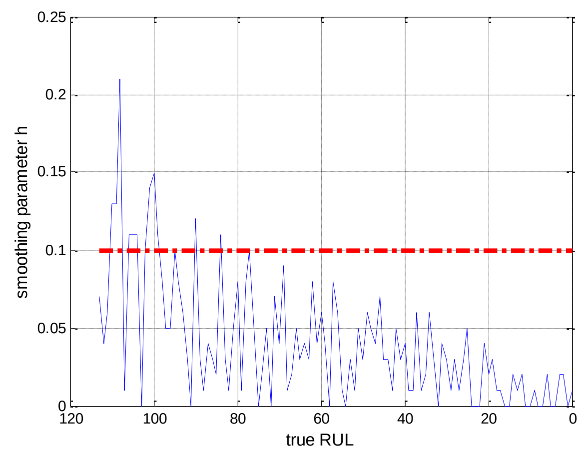


Figure 4 Optimized smoothing parameter *h*

## 5. CONCLUSION

In this work, we have proposed a PF-OTKS approach for the RUL prediction of degrading components based on a model of degradation with unknown parameters. We have assumed to know the model of the degradation process and to be able to perform measurements of quantities related to the component degradation; on the other side, we have assumed that we do not know the true value of the degradation model parameters nor we have available observations of degradation trajectories in similar components.

The results of PF-OTKS obtained in a numerical case study regarding battery degradation have shown that the proposed method can provide estimates of the component RUL and model parameters, which are more satisfactory than those obtained with PF-KS. The proposed approach will be further investigated in a situation in which the degradation model is partly unknown.

## ACKNOWLEDGEMENT

Yang Hu gratefully acknowledges the financial support from China Scholarship Council (No. 201206110018). The participation of Enrico Zio to this research is partially supported by the China NSFC under grant number 71231001. The participation of Piero Baraldi and Francesco Di Maio is supported by the European Union Project INNovation through Human Factors in risk analysis and management (INNHF, *www.innhf.eu*) funded by the 7th framework program FP7-PEOPLE-2011- Initial Training Network: Marie-Curie Action.

## NOMENCLATURE

| | |
|---|---|
| $d_t$ | Degradation state at time *t* |
| $\mathbf{p}_t$ | Vector of parameter values at time *t* |
| $\gamma$ | Process noise representing the degradation process uncertainty |
| $z_t$ | Measurement of the degradation state $d_t$ |
| $\sigma_n$ | Variance measurement noise |
| $N$ | Number of particles |
| $w_t^i$ | Weight associated to particle *i at time t* |
| $d_t^i$ | Degradation state of particle *i* at time *t* |
| $\mathbf{p}_t^i$ | Model parameters contained in particle *i* at time *t* |
| $RUL_t^i$ | RUL of particle *i* at time *t* |
| $\hat{d}_t$ | Estimate of $d_t$ |
| $\hat{\mathbf{p}}_t$ | Estimate of $\mathbf{p}_t$ |
| $RUL_t$ | Prediction of RUL at time *t* |
| $\tilde{\mathbf{p}}_t^i$ | Parameter values of particle *i* after shrinkage |

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