Original Article

Institution of MECHANICAL ENGINEERS

Journal of MECHANICAL ENGINEERING SCIENCE

Proc IMechE Part C:
J Mechanical Engineering Science
2020, Vol. 234(5) 1057–1068

DOI: 10.1177/0954406219888544
journals.sagepub.com/home/pic
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Tool wear condition monitoring based on wavelet transform and improved extreme learning machine

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Abstract

In machining process, tool wear is an inevitable consequence which progresses rapidly leading to a catastrophic failure of the system and accidents. Moreover, machinery failure has become more costly and has undesirable consequences on the availability and the productivity. Consequently, developing a robust approach for monitoring tool wear condition is needed to get accurate product dimensions with high quality surface and reduced stopping time of machines. Prognostics and health management has become one of the most challenging aspects for monitoring the wear condition of cutting tools. This study focuses on the evaluation of the current health condition of cutting tools and the prediction of its remaining useful life. Indeed, the proposed method consists of the integration of complex continuous wavelet transform (CCWT) and improved extreme learning machine (IELM). In the proposed IELM, the hidden layer output matrix is given by inverting the Moore–Penrose generalized inverse. After the decomposition of the acoustic emission signals using CCWT, the nodes energy of coefficients have been taken as relevant features which are then used as inputs in IELM. The principal idea is that a non-linear regression in a feature space of high dimension is involved by the extreme learning machine to map the input data via a non-linear function for generating the degradation model. Then, the health indicator is obtained through the exploitation of the derived model which is in turn used to estimate the remaining useful life. The method was carried out on data of the real world collected during various cuts of a computer numerical controlled tool.

Keywords

Tool condition monitoring, features extraction, acoustic emission, prognostics and health management, improved extreme learning machine, complex continuous wavelet transform, remaining useful life

Date received: 21 February 2019; accepted: 22 October 2019

Introduction

In the metal cutting field, tool wear is considered among the most critical conditions affecting workpiece surface quality. Developing a reliable monitoring system towards high precision, high speed and automation manufacturing is required. As a result, an improved quality, reduced downtime and lower production costs can be achieved. Generally, tool wear condition monitoring can be classified into two main categories. The first one uses a direct method such as optical sensors, CCD camera, and tool work piece junction resistance. Another one employed indirect method such as acoustic emission, force and vibration sensors.[1,2] With this method, the cutting process can run without interruption for fully automated manufacturing systems. Consequently, the implementation of sensors-based PHM system performs a significant contribution to assess the machining status of cutting tools and predicting its RULs. As a result of the impact of these issues, a recent PHM research on tool wear has been successfully developed. As argued in Elattar et al.,[3] the prognosis can be categorized into three principal approaches: model-based, experience-based and data-driven prognostic. In model-based prognostic, the degradation mechanism of the physical behavior can be established through mathematical formulas (Taylor's equation, Paris Law, etc.). This approach

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gives more precise results if accurate models are built. However, the main drawbacks are: the difficulty in modeling stochastic systems, expert knowledge is required and high implementation cost.[4] Experience-based approach uses probabilistic or stochastic models of the degradation phenomenon. It takes into account the data of the experience gathered during a significant period of time to adjust the parameters of some reliability models. The most commonly used distribution functions are normal, Weibull and exponential distributions which can be fitted to the historical data, and then the RUL is derived from the best fit distribution. The main drawback and limitation related to this approach are the huge and significant amount of exploitation data which are required for determining the parameters of the model.[5] The data-driven approach attempts to derive models directly from the acquired monitoring data provided by sensors for the continuous health assessment of the operating systems and prediction of its RULs. This approach is more appropriate and considered as an alternative to other approaches due to a low cost, simplicity of implementation, and any need of prior mathematical model of degradation. Data-driven prognostic approach is generally divided into two categories; statistical and artificial intelligence-(AI) based approaches. Data-driven (statistics based) approach includes essentially regression models (Wiener process, Gamma process, proportional hazard models, and hidden Markov model), and it suffers from several drawbacks.[4] In the category of AI approach, several techniques are applied for modeling and monitoring machining systems, most of them are: artificial neural networks (ANN), fuzzy logic, genetic algorithms, support vector machines (SVMs), neuro-fuzzy systems, ELM, etc. The fuzzy logic-based tool condition monitoring (TCM) algorithms are limited, because fuzzy rules are always developed by experts due mainly to the complexity of the models and lack of learning capability. Neural networks and fuzzy neural systems in turn generate black box models as well as the selection of the network structure is complicated.[6] Moreover, the neural network appears to be very susceptible to drop into a local minimum and also involves a lot of data to be trained.[7] As an alternative to ANN, SVMs are increasingly used for solving classification and regression problems. Besides the advantages of SVMs, they have some drawbacks to be considered, such as selecting Kernel function parameters, the theoretical shortcomings within the Kernel function for non-linear classification problems, and it is unsuitable when processing large-scale data.[7,8] Recently, Huang et al.[9] developed a new learning algorithm named ELM for the SLFN (single layer feed forward neural networks) architecture. The ELM has the advantages to be offered by its lower calculating cost, its generalization performance and its simplified deployment.

