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CNC machine tool's wear diagnostic and prognostic by using dynamic Bayesian networks

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ABSTRACT

The failure of critical components in industrial systems may have negative consequences on the availability, the productivity, the security and the environment. To avoid such situations, the health condition of the physical system, and particularly of its critical components, can be constantly assessed by using the monitoring data to perform on-line system diagnostics and prognostics.

The present paper is a contribution on the assessment of the health condition of a computer numerical control (CNC) tool machine and the estimation of its remaining useful life (RUL). The proposed method relies on two main phases: an off-line phase and an on-line phase. During the first phase, the raw data provided by the sensors are processed to extract reliable features. These latter are used as inputs of learning algorithms in order to generate the models that represent the wear's behavior of the cutting tool. Then, in the second phase, which is an assessment one, the constructed models are exploited to identify the tool's current health state, predict its RUL and the associated confidence bounds. The proposed method is applied on a benchmark of condition monitoring data gathered during several cuts of a CNC tool. Simulation results are obtained and discussed at the end of the paper.

1. Introduction

The maintenance activity plays a major role in industrial systems as it permits to improve the availability, reliability and security, while reducing the life cycle cost. There exist several types of maintenance, which can be classified into two main categories, namely: curative and preventive maintenances [1,2]. In the first case, the interventions are done only after the observation of the failure, whereas in the second case they are realized either systematically or conditionally to the health condition of the system. This type of maintenance is commonly termed as a condition based maintenance (CBM). Indeed, the condition of the industrial system is continuously monitored and inspected by a set of sensors. The data recorded by these latter are then processed in order to extract relevant features that allow to estimate the current health state and to project this one in the future. The estimated and projected states are then used to take appropriate maintenance decisions. Diagnostic aims at assessing the component's current condition and identifying the cause of its failure, whereas prognostic is used to predict its future health state in order to anticipate the failure [3–6].

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Formally, failure prognostic consists of estimating the time before failure or the remaining useful life (RUL) and the associated confidence value. It can be realized by using three main approaches [7,8], namely: model-based prognostic, experience-based prognostic and data-driven prognostic. Model-based prognostic consists of studying each component or sub-system in order to establish for each one of them a mathematical model of the degradation phenomenon. The derived model is then used to predict the future evolution of the degradation and thus the related RUL value. Experience-based prognostic methods use mainly probabilistic or stochastic models of the degradation phenomenon, or of the life cycle of the components, by taking into account the data and knowledge accumulated by experience during the whole exploitation period of the industrial system. Data-driven prognostic is based on the transformation of the monitoring data into relevant behavioral models permitting to predict the RUL and the associated confidence.

This paper deals with the assessment of the cutting tool's health condition of computer numerical control (CNC) machines through the utilization of dynamic Bayesian networks (DBN). The proposed method belongs to the data-driven prognostic approach and aims at transforming the raw monitoring data provided by the sensors into behavioral models that represent the evolution of the cutting tool's degradation. The obtained models are then used to continuously estimate the current state of the cutting tool and calculate its RUL. The choice of this approach dwells in the fact that in the assessment of the cutting tool's condition of CNC machines, the main problem is that deriving a behavioral model in an analytical form that best fits the dynamic of the tool's wear is not a trivial task. Furthermore, finding experience data for a long period of time is expensive and not easy in practice. This is why the utilization of the data provided by the monitoring sensors may be a trade-off between the model-based prognostic and the experience-based prognostic. Thus, the idea behind this contribution is the transformation of the raw monitoring data into relevant models representing the wear's behavior of the cutting tools of CNC machines.

The proposed method relies on two main phases: a learning phase and an assessment phase, as this is done in the framework of data-driven system health monitoring and prognostic [9,10]. During the first phase, the raw data are used to extract reliable features, which are then used to learn behavioral models representing the dynamic of the degradation in the cutting tool. The modeling of the degradation is done by using a mixture of Gaussians Hidden Markov Model (MoG-HMM) represented by a DBN. This probabilistic graphical model allows to use continuous observations and also to speed up the inference by using the algorithms proposed for DBNs [11]. In the second phase, the learned models are exploited on line to assess the current health state of the cutting tool and to estimate the value of the RUL and its associated confidence value.

The paper is organized as follows: in Section 2 the diagnostic and prognostic paradigms are presented, where some definitions and the related state of the art are given, Section 3 is dedicated to the proposed diagnostic and prognostic method and finally, an application example and simulation results are given in Section 4.

2. Diagnostic and prognostic framework

2.1. Definitions

The term prognostic founds its origin in the Greek word "*prognôstikos*", which means "to know in advance". Prognostic is well used in medical domain, where doctors try to make predictions about the health of a patient by taking into account the actual diagnosis of a disease and its evolution compared with other similar observed cases. This reasoning can be transposed into the industrial domain where the patient is a machine, an industrial system or a component.

Several definitions have been given in the literature about industrial prognostic [7,12–14], where three main points are highlighted: the system's actual state, the projection (or extrapolation) of this latter, and the estimation of the remaining time before failure. These definitions are then normalized by the ISO 13381-1 standard [15] in which prognostic is defined as the estimation of the operating time before failure and the risk of future existence or appearance of one or several failure modes. This standard defines the outlines of prognostic, identifies the data needed to perform prognostic and sets the alarm thresholds and the limits of system's reset (total shut-down). The main steps to perform prognostic, as defined in the standard, are summarized in Fig. 1.

The first step consists of monitoring the system by a set of sensors or inspections achieved by operators. The monitored data are then pre-processed to be used by the diagnostic module. The output of this module is an identification of the actual operating mode (more details on failure diagnostic can be found in [3–5]). This mode is then projected in the future, by using adequate tools, in order to predict the system's future state. The intersection point between the value of each projected parameter or feature and its corresponding alarm threshold permits to estimate the RUL (Fig. 2). Finally, appropriate maintenance actions can be taken depending on the estimated RUL. These actions may aim at eliminating the origin of the failure, which can lead the system to evolve to any critical failure mode, delaying the instant of a failure by some maintenance actions or simply stopping the system if this is judged necessary.

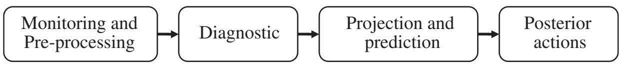

Fig. 1. Prognostic steps according to ISO 13381-1 [16].