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Article *in* Journal of Manufacturing Systems · July 2015

DOI: 10.1016/j.jmsy.2015.03.005

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Journal of Manufacturing Systems 36 (2015) 35–45

Contents lists available at ScienceDirect

Journal of Manufacturing Systems

journal homepage: www.elsevier.com/locate/jmansys

Enhanced particle filter for tool wear prediction

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ARTICLE INFO

Article history:
Received 22 November 2014
Received in revised form 10 March 2015
Accepted 12 March 2015

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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http://dx.doi.org/10.1016/j.jmsy.2015.03.005
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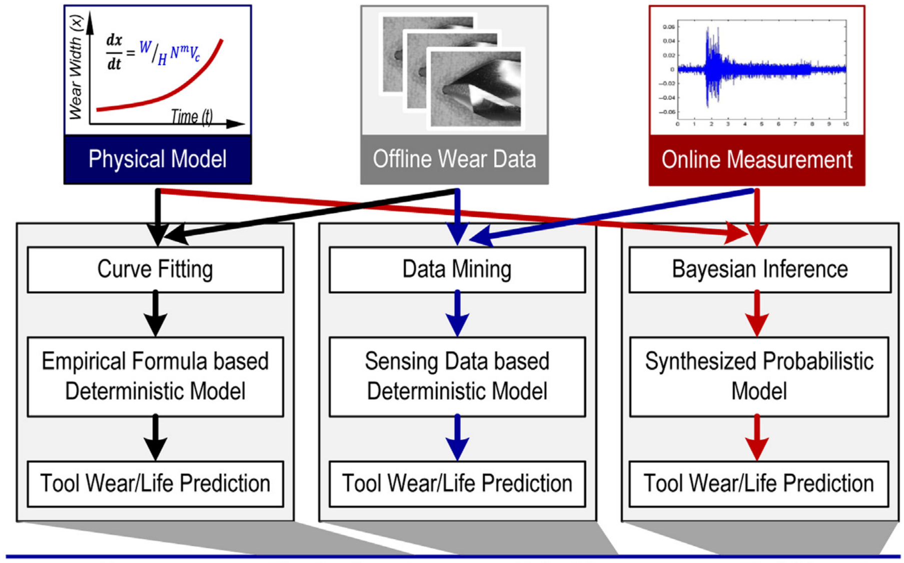

Type	Physics-based	Data driven	Model-based
Input data	Offline meas.	Online & Offline meas.	Online Meas.
Data needed	Long	Long	Short
Quantify uncertainty	No	No	Yes

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 data acquired using a ball nose tungsten carbide cutter on a CNC milling machine. Finally, conclusions are drawn in Section 5.

2. Theoretical framework

2.1. Particle filter

Particle filter (PF), as one of sequential Monte Carlo techniques, has been widely studied in different applications such as mobile robot localization [26], object tracking [27], and chemical mechanical planarization process [28] which involve nonlinear system and/or non-Gaussian noise. Such cases are difficult to model based on Kalman filter or its variations. Particle filter provides a numerical approximation solution based on Bayesian inference, where the posterior probability density function of a state is represented by a set of random samples (or particles) with associated weights [21].

In machining tool wear prediction, tool wear condition is usually difficult to be observed unless it is measured offline by costly equipment (e.g., microscope, surface profiler). Online sensing techniques, such as vibration, acoustic emission, and dynamic force, are readily measured in process. Such scenario can be well described using mathematical model in *Bayesian framework* [29] as follows.

(a) A state equation describing the underlying tool wear growth with time:

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

where k is the time index, and x_k is the tool wear state at time k. f_k describes the state transition function from state x_{k-1} to x_k considering order-one Markov process. μ_{k-1} is the process noise representing uncertainty in tool wear process. The state transition probability $p(x_k|x_{k-1})$ is defined in Eq. (1) with the probability distribution of process noise. This state equation can be constructed according to physical knowledge of degradation process such as tool wear rate model.

(b) A measurement equation linking online measurement to unobservable tool wear state:

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

where h_k is a measurement function representing the relation between online measurement z_k and unobservable degradation state x_k. ν_k is the sequence of measurement noise. The measurement z_k is conditionally dependent on tool wear state x_k, which can be described as measurement probability $p(z_k|x_k)$.

(c) A set of online measurement acquired in experiments:

$$z = \left\{z_1, z_2, \ldots, z_k\right\} \tag{3}$$

In *Bayesian framework*, the idea is to find the posterior probability distribution $p(x_{k+l}|z_k)$ of future tool wear state given the present measurement acquired in an experiment. The posterior probability distribution can be recursively computed in two stages: *prediction* and *update*. Given the posterior probability distribution $p(x_{k-1}|z_{k-1})$ at time $k-1$, the prediction stage is to estimate the probability distribution $p(x_k|z_{k-1})$ via the Chapman–Kolmogorov equation [29] as

$$p(x_k|z_{k-1}) = \int p(x_k|x_{k-1})\, p(x_{k-1}|z_{k-1})\, dx_{k-1} \tag{4}$$

Upon new measurement z_k available, the posterior probability distribution $p(x_k|z_k)$ of current tool wear state x_k is updated via Bayes rule [29].

$$p(x_k|z_k) = \frac{p(x_k|z_{k-1})\, p(z_k|x_k)}{p(z_k|z_{k-1})} \tag{5}$$

where $p(z_k|z_{k-1})$ is the normalizing factor which can be calculated as

$$p(z_k|z_{k-1}) = \int p(x_k|z_{k-1})\, p(z_k|x_k)\, dx_k \tag{6}$$

For l-step ahead prediction, the posterior probability distribution $p(x_{k+l}|z_k)$ can be obtained according to Eqs. (4)–(6) as [30]

$$p(x_{k+l}|z_k) = \int \cdots \int \prod_{j=k+1}^{k+l} p\left(x_j|x_{j-1}\right) p(x_{k-1}|z_{k-1}) \prod_{j=k+1}^{k+l} dx_{j-1} \tag{7}$$