Mostly, the key steps involved in the AI data-driven-based approach include data acquisition, data processing, model learning and decision making. The raw monitoring data generated during machining are non-linear and cannot be used without processing to predict the tool wear. The advanced signal processing techniques such as fast Fourier transform, Hilbert transform, empirical mode decomposition, wavelet transform (WT), etc. have the ability to extract and select the reliable features from acquired signals. Among these methods, WT is considered the most successful investigated techniques due to the non-stationary characteristics of the gathered signals. The extracted trends should be used to make a model describing the evolution of the degradation phenomenon. The proposed prognostic model IELM is achieved by inverting the Moore–Penrose generalized inverse of the hidden layer output matrix. In decision making, when the degradation exceeds the alarm threshold, the algorithm starts predicting the RUL. The threshold can be determined based on the manufacturer's requirements.

The benefits done by ELM and WT are the reason to propose a data-driven prognostic approach by using CCWT and IELM. The IELM is basically an extension of the existing ELM algorithm for SLFNs. Concerning the CCWT, the complex wavelets are more useful tools for signal processing in comparisons to real wavelets.[10]

The main contribution of the proposed paper is based on the data-driven prognostic method to evaluate the current health condition of cutting tools and predict its RUL. The proposed method is performed in two phases: a learning (offline) and a testing phase (online). One cutter is considered for training and the other one for testing. The essential steps involved in a learning (offline) phase are: data acquisition, feature extraction, model learning. The acquired data from AE sensors are usually concealing relevant information about the degradation evolution of cutting tools. Consequently, their direct use in prognostic is not easy. Therefore, it is necessary to extract and to select more explicit feature vectors in different domains (time, frequency, and time-frequency) in order to estimate the health status of a cutting tool at every instant. That means transforming data from the original feature space to a new one of lower dimensionality. This step named feature extraction which is the key to build the effective model describing the evolution of the degradation phenomenon. To extract useful features of the raw data issued from the AE sensors, the authors tested several families and type of wavelets as: continuous wavelet transform (CWT), discrete wavelet transform (DWT), wavelet packet transform (WPT), and CCWT. Due to the complexity of the AE signals, the best results were found by (Shannon 2–3) wavelet at the level six. The root mean square (RMS) of the rapport real and image coefficients for each frequency band has been taken as tool wear monitoring features. These features are continuously entered into the learning algorithm IELM. The output result has a monotone increasing or decreasing trend of a degrading cutting tool which represents the most appropriate data-driven prognostic model (learning model). Then, the selection of the useful extracted features depends on the obtained output result. After offline features selection and establishing appropriate data-driven prognostic model representing the cutting tool's degradation behavior, the next step is the testing phase where a new cutter is taken. Within this phase, extracted features are continuously injected into the learned model. The output result represents the health indicator which is used to evaluate the current health condition and predict the RUL of cutting tools with identical previous operating conditions used in the offline phase. The significant performances achieved by the CCWT and the IELM are shown by the obtained results for making the appropriate maintenance decision.

