7.3 Tool life prediction for sustainable manufacturing

J. Wang, P. Wang, and R. X. Gao
Department of Mechanical Engineering, University of Connecticut, USA

Abstract
Prediction of tool wear is essential to maintaining the quality and integrity of machined parts and minimizing material waste, for sustainable manufacturing. Past research has investigated deterministic models such as the Taylor tool life model and its variations for tool wear prediction. Due to the inherent stochastic nature of tool wear and varying operating conditions, the accuracy of such deterministic methods has shown to be limited. This paper presents a stochastic approach to tool wear prediction, based on the particle filter. The technique integrates physics-based tool wear model with measured data to establish a framework, by iteratively updating the tool wear model with force and vibration data measured during the machining process, following the Bayesian updating scheme. Effectiveness of the developed method is demonstrated through tool wear experiments using a ball nose tungsten carbide cutter in a CNC milling machine.
Keywords:
Tool Wear Prediction, Particle Filter, Bayesian Updating

1 INTRODUCTION

Advances in modern sustainable manufacturing have led to better product quality, increased flexibility and productivity [1-3]. Generally, such benefits are dependent on trouble-free operations of the various machine elements [4]. In machining industry, 20% of downtime is attributed to tool failures [5]. Therefore, tool condition monitoring and life prediction plays an important role in resulting improving machine productivity, maintaining the quality and integrity of the machined part, minimizing material waste, and reducing cost for sustainable manufacturing.

Numerous efforts have been made to develop methods for tool condition monitoring and life prediction techniques during the past two decades [6, 7]. One common approach to assess the machining performance is tool wear/life analysis [8]. The relationship between tool life and cutting speed can be described by physics-based model, such as the Taylor tool life equation [9] and its variations [8], for a selected cutting speed. However, the parameters in Taylor tool life equation are usually described using deterministic values. Therefore, they cannot capture the stochastic properties of real machining process and tool-to-tool performance variation. On the other hand, its effectiveness is also limited on a particular combination of tool and workpiece.

Increasing demand for system reliability has accelerated the integration of sensors into the manufacturing system for timely acquisition of the working status of machining tools. A general approach is to measure the process parameters that are indirectly correlated to the tool performance, such as cutting force [10], tool vibration [11], and acoustic emissions [12], spindle power [13], etc., then transforms these indirect measurements into models for condition and performance monitoring [14]. Different models have been developed and evaluated for tool wear analysis. For example, a continuous hidden Markov model is investigated using the vibration measurements for tool wear monitoring [15], An adaptive fuzzy neural network and wavelet transform are applied to tool wear condition monitoring [16]. A comprehensive review on neural network for tool wear monitoring is discussed in [17]. In [18], a multi-sensor fusion model for tool condition monitoring was developed based on different pattern classifiers (e.g., support vector machine, multilayer perceptron neural network, radial basis function neural network), and analysis results showed that the performance of support vector machine outperformed other two techniques. These above models are categorized as data driven approach. Such model may be accurate for short time prediction, but introduce high variation in long-term prediction. On the other hand, data driven approach requires a substantial amount of historical data to train the model, and obtaining the required run-to-failure data is typically a costly and time consuming process.

To tackle this problem, this paper presents a tool life prediction method based on Bayesian inference to update the physics-based model with online data measurements. The parameters in physics-based model are described using probability distribution to incorporate the stochastic property of machining process into the model. A particle filter based recursive filtering scheme is investigated to estimate the model parameters and tool state based on data measurements for tool life prediction. Tool wear test data from ball nose cutters in a CNC machines are analyzed to evaluate the presented method.

The rest of the paper is constructed as follows. After introducing the theoretical background knowledge of particle filter in Section 2, details of the particle filter based tool life prediction model is discussed in Section 3. The selection of system model and measurement model based on wear growth model and feature extraction/selection is also discussed respectively. The effectiveness of the technique is experimentally demonstrated in Section 4, based on run-to-failure data acquired using a ball nose tungsten carbide cutter

G. Seliger (Ed.), Proceedings of the 11th Global Conference on Sustainable Manufacturing - Innovative Solutions
ISBN 978-3-7983-2609-5

in a CNC milling machine. Finally, conclusions are drawn in Section 5.