As discussed above, Eqs. (4)–(6) give exact analytic Bayesian solution. However, for nonlinear system with non-Gaussian noise, the integral operation in Eq. (4) is intractable due to high dimensional computation [30]. To address this problem, PF is developed using sequential Monte Carlo sampling method based on random samples (particles) representing of probability densities for nonlinear and non-Gaussian system [21]. The posterior probability distribution $p(x_{k-1}|z_{k-1})$ at time $k-1$ is represented by a set of random samples or particles $x^i{}_{k-1}$, $i = 1, 2, \ldots, N$, with corresponding weight w^i_{k-1}. The integral operation in Eq. (4) is then approximated as the sum of these random numbers as [29]

$$\begin{aligned} p(x_k|z_{k-1}) &= \int p(x_k|x_{k-1})\, p(x_{k-1}|z_{k-1})\, dx_{k-1} \\ &\approx \sum_{i=1}^{N} w^i_{k-1} \delta\left(x_{k-1} - x^i_{k-1}\right) p(x_k|x_{k-1}) = \sum_{i=1}^{N} w^i_{k-1} p\left(x_k|x^i_{k-1}\right) \end{aligned} \tag{8}$$

where i is the index of particle, $\delta(\bullet)$ is the delta function, and N is the total number of particles which affects the accuracy of represented probability distribution, and computational efficiency. In the update step, the weight of each particle is updated based on the likelihood of the observation z_k at time k as

$$w^i_k \propto w^i_{k-1} p\left(z_k|x^i_k\right) \tag{9}$$

Similarly, posterior probability distribution $p(x_{k+l}|z_k)$ in the l-step ahead prediction can be obtained as

$$p(x_{k+l}|z_k) \approx \sum_{i=1}^{N} w^i_{k+l-1} p\left(x_{k+l}|x^i_{k+l-1}\right) \tag{10}$$

In the implementation of particle filter, resampling is applied in every single step to obtain equally weighted samples so as to avoid degeneracy problem of the algorithm [29]. The particles are resampled from importance distribution with associated weights. Those particles with a very small weight are eliminated, while those particles with high weights are duplicated.

2.2. Support vector regression model

Support vector regression (SVR) is based on statistical learning theory for regression analysis [31]. Comparing with other data mining techniques such as artificial neural networks (ANN), it reveals good generalization capability and needs less training samples. SVR transforms the original feature space into a higher dimensional space to determine an optimal hyperplane by maximizing the separation distances among the classes. Given an input training data set $\boldsymbol{z} \square \chi$, the transformed higher dimensional feature space can be obtained as

$$\boldsymbol{z}' = \phi(\boldsymbol{z}) \tag{11}$$

where ϕ is the transformation function. A hyperplance $f(\boldsymbol{z}')=0$ can be formulated as

$$f\left(\boldsymbol{z}'\right)=\tau^T\boldsymbol{z}'+b=\sum_{j=1}^{n}\tau_j z_j'+b=0 \tag{12}$$

where $\boldsymbol{\tau}$ is a n-dimensional vector and b is a scalar. The vector $\boldsymbol{\tau}$ and scalar b are used to define the position of separating hyperplane. This hyperplane is built to maximize the distance D among the closest class through the following optimization.

$$\max_{v\in R^n, b\in R} D, \text{ subject to} y_i\left(\tau^T z_j'+b\right)\geq D, \quad \forall i \tag{13}$$

where y_i is the class labeler. For example, it is labeled as $\{-1, 1\}$ for two classes. Taking into account the noise with slack variables ξ_i and error penalty C, Eq. (13) can be rewritten as

$$\min_{v,\xi\in R^n, b\in R}\left\{\frac{1}{2}\|\tau\|^2+C\sum_{i=1}^{N}\xi_i\right\}$$
$$\text{subject to}\ \xi_i\geq 0, \quad y_i\left(\tau^T\phi(z_i)+b\right)\geq 1-\xi_i, \quad \forall i \tag{14}$$

The hyperplane can be determined as the following *sign* function (sgn(t) = 1 for $t\geq 0$, and *sgn*(t) = −1 for $t<0$). The linear decision function is given by

$$f(z)=sgn\left(\sum_{i,j=1}^{N}y_i\alpha_i\left(\phi^T(z_i)\phi\left(z_j\right)\right)+b\right) \tag{15}$$

here α is the Lagrange multiplier. The hyperplane function can be determined by kernel function $K(z_i, z_j)=\phi^T(z_i)\phi(z_j)$ by computing the inner products without specifying the explicit form of transformation function. Different kernels can be formulated such as linear, polynomial, Gaussian RBF, and Sigmoid kernel functions. Accordingly, the associated decision function for regression analysis is expressed as

$$f(\boldsymbol{z})=sgn\left(\sum_{i,j=1}^{N}y_i\alpha_i K\left(z_i, z_j\right)+b\right) \tag{16}$$

The theoretical background of particle filter and support vector regression discussed here forms the basis of tool wear prediction method formulated in the next section.

3. Formulation of wear prediction model

The tool wear process presents stochastic property due to various factors, including different material properties, and tool-to-tool variations, etc. [25]. The parameters associated with deterministic physics-based models are usually obtained under laboratory controlled test; thus they may be different from those in service under different operating conditions. In this study, the parameters in the model are described in probability distribution functions to incorporate the stochastic nature of tool wear process. Particle filter is applied to estimate both system state and model parameters in a recursive manner based on Bayesian inference. Model parameters are identified during the state estimation period based on available measurement. The system state is then predicted according to the identified model parameters in the desired prediction horizon. One limitation associated with conventional particle filter based prediction model is that the model parameters could not be updated during the prediction period. Therefore, the prediction result may not be accurate or robust, especially for lone term prediction with limited online measurement available [32]. To address this issue, regression techniques can be used to predict the online measurement based on trend analysis. The predicted measurement is then fused into particle filter to update model parameters during the prediction period, resulting in a more reliable tool wear prediction approach. Therefore, *two scenarios* of particle filter based tool wear prediction are investigated in this study.