This paper will first review the PHM, TCM and RUL techniques in the next section. The RUL estimation using the proposed method that is based on the CCWT and IELM is then given. The subsequent section provides the simulation and discusses the results. Conclusions and suggestions for future work are highlighted in the last section.

Prognostics and health management of TCM

PHM is a new engineering approach that enables a real-time health assessment of a tool condition and its future state. This technique, which is illustrated in Figure 1, is usually described as the combination of seven modules[11]: data acquisition, manipulation, condition assessment, diagnostic, prognostic, decision-making and human machine interface (HMI). The first module is the data acquisition which is the process of collecting, converting, and recording useful data using appropriate acquisition systems. In the data manipulation, the acquired waveform data (raw signals) are analyzed and interpreted to extract the useful information that represents the system's behavior. The condition assessment uses the extracted features and degradation level to assess the current condition. On the basis of the existing state and the detection and/or diagnosis results of systems, an estimate of future progress including the RUL is made by the prognostic. Decision-making module is to provide and recommend decisions and actions for maintenance and logistic. The last module is HMI that provides a means of presenting and storing different forms of useful information. It can communicate with all other modules for online or further usage. PHM aims to assess the physical system's current state and calculate its RUL before the failure. The goal is to maximize the operational availability and safety of the target system, and better manage their health. An illustration of a RUL is given in Figure 2.

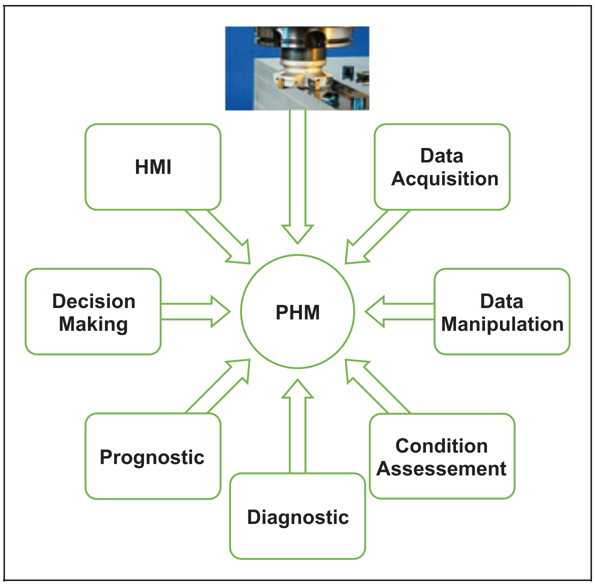

Figure 1. PHM cycle.

Failure prognostic paradigm

The International Standard Organization (ISO), defines the prognostic as: an estimation of time to failure and risk for one or more existing and future failure modes.[12] The classification of failure prognostics was made according to the following criteria: cost of the life cycle, precision, complexity and applicability. It can be done by using several methods which are regrouped in three main approaches: model-based approach, physic-based approach and data-driven prognostic (see Figure 3).

In model-based prognostic (also called the physics of failure prognostics), a component/machine and its degradation phenomenon are represented by a mathematical law. The given model is able to predict the future evolution of the degradation and estimating its RUL. Recently, several works have been undertaken

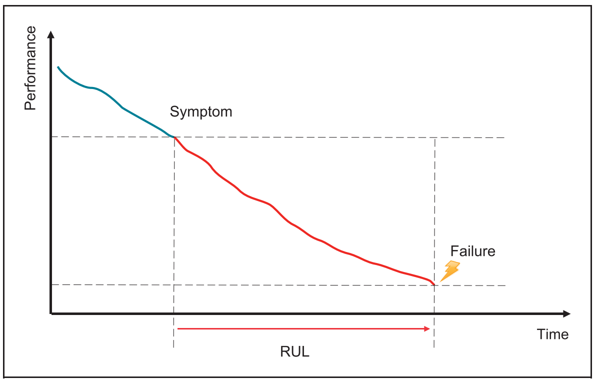

Figure 2. Illustration of RUL.

