Fault Prognosis with Stochastic Modelling on Critical Points of Discrete Processes

Thi-Bich-Lien Nguyen[1], Mohand Djeziri[2], Bouchra Ananou[3], Mustapha Ouladsine[4], Jacques Pinaton[5]

[1,2,3,4] *LSIS UMR CNRS 7296, Aix Marseille University, France*
thi.bich.lien.nguyen@lsis.org, mohand.djeziri@lsis.org

[5] *STMicroelectronics*

ABSTRACT

The primary role of a machine tool is produce the good quality parts, but a machine tool goes always through a process of degradation and wear which will affect the accuracy and precision of machining and the quality of products. Therefore, monitoring the degradation of machine tool and quantifying its health is very important. The degradation level of a machine can be qualified by an index which is called health indicator (HI). Based on the HI, fault prognosis can provide the Remaining Useful Life (RUL) of machine which is useful for an effective maintenance policy, thus, that helps to increase efficiency of operations and manufacturing. However, the HI is not usually predetermined in most Discrete Manufacturing Processes (DMP). This paper presents a new method of HI extraction based on the degradation reconstruction. The HI is then modeled with a stochastic process. For the online supervision, the RUL is estimated for each inspection time.

1. INTRODUCTION

Fault prognosis of industrial systems is one of central issues of Condition Based Maintenance (CBM). It is important to minimize the downtime of machinery and production, and thus to increase efficiency of operations and manufacturing. Till now, the production units in most DMP use a strategy of Preventive and Corrective Maintenance which is less efficient than the CBM, and few studies are conducted on this subject. There is not yet an efficient method which is capable to extract the underlying state of DMP tools because of their complex processes, which are highly non-linear, time varying and usually exhibit batch-to-batch variation disturbances.

In semiconductor manufacturing, a survey of data-driven prognosis of (Thieullen, Ouladsine, & Pinaton, 2012) shows that, most of the HI are calculated as the values of the indexes such as Squared Prediction Error (SPE), Hotellings T2, Mahalanobis distance, etc. In this paper, the health index is not built from these indexes but from the trend of critical points of sensors. Based on the same principles of reconstruction-based fault identification (Yue & Qin, 2001), (Gang, Qin, Ji, & Zhou, 2010), a method of degradation detection and identification is proposed. The EWMA Hybrid-wise Multiway PCA (E-HMPCA) (Zhang, 2008) which is an extension of Principal Component Analysis (PCA) is used to perform degradation detection and diagnosis for the batch process machine. This is because E-HMPCA combines the advantages of both batch-wise and variable-wise unfolding approaches. Moreover, the EWMA algorithm considers the time dependencies. The index SPE is calculated and is compared to its upper control limit (UCL) to detect the degradation. The significant sensors which carry the degradation information of machine are localized and their critical points are identified based on an optimization algorithm. The HI is then extracted for the failure prognosis.

This paper proposes a new fault prognosis method for DMP tools, as illustrated in the schema of Figure 1. The on-line supervision is supported by the off-line analysis. A degradation reconstruction is executed to determine the set of critical points of processes which are considered representing the tool's underlying state. Then an indicator of degradation is extracted from the evolution of these points and is modelled with an adequate stochastic process to predict the Remaining Useful Life (RUL). In on-line supervision, the value of RUL is updated for each inspection time. A real case application using data collected in STMicroelectronics Rousset is presented to illustrate the efficiency of the proposed method.

The remaining of this paper is organised as follows. Sec-

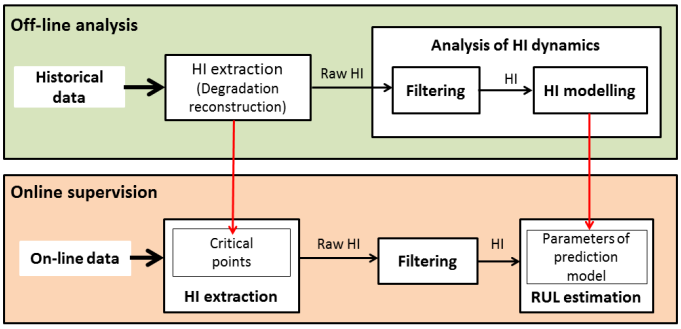

Figure 1. Schema of fault prognosis

tion 2 presents the off-line analysis where 2.1 provides the formulation of health index contribution, 2.2 describes the degradation modelling based on an adequate process. The online supervision procedure is proposed in section 3. Section 4 presents a real case application using data collected in STMicroelectronics. Section 5 gives the conclusion.