2 PARTICLE FILTER

Particle filter, as one of the sequential Monte Carlo techniques, has been widely studied in applications involving high nonlinearities and/or non-Gaussianity. Such cases are difficult to model based on Kalman filter or its variations [19]. Particle filter is a recursive numerical method based on the Bayesian inference, where the posterior probability density function of a state is represented by a set of random samples (named particles) with associated weights [20].

Considering a nonlinear dynamical system, it can be modeled as:

$$x_k = f_k(x_{k-1}, u_{k-1}) \tag{1}$$

where k is the time index, x_k is the base state, f_k is the nonlinear function of state x_{k-1}, and μ_{k-1} is the sequence of process noise. The objective of prediction is to recursively estimate the state x_k from measurements z_k. The measurement model can be described as:

$$z_k = h_k(x_k, v_k) \tag{2}$$

where h_k is a nonlinear function representing the relation between measurements and state. v_k is the sequence of measurement noise. Given the measurements $z_{1:k}$ are available, the belief $p(x_k|z_{1:k})$ of state x_k can be calculated based on Bayesian theory through prediction and updating. Given the probability density function $p(x_{k-1}|z_{k-1})$ and measurements $z_{1:k-1}$ at time $k\text{-}1$, the probability density function $p(x_k|z_{k-1})$ at time k can be predicted via Chapman-Kolmogorov equation [20].

$$p(x_k \mid z_{1:k-1}) = \int p(x_k \mid x_{k-1})\, p(x_{k-1} \mid z_{1:k-1})\, dx_{k-1} \tag{3}$$

here, $p(x_k|x_{k-1}) = p(x_k|x_{k-1}, z_{1:k-1})$ which is described in Eq. (1) for a first order Markov process. When the measurement z_k becomes available at time k, the probability density function $p(x_k|z_{1:k})$ can be updated through Bayes' rule.

$$p(x_k \mid z_{1:k}) = \frac{p(z_k \mid x_k)\, p(x_k \mid z_{1:k-1})}{p(z_k \mid z_{1:k-1})} \tag{4}$$

where the likelihood function $p(z_k|x_k)$ is described in measurement model, z_k can be used to tune the prior density to obtain the posterior density of current state [20]. $p(z_k|z_{k-1})$ is the normalizing constant which is calculated as:

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

The above operations describe the recursive Bayesian approach for posterior density. However, posterior density usually cannot be determined analytically since the analytical solution in intractable. To address it, particle filter present an approach to approximate the posterior density as [20]:

$$p(x_{0:k} \mid z_{1:k}) \approx \sum_{i=1}^{N_s} \omega_k^i \delta(x_{0:k} - x_{0:k}^i) \tag{6}$$

where δ(*) is the Dirac delta function, $\{x_{0:k}^i, i = 0, ..., N_s\}$ is the random samples with associated weights ω_k^i, N_s is the total number of the random samples. k is the time index, i is the index number of random samples. There are mainly two steps in particle filter method as shown in Figure 1. Sequential importance sampling, as the first step, is used to approximate the probability distribution since the target distribution is usually difficult to obtain directly. In the first step, a number of particles are drawn to represent the importance distribution function. The importance weight of each particle is calculated accordingly to correct the importance distribution function. Sequential importance sampling helps reducing the number of samples required to approximate the posterior probability distributions, thus increasing the computational efficiency of particle filter. To avoid degeneracy of importance weights over time, sequential importance resampling as the second step is usually performed. The particles are resampled from importance distribution with associated normalized importance weights. Those particles with a very small weight are eliminated, while those particles with high weights are duplicated.

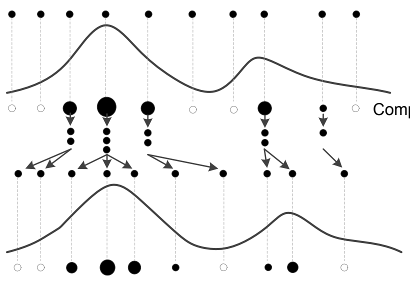

Figure 1. Visualization of sequential importance sampling and resampling.