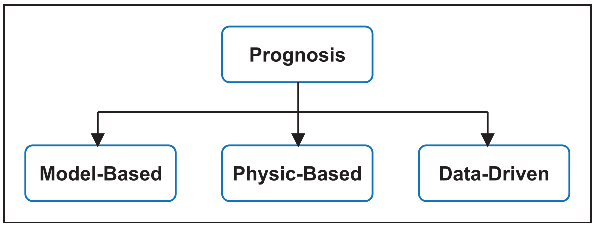

Figure 3. Main prognostic approaches.

to use a model-based prognostic.[13,14] This approach gives more precise results; however, in practice, it is almost impractical, since many physical processes are too complex due to nonlinearities, stochasticity and non-stationarities, etc. Moreover, the cost of implementation is higher.

Experience-based prognostic mainly uses the data of the experience accumulated over time to adjust the model parameters.[5] Some of the published researches using these approaches can be found in Samrout et al.[15] The advantage of this prognostic approach is that it requires less detailed information than other approaches, because the significant data are available and it is easy to apply to any system. However, its accuracy is not high because it is only based on the analysis of a previous experience.

Data-driven prognostic approach is also known as data mining or machine learning techniques that have a better applicability compared to other approaches. It requires a large amount of historical measurements delivered by sensors to establish an accurate prognostic model that track the evolution of the system degradation and predict its RUL. This approach can often be deployed quicker and cheaper compared to other approaches due to the simplicity of implementation and no requirements to for the degradation of mathematical model.[16]

In the literature, many researchers have proposed various methods to deal with data-driven RUL prediction problems.

Niu et al.[17] proposed prognostics system based on monotonic similarity modeling. The performance of this framework was demonstrated by bearing life cycle data. Blind source separation techniques were used by Benkedjouh et al.[18] for RUL estimation of cutting tools. Mosallam et al.[19] applied a Bayesian approach for RUL prediction. The results showed the effectiveness of the method in predicting the RUL of the battery and turbofan engine.

Similarly, SVM is a new machine learning method based on statistic learning theory. Li et al.[20] proposed a new method that combines least squares support vector regression (SVR) and strong tracking particle filter for RUL prediction of bearings. Recently, Rai et al.[21] proposed a new bearing health index integrated with SVR to calculate its RUL.

Concerning the RUL prediction of cutting tools, interesting research results were reported by Benkedjouh et al.[22] using SVR.

Besides these methods, there has been a growing interest to connectionist techniques such as neural networks and neural-fuzzy systems.[23,24] Razavi-Far et al.[25] studied the lithium-ion batteries degradation and estimated their RUL by using neural, neuro-fuzzy networks, group method of data handling, and random forests. The obtained results demonstrated that the neuro-fuzzy subtractive clustering and random forests predictors outperformed other competitors. Javed et al.[26] proposed a prognostic model based on the summation wavelet-ELM and subtractive-maximum entropy fuzzy clustering to show the evolution of the machine degradation by simultaneous predictions, discrete state estimation and improving the accuracy of RUL. Another application of ELM approach is given in Cojbasic et al.[27]

In milling TCM, WT is a powerful signal processing technique that yields useful features that are highly sensitive to the tool conditions due to the non-stationary characteristics of the gathered signals. The WT can decompose AE signals into different frequency bands in the time domain in order to extract the useful features. It describes a signal of interest by using the correlation with the translation and dilatation of a function called mother wavelet. Basically, the WT includes CWT and DWT. The CWT is a non-orthogonal and redundant transform that provides a better performance than the shift-variant DWT. The time-invariance property is particularly important in keeping the wave shape.[28] There have been many applications of wavelet transforms for TCM. As reported in Benkedjouh et al.,[22] Daubechies wavelet packet decomposition is used to extract features in the raw signals on a milling machine and then reduced. Based on these features, the model representing wear evolution is then established. In the same research area, Zhang et al.[29] applied the wavelet packet transform on the raw vibration signals acquired from milling machine for extracting the time–frequency trends which are then used by neuro-fuzzy network.

RUL estimation based on CCWT and IELM

The essential steps involved in the proposed method are given in Figure 4. The estimation of the RUL is done in two principal phases, as shown in Figure 5: a learning phase (offline) and a testing phase (online). One cutter is considered for training and the other one for testing.

