Journal of Process Control 48 (2016) 72–80

Contents lists available at ScienceDirect

Journal of Process Control

journal homepage: www.elsevier.com/locate/jprocont

Fault prognosis for batch production based on percentile measure and gamma process: Application to semiconductor manufacturing

T.B. Lien Nguyen[a,*], Mohand Djeziri[a], Bouchra Ananou[a], Mustapha Ouladsine[a], Jacques Pinaton[b]

[a] Aix Marseille University, CNRS, ENSAM, UTLN, LSIS – UMR 7296, 13397 Marseille, France
[b] STMicroelectronics, 13106 Rousset Cedex, France

ARTICLE INFO

Article history:
Received 3 February 2016
Received in revised form 16 June 2016
Accepted 16 October 2016
Available online 3 November 2016

Keywords:
Batch manufacturing processes
Fault prognosis
Multidimensional data processing
Percentile measure
Stochastic process

ABSTRACT

Batch manufacturing processes (BMP) play an important role in many production industries, such as in semiconductor, electronic and pharmaceutical industries. They generally exhibit some batch-to-batch or unit-to-unit variations due to many reasons such as variations in impurities and deviations of the process variables from their trajectories. The process monitoring for these systems has been considered as rather fault diagnosis than as fault prognosis, this latter has received scarce attention in the literature. This paper presents a data-driven prognostic method for BMP organized in three steps. The first step allows to reduce the data size and to extract a raw health index which represents the operating state of the system. In the second step, variations in the health index are processed by the percentile measure which is use in a way that gives rise to monotonic profiles. In the third step, these profiles are modelled by gamma process as it is the most appropriate for the stochastic modelling of monotonic and gradual deterioration. The remaining useful life (RUL) is then estimated using an aggregate probability density function (pdf) with a confidence interval (CI) that ensures the safety margins in industry. Finally, the proposed method is applied on semiconductor manufacturing equipment with two industrial datasets provided by STMicroelectronics.

1. Introduction

Maintenance plays a key role in reliability engineering of industrial manufacturing processes. Products have become more and more complex while better quality and higher reliability are required, this makes the traditional maintenances (breakdown maintenance and preventive maintenance) a major expense of many industrial companies [1]. Condition-based maintenance (CBM) is a promising solution to this issue as it is a maintenance program that recommends maintenance actions based on the information collected through condition monitoring [2]. Dealing with fault prediction before it occurs, fault prognostics is one of the central issues in CBM. It attempts to minimize the downtime of machines and production; and thus to increase the efficiency of operations and manufacturing [3]. It has attracted a lot of interest from the industrial and scientific community [4–6] but most prognostic research work to date has been theoretical, there are few published examples of prognostic models being applied in the industrial field [7].

From a methodological point of view, there exist three approaches for fault prognostics in the literature [7,8]: physical model-based approaches, knowledge-based approaches and data driven approaches. Fault prognostics based on physical models are based on the physical modelling of the system behaviour and the degradation process to estimate the RUL [9–11]. These approaches give accurate results but their main limitation is the difficulty in obtaining an accurate model of the degradation evolution for complex systems, due to lack of physical knowledge on the degradation dynamic. Fault prognosis based on experience formalizes the deterioration of components initiated by the prior knowledge and expert judgement; such as in [12], from a sufficient amount of knowledge of energy conversion processes, an expert system with a fuzzy logic protocol and an intelligent agent prototype is developed; [13] uses a belief rule base to model environmental factors and a hidden Markov model to predict the hidden failure

Abbreviations: RUL, remaining useful life; CI, confidence interval; pdf, probability density function; HI, health index; EMD, empirical mode decomposition; DWT, discrete wavelet transform; PECVD, plasma enhanced chemical vapour deposition; SACVD, sub-atmospheric chemical vapour deposition.

* Corresponding author.
E-mail addresses: tblien.nguyen198@gmail.com (T.B.L. Nguyen), mohand.djeziri@lsis.org (M. Djeziri).

http://dx.doi.org/10.1016/j.jprocont.2016.10.003
0959-1524/

Nomenclature

i, j, k	index of product, sensor and observation
I	number of products
J	number of sensors
K	number of observations
$x_i^{(j,k)}$	measurement value at i, j, k
$\mathcal{X}$	matrix of moving points
(jm, km)	moving points (jm, km)
(js, ks)	significant points (js, ks)
$\mathcal{X}_r$	reduced data matrix
X_t	health index at time t
L_N	threshold of normal operating conditions
L_F	failure threshold
T_y	set of time t_i satisfying $X_{ti} < y$ and $X_{ti+1} \geq y$
T_y^p	percentile p of T_y
Z^p	profile of pth percentile of health index X_t
Z_τ^p	value of profile Z^p at time τ
$(\hat{u}, \hat{c}, \hat{b})$	estimated parameters of Gamma process
$f_{p,RUL}$	pdf of RUL of profile Z^p
f_{RUL}	aggregate pdf of RUL
RUL_e	expected RUL
RUL_r	real RUL

