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Enhanced particle filter for tool wear prediction

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ABSTRACT

Timely assessment and prediction of tool wear is essential to ensuring part quality, minimizing material waste, and contributing to sustainable manufacturing. This paper presents a probabilistic method based on particle filtering to account for uncertainties in the tool wear process. Tool wear state is predicted by recursively updating a physics-based tool wear rate model with online measurement, following a Bayesian inference scheme. For long term prediction where online measurement is not available, regression analysis methods such as autoregressive model and support vector regression are investigated by incorporating predicted measurement into particle filter. The effectiveness of the developed method is demonstrated using experiments performed on a CNC milling machine.

1. Introduction

As a major element in manufacturing machines [1,2], failure of machine tools can attribute up to 20% of machine downtime [3]. To ensure high productivity, reduce cost, minimize material waste, and maintain the quality of machined part, tool condition monitoring and remaining service life prediction play an important role for sustainable manufacturing.

Increasing demand for system reliability in modern sustainable manufacturing has accelerated the integration of sensors into manufacturing system for timely acquisition of working status of machining tool. The sensors including force transducer [4], accelerometer [5], acoustic emission sensor [6], spindle motor current probe [7], microscope, and surface profiler, etc. have been investigated in the literature. According to the sensing mechanism related to the tool status, the sensing techniques can be categorized into two approaches: direct sensing and indirect sensing [8]. Direct sensing approach utilizing microscope and surface profiler can measure the actual quantity directly indicating the tool condition (e.g., tool wear width). Such direct sensing approach is usually performed *offline* and interrupts normal machining operations. On the other hand, indirect sensing approach, such as force, vibration, acoustic emission, and spindle motor current, measures auxiliary in-process quantities which are the indirect indicators of tool condition. The tool condition is then deduced from in-process measurement. The indirect sensing approach can be performed *online* to continuously monitor the machining process; thus it is more suitable for real applications.

Numerous efforts have been made to develop methods for tool condition monitoring and life prediction techniques based on the sensing measurement. According to the usage of sensing information, these methodologies can be categorized as: (1) physics-based approach, (2) data-driven approach, and (3) model-based approach (also called physical–statistical modeling approach), as illustrated in Fig. 1.

Physics based approach typically describes the failure modes or physics of system using empirical model which is usually expressed as a series of ordinary or partial differential equations according to physics law [9]. For tool wear/life prediction, tool life model (e.g., Taylor's tool life equation, Taylor's extended tool life equation, and Hastings tool life equation, etc.) and tool wear rate model (e.g., Takeyama and Murata's wear rate model, and Usui's wear rate model, etc.) have been widely investigated in the literature [10–13]. A comprehensive summary of physics-based approaches for tool life prediction can be found in [14]. It usually involves identifying one or more parameters in an empirical model using offline measurement (i.e., tool wear width) through extensive experiments. The remaining useful life or wear severity is then estimated by solving deterministic equations based on determined parameters. For practical application, physics-based approach may not be the most practical solution since it is usually difficult or impossible to obtain extensive offline measurement in real application. On the other hand, it fails to incorporate uncertainties in manufacturing operations and component variation.

Data-driven approach does not need the physical knowledge. It derives a model representing the relationship between online and

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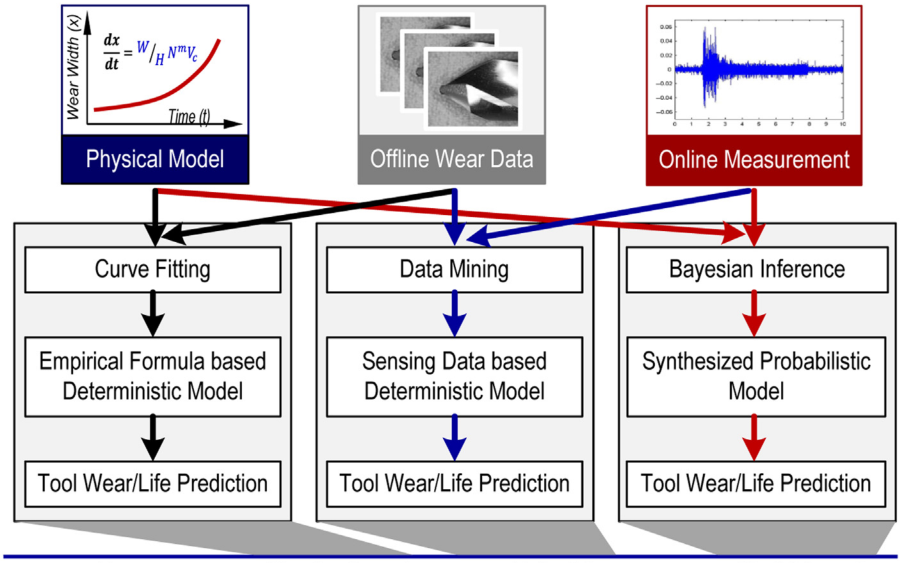
0278-6125/



