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Procedia CIRP 48 (2016) 236 – 241

www.elsevier.com/locate/procedia

23rd CIRP Conference on Life Cycle Engineering

Stochastic Tool Wear Prediction for Sustainable Manufacturing

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Abstract

To provide scientific support for decision-making in critical applications such as maintenance scheduling and inventory management, tool wear monitoring and service life prediction are of significance to achieving sustainable manufacturing. Past research typically assumed time-invariant machining settings in modeling wear progression, hence is limited in accurately tracking varying wear rates. This paper presents a stochastic joint-state-and-parameter model with machining setting as a parameter that affects the state evolution or tool wear propagation. The model is embedded in a particle filter for recursive wear state prediction. Effectiveness of this method is verified through experimental data measured on a CNC milling machine.

Keywords: Tool wear prediction; stochastic modeling; particle filter

1. Introduction

Sustainable manufacturing purses environmental and societal safety besides economic benefit [1]. Specifically, the goals of sustainable manufacturing are improving manufacturing efficiency, extending product life, reducing energy and resource improvement, minimizing toxic waste and occupational hazards. Machine tool should play an important role in achieving the sustainable manufacturing, since it has an almost 100 billion consumptions each year [2].

The post-use of machining tool can significantly reduce material consumption and increase economic benefit, through regenerating of retired tools, by recover, recycle, redesign based on former performance, remanufacture and redesign [3], as shown in Fig. 1. Advanced monitoring of machining tool wear progression and understanding its underlying physical nature can benefit:

- Predicting accurately the tool remaining useful life of tool, reducing the cost due to additional downtime and unscheduled maintenance;
- Optimizing machining planning, finding optimal machining settings that can increase extend tool life and increase manufacturing efficiency.

Past researches indicated that the tool wear propagation would vary with different machining settings (e.g. cutting speed, feed rate, cut depth and workpiece material). As an example shown in Fig. 2, the relationship between tool wear rate and feed rate under certain cutting speed (in symbol v) and depth is quadratic, which means an optimal feed rate exists for longest tool life. In this paper the physics-based wear modelling with respect to machining settings is focused, through which it is expected to optimize operating scheduling.

Fig. 1 life cycles of machining tool in sustainable manufacturing

doi:10.1016/j.procir.2016.03.101

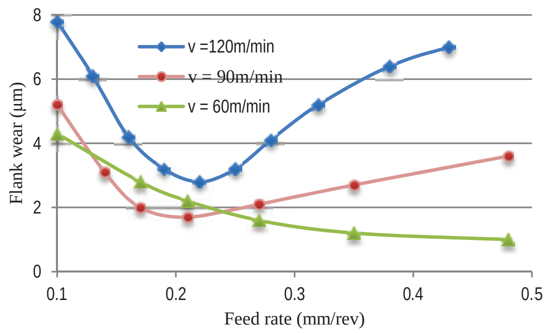

Fig. 2 Effect of feed rate on tool flank wear [4]

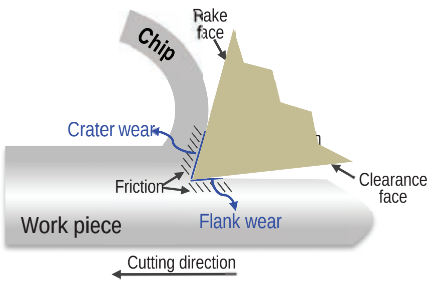

Fig. 3 Mechanism for friction and tool wear

Most studies on wear mechanism numerically establish relationships between propagation of tool wear (width, measured by microscope) and machining settings and material prosperities, and label/determine the coefficients in the equations with large amount of experimental data [5]. For example, a generalized form of extended Taylor's law is presented to predict the tool life as a function of cutting parameters and workpiece hardness [6]. Different mechanisms, such as abrasion (Fig. 3), adhesion and diffusion are investigated to describe tool wear rate under different machining settings and materials [7]. Additional factors, such as the geometry of tool [8] and cutting temperature [9], have also been investigated. Since no derived equations can exhaust the physical nature of tool wear, labelled parameters based on the experimental data would vary with different machining situations. Under this scenario, parameters need to be iteratively calibrated, which is time-consuming and therefore not practicable.

