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Remaining useful life estimation based on nonlinear feature reduction and support vector regression

T. Benkedjouh [b], K. Medjaher [a,*], N. Zerhouni [a], S. Rechak [c]

[a] FEMTO-ST Institute, UMR CNRS 6174 - UFC/ENSMM/UTBM Automatic Control and Micro-Mechatronic Systems Department 24, rue Alain Savary, 25000 Besançon, France
[b] EMP, Laboratoire de Mécanique des Structures (LMS), Bordj El Bahri, Algiers, Algeria
[c] ENSP, Laboratoire de Génie Mécanique, El-Harrach, Algiers, Algeria

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ABSTRACT

Prognostics and health management (PHM) of rotating machines is gaining importance in industry and allows increasing reliability and decreasing machines' breakdowns. Bearings are one of the most components present in mechanical equipments and one of their most common failures. So, to assess machines' degradations, fault prognostic of bearings is developed in this paper. The proposed method relies on two steps (an offline step and an online step) to track the health state and predict the remaining useful life (RUL) of the bearings. The offline step is used to learn the degradation models of the bearings whereas the online step uses these models to assess the current health state of the bearings and predict their RUL. During the offline step, vibration signals acquired on the bearings are processed to extract features, which are then exploited to learn models that represent the evolution of the degradations. For this purpose, the isometric feature mapping reduction technique (ISOMAP) and support vector regression (SVR) are used.

The method is applied on a laboratory experimental degradations related to bearings. The obtained results show that the method can effectively model the evolution of the degradations and predict the RUL of the bearings.

1. Introduction

Prognostics and health management (PHM) of industrial systems is a central activity of intelligent maintenances, such as condition-based maintenance (CBM) and predictive maintenance (PM). PHM deals with condition monitoring, fault detection, fault diagnostics, fault prognostics and decision support. It can concern the whole industrial system as well as its critical components. The analysis of the experience feedback performed on electrical machines by the electric power research institute (ERPI), and researchers in the reliability of electrical machines, has shown that the bearings and the stator are the components which present the most failures (Medjaher et al., 2012). Consequently, doing PHM on these components may increase the availability, the reliability and security of the machines. The purpose of PHM on rotating machinery is not only to detect the faults but also to predict how much longer the machine can operate safely and perform its function. Interesting reviews on prognostics are given in Jardine et al. (2006) and Heng et al. (2009). Failure prognostics can be done by using three main approaches: model-based, data-driven and hybrid prognostics. Among these approaches, data-driven prognostics offer a trade off in terms of precision and complexity.

Bearings' prognostics target the prediction of RUL in order to minimize the time breakdown and maintenance costs. Most of prognostic methods related to bearings can be considered within the data-driven approach and use vibrations analysis (Jardine et al., 2006). In this framework, Shao and Nezu (2000) proposed a progression-based prediction model for remaining useful life of bearings, Haitao et al. (2006) estimated the RUL of bearings by using both a proportional hazard model and a logistic regression. Gebraeel et al. (2004) used the feedforward neural networks (FFNNs) to project the degradation by computing exponential parameters that give the best exponential fit. Similarly, Huang et al. (2007) proposed a self organizing map (SOM) and an artificial neural network based method for performance degradation assessment and residual life prediction of bearings, Yan and Lee (2005) utilized a logistic regression to achieve machine performance assessment and finally, Lingjun et al. (2005) applied support vector data description (SVDD) to assess the equipment health state and to detect bolt crack.

One of the main challenges in prognostic of bearings is how to construct and evaluate health indicators from available features, which can represent the degradation states. In practice, the construction of health indicators depends on the nature of the degradations and the related monitoring data provided by the

* Corresponding author. Tel.: +33 3 81 40 27 96; fax: +33 3 81 40 28 09.
E-mail address: kamal.medjaher@ens2m.fr (K. Medjaher).

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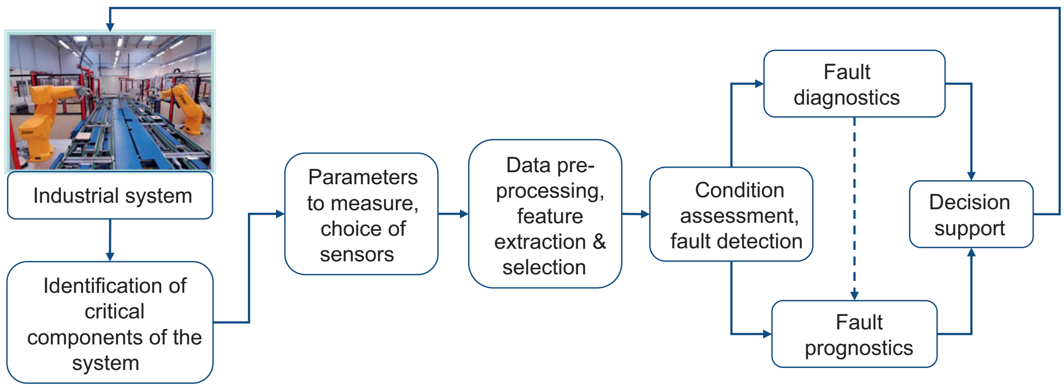