The learning phase aims to extract dominant features which are contained in the gathered AE signals. The CCWT, particularly at the six levels of the (Shannon 2–3) wavelet, is used to decompose AE signals. The RMS of the rapport real and image coefficients for each frequency band are taken as tool wear monitoring features. These features are then fed learning algorithms IELM for establishing the most

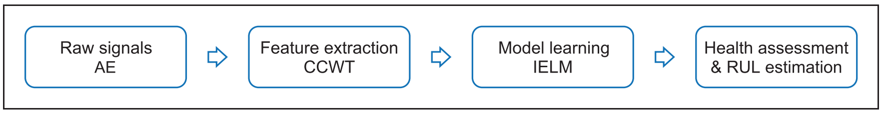

Figure 4. The main steps of the data-driven prognostic method.

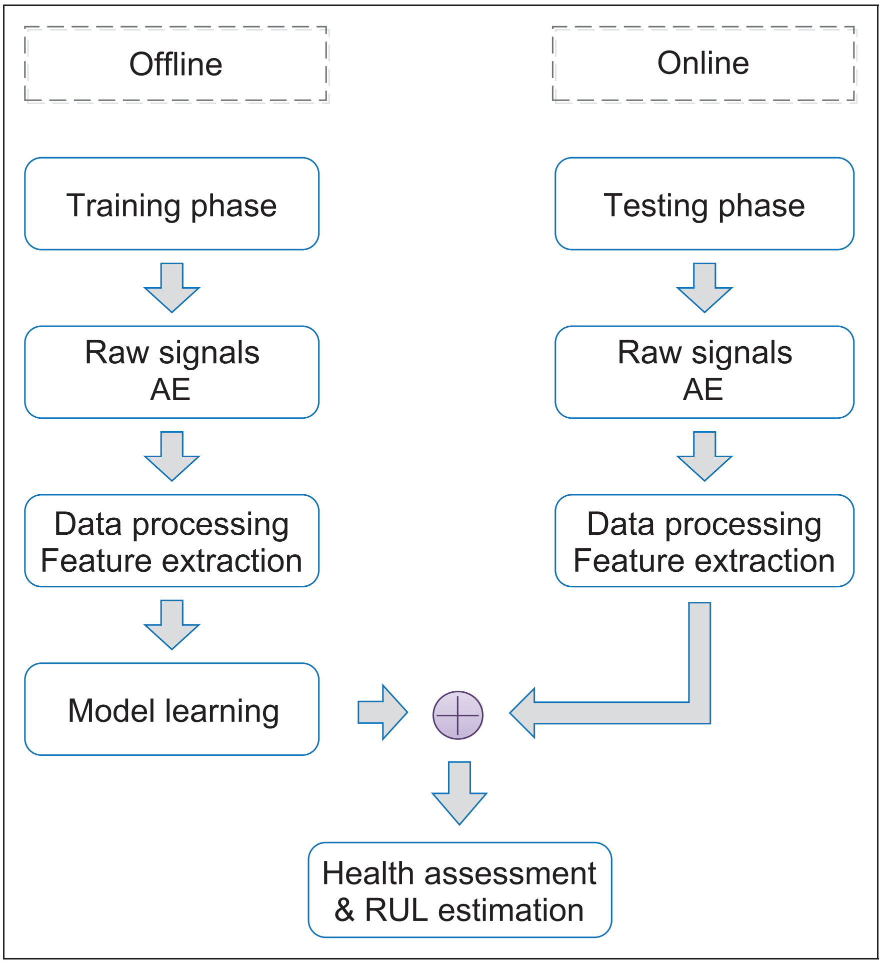

Figure 5. RUL estimation steps.

appropriate data-driven prognostic model (learning model) describing the wear evolution of cutting tools. The next step is the testing phase where a new cutter is taken. Within this phase, extracted features are continuously injected into the learned model. The output result represents the health indicator which is used to evaluate the current health condition and predict the RUL of cutting tools with identical previous operating conditions used in the offline phase.