(1) Conventional particle filter. In the prediction period, the tool wear sate is predicted without updating the model parameters due to lack of measurement.
(2) Integrate the predicted measurement by regression analysis into particle filter. The predicted measurement can be obtained based on the trend of signal itself (autoregressive model) or the trending analysis of historical data (support vector regression). The predicted measurement is then incorporated into the prediction period of particle filter to update the model parameters for tool wear prediction.

These two scenarios are illustrated in the framework of tool wear prediction as shown in Fig. 2.

The regression analysis method is noted in dash line for scenario 2. Take support vector regression as an example, a model is off-line trained based on historical data (including online and offline measurement) collected from systems with similar tool wear growth trajectories. The trained model will then be tuned using the available online measurement from the system of interest to incorporate new system dynamics to predict the measurement in future. The predicted measurement is then fed into the particle filter framework to perform tool wear state estimation together with model parameter identification in a recursive manner. In particle filter, system equation and measurement equation are the main components; their details are discussed as follows.

3.1. System equation

System equation describes underlying tool wear growth behavior evolving with time. For tool wear/life prediction, wear width is the direct indicator of wear severity. Based on physical knowledge [33], the relationship between tool wear rate $\mathrm{d}\theta/\mathrm{d}t$ and the changes of applied load is expressed as

$$\frac{\mathrm{d}\theta}{\mathrm{d}t}=\frac{G}{H}N^m V_c \tag{17}$$

where θ is the tool wear width, and H is the hardness of the softer in the pair of tool and work piece which is in contact. G represents the wear coefficient depending upon the materials and temperatures. V_c is the velocity of rubbing, m is a constant depending on the nature of the layer removed, and N denotes the normal load on surface [34]. In real applications, it is usually difficult or impossible to obtain these coefficients. On the other hand, it is noticed that the tooling force will increase as the tool gets worn. As presented in [35], normal load is proportional to the wear width. Thus, the normal load N can be approximated as a linear relationship of wear width θ.

$$N=a\cdot\theta \tag{18}$$

Here, α is a coefficient. Eq. (17) can be reformulated as:

$$\frac{\mathrm{d}\theta}{\mathrm{d}t}=\frac{G}{H}(\alpha\theta)^m V_c=\left(\frac{G}{H}\alpha^m V_c\right)\theta^m \tag{19}$$

To improve the efficiency of the model, these coefficients $G/H\alpha^m V_c$ can be reduced as a new coefficient C. An empirical model which has less number of coefficients but keeps the inherent exponential relationship is derived as:

$$\frac{\mathrm{d}\theta}{\mathrm{d}t}=C\theta^m \tag{20}$$

where model parameters C and m are the combination of above coefficients. The probability distributions of these two parameters

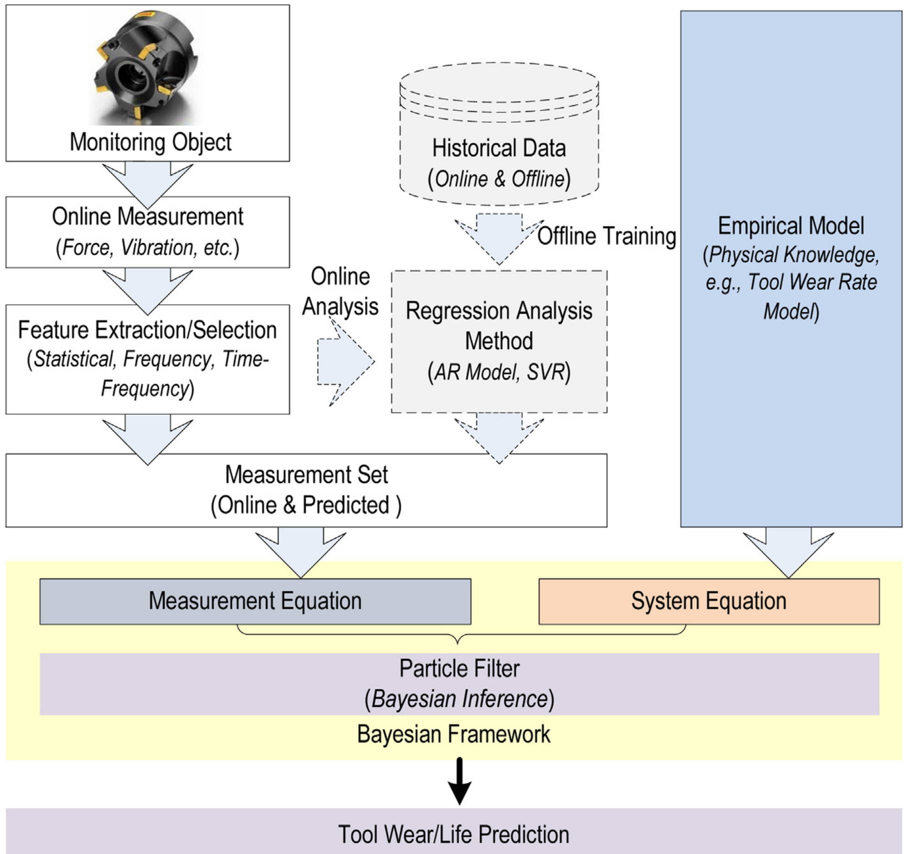

Fig. 2. Framework of particle filter based tool wear prediction method.

could be roughly estimated based on available data or experience. Considering the tool wear width θ as the tool wear state x, Eq. (20) can be rewritten as (by replacing θ with x)

$$\frac{dx}{dt} = Cx^m \tag{21}$$

Due to the discrete nature of measurement, the model is rewritten in the form of state transition function:

$$x_k = C_{k-1} x_{k-1}^{m_{k-1}} dt + x_{k-1} \tag{22}$$

The model parameters m_{k-1}, C_{k-1} are modeled as probability distribution functions to incorporate the stochastic property of tool wear process. The tool wear state x_k is estimated and predicted using particle filter based on online in-process measurement.