Fig. 1. Component-oriented PHM framework.

sensors (Xi et al., 2000). In this domain, the raw monitoring signals are pre-processed and used to extract features. However, the number of features can be of high dimensionality and can be reduced before building the health indicator. Various techniques for data reduction have been proposed in the literature (Maaten et al., 2009). Among these techniques, principal component analysis (PCA) (Jackson, 1991) is one of the most used. Thus, Liao and Lee (2009) utilized the PCA to extract features by using wavelet packet decomposition (WPD) on vibration signals of bearings. Recently, Malhi and Gao (2004) proposed a PCA-based feature selection approach for bearing fault classification. However, PCA is a linear reduction technique.

The main contribution of this paper concerns the utilization of the isometric feature mapping (ISOMAP) technique, to perform nonlinear feature reduction, combined with nonlinear support vector regressions (SVR) to construct health indicators allowing the estimation of the health state of bearings and predict their RUL. The purpose of the ISOMAP technique is to find a small number of features that represent a large number of observed dimensions. ISOMAP has the advantage to be nonlinear and noniterative and gives globally optimal solutions (Tenenbaum et al., 2000). The objective of the SVR is to estimate the relation between an input and output random variable under the assumption that the joint distribution of the input and the output variables is completely unknown. The SVR technique has been successfully applied in various machine learning problems, which are especially prominent for regression (Schölkopf and Smola, 2002) and in different applications such as sunspot frequency prediction (Collobert and Bengio, 2001) and drug discovery (Demiriz et al., 2001). In this paper, the SVR is used to learn the nonlinear degradation models of the bearings.

The method proposed in this paper is divided into two steps: an offline step and an online step. The offline step is used to learn the bearings' degradation models by using the ISOMAP and the SVR techniques. This step is also used to learn more about the variability of the monitoring data, to tune the parameters of the ISOMAP and SVR techniques and to define the failure thresholds of the bearings. The online step uses the models learned during the offline step to assess the current health state of new tested bearings and to predict their RUL.

This paper is organized as follows. Section 2 presents the framework for component-based PHM, Section 3 describes the proposed method for RUL estimation of bearings based on ISOMAP and SVR, Section 4 deals with experimental verification and results and finally, Section 5 concludes the paper.

2. Component-oriented prognostics and health management

Prognostics and health management (PHM) is a central activity for the implementation of condition based maintenance (CBM) and predictive maintenance (PM). PHM includes seven modules (Lebold and Thurston, 2001), one of them is failure prognostics. The international standard organization defines failure prognostics as the estimation of the operating time before failure and the risk of existence or later appearance of one or more failure modes (AFNOR, 2005), whereas most reported literature related to PHM defines it as the estimation of remaining useful life (RUL) (Jardine et al., 2006; Tobon-Mejia et al., 2012; Heng et al., 2009). The estimation of RUL can be done by using three main approaches: model-based prognostics (also called physics of failure), data-driven prognostics and hybrid prognostics (combination of both previous approaches). Each one of these approaches has its strength and its weakness. Model-based prognostics gives more precise results, but its implementation is difficult because in most applications the construction of the physical model is not a trivial task. Data-driven prognostics relies on the data provided by the sensors to extract features which are then used to build models for RUL estimation. This approach is easy to implement but the results it provides are less precise than those of model based approach. Finally, hybrid approach takes the best of both previous approaches, but also some of their weaknesses.

The contribution presented in this paper belongs to data-driven prognostics with the hypothesis that the RUL estimation is done on the critical components of the industrial system. Fig. 1 shows the framework of the component-oriented prognostics.

In this paper we make an assumption that the prognostic of the whole industrial system corresponds to prognostic of its critical components. The first step of the prognostic process is then to identify the critical components. This step is followed by the definition of the degradation phenomena, the parameters to monitor and the sensors to install. The raw data provided by the sensors are then processed to extract features and health indicators, which are used to do fault detection, diagnostics, prognostics and decision support on the industrial system. In the following of the paper, only feature extraction/reduction and fault prognostics are concerned.

3. RUL estimation based on ISOMAP and SVR

The main steps of the proposed contribution are shown in Fig. 2. Feature extraction and reduction and degradation modeling steps will be described in the following of the paper.

3.1. Feature extraction and reduction

This section presents the feature extraction and reduction technique. The features are first extracted from raw monitoring signals by using wavelet packet decomposition. This latter technique allows calculating the energy of the nodes at each level of