3 TOOL LIFE PREDICTION FRAMEWORK

The tool life presents stochastic property due to many factors, such as different material property and tool-to-tool variations. On the other hand, the parameters associated with deterministic physics-based models are usually obtained from laboratory test, thus could be different from those in service due to different operating conditions. In such case, The parameters can be described in probability distribution to incorporate the stochastic property of too life prediction into the model. Particle filter can be applied to estimate both system state and model parameters. Hence, a particle filter based tool life prediction framework is formulated as shown in Figure 2. Two different types of measurements was used including direct measurements (direct indicator of tool wear severity, e.g., wear width) and indirect measurements (indirect indicator of tool wear severity, e.g., vibration, cutting force, etc.). Indirect measurements are acquired online for tool condition monitoring, while indirect measurements are obtained offline for evaluating the performance of presented method. The details of the presented method are discussed as follows.

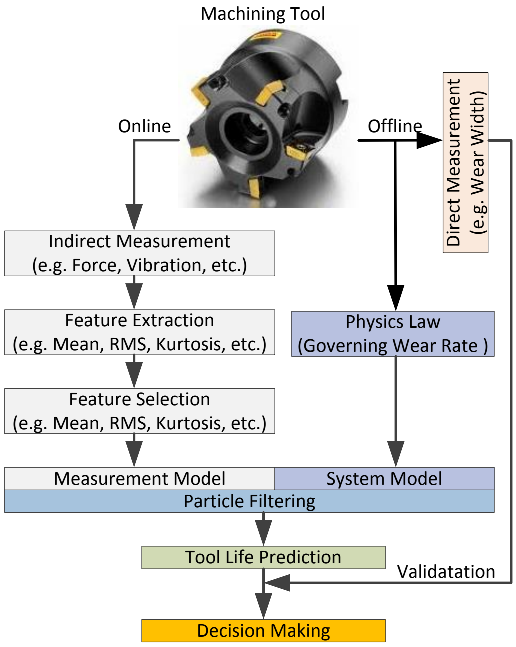

Figure 2: Framework of tool life prediction.

3.1 System model

System model is needed to describe system's state evolving behavior which could not be measured through online sensing. For Tool life prediction, wear width could be the indicator of wear severity. In [21], it showed the relationship between the wear rate and the changes of applied load. It can be expressed as:

$$d\upsilon/dt = Z/H \, N^m V_c \tag{7}$$

where H is the hardness of the softer in the pair of tool and work piece. Z represents the wear coefficient depending upon the materials and temperatures in contact. V_c is the velocity of rubbing, m is a constant depending on the nature of the layer removed, N denotes the normal load on surface [22]. Normal load can be considered as proportional to the wear width [21], which as be approximated as wear width v. In tool life prediction, it is usually difficult to estimate these coefficients. To circumvent the problem, an empirical model is developed by representing the defect dimension as spall area x [4]:

$$d\upsilon/dt = C\upsilon^m \tag{8}$$

Here, the model parameters C and m need to be determined. The model can be rewritten in the form of a state transition function:

$$\upsilon_k = C_{k-1}\upsilon_{k-1}^{m_{k-1}}dt + \upsilon_{k-1} \tag{9}$$

The model parameters m_{k-1}, C_{k-1} as well as damage state v_k are estimated and updated using particle filter, based on measurement model.

3.2 Measurement model

During the tool wear process, the actual wear width is generally unknown without interrupting the machining operation. On the other hand, the data analysis of vibration and cutting force has been widely employed for tool condition monitoring and remaining life prediction, since tool wear propagation can be well reflected by its vibration and cutting force. However, due to the typically low signal to noise ratio, it is difficult to model the relationship between raw data and tool wear width (denoted by measurement function h_k in Eq. 2). To tackle the problem, feature extraction is performed to reduce the data dimensionality without losing the information of tool wear signature. The relationship between extracted feature and defect size is expected to be modeled using a simple function.

Different features from the time and frequency domains could be extracted. Based on prior studies [23], statistical features are more sensitive to the tool wear. Eight different statistical features from vibration and force data are extracted including mean value, root mean square (RMS), variance, maximum value, crest factor (CF), Kurtosis, peak to average ratio (P/AR), skewness as summarized in Table 1. Different features represent different information about tool conditions. For example, RMS is a measure for the magnitude of a varying quantity. It is also related with the energy of the signal. Skewness is used to characterize the degree of signal asymmetry of the distribution around its mean, and Kurtosis indicates the spikiness of the signal.