3.2. Measurement equation

During tool wear process, online measurement can acquire the in-process parameters such as cutting force and vibration as the indirect indicators for tool wear state. Due to low signal-to-noise ratio (SNR) of measurement, it is usually difficult to model the relationship between raw online measurement and tool wear state. To tackle the problem, effective feature extraction and representation techniques are performed to reduce data dimension without losing the signature of tool wear. The relationship between extracted feature and tool wear state is expected to be modeled as a simple function.

Different features from statistical, frequency, and time–frequency domains are extracted as summarized in Table 1.

Four typical statistical features including mean value, root mean square (RMS), variance, and Kurtosis are extracted in statistical domain. RMS is a measure for the magnitude of a varying quantity. It is also related to the energy of the signal. Kurtosis indicates the spikiness of the signal. Features from the time–frequency domain provide another perspective of tool wear condition, and may reveal information that is not found otherwise in the statistical domain. Features from the frequency domain provide another perspective of tool wear condition, and reveal information that are not found in the statistical domain. In frequency domain, spectral mean and spectral variance are extracted, where $S(f_i)$ is the power spectrum density which is obtained by Welch method. In time–frequency domain, wavelet transform can be used for signal denoising and feature extraction. The wavelet coefficient with higher energy is selected which is related to characteristic frequency in machining (number of flutes times the spindle rotating frequency). Thus, the

Table 1
List of extracted features.

Domain	Features	Expression
Statistical	Mean	$\bar{z} = 1/N \sum_{i=1}^{N} \lvert z_i \rvert$
	RMS	$z_{\mathrm{RMS}} = \sqrt{\frac{1}{n}(z_1^2 + z_2^2 + \cdots + z_n^2)}$
	Variance	$z_{var} = 1/N \sum (z_i - \bar{z})^2$
	Kurtosis	$z_{\mathrm{KURT}} = \frac{1}{n} \sum_{n}^{N} \left(\frac{z_i - \mu}{\sigma}\right)^4$
Frequency	Spectral mean	$\bar{f} = \sqrt{\sum_{i=1}^{k} f_i^2 S(f_i) / \sum_{i=1}^{k} S(f_i)}$
	Spectral Kurtosis	$f_{var} = \sum_{i=1}^{k} \left(\frac{f_i - \bar{f}}{\sigma}\right)^4 S(f_i)$
Time–frequency	Wavelet energy	$E_{\mathrm{WT}} = \sum_{i=1}^{N} wt_{\varphi}^2(i)/N$
	Energy ratio	$R_{\mathrm{wt}} = E_{\mathrm{WT}}^x / E_{\mathrm{WT}}^z$

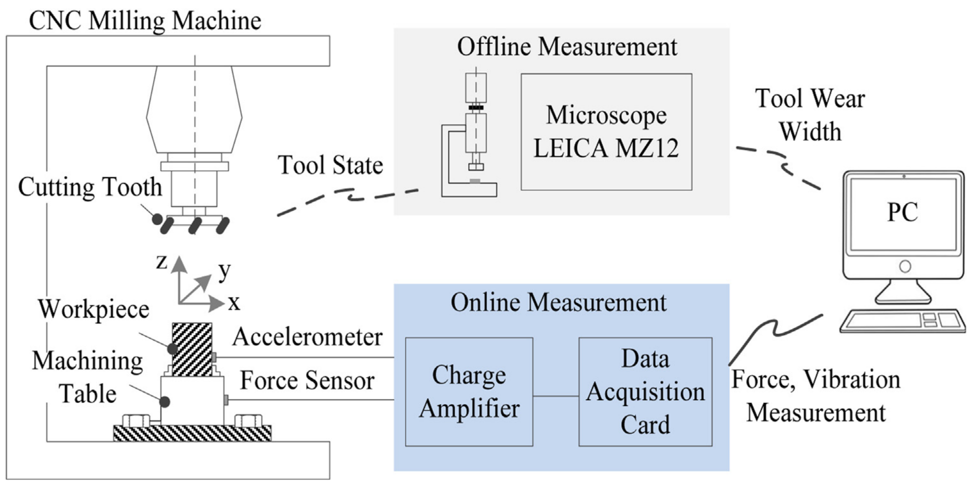

Fig. 3. Schematic diagram of experimental setup.

energy of selected wavelet coefficient is extracted as a feature. As discussed in [35], tool wear (e.g., flank wear) causes the increase of forces in the feed and normal directions while the force ratio is a good indicator of tool wear. The ratio of wavelet energies in different directions is also extracted as a feature for tool wear prediction. In total, eight features are extracted from online measure.