Type	Physics-based	Data driven	Model-based
Input data	Offline meas.	Online & Offline meas.	Online Meas.
Data needed	Long	Long	Short
Quantify uncertainty	No	No	Yes

Fig. 1. Comparisons of tool wear prediction methods.

offline measurement based on historical data using data mining techniques [15]. The data is transformed into a hypothesis space, in which the relationship between the online and offline measurement is easily described through automated search of the best hypothesis space. Different artificial intelligence techniques have been investigated in tool wear prediction, including artificial neural network [16], support vector machine [17], and logistic regression [18], etc. Such model may be accurate for short-time prediction, but may introduce high variation in long-term prediction. The limitation of these data-driven approaches can be identified: (1) a large amount of historical data is required in data-driven approach. It is usually a costly and time-consuming process to obtain the required run-to-failure data. (2) Lack of generality is another drawback. The obtained model may be applicable to the machine under specific operation condition, instead of covering variations in machining operation [9].

In comparison, model-based approach takes advantage of the physical knowledge established and data collected to enhance the performance of prediction. Given the physical knowledge governing tool wear growth has been well established in physics-based approach, model-based approach adopts the physical knowledge as a state space model of tool wear and represents the tool wear evolving with time. Since the tool wear is usually not directly accessible, tool wear state needs to be estimated or predicted from online measurement, in which Bayesian inference provides a rigorous mathematic framework. Based on Bayesian inference, the present tool wear state is estimated based on previous tool wear state. The estimated tool wear state is then updated using new online measurement. For multi-step-ahead prediction, recursive process is applied to predict the tool wear state in the desired prediction horizon. Depending on system type and noise assumption, different approaches including Kalman filter (for linear system and Gaussian noise) [19], extended Kalman filter (for weak nonlinear system and Gaussian noise) [20], and particle filter (for nonlinear system and non-Gaussian noise) [21] can be used to implement model based prognosis. Particle filter (PF) is a numerical approximation method to achieve Bayesian inference using sequential Monte Carlo method based on point mass (or 'particle') representation of probability densities to tackle nonlinearity and non-Gaussianity of modeling in underlying dynamics of physical system [21]. Particle filter for tool life prediction is firstly investigated in [22]. In Refs. [23,24], an integrative approach of enhanced particle filter, support vector machine, and autoregressive moving average with eXogenous model is investigated for tool wear prediction, in which support vector machine (SVM) based autoregressive moving average with eXogenous model is used as state transition model, and an enhanced particle filter approach executing a monotonic resampling approach is investigated for Bayesian inference.

To address the stochastic nature [25] and nonlinear process in tool wear growth, this paper presents a probabilistic tool wear prediction method by recursively updating the physical model with online measurement based on particle filter. The parameters in physical model are described as probability distribution functions to incorporate the stochastic property of tool wear growth. A particle filter based recursive Bayesian inference scheme is investigated to estimate the model parameters and tool state based on online measurement for tool life prediction. For long term prediction with limited online measurement available, the model parameters cannot be updated during the prediction period due to lack of online measurement; thus tool life prediction may not be accurate and robust. To tackle this issue, regression analysis techniques such as autoregressive model, and support vector regression are investigated to predict the future measurement. The predicted measurement is then fused into particle filter framework to predict tool wear state or remaining useful life. Tool life test data from ball nose cutters in a CNC milling machines is analyzed to evaluate the performance of presented method.

The rest of the paper is constructed as follows. After introducing the theoretical background of particle filter and support vector regression in Section 2, details of the particle filter based tool life prediction method is discussed in Section 3. The formulation of system equation and measurement equation based on tool wear rate model and feature extraction/selection techniques is also discussed, respectively. The effectiveness of the presented technique is experimentally demonstrated in Section 4, based on run-to-failure