of a continuous stirred tank reactor; [14,15], etc. The advantage of these approaches is the facility of implementation in the industrial context; however, their accuracy and applicability is limited by the uncertainty caused by the humane appreciation of the current state of degradation and its future evolution. The data driven approaches, considered as a good compromise between the accuracy and the applicability, can be classified into two categories [7]: statistical methods and artificial intelligence (AI) methods. The statistical methods determine the RUL of system with respect to the expected risk of deterioration under known operating conditions [16–18]. The AI methods compute the RUL by mimicking the human brain structure as they consist of simple processing elements connected in a complex layer structure [19,20]. However, the implementation of data driven methods for fault prognostics requires the availability of a rich database for learning.

The modern production machines are increasingly equipped with sensors for the purposes of control and monitoring, generating thus a large amount of data to be processed. Till now, the implementation of CBM strategies is constrained by the unavailability of fault prognostic methods based on multidimensional data. The complexity of these systems makes it difficult to use the methods based on physical models; and the continued development of tools and production techniques makes it difficult to formalize timely expert knowledge. Whereas, due to the advance of the modern sensor systems, data storage and processing technologies, the data-driven methods are increasingly used for the fault diagnosis purpose [21–23] as well as for fault prognostic purpose [18,24,17,25]. However, most of the existing works for fault prognostics propose solutions to the continue processes rather than the BMP. A BMP is an equipment which processes or produces *distinct* items or separate unit of products, such as in food, semiconductor, electronic and pharmaceutical industries. Therefore, the obtained measurement of a BMP is three dimensional data: product, sensor and observation (sampling time); this is different from continues processes which give two dimensional data of sensor and observation. A more concrete formulation of a BMP data is: a three dimensional (3D) data matrix of size $I \times J \times K$ where I is the number of products, J is the number of sensors and K is the number of observation (sampling time). Each point of this data matrix is signed $x_i^{(j,k)}$,

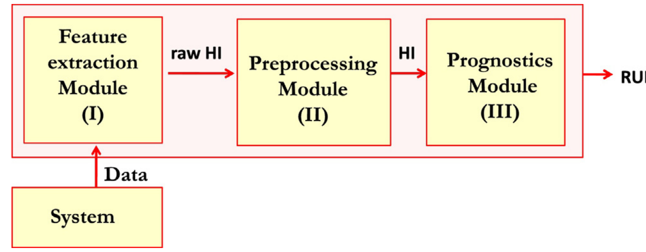

Fig. 1. Overview of the proposed method.

where $i \in \{1, \ldots, I\}, j \in \{1, \ldots, J\}, k \in \{1, \ldots, K\}$ are respectively the index of product, sensor and observation.

The first issue in BMP fault prognostics is the health index (HI) extraction from a large data size, which is not focused so much in existing works. The second issue is the RUL prediction based on this HI which is subject to a significant variability, since the HI in many industrial applications describe a trend with disturbances, noise and aberrant values [18,24–27]. The existing preprocessing methods such as frequency methods (low-pass filters, wavelet decomposition) or statistical methods [28] results in one profile, that leads to an information loss and a deformation of the obtained profile. Moreover, the frequency methods require knowledge of the frequency that carries the degradation, which is not well known in real applications. The statistical methods are based on the averaging, which can lead to the elimination of variability related to degradation.

In this paper, we propose a novel method to overcome these issues. As shown in Fig. 1, the inputs of the fault prognostic algorithm are the raw measurements of the sensors installed on the system. The first module, *feature extraction module*, concerns the generation of a health index that represents degradation state of the system from a large data set, which is developed in our previous works [29–31]. The second module, *preprocessing*, contributes in processing the raw health index by a new method, called *percentile method*, which conserves the major part of information existing in the health index (HI) while isolating useful information (the degradation) from noises, uncertainties and various external disturbances. The third module of the developed approach, *prognostic module*, is dedicated to the proposition of a RUL estimation method based on a pdf aggregation of the profiles generated by the preprocessing module. The paper focuses on the modules II and III of the method.

The paper is organised as follows: Section 2 gives a resume of a raw HI extraction method based on significant points, as it is proved to give the most characterized HI among our developed methods related to this issue [31]. Section 3 presents a preprocessing technique based on the percentile notion to extract degradation profiles from the raw HI. In Section 4, these profiles are then modelled by a gamma process and the RUL is estimated using an aggregate pdf. Section 5 gives two applications of the proposed method on machine datasets provided by STMicroelectronics, where the prognostic performance metrics are also implemented. The conclusion is given in Section 6.

2. Health index extraction

The HI extraction method used in this work is called significant points (SP) method. It is detailed in [29] and is compared to other HI extraction methods in [31]. The SP method for HI extraction is summarized in the following steps:

1. Identifying the moving sensor-observation points (jm, km) which have an important variation between the first products (considered as good quality products) and the degraded product. The