A number of features are extracted from the measurements for representing the raw signals for motor defect classification. For improved computational efficiency in tool wear prediction, a proper feature selection strategy is needed to lower the dimension of feature space. Different feature selection techniques have been investigated, including genetic algorithm, principle component analysis (PCA) [36], and correlation analysis [37], etc. Generally, it is difficult to determine which feature is more sensitive to tool conditions. A good feature should present consistent trend with wear 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

$$\mathrm{PCC} = \frac{\sum_i (x_i - \bar{x})(z_i - \bar{z})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (z_i - \bar{z})^2}} \tag{23}$$

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

4. Experimental evaluation

4.1. Experimental setup

To experimentally analyze the performance of presented particle filter based tool life prediction method, a set of experimental data measured from a high speed CNC machine under drying milling operation is used [38]. A three-flute ball nose tungsten carbide cutter was tested to mill a workpiece (material: stainless steel, HRC52) in down milling operation. The workpiece has been preprocessed to remove the original skin layer containing hard particles. The speed of spindle was running at 10,400 rpm while the feed rate was set as 1,555 mm/min in x direction. The depth of cut (radial) was 0.125 mm in y direction while the depth of cut (axial) in z direction was 0.2 mm. A Kistler quartz 3-component platform dynamometer was mounted between the workpiece and machining table to measure the cutting forces. Three Kistler Piezo accelerometers were mounted on the workpiece to measure the machine tool vibration in x–z directions, respectively [38]. The diagram of experimental setup is shown in Fig. 3.

4.2. Data processing

During the tool wear test, online measurement including force and vibration in three directions (x–z) was recorded at the sampling frequency 50 kHz using DAQ *NI PCI1200*. The online measurement was saved in a computer. The flank wear of each individual flute was measured offline using a LEICA MZ12 microscope after finishing each surface (finishing each surface is considered to be one cut number in the following data analysis). A total of around 300 data files (one data file is corresponding to one cut number) were collected during the tool life test. The features discussed in Table 1 were extracted from force and vibration measurement. Fig. 4 shows the extracted normalized features from force signal in y direction, and actual flank wear.

Correlation analysis is performed to select representative features, based on the Pearson correlation coefficients. The correlation coefficients between the extracted features and actual wear are calculated as shown in Table 2. The ratio of wavelet energy in the x-direction to the one in the z-direction extracted from online force measurement has the highest correlation coefficient of *0.985*. The fused feature, obtained from principal component analysis (PCA) has also been used, which shows a correlation coefficient of *0.968* with the actual tool wear measured offline. Based on the high correlation, the wavelet energy in the x-direction to the one in the z-direction from online force measurement has been selected as the representative feature to construct the measurement equation,

Table 2
Correlations between the extracted features and actual tool wear.

	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
Kurtosis	0.182	0.703	0.514	0.655	0.527	0.582
Spectral mean	0.461	0.399	0.435	0.553	0.895	0.337
Spectral Kurtosis	0.641	0.896	0.483	0.941	0.861	0.849
Wavelet energy	0.966	0.976	0.969	0.958	0.943	0.639
Energy ratio	0.985 (x/z)			0.93 (x/z)		

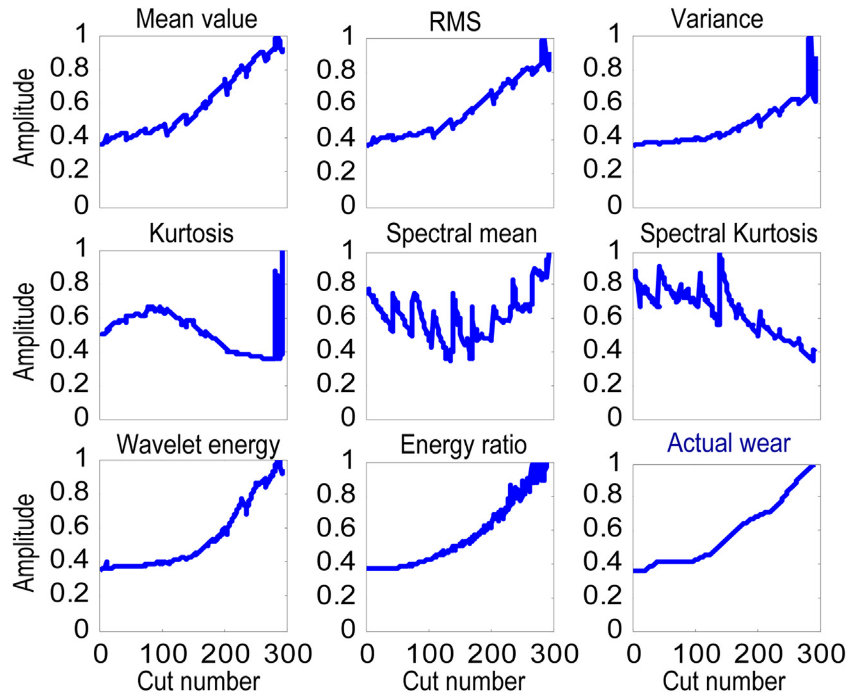

Fig. 4. Extracted features of force signal in y-direction.

which links the selected feature from online measurement to the tool wear state measured offline, as

$$z_k = x_k + \upsilon_k \tag{24}$$

where k is an index. z_k denotes the selected feature extracted from the online force measurement, x_k represents the tool wear state, and υ_k is the sequence of measurement noise which is assumed to follow the normal distribution (with zero mean and variance set as 0.04, derived from historical data).

4.3. Performance evaluation

Based on the system equation (denoted by Eq. (22)) and measurement equation (denoted by Eq. (24)), the state transition probability $p(x_k|x_{k-1})$ and measurement probability $p(z_k|x_k)$ can be obtained as a priori. The posterior distribution function of future tool wear state $p(x_{k+l}|z_k)$ can be predicted using the particle filter. In the system equation, the model parameters m and C are modeled as probability distributions following the uniform distribution, to incorporate the stochastic property of the tool wear process. In this study, the selected features from online force measurement in the first 200 cutting numbers are selected as available information to predict the tool wear state in the next 100 cutting numbers. Fig. 5 shows the probability distribution of model parameters m and C during the learning stage and prediction stage of the particle filter, respectively.