2. OFF-LINE ANALYSIS

2.1. Heath indicator extraction

2.1.1. Identification of degraded sensors

From the measurement of machine during processing a set of products, a data matrix X of three dimensional matrix $I \times J \times K$ is obtained, respectively I is number of products, J is the number of sensors and K is the number of observations (sampling time).

Suppose that the first n products ($n < I$) are considered respecting the good quality norm. These n products are thus used to build the degradation detection index.

The data of these n products is unfolded according to batch-wise, it is then mean-centered and rearranged in a variable-wise structure, it becomes a $((n \times K) \times J)$ matrix. This hybrid-wise unfolding combines the advantages of both batch-wise and variable-wise unfolding approaches. Then the algorithm EWMA is employed for considering time dependencies.

After the unfolding step, X $((n \times K) \times J)$ is decomposed by PCA:

$$X = TP^T \tag{1}$$

where T and P are score and loading matrices. n_{pc} is the number of the more significant principal components which are sufficient to explain the variability of data. The matrices of n_{pc} first columns of $\mathcal{T}$ and P are signed respectively $\hat{\mathcal{T}}$ and $\hat{P}$. $\tilde{C}$ is the projection matrix onto the residual subspace:

$$\tilde{C} = (\mathbb{I} - \hat{P}\hat{P}^T) \tag{2}$$

Call e_k $(J \times n)$ and X_k $(n \times J)$ are respectively the projection on the residual subspace and the data matrix of the k^{th} observation of all the batches. The relation between them is given as:

$$e_k = \tilde{C}X_k^T \tag{3}$$

Signing:

$$X_{E,k} = \lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} X_j \tag{4}$$

EWMA is used to filter the covariance matrix $S_{E,k}$ and the residual subspaces projection $e_{E,k}$ as:

$$\begin{aligned} e_{E,k} &= \lambda e_k + (1-\lambda)e_{E,k-1} = \lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} e_j \\ &= \lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} \tilde{C} X_j^T \\ &= \tilde{C} \times \left(\lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} X_j^T \right) = \tilde{C} X_{E,k}^T \end{aligned} \tag{5}$$

The coefficient λ $(0 \leq \lambda \leq 1)$ represents the degree of weighting decrease that determines the weight of older data in the calculation.

Degradation detection indices Call $X_{new,k}$ $(1 \times J)$ is the k^{th} observation of a new batch X_{new} $(K \times J)$. $X_{new,E,k}$ is calculated in the similar way:

$$X_{new,E,k} = \lambda \sum_{j=1}^{k} (1-\lambda)^{k-j} X_{new,j} \tag{6}$$

and

$$e_{new,k} = \tilde{C} X_{new,k}^T \tag{7}$$

$$\begin{aligned} e_{new,E,k} &= \lambda e_{new,k} + (1-\lambda) e_{new,E,k-1} \\ &= \tilde{C} X_{new,E,k}^T \end{aligned} \tag{8}$$

In E-HMPCA, fault detection is ensured by classical PCA detection index as Squared Prediction Error (SPE) for each observation k:

$$SPE_{E,new,k} = e_{new,E,k}^T e_{new,E,k} \tag{9}$$

The process is considered reliable if SPE is under their upper control limit (UCL):

$$UCL_{E,k}^{SPE} = \frac{v_{E,k}}{m_{E,k}} \chi^2_{2m^2_{E,k}/v_{E,k}} \tag{10}$$

where $m_{E,k}$ and $v_{E,k}$ are the mean and variance of the $SPE_{E,k}$ at the observation k of training data.

Degradation estimation via reconstruction The degradation reconstruction estimates the normal values X^* by eliminating the effect of a degradation direction $\mathcal{F}_r$ on the SPE. A reconstruction $X_{r,k}$ from X_k (k is the index of observation) can be calculated as follows:

$$X_{r,k} = X_k - \Xi_r \hat{F}_{r,k} \tag{11}$$

where $\hat{F}_{r,k}$ is the estimated degradation magnitude along degradation direction matrix Ξ_r such that $X_{r,k}$ is closest to the normal region. From (Mnassri, El Adel, & Ouladsine, 2013), the $\hat{F}_{r,k}$ and the projection of the reconstructed sample onto SPE-subspace is given:

$$\hat{F}_{r,k} = \left(\Xi_r^T \tilde{C} \Xi_r\right)^{-1} \Xi_r^T \tilde{C} X_k^T \tag{12}$$

$$\tilde{C}^{\frac{1}{2}} X_{r,k}^T = \left(\mathbb{I} - \tilde{C}^{\frac{1}{2}} \Xi_r \left(\Xi_r^T \tilde{C} \Xi_r\right)^{-1} \Xi_r^T \tilde{C}^{\frac{1}{2}}\right) \tilde{C}^{\frac{1}{2}} X_k^T \tag{13}$$