Generally, it is difficult to determine which feature is more sensitive to tool conditions. A good feature should present consistent trend with defect propagation. In this study, Pearson Correlation coefficient is adopted to select features. Pearson correlation coefficient is a statistical measure of independence of two or more random variables which is defined as:

$$PCC = \frac{\sum_i (x_i - \bar{x})(z_i - \bar{z})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (z_i - \bar{z})^2}} \tag{10}$$

where x is the actual wear width, z is the extracted feature. The feature with highest correlation coefficient is selected as the one of interest.

Table 1: Summary of extracted features

Features	Expression
Mean value	$\bar{X} = 1/N \sum_{i=1}^{N} \lvert x_i \rvert$
RMS	$X_{RMS} = sqrt((x_1^2 + x_2^2 + \cdots + x_N^2)/N)$
Variance	$X_{var} = 1/N \sum_N (x_i - \bar{X})^2$
Maximum	$X_M = \max(x_i)$
CF	$C_F = X_M / x_{RMS}$
Kurtosis	$X_{KURT} = 1/N \sum_N ((x_i - \mu)/\sigma)^4$
P/AR	$X_{PAR} = X_M / \bar{X}$
Skewness	$X_{SKEW} = 1/N \sum_N \left(x_i - \mu / \sigma \right)^3$

4 EXPERIMENTAL STUDY

4.1 Experimental setup

To experimentally analyze the performance of the developed particle filter-based tool life prediction method, a set of tool wear test data measured from a high speed CNC machine (Roders Tech RFM760) while performing drying milling is analyzed [14]. The spindle speed was 10,400 rpm. A two-flute ball nose tungsten carbide cutter was tested to mill a workpiece of stainless steel (HRC52) in down milling operations. The feed rate was set as 1,555 mm/min. The workpiece has been pre-processed to remove the original skin layer containing hard particles. A Kistler quartz 3-component platform dynamometer was mounted between the workpiece and machining table to measure the cutting forces. In addition, three Kistler piezo accelerometers were mounted on the workpiece to measure the machine tool vibrations during the cutting process, in the x-, y-, and z- directions, respectively [14]. Figure 3 shows a diagram of the experimental setup.

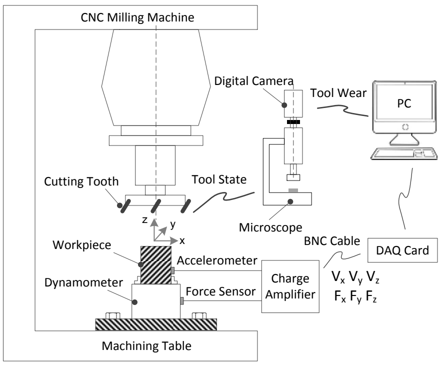

Figure 3. Schematic diagram of experimental setup.

During tool wear test, force and vibration data in three directions (x, y, z) was recorded at the sampling frequency 12 kHz using NI PCI1200 data acquisition and was then saved in a computer. The flank wear of each individual tooth was measured by a LEICA MZ12 microscope after finishing each surface (cutting depth 0.2 mm). A total of 300 data files were collected to record the tool wear process. The features discussed in Table 1 were computed and extracted from force and vibrations signals in these 300 data files to construct the measurement model. Figure 4 shows the extracted normalized features from force signal in the y-direction, and measured normalized flank wear. From these features, a saw-tooth-like behavior is identified, which can be attributed to the switching of the cutting layers during the machining experiments. Such switching operation is modeled as measurement noise in the measurement model. Next, Pearson correlation coefficient between each feature and actual wear was calculated as shown in Table 2.

The mean of force signal in the y-direction was selected to construct the measurement model, since it has the highest correlation coefficient (0.959). To study the effect of fusing multiple features to possibly improve the correlation, feature fusion based on the Principal Component Analysis (PCA) was also performed in this study, and a correlation coefficient of 0.956 with the tool wear length was obtained. Since this value is lower than 0.959, the mean force in the y-direction was selected to construct the measurement model.

