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Review

Supervision and prognosis architecture based on dynamical classification method for the predictive maintenance of dynamical evolving systems

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ABSTRACT

In this paper, we are concerned by the improvement of the safety, availability and reliability of dynamical systems' components subjected to slow degradations (slow drifts). We propose an architecture for efficient Predictive Maintenance (*PM*) according to the real time estimate of the future state of the components. The architecture is built on supervision and prognosis tools. The prognosis method is based on an appropriated supervision technique that consists in drift tracking of the dynamical systems using *AUDyC* (AUto-adaptive and Dynamical Clustering), that is an auto-adaptive dynamical classifier. Thus, due to the complexity and the dynamical of the considered systems, the Failure Mode Effect and Criticity Analysis (*FMECA*) is used to identify the key components of the systems. A component is defined as an element of the system that can be impacted by only one failure. A failure of a key component causes a long downtime of the system. From the *FMECA*, a Fault Tree Analysis (*FTA*) of the system are built to determine the propagation laws of a failure on the system by using a deductive method. The proposed architecture is implemented for the *PM* of a thermoregulator. The application on this real system highlights the interests and the performances of the proposed architecture.

Contents

1. Introduction

The main objective of the *PM* is to improve the availability and the reliability of industrial systems by reducing the costs associated with their maintainability [13,41,39,6,24]. In literature, *PM* is often referred to as Condition-Based Maintenance (*CBM*). However, the

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CBM is a methodology based on the continuous survey of working conditions to detect an abnormal situation (e.g. the exceeding of a controlled parameter threshold level), to do maintenance actions before a failure occur. While, with *PM*, it possible to predict when the controlled quantity value will reach or exceed the threshold values. With the *PM*, the staff will then be able to plan *PM* action, depending to the operating conditions, the component substitution or revision is really unavoidable [3]. Thus, approaches and definition of the *PM* are proposed in [31,5,43]. The maintenance strategies presented in [41,39,6,24], require the online monitoring of the system and the prognostic of failures. The Implementation of solutions Prognostics and Health Management (*PHM*) is a growing part in the activities of maintenance. Thus, the supervision and prognosis tools for *PM* are now considered one of the main levers in search of a performance overall [12]. *PHM* aims at estimating the remaining useful life of a system (RUL) [22]. Different modeling approaches for *PHM* can be found in [28]. The supervision and prognosis are performed according to knowledge-based, model-based approach [29,34] and data-driven approach [28]. Both latter approaches have their own strengths and limitations in prognostic applications. Therefore, a new prognostic approach combining data-driven and model-based approaches is proposed in [23,16,18,33]. This new prognosis approach is a hybrid prognostic approach. Model-based approaches require the physical laws which rule the dynamical of the systems [59]. However, for complex system and most of the real systems, a mathematical model is generally not available. Finally, data-driven approaches are prioritized when no prior knowledge and no mathematical models are available.

The mathematical model of dynamical and complex systems is difficult to obtain for a lot of real applications, then data-driven approaches are suitable to develop a supervision and prognosis tools for *PM* of dynamical systems. A dynamical system is a system whose behavior evolves over time. The most popular data-driven process monitoring approaches include Principal Component Analysis (*PCA*) [2], Sliding Windows SUM (SW-CUSUM), Nearest Neighbor [32], Support Vector Machine [54] and Pattern Recognition Techniques (*PRT*) [17,15,40].

But a focus is made on *PRT*. The *PRT* approaches aim at determining the similarity between measured data which characterize the operating states of a system. An overview of *PRT* methodology in the field of pattern recognition are proposed in [45,37] by considering two main streams: supervised and unsupervised learning. Supervised learning is a technique for creating a function for a training data (all the data are labeled). The training data consists of pairs of input objects (a vector of characteristics) and desired output. Unsupervised learning is a method of learning where a model is fit to observations (unlabeled data). It is distinguished from supervised learning by the fact that there is no a prior output. Shukhat proposed in [51] a supervised fuzzy pattern recognition algorithms which consists in determining the partition between several classes.

A pattern recognition based on supervision is proposed in [49], to maintain the control performances of a system under degraded conditions. In [46], a fuzzy clustering method is proposed in the context of labeled patterns, with the aim is to optimize the reconciliation between data and the patterns. In general case when partial knowledge are considered, then the *PRT* are semi-supervised [14,21,11,26,58]. The goal of semi-supervised learning is to understand how combining labeled and unlabeled data may change the learning behavior, and design algorithms that take advantage of such a combination. A semi-supervised learning is of great interest in machine learning and data mining because it can use readily available unlabeled data to improve supervised learning tasks when the labeled data are scarce or expensive. Thus, a prior knowledge about the functioning modes is considering and this initial knowledge is enriched on-line. The recent *PRT* include *LAMDA* (Learning Algorithm for Multivariable Data Analysis) [7], Fuzzy Pattern Matching (*FPM*) [42] and *AUDyC* [36]. The method *LAMDA* consists in defining and recognizing classes according to heuristic rule of Maximal Adequacy and a Greater Adequacy Degree [30]. But, the *LAMDA* methodology is not really adapted for dynamical clustering. Sayed-Mouchaweh presents in [42] an overview of the *PRT* for the diagnosis of dynamical systems. Moreover, a semi-supervised classification method based on *FPM* is proposed. No prior knowledge about the classes is needed, because the characteristics of each classes are sequentially learned on line. However, for *FPM* method, the old and new observations have the same weight, and using this method depends on the classes separability. Finally, the *AUDyC* methodology was proposed in [36] in order to supervise dynamical systems. No prior knowledge about the classes or significance of the measured variables is necessary. The classes corresponding to the operating mode of the system may have complex shapes (or structures) formed by one or more Gaussian prototype that are enough close to each other. A prototype is defined by a single Gaussian density. They are adapted continuously, allowing to update the knowledge base, by integrating quickly the occurrence of a new operating mode. *AUDyC* algorithm is particularly well adapted for the supervision of dynamical and complex systems without prior knowledge, as it is shown in [56]. The supervision approach proposed in this paper is based on the *AUDyC* methodology.

In this paper, the Possibility Function (*PF*) of each system's component presented in [57] is replaced by Possibility Function by Episode (*PFE*). The latter can be estimated by the experience feedback (this took time) or by monitoring (supervisor) module tracks on real time the degradation's evolution of each component. Here, the degradation indicators are obtained by the supervision of the characteristic intrinsic of components. In [57], the *PF* of each component is represented by triangular fuzzy numbers and the estimation of *PFE* is based on the degradation indicator of each system's component. Thus, the *PFE* of top event results from the propagation of basic events according to the causal relationships [27,57]. Failure possibility is the possibility that the component fails depending to the evolution of the normal mode towards to failure mode of a component *i*.

This paper is organized as follows. The proposed supervision and prognosis architecture and definition of the methodology of *FMECA* are presented in Section 2. In Section 3, we briefly review same notation and definition of a *FTA* and the concept of dynamical failure

Table 1
Different types of faults for a component.

	Brutal	Quick drift	Slow drift
Characteristics	By a jump (normal mode to default mode	The trajectory of the degradation is concave	The trajectory of the degradation is convex
Detectability	Yes	Yes	Yes (not easy to detect)
Prognosability	No	Yes	Yes
Feasibility of developing a prognosis module	No	Yes	Yes
Examples	Sharp break	Running-in (new car)	fouling of a component