Singular value decomposition of $\tilde{C}^{\frac{1}{2}} \Xi_r$:

$$\tilde{C}^{\frac{1}{2}} \Xi_r = \Xi_r^0 D_r V_r^T \tag{14}$$

Call $e_{r,k}$ is the e_k after reconstruction.

$$\begin{aligned} e_{r,k} &= \tilde{C} X_{r,k}^T \\ &= (I - \Xi_r^0 \Xi_r^{0^T}) \tilde{C} X_k^T \end{aligned} \tag{15}$$

After the EWMA filter, the residual subspaces become:

$$\begin{aligned} e_{r,E,k} &= \lambda \textstyle\sum_{j=1}^{k} (1-\lambda)^{k-j} e_{r,k} \\ &= \lambda \textstyle\sum_{j=1}^{k} (1-\lambda)^{k-j} (I - \Xi_r^0 \Xi_r^{0^T}) \tilde{C} X_k^T \\ &= (I - \Xi_r^0 \Xi_r^{0^T}) \tilde{C} X_{E,k}^T \\ &= (I - \Xi_r^0 \Xi_r^{0^T}) e_{E,k} \end{aligned} \tag{16}$$

The index SPE after reconstruction of a new batch X_{new} at observation k is:

$$SPE_{r,E,new,k} = e_{r,E,new,k}^T e_{r,E,new,k} \tag{17}$$

The degradation direction matrix Ξ_r is considered the true degradation variables if the SPE is below their new UCL, which are given as follows:

$$UCL_{SPE_{r,E,k}} = \frac{v_{r,E,k}}{m_{r,E,k}} \chi^2_{2m^2_{r,E,k}/v_{r,E,k}} \tag{18}$$

where $m_{r,E,k}$ and $v_{r,E,k}$ are the mean and variance of the $SPE_{r,E,k}$ at the observation k of training data. Notice that the subscript r designates one set among the assumed degraded variable sets. The total number of possible sets of J sensors is:

$$C_J^1 + C_J^2 + ... + C_J^{J-1} = 2^J - 2$$

is really large when $J \geq 8$. To reduce the number of candidate variable sets, an analysis of the SPE-contribution may help. An illustration of this is provided in section 4.

2.1.2. Health indicator extraction

After subsection 2.1.1, the degraded sensors set $\{\mathcal{J}s\} = \{j_1, ..., j_S\}$ is determined where S is the number of sensors. The critical points are then identified via an algorithm with the idea: the critical point of a degraded sensor js is the observation interval k_j at which the variance is the maximum:

$$k_{js} = \arg\max_k \{Var(\tilde{X}_{i,k}^{js}), \quad i = n+1 \to I\} \tag{19}$$

where $\tilde{X}_k^{js} = \frac{X_{i,k}^{js} - m_k^{js}}{\sigma_k^{js}}$, $X_{i,k}^{js}$ is the measurement of product i at observation k of sensor js; $m_k^{js} = mean(X_{i=1\to n,k}^{js})$, $\sigma_k^{js} = standard\ deviation\ (X_{i=1\to n,k}^{js})$. With this algorithm, the point (js, k_{js}) is considered representing the degradation dynamics of the process. It is because a machine which carries the degradation process, this process will come out in some way of the evolution of the degraded sensors. The variance of the measurement $X_{i,k}^j$ from the beginning of degraded batch $n+1$ (because the first n batches are considered as good quality) to the last batches I is the most logical way which presents this degradation process.