Table 2: Correlations between the extracted features and actual tool wear length

	Force			Vibration		
	X	Y	Z	X	Y	Z
Mean	0.885	0.959	0.942	0.943	0.936	0.955
RMS	0.878	0.949	0.942	0.942	0.936	0.956
Variance	0.911	0.944	0.943	0.937	0.935	0.947
Maximum	0.928	0.912	0.947	0.934	0.928	0.949
CF	0.707	0.799	0.599	0.892	0.868	0.897
Kurtosis	0.182	0.703	0.514	0.655	0.527	0.582
P/AR	0.414	0.880	0.662	0.432	0.539	0.591
Skewness	0.106	0.766	0.494	0.690	0.555	0.666

The measurement model is given as:

$$z_k = x_k + v_k \tag{11}$$

where z_k represents the extracted feature, e.g. mean value of force signal in y-direction, x_k denotes the system state, characterized by tool wear width. v_k is the measurement noise.

In the system model, a tool wear growth model is needed by taking into consideration the model parameters as a probabilistic distribution. In this study, the model parameters C and m shown in Eq. 9 are modeled as uniform distributions. Based on the tool wear growth model (denoted by Eq. 9) and measurement model (denoted by Eq. 11), particle filter is performed to predict the tool wear growth. Figure 5 shows the low-term (45 steps ahead) prediction result using particle filter. It is found that the median of predicted tool wear width is close to follow the trend of actual wear width of tool. The maximum error between the median of predicted tool wear width and the actual wear width is around 5%, thus confirming the effectiveness of presented method for long-term tool life prediction.

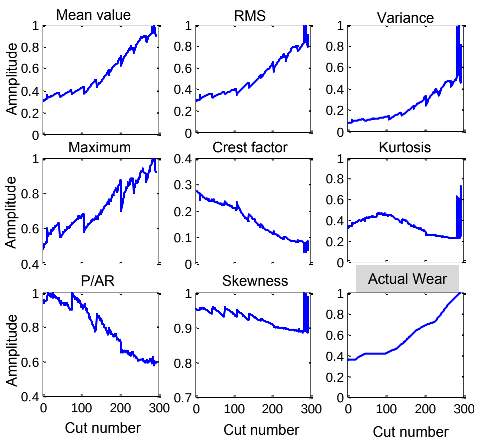

Figure 4. Extracted features from force sensor in y-direction.

5 CONCLUSIONS

Prediction of tool life is an integral part in achieving sustainable manufacturing by improving a machine system's overall reliability, thus requires comprehensive and systematic study. This paper presents a particle filter-based tool life prediction framework. A physical-based tool wear rate model is chosen as the system model, which described the governing physics of the tool wear process. The mean value from force signal is selected as the feature of interest to construct the measurement model, based on the correlation criterion. The performance of the developed method is demonstrated b using wear tests of ball nose tungsten carbide cutters in a CNC milling machine, and good result has been received. A broad range of experiments will be performed as future studies to investigate the robustness of the particle filter based method, under different operating conditions.

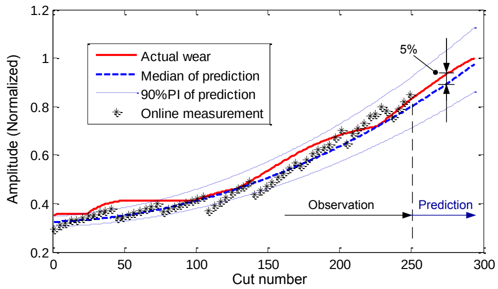

Figure 5. Predicted tool wear using particle filter.

6 ACKNOWLEDGMENTS

This research is partially supported by the National Science Foundation under award EFRI-0735974.

7 REFERENCES

[1] Wiendahl, H.P., Elmaraghy, H.A., Nyhuis, P., Zäh, M.F., Wiendahl, H.H., Duffie, N., Brieke, M., 2007, Changeable Manufacturing – Classification, Design, and Operation, CIRP Annals - Manufacturing Technology, 56/2:783-839.

[2] Bi, Z.M., Lang, S.Y.T, Shen, W., Wang, L., 2008, Reconfigurable Manufacturing Systems: the State of the Art, International Journal of Production Research, 46/4: 967-992.

[3] Mohring, H.C. Litwinski, K.M., Gummer, O., 2010, Process Monitoring with Sensory Machine Tool Components, CIRP Annals - Manufacturing Technology, 59/1: 383-386.