Experimental study

The experimental setup named Matsuura machining center MC-510 V is used to validate the proposed approach.[30] This setup provides the experimental data recorded from runs on a milling machine. Acoustic emission, vibration and current sensors are each installed on the table and the spindle of this platform. The total number of cases is 16 and it depends on a number of runs, which are related to the degree of flank wear. The measured flank wear was taken between runs at irregular intervals until the wear limit was reached and in some cases beyond. The given data are structured at 167 samples, and the variables are shown in Table 1. The acquired data are related to tools wear in different operating conditions with cutting speed of 200 m/min and a maximal sampling rate can reach 100 KHz. A depth of cut, feed and type of material are reported in Table 2. As already mentioned, we focus only on signals taken from the acoustic emission sensors mounted on the table. The signal from the acoustic emission sensor goes into the single-ended terminal of an acoustic emission preamplifier (DUNEGAN/ENDEVCO, model 1801 with integrated 50 KHZ high pass filter). Acoustic emission sensor model is WD 925 (PHYSICAL ACOUSTIC GROUP, frequency range up to 2 MHz).

Table 1. Set of milling operation variables and their description.

Field name	Description
Case	Case number
Run	Counter for experimental runs in each case
VB	Flank wear, measured after runs; Measurements for VB were not taken after each run
Time	Duration of experiment (restarts for each case)
DOC	Depth of cut (does not vary for each case)
Feed	Feed (does not vary for each case)
Material	Material (does not vary for each case)
smcAC	AC spindle motor current
smcDC	DC spindle motor current
vib_table	Table vibration
vib_spindle	Spindle vibration
AE_table	Acoustic emission at table
AE_spindle	Acoustic emission at spindle

Table 2. Operating conditions.

Case	Cutters	Depth of cut (mm)	Feed (mm)	Material
1	C2	0.75	0.5	Cast iron
2	C3	0.25	0.5	Cast iron
3	C4	1.5	0.25	Cast iron
4	C5	1.5	0.5	Steel
5	C8	0.75	0.5	Steel
6	C9	1.5	0.5	Cast iron
7	C12	0.75	0.5	Cast iron
8	C13	0.75	0.25	Steel
9	C14	0.75	0.5	Steel
10	C15	1.5	0.25	Steel
11	C16	1.5	0.5	Steel

Figure 6 shows the experiment setup. A sample of raw signals of the acoustic sensors mounted on the table is shown in Figure 7; and the variation of statistic indicators (RMS, Skewness, and Kurtosis) as function of cutting cycles of the cutter C4 is also plotted in Figure 8.

Feature extraction based on complex continuous wavelet transform

In condition monitoring, the complex wavelet transform is considered the most efficient method compared to real wavelet for capturing and extracting the useful features of analyzed signals. In CCWT, CWT coefficients are calculated by using complex wavelets. The most used of such wavelets are: complex

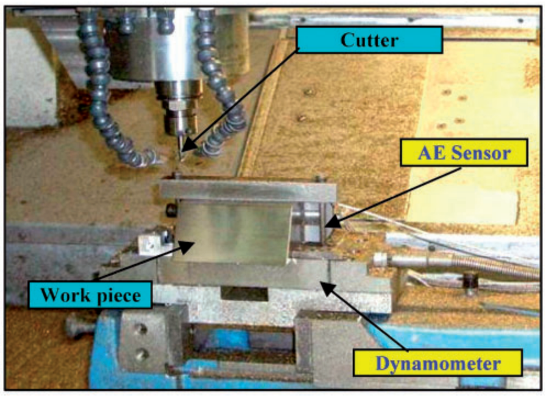

Figure 6. Experimental setup.

Gaussian wavelets, complex Morlet wavelet, complex Daubechies wavelets, complex Shannon wavelets which are based on Frequency B-spline wavelets.