Fig. 6 shows the long-term (approximately 100 steps ahead) tool wear prediction result using the conventional particle filter. The solid red line represents the normalized actual tool wear width, which is measured offline for tool wear test. The black '*' symbol denotes the selected features from online force measurement in the first 200 cutting numbers as a priori information. The blue dashed line represents the tool wear state in the next 100 cutting numbers predicted by the conventional particle filter. It is found that the median of the predicted tool wear state closely follows the trend of the actual tool wear width, which is measured offline.

The estimated tool wear state with threshold setting (e.g., amplitude '1' is set as threshold) can be used to determine the remaining useful life of machining tool. The uncertainty of remaining useful life is also quantified in a probabilistic manner as shown in Fig. 7. By selecting the highest probability, the estimated remaining useful life using conventional particle filter is around 86 cut numbers, while the actual remaining useful life is around 95 cut numbers.

The distributions of the model parameters m and C remain constant, given that no online measurement is available to update the model parameters during the prediction stage (e.g., 100 cutting numbers ahead). To address this issue, regression analysis based on autoregressive model and support vector regression have been investigated to predict the online measurement (here the features from the online measurement is used) as the input during the prediction stage. The autoregressive model is a representation of a random process. The output of an autoregressive model is expressed using a linear regression of the previous measurement plus an error term:

$$z[n] = -\sum_{k=1}^{p} \alpha[k]\, z[n-k] + e[n] \tag{25}$$

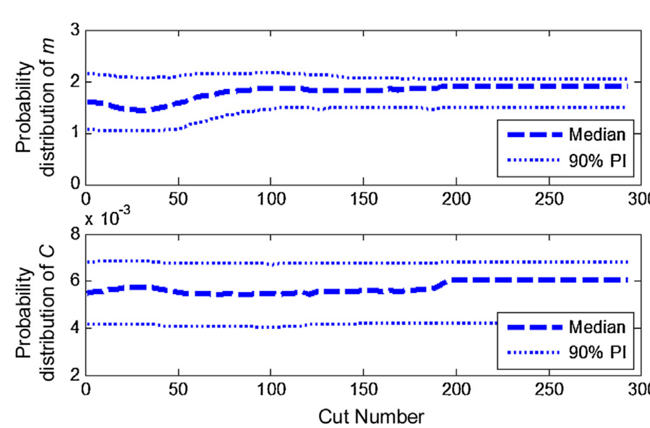

Fig. 5. Distribution of model parameters m and C used in the conventional particle filter.

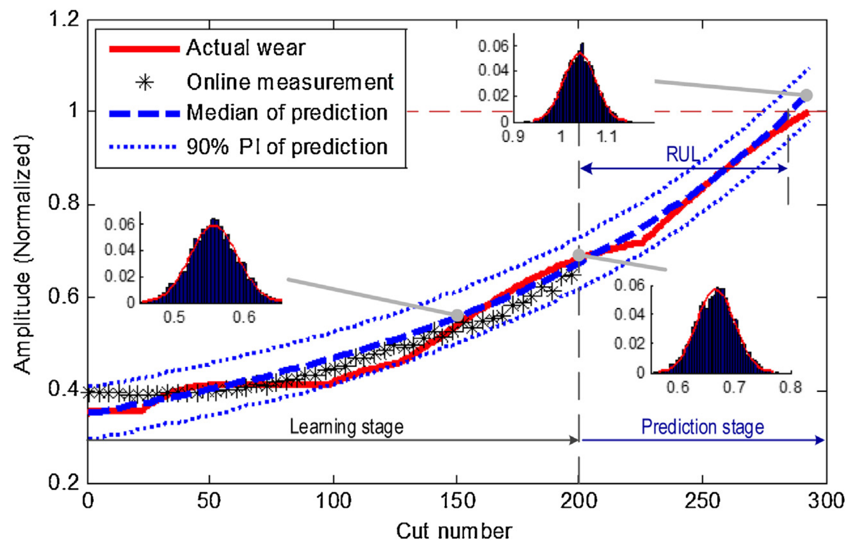

Fig. 6. Predicted tool wear using conventional particle filter.

where p is the model order determined by an order selection criterion, such as the Akaike information criterion, final prediction error, or minimum description length. $e[n]$ is an error term, which is modeled as a Gaussian white noise series with zero means and variance σ^2. Support vector regression trains a model firstly based on the historical data, then predicts the measurement at the prediction stage (e.g., 100 cutting numbers ahead) using the trained model and selected feature from online measurement during the learning stage (e.g., first 200 cutting numbers). The predicted measurement is then incorporated into the prediction stage of the particle filter.

Figs. 8 and 11 show the probability distributions of model parameters m and C in the integrative autoregressive model and particle filter (AR–PF) and integrative support vector regression and particle filter (SVR–PF), respectively. It is found that the probability distributions of model parameters have been updated based on the predicted measurement at the prediction stage.

The predicted tool wear state using AR–PF based on state transition probability and updated model parameters is shown in Fig. 9, while Fig. 12 shows the prediction result using SVR–PF. It is found that the accuracy of the prediction results using AR–PF and SVR–PF has been improved over the conventional particle filter (e.g., around 2% at 200 step ahead prediction). Accordingly, the distribution of estimated remaining useful life using integrated approach of particle filter and autoregressive model is shown in Fig. 10, while the distribution estimated remaining useful life using integrated approach of particle filter and support vector regression model is shown in Fig. 13. By selecting the highest probability, the estimated remaining useful life in AR–PF approach is around 96 cut numbers, while the estimated remaining useful life in SVR–PF approach is around 92 cut numbers. Comparing with the actual remaining useful life 95 cut numbers, the estimation accuracy of remaining useful life results using AR–PF and SVR–PF is also improved over the conventional particle filter.