The measure value of them is $X_{i,k_{js}}^{js}$ with $i \in 1, ..., I$. They are then arranged in a new matrix $\mathcal{X}_c$:

$$\mathcal{X}_c = \begin{pmatrix} X_{n+1,k_{j1}}^{j1} & X_{n+1,k_{j2}}^{j2} & \cdots & X_{n+1,k_{jS}}^{jS} \\ X_{n+2,k_{j1}}^{j1} & X_{n+2,k_{j2}}^{j2} & \cdots & X_{n+2,k_{jS}}^{jS} \\ \vdots & \vdots & \ddots & \vdots \\ X_{I,k_{j1}}^{j1} & X_{I,k_{j2}}^{j2} & \cdots & X_{I,k_{jS}}^{jS} \end{pmatrix} \tag{20}$$

$\mathcal{X}_c$ is then mean-centered and unit-deviation scaled and is decomposed by PCA:

$$\mathcal{X}_c = T_c P_c^T \tag{21}$$

Each point of $\{j_1, ..., j_S\}$ set has a progressively increasing or decreasing evolution, but the increasing is just an inverse trend of decreasing and vice versa. Therefore, the trend of all these points can be presented in a vector, that is the first PC of $\mathcal{X}_c$, assigned I_0:

$$I_0 = \mathcal{X}_c P_{c1} \tag{22}$$

where P_{c1} is the first eigenvector of P_c.

2.2. Analysis of health indicator dynamics

Applying the health index extraction presented in the previous section, a *common form* of the indicator is provided in Fig. 2, called I_0 (applied on a real data provided by STMicroelectronics). It is highly noisy with a *large variance* over time. We might think that I_0 can be modelled with the Wiener process, which considers the HI as:

$$I_0(t) = x_0 + \mu t + \sigma B(t) \tag{23}$$

where x_0, μ, σ are constant, $B(t)$ is the Brownian movement. (23) can be rewritten as followings:

$$\begin{aligned} I_0(t+1) &= I_0(t) + \mu\big((t+1) - t\big) + \sigma B(1) \\ \Leftrightarrow I_0(t+1) - I_0(t) &= \mu + \sigma B(1) \end{aligned} \tag{24}$$

thus, the variance of $\Delta_t = I_0(t+1) - I_0(t)$ does not depend on t. Figure 3 shows Δ_t of I_0, which demonstrates that Δ_t is dependent on t. Therefore, the Wiener process is not adequate to modelling this raw HI.

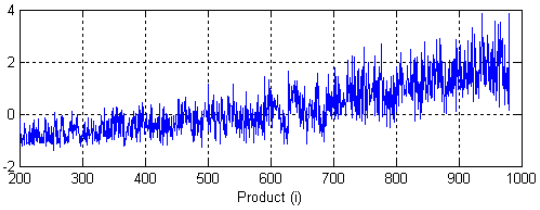

Figure 2. Raw health index I_0

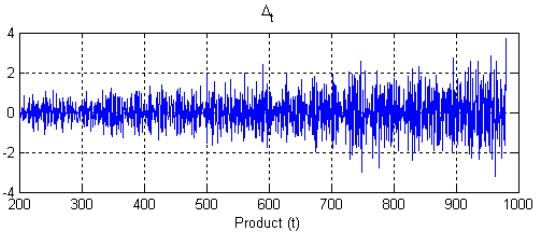

Figure 3. Variation of I_0 between $(t+1)$ and t

Therefore, it is necessary to choose an another method for HI modelling.

2.2.1. Filtering:

A real health indicator is always *monotonic* over time because we assume that the degradation is not reversible. However, under the influence of perturbations of machine, of environment and significant disturbances of quality of input products, I_0 is not monotonic. First, a low-pass filter (e.g: an average filter with a window size of 10) is used to eliminate high frequency noises, the result is called I_1 and given in the Fig. 4.

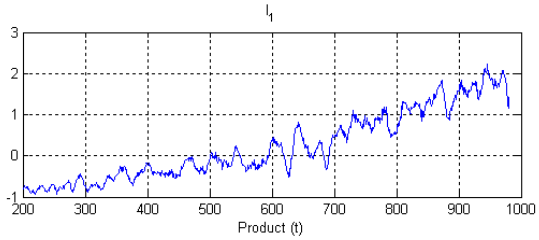

Figure 4. Health indicator I_1

Then, if I_1 *increases* progressively, the higher values reflect the degradation better than their lower neighbour values and inversely if I_1 *decreases* progressively. Therefore, an algorithm is proposed to eliminate disturbances and to *monotonize* the indicator: I_1 is analysed to structure a *top curve* I_t which is then considered as health indicator if I_1 *increases* or a *bottom-curve* I_b if I_1 *decreases*. This algorithm is presented for an increasing index as follows (for a decreasing indicator it is the same but replacing "maximum" by "minimum" and replacing the signs by their opposite sign):