Shannon wavelets are mainly characterized by its Fourier transform which is constant over some interval of frequencies except the origin and zero elsewhere.[10] The expression of the CWT for real signals is defined as[28]

$$CWT(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} y(t)\psi^*\left(\frac{t-b}{a}\right)\mathrm{d}t \tag{1}$$

where $\psi^*(t)$ denotes the complex conjugate of the continuous wavelet function $\psi(.)$. a and b represent the scale and translation parameters, respectively. $y(t)$ denotes the signal to be transformed and $CWT(a, b)$ is the wavelet spectrum. A complex Shannon wavelet is defined by

$$\psi^*(t) = \sqrt{f_b}\,\sin(f_b x)e^{2i\pi f_c t} \tag{2}$$

where f_b and f_c are a bandwidth parameter and a wavelet center frequency, respectively. The CCWT at each scale gives four coefficients: Real, imaginary parts, modulus and angle.

For extracting the relevant features from the AE signals, the CCWT, particularly at the six levels of the (Shannon 2–3) wavelet, was used. The RMS of the rapport real and image coefficients for six levels was carried out. Figures 9 and 10 show RMS (real)/RMS (image) coefficients extracted from six levels of AE signals of cutters C4 and C15, respectively.

IELM-based prognostic

ELM has been widely applied to many real-world applications and is now gaining attention within the data-driven prognostic. The ELM developed by Huang et al.[9] was initially proposed for SLFNs and then extended to the generalized SLFNs with wide types of hidden neurons. The ELM consists of the input, the hidden, and the output layer. In ELM,

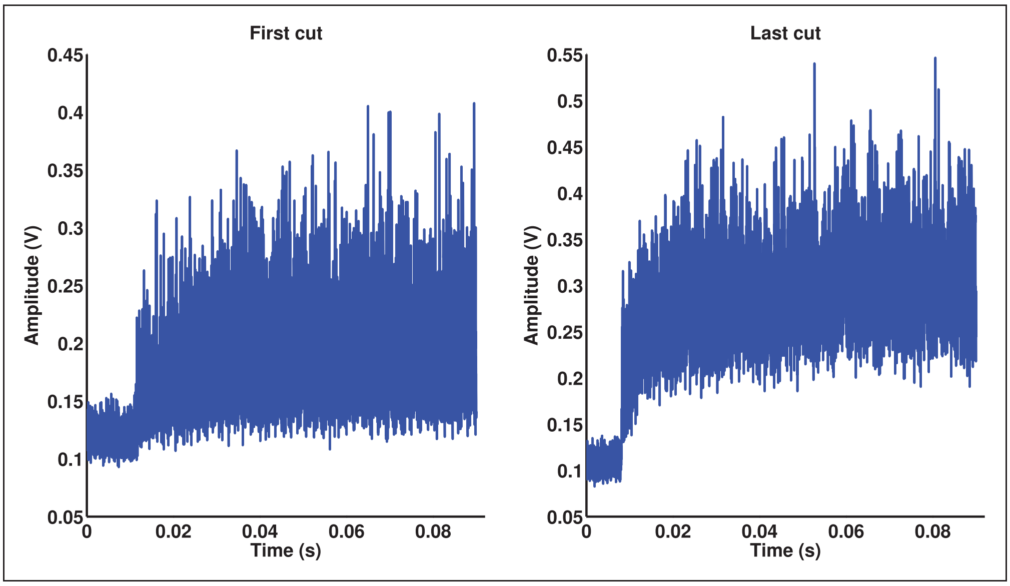

Figure 7. Acoustic emission signals of the cutter C4.