The other approach, instead, employs observable sensor measurement (e.g. current, force, vibration, and acoustic emission) to infer the wear status and determine the wear model without interrupting the machining process. The inference can be achieved by a model-based approach, which embeds the analytical models representing the dynamic process (e.g. tool wear) in a filtering (e.g. Kalman filter or particle filter). It can account for the stochasticity of the process and noise embedded in the measurement [10], providing more explanation on the prediction results. Compared to Kalman filter, particle filter (PF) has no Gaussian assumption and stronger capability to describe a non-linear system [11], thus it is investigated as the main technique in this paper.

To achieve the goal that directly determine the tool wear growth with respect to machining settings in the manufacturing process, this paper a stochastic joint-state-and-parameter estimation framework based on PF with machining settings as parameters that affects the tool wear propagation, based on past work [12]. One state evolution model describing wear progression and one measurement model describing relationship between wear and sensor measurements are defined under the framework. Coefficients in these two models are assumed to vary with machining settings and estimated by an improved particle filter (PF), which can achieve better estimation accuracy with fewer particles through an adaptive resampling strategy.

2. Particle filter based prediction

A dynamic system can be estimated through Bayesian inference with a state model and a measurement model. The state model describes the evolution of the state (variables x representing tool wear in this paper) over time, which is conditionally based on machining settings D (e.g. spindle speed, feed rate, cutting depth, material prosperity) and parameters θ (or coefficients, describing the effects of setting factors) θ and process noise w which denotes the randomness of tool wear propagation and wear modelling error.

$$x_k = f_k\left(x_{k-1}, D_k, \theta_k, w_k\right) \tag{1}$$

where f_k describes the state transition function from state x_{k-1} to x_k considering an order-one Markov process [13]. The discrete sampling time is denoted by k. The measurement model, describe the relationship between sensor measurement and machining settings and wear severity is given by:

$$z_k = h_k\left(x_k, D_k, \phi_k, v_k\right) \tag{2}$$

where h_k is the measurement function representing the relation between observable sensor output z_k and an unobservable degradation state x_k. $_k$ denotes the effects of the machining settings in the measurement model. Measurement noise caused by environmental noise and/or limitations of sensors is denoted by v_k. Generally, both state and measurement models are nonlinear in practical applications. The estimation of x_k given available information of measurement z_k and machining setting D_k can be achieved through calculating the posterior probability density function (pdf) $p(x_k|z_k)$ via Bayesian inference through two steps: prediction and update, as illustrated in (3) and (4).

$$\begin{aligned} p\left(x_k, \theta_k, \phi_k \mid z_{k-1}, D_k\right) = \int p\left(x_k, \theta_k, \phi_k \mid x_{k-1}, \theta_{k-1}, \phi_{k-1}, D_k\right) \\ p\left(x_{k-1}, \theta_{k-1}, \phi_{k-1} \mid z_{k-1}\right) dx_{k-1}\theta_{k-1}\phi_{k-1} \end{aligned} \tag{3}$$

$$\begin{aligned} p(x_k, \theta_k, \phi_k \mid z_k, D_k) &= \frac{p(z_k \mid x_k, \theta_k, \phi_k)\, p(x_k, \theta_k, \phi_k \mid z_{k-1})}{p(z_k \mid z_{k-1}, D_k)} \\ &= \frac{p(z_k \mid x_k, \theta_k, \phi_k)\, p(x_k, \theta_k, \phi_k \mid x_{k-1}, \theta_{k-1}, \phi_{k-1}, D_k)\, p(x_{k-1}, \theta_{k-1}, \phi_{k-1} \mid z_{k-1})}{p(z_k \mid z_{k-1}, D_k)} \end{aligned} \tag{4}$$

where $p(z_k|z_{k-1})$ is can be calculated as:

$$p(z_k \mid z_{k-1}, D_k) = \int p(x_k, \theta_k, \phi_k \mid z_{k-1}, D_k)\, p(z_k \mid x_k, \theta_k, \phi_k)\, dx_k \theta_k \phi_k \tag{5}$$