Step 1: Searching the maximum *peaks* of I_1
$\{I_1(i), i = 1 \rightarrow I\}$ is divided into several subsets:
$\{I_{1,u}(i), i = 1 + wu \rightarrow w + wu\}$, u, w are integers
$w > 1$ (e.g:$w = 10$), $u = 0, 1..., [I/w]$
- If $\exists u : max(I_{1,u}(i)) > max(I_{1,u-1}(i), I_{1,u+1}(i))$
  $\Longrightarrow max(I_{1,u}(i))$ is a maximum peak
  $\Longrightarrow I_t = I_t \cup max(I_{1,u}(i))$

Step 2: *Monotonizing* I_t
- Eliminating minimum peaks of I_t:
  $I_t(i) \leq min(I_t(i-1), I_t(i+1))$ (this step is executed several times till there is no minimum peak on I_t)
- Eliminating $I_t(end)$ if $I_t(end) \leq I_t(end-1)$

After this step, the last value of I_t is the maximum. Signing i_{max} is the index of product of this last value. $I_t(i_{max}) = I_1(i_{max})$ and $I_1(i_{max})$ is also the maximum value of I_1

Step 3: Interpolating and extrapolating I_t by *linear* method for all product $i, i \in \{1, ..., i_{max}\}$

2.2.2. Health index modelling

Gamma process is widely used for the deterioration modelling because it is suitable to model gradual damage monotonically accumulating over time such as wear, crack growth, degrading health index, etc. which is presented clearly in a survey of Gamma process (Van Noortwijk, 2009). Therefore, in this work, Gamma process is chosen to model Y.

A random quantity Y has a gamma distribution with shape parameter $\nu > 0$ and scale parameter $u > 0$ if its probability density function is:

$$Ga(y|\nu, u) = \frac{u^\nu}{\Gamma(\nu)} y^{\nu-1} exp(-uy), \quad y > 0 \tag{25}$$

where $\Gamma(a) = \int_{t=0}^{\infty} t^{a-1}e^{-t}dt$. It is assumed that the expected deterioration can be described as a power law between cumulative deterioration and time:

$$E(Y(t)) = \frac{\nu(t)}{u} = \frac{ct^b}{u} \tag{26}$$

Consider a gamma process with shape function $\nu(t) = ct^b$ and scale parameter u. A data set consists of inspection times $t_i, \quad i = 1, ..., n$ where $0 = t_0 < t_1 < ... < t_n$, and corresponding of the cumulative deterioration $y_i, \quad i = 1, ..., n$, where $0 < y_0 \leq y_1 \leq ... \leq y_n$.

The parameters (u, c, b) of the gamma process have been estimated by combining the methods of least squared and maximum likelihood (Bakker & van Noortwijk, 2004). First, b can be estimated using the least-squares method:

$$b = \frac{\sum_{i=1}^{n} log(\frac{t_i}{t_n}) log(\frac{y_i}{y_n})}{\sum_{i=1}^{n} [log(\frac{t_i}{t_n})]^2} \tag{27}$$

Then the parameters u and c can be estimated by using the method of moments (Van Noortwijk, 2009)

$$\frac{\hat{c}}{\hat{u}} = \frac{\sum_{i=1}^{n} \delta_i}{\sum_{i=1}^{n} w_i} = \frac{y_n}{t_n^b} = \bar{\delta} \tag{28}$$

$$\frac{y_n}{\hat{u}}(1 - \frac{\sum_{i=1}^{n} w_i^2}{[\sum_{i=1}^{n} w_i]^2}) = \sum_{i=1}^{n} (\delta_i - \bar{\delta} w_i)^2 \tag{29}$$

where $w_i = t_i^b - t_{i-1}^b$, $\delta_i = y_i - y_{i-1}$.

3. ON-LINE SUPERVISION

For on-line supervision: assigning i^n is the index of product. For a new product i^n processed on machine, the obtained data is used to calculate the health indicator and to estimate the RUL. We repeat again that the *time unit* here is the duration of processing a product on machine, thus, it is also the index of product.