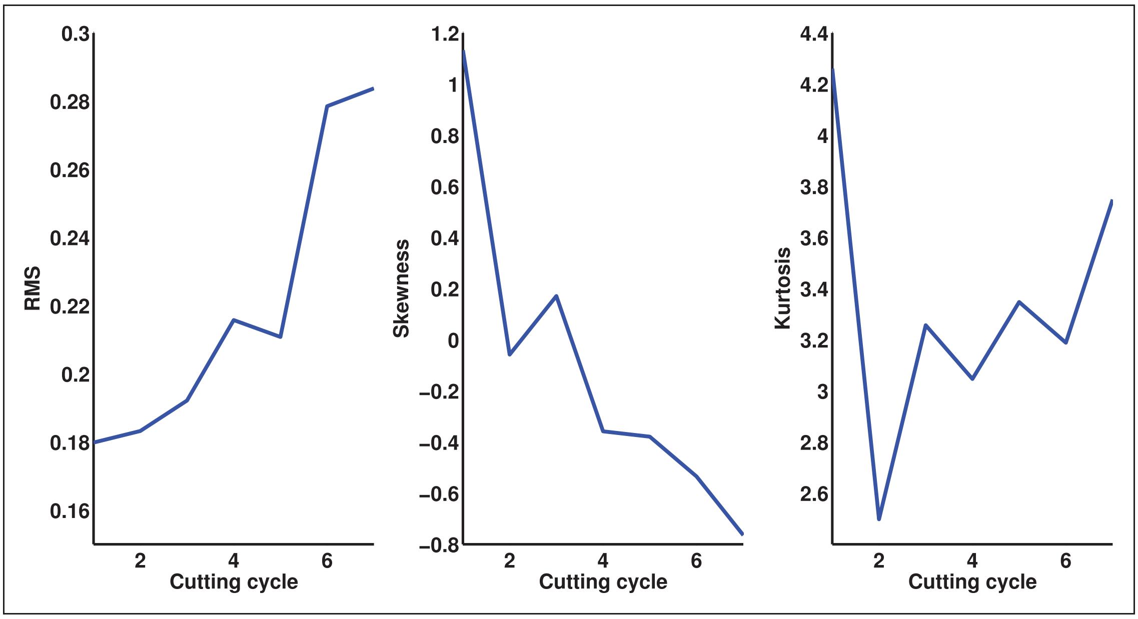

Figure 8. Variation of statistic indicators as function of cutting cycles of the cutter C4.

the input weights are chosen randomly, output weights are determined analytically, and hidden nodes can be randomly generated. This algorithm offers significant advantages such as better generalization performance by reaching both the smallest training error and the smallest norm of output weight, and it runs extremely fast compared to other conventional methods. In addition, it requires less human interventions, except the number of hidden neurons.[9]

In the literature, many improved ELMs have been proposed by researchers. Li et al.[31] proposed the ridge regression-ELM algorithm which calculates analytically the output weight matrix. In their results, the perturbation problems were well solved. Javed et al.[32] suggested an improvement to ELM that enhances the reliability of RUL estimates. For a good starting point of the random weight initialization, a procedure based on Nguyen Widrow parameter adjustment was used. Also, for processing hidden layer, they used a complex activation function in place of the traditional one. Zhang et al.[33] proposed a modified ELM based on PCA (P-ELM) to overcome the multicollinear problem in the calculation of the output weight matrix. By reducing the dimension of hidden layer output matrix, the raise in training speed has been guaranteed. This improvement has more stability in handling the contaminated industrial data

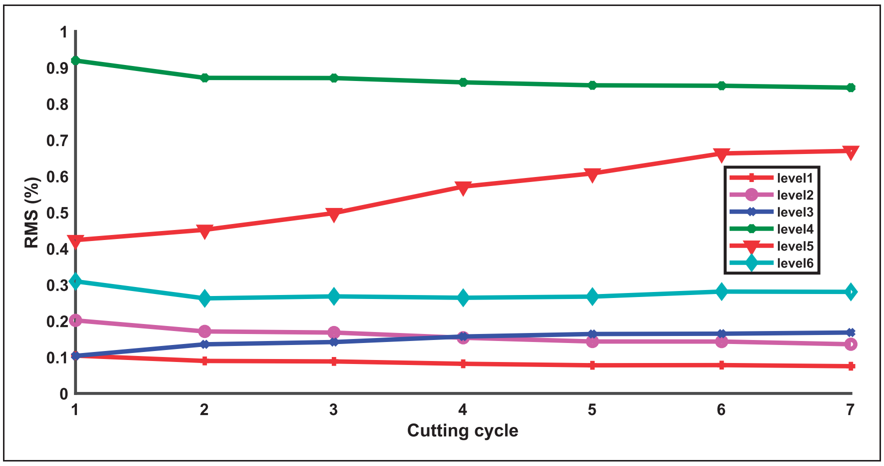

Figure 9. RMS (real)/ RMS (image) coefficients extracted from six