To quantify the prediction accuracy of these three techniques (e.g., conventional PF, AR–PF, and SVR–PF), root mean square error (RMSE) is defined as the square root of the average of the square of all difference between estimated tool wear width $\hat{x}_j$ and actual tool wear width x_j.

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(\hat{x}_j - x_j\right)^2} \tag{26}$$

Based on root mean square error, the performances of these three techniques are compared as shown in Fig. 14 under different-steps-ahead prediction. It is found that the prediction accuracy of these three techniques is improved as more online measurement available. With predicted measurement incorporated in the prediction period of particle filter, the prediction accuracy of AR–PF and SVR–PF is improved over conventional PF. Generally, SVR–PF shows better performance than AR–PF under different-step-ahead prediction.

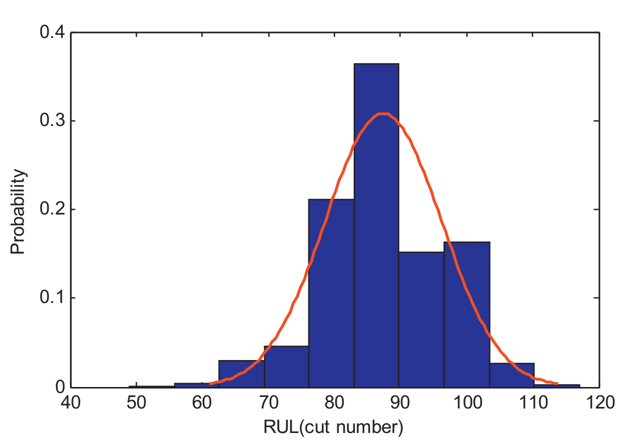

Fig. 7. Estimated remaining useful life (RUL) using conventional particle filter.

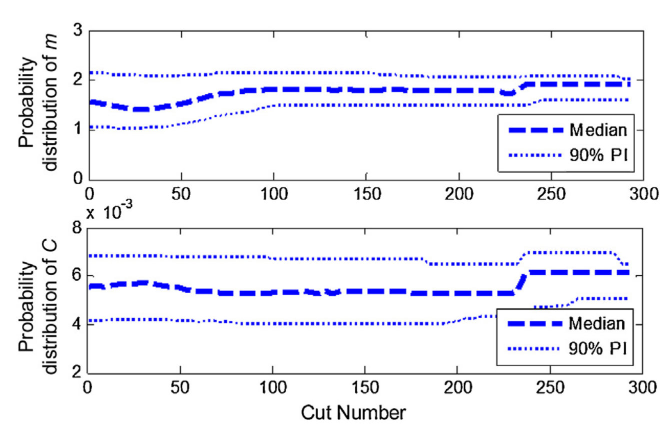

Fig. 8. Distribution of model parameters m and C used in the integrated particle filter and autoregressive model (AR–PF).

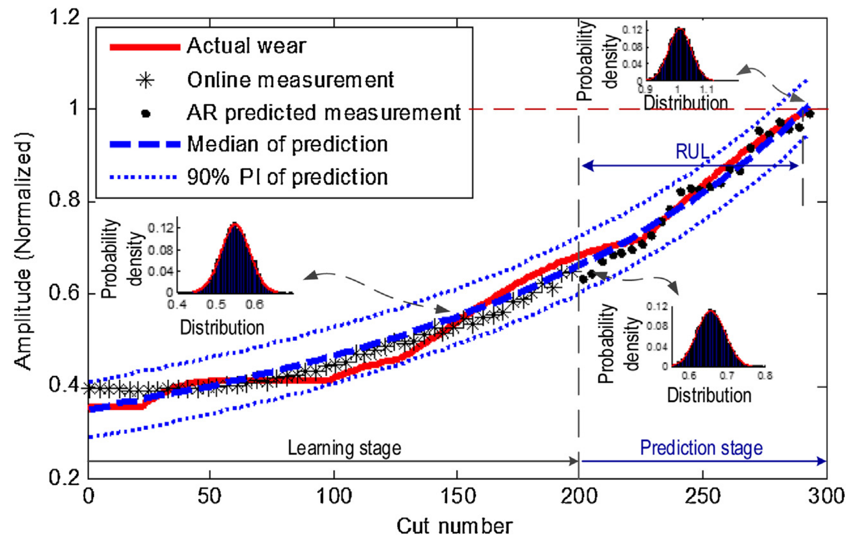

Fig. 9. Predicted tool wear using integrated approach of particle filter and autoregressive model (AR–PF).

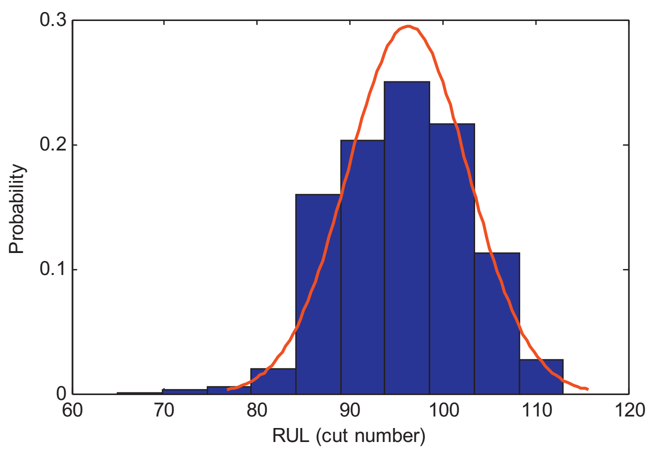

Fig. 10. Estimated remaining useful life (RUL) using integrated approach of particle filter and autoregressive model (AR–PF).