3.1. Extraction of HI and filtering

From the equation (22), the value of raw health index at product i^n is calculated as:

$$I_0(i^n) = \mathcal{X}_c(i^n) \times P_{c1} \tag{30}$$

where $\mathcal{X}_c(i^n) = \begin{pmatrix} \bar{X}^{j1}_{i^n,k_{j1}} & \bar{X}^{j2}_{i^n,k_{j2}} & \dots & \bar{X}^{jS}_{i^n,k_{jS}} \end{pmatrix}$, each value $\bar{X}^{js}_{i^n,k_{js}}$ is computed from the raw measurement value $X^{js}_{i^n,k_{js}}$ of online data as follows:

$$\bar{X}^{js}_{i^n,k_{js}} = \frac{X^{js}_{i^n,k_{js}} - m^{js}_{k_{js}}}{d^{js}_{k_{js}}} \tag{31}$$

$m^{js}_{k_{js}}, d^{js}_{k_{js}}$ are respectively mean and standard deviation of the critical points (js, k_{js}) of off-line data, P_{c1} is the eigenvector given in subsection 2.1.

The curve I_0 for $1 \to i^n$ is then similarly filtered and the obtained health index called $Y_n(1 \to i^n_{max})$, see 2.2.1.

3.2. RUL estimation

A failure threshold L is predefined. Supposing that the health index is increasing (if it decreases, the method is the same but with opposite signs). When Y_n exceeds the normal operating threshold T_N, the prognosis model is launched. The cumulative distribution function (cdf) of time to failure (Van Noortwijk, 2009) with the upper threshold L is:

$$\begin{aligned} F(t) = & \quad Pr\{T_L \leq t\} = Pr\{X(t) \geq L\} \\ = & \quad \int_{x=L}^{\infty} f_{X(t)}(x)dx = \frac{\Gamma(\nu(t), Lu)}{\Gamma(\nu(t))} \end{aligned} \tag{32}$$

where $\Gamma(a, x) = \int_{z=x}^{\infty} z^{a-1}e^{-z}dz$

At the moment t_n, the value of $X(t_n)$ is known as x_n. The definition of the RUL at time t_n can be represented by the first passage time of $\{X(t), t \geq t_n\}$ crossing L as $h_{t_n} = inf\{h_{t_n} : X(t_n + h_{t_n}) \geq L | X(t_n) < L\}$. The cdf of RUL can be written:

$$\begin{aligned} F(h_{t_n}) = & \quad Pr\{X(t_n + h_{t_n}) \geq L\} \\ = & \quad Pr\{X(t_n + h_{t_n}) - X(t_n) \geq L - x_n\} \\ = & \quad \int_{x=L-x_n}^{\infty} Ga(\nu(h_{t_n} + t_n) - \nu(t_n), u)dx \\ = & \quad \frac{\Gamma(\nu(h_{t_n} + t_n) - \nu(t_n), (L - x_n)u)}{\Gamma(\nu(h_{t_n} + t_n) - \nu(t_n))} \end{aligned} \tag{33}$$

The probability density function (pdf) of RUL is:

$$f(h_{t_n}) = \frac{\delta}{\delta h_{t_n}} [\frac{\Gamma(\nu(h_{t_n} + t_n) - \nu(t_n), (L - x_n)u)}{\Gamma(\nu(h_{t_n} + t_n) - \nu(t_n))}] \tag{34}$$

The expected RUL is:

$$E(h_{t_n}) = \int_{h_{t_n}=0}^{\infty} h_{t_n} f(h_{t_n}) dh_{t_n} \tag{35}$$

The value of x_n is updated for the online supervision, which updated the RUL estimation.

4. APPLICATION

This section provides the result of application of the proposed method on real industrial data from STMicroelectronics. Measured variables are sampled at 1 second intervals during a process, for 351 observations of totally 19 sensors for one month of production, which represents about 1000 wafers from the first wafer to the last one. The data is preprocessed by Dynamic Time Warping technique to obtain the common length trajectories.

4.1. Off-line analysis

4.1.1. Health indicator extraction

The first two hundred wafers $n = 200$ are used to build the UCL of SPE. The last batch is considered *bad quality*. Fig. 5 gives the result of degradation detection. The violations before $k = 20$ are characterized as in short duration, appear on step/phase changes and not repeatable unit-to-unit, therefore, they are spurious violations. Meanwhile, the violations from $k = 118$ to $k = 351$ exhibit the drift of machine's quality, this is because of their long durations and their unit-to-unit repeat since the last wafers. The most observation at which the SPE is significant is $k = 351$. Thus, the contribution of SPE at this observation is investigated. The candidature sensors are $1, 2, 9, 10, 12$ and 18.