[4] Zhou, Z.D., Chen, Y.P., Fuh, J.Y.H., Nee, A.Y.C., 2000, Integrated Condition Monitoring and Fault Diagnosis for Modern Manufacturing Systems, CIRP Annals - Manufacturing Technology, 49/1:387-390.

[5] Kurada S., and Bradley C., 1997, A review of machine vision sensors for tool condition monitoring, Computer in Industry, 34:55-72.

[6] Rehorn A.G., Jiang J., Orban P.E., 2005, State-of-the-art methods and results in tool condition monitoring: a review, Int. J. Adv. Manuf. Technol., 26:693-670.

[7] Teti R., Jemielniak K., O'Donnell G., Dornfeld D., 2010, Advanced monitoring of machining operations, CIRP Annals - Manufacturing Technology, 59:717-739.

[8] Marksberry P.W., and Jawahir I.S., 2008, A comprehensive tool-wear/tool-life performance model in the evaluation of NDM (near dry machining) for sustainable manufacturing, International Journal of Machine Tools & Manufacture, 878-886.

[9] Mills B., Redford A., Manufacturing of Engineering Materials, Applied Science, London, 1983, p. 20.

[10] Bhattacharyya P., Senupta D., Mukhopadhaya S., 2007, Cutting force based real-time estimation of tool wear in face milling using a combination of signal process techniques, Mechanical Systems and Signal Processing, 21/6:2665-2683.

[11] Yesilyurt I. and Ozturk H., 2007, Tool condition monitoring in milling vibration analysis, International Journal of Production Research, 45/4:1013-1028.

[12] Jemielniak K., and Otman O., 1998, Catastrophic tool failure detection based on acoustic emission signal analysis, CIRP Annals - Manufacturing Technology, 47/1:31-34.

[13] Ghosh N., Ravi Y.B., Patra A., Mukhopadhyay S., Paul S., Mohanty A.R., Chattopadhyay A.B., 2007, Estimation of tool wear during CNC milling using neural network based sensor fusion, Mechanical Systems and Signal Processing, 21:466-479.

[14] Li. X., Lim B.S., Zhou J.H., Huang S., Phua S.J., Shaw K.C., Er M.J., 2009, Fuzzy neural network modeling for tool wear estimation in dry milling operation, Annual Conference of the Prognostics and Health Management Society, San Diego, CA, September 27-October 1, 2009, pp. 1-11.

[15] Vallejo Jr A.G., Flores J.A.N., Menendez R.M., Sucar L.E., Rodriguez C.A. 2005, Tool-wear monitoring based on continuous hidden Markov models, LNCS 3773, (Lazo M.,and Sanfeliu A., Eds.), Springer-Verlag Berlin Heidelberg, pp. 880-890.

[16] Li S. and Elbestawi M.A., 1996, Tool condition monitoring in machining by fuzzy neural networks, Journal of Dynamic Systems, Measurement and Control, Transactions of ASME, 118:665-672.

[17] Sick B., 2002, On-line and indirect measurement tool wear monitoring in turning with artificial networks: a review of more than a decade of research, Mechanical Systems and Signal Processing, 16/4:487-546.

[18] Cho S., Binsaeid S., Asfour S., 2010, Design of multisensory fusion-based tool condition monitoring system in end milling, Int. J. Adv. Manuf. Technol., 46:681-694.

[19] Sun J., Zuo H., Wang W., Pecht M.G., 2012, Application of a state space modeling technique to system prognostics based on a health index for condition-based maintenance, Mechanical Systems and Signal Processing, 28:585-596.

[20] Arulampalam M.S., Maskell S., Gordon N., Clapp T., 2002, A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking, IEEE Transactions on Signal Processing, 50/2:174-188.

[21] Archard J.F., 1953, Contact and rubbing of flat surfaces, Journal of Applied Physics, 24/8:981-988.

[22] Choudhury S.K., Srinivas P., 2004, Tool wear prediction in turning, Journal of Materials Processing Technology, 153-154:276-280.

[23] Dong J., Subrahmanyam K.V.R., Wong Y.S., Hong G.S., Mohanty A.R., 2006, Bayesian-inference–based neural networks for tool wear estimation, Int. J. Manuf. Technol., 30:797-807.