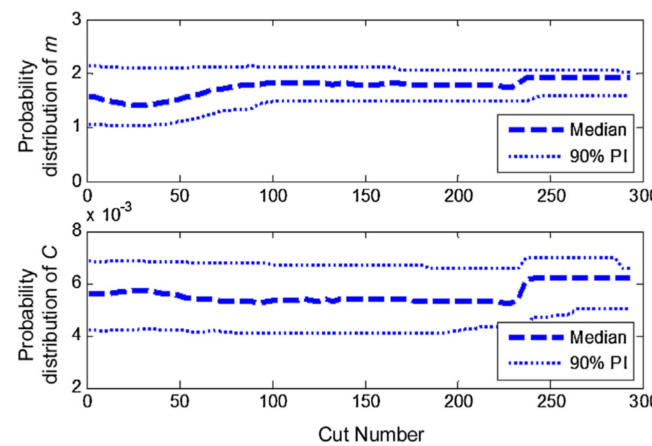

Fig. 11. Distribution of model parameters m and C used in the integrated particle filter and support vector regression model (SVR–PF).

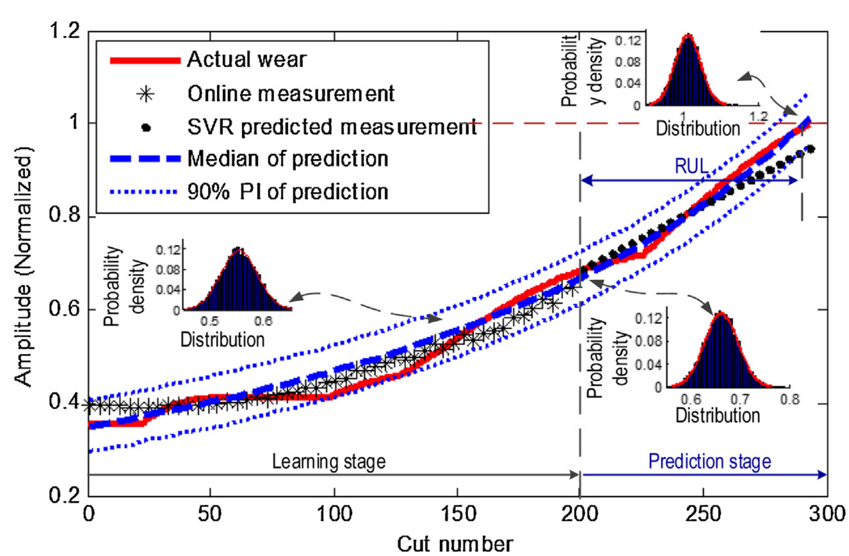

Fig. 12. Predicted tool wear using integrated approach of particle filter and support vector regression (SVR–PF).

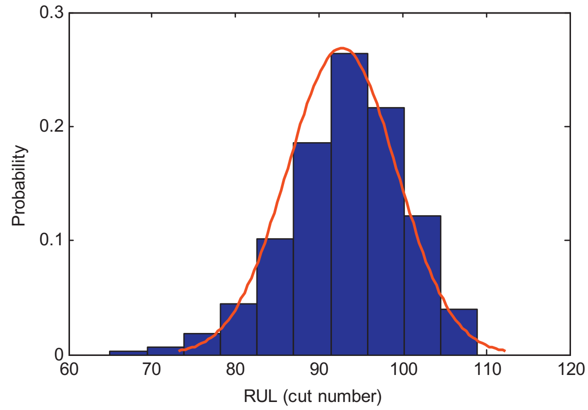

Fig. 13. Estimated remaining useful life (RUL) using integrated approach of particle filter and support vector regression (SVR–PF).

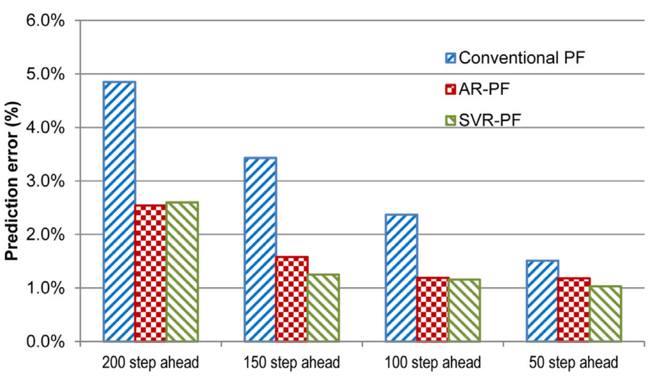

Fig. 14. Performance comparison of prediction techniques (conventional PF, AR–PF, and SVR–PF) under different steps.

5. Conclusion

Tool wear and remaining service life prognosis has raised much research interest to improve system reliability, ensure machining quality, and enable condition-based, intelligent maintenance for sustainable manufacturing. The particle filter algorithm described in this paper utilizes both the physical knowledge established in the literature and measurement data obtained experimentally to manage the uncertainty of measurement and stochastic property of the tool wear process. The results of the study indicate that:

(1) Particle filter, as a probabilistic model rooted in the Bayesian theory is an effective tool for providing verifiable prediction of the tool wear state within given confidence intervals to manage uncertainty;
(2) Regression analysis methods such as autoregressive model and support vector regression have shown to improve the performance of particle filter, yielding better prediction accuracy.

Future research will investigate both the robustness of the developed algorithm with more experimental tests under different operational conditions and its suitability for other types of applications. The goal is to enhance sensing data interpretation for more reliable, "trustworthy" sensing, which ultimately contributes to improved reliability in system degradation prediction.

Acknowledgments

This research was partially supported by National Science Foundation under grants CNS-1239030 and CMMI-1300999, and Science Foundation of China University of Petroleum, Beijing (no. 2462014YJRC039). Valuable comments from the anonymous reviewers are sincerely appreciated.

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