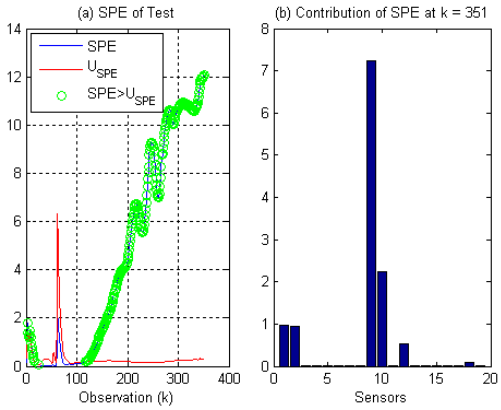

Figure 5. Degradation detection and SPE contribution

The result of degradation reconstruction on these sensors are given in Fig. 6. We see that there are 4 cases whose reconstruction make SPE under the threshold UCL. The set of *case 3* is the set which consists the common sensors of the others cases. Thus, the significant sensors are $\{9, 10, 18\}$. The critical point of these sensors are determined as given in Fig. 7. Then the HI extracted from these points are shown in Fig. 2.

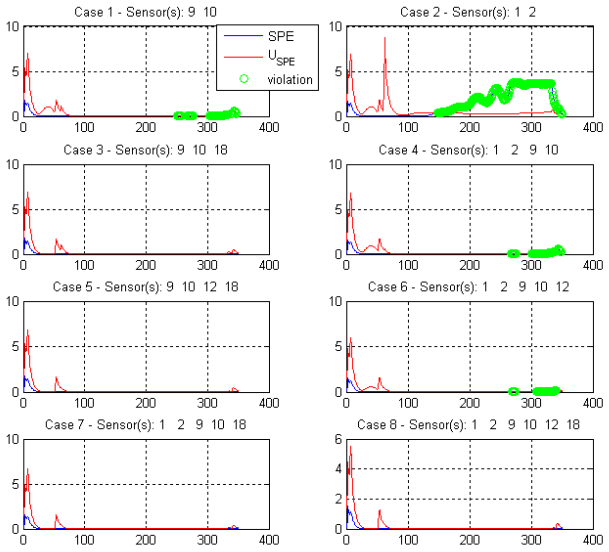

Figure 6. Reconstruction of degradation

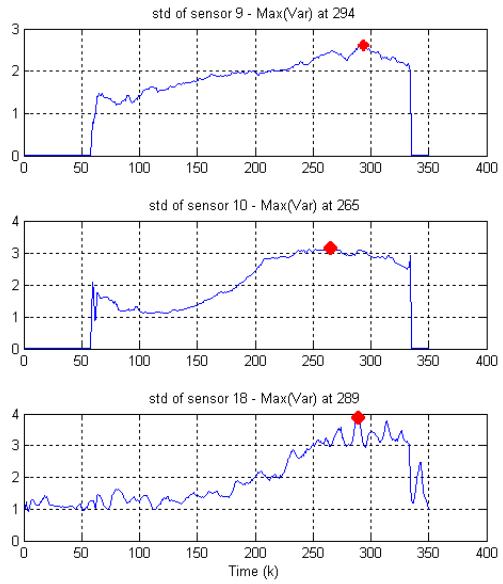

Figure 7. Variance of observation points of sensors

4.1.2. Analysis of health indicator dynamics

Applying the filtering proposed in 2.2.1, the health index Y is given in Fig. 8. The *normal operating threshold* is *predefined* $T_N = -0.5$ and the *failure threshold* is predefined $L = 2.3$.

The parameter result of *health indicator modelling* is $u = 604.7$, $c = 0.94$ and $b = 1.15$.

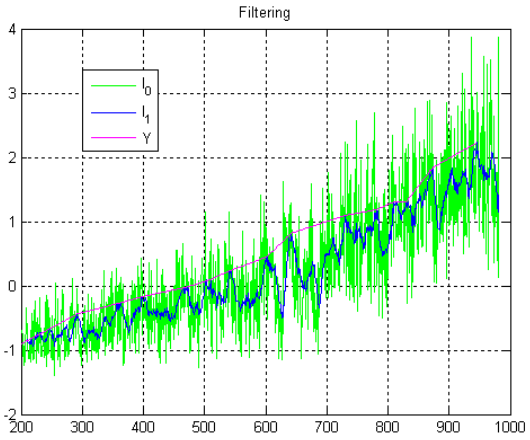

Figure 8. Health indicator

4.2. Online supervision

Assuming that the reference HI represents all the system dynamics of degradation in the considered operating mode; to validate the prognosis model, the online data is generated by a simulator which takes into account the dynamics of historical data. One profile of online HI is given in Fig. 9 compared to the off-line one (shifting forward with n=200). At each inspection time i^n, the available online data is known only for $t = 1, ..., i^n$. When $Y_n(i^n_{max}) > T_N$, (see section 3.1), the degradation alarm launches the prognosis model.

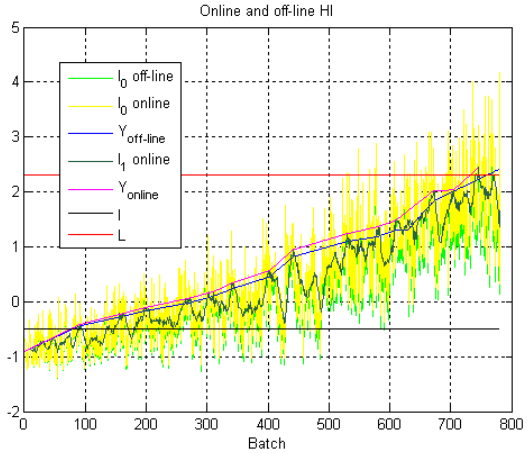

Figure 9. Online data

At each inspection time i^n, the real failure time is 731 thus the real RUL is $(731 - i^n)$. Hence, the estimate RUL (the expected RUL, equation (35)) and the real RUL can be compared as given in Fig. 10. The result shows that the RUL estimation of almost inspection times gives a small error. This error is really small during $i = 260 \rightarrow 430$ and $i = 530 \rightarrow 660$ due to the updating of last value of Y in the equation 33. However, from $i = 673$, the error becomes larger. The reason for this is found in Fig. 9, that the degradation (Y-online) decelerates during $i = 673 \rightarrow 704$ then it re-accelerates. The degradation is much fluctuating during some small intervals but the average rate of Y-online is generally fitted to Gamma process, that's why the error is smaller before $i = 673$. This profile is a particular example, which implies that the method adapts to the available data but an improvement of the proposed method is necessary to overcome the influences of local fluctuations.

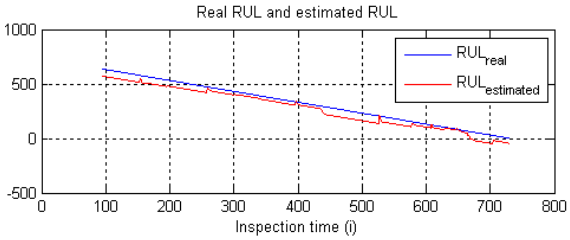

Figure 10. Estimation error

The *root mean squared error* of RUL estimation is 49 time units (equivalent to the duration of processing 49 wafers or nearly 2 lots in STMicroelectronics manufacturing) is a small error.

5. CONCLUSION

This paper proposed a method of health indicator contribution for discrete manufacturing processes based on degraded sensors identification via degradation reconstruction. The Gamma process is used for HI modelling. An application of the proposed method on a real industrial case shows a small error of RUL estimation for the online supervision. A further improvement of the proposed method is necessary to overcome the influences of local fluctuations of HI in some particular situations.

REFERENCES

Bakker, J., & van Noortwijk, J. (2004). Inspection validation model for life-cycle analysis. In *Bridge maintenance, safety, management and cost, proceedings of the second international conference on bridge maintenance, safety and management (iabmas), kyoto, japan* (p. 18-22).

Gang, L., Qin, S. J., Ji, Y., & Zhou, D. (2010). Reconstruction based fault prognosis for continuous processes. *Control Engineering Practice*, *18*(10), 1211-1219.

Mnassri, B., El Adel, E. M., & Ouladsine, M. (2013). Generalization and analysis of sufficient conditions for pca-

based fault detectability and isolability. *Annual Reviews in Control*, *37*(1), 154-162.

Thieullen, A., Ouladsine, M., & Pinaton, J. (2012). A survey of health indicators and data-driven prognosis in semiconductor manufacturing process. In *8th ifac symposium on fault detection, supervision and safety of technical processes (safeprocess)* (Vol. 8, p. 19-24).

Van Noortwijk, J. (2009). A survey of the application of gamma processes in maintenance. *Reliability Engineering & System Safety*, *94*(1), 2-21.

Yue, H. H., & Qin, S. J. (2001). Reconstruction-based fault identification using a combined index. *Industrial and Engineering Chemistry Research*, *40*(20), 4403-4414.

Zhang, Y. (2008). *Improved methods in statistical and first principles modeling for batch process control and monitoring* (PhD dissertation). University of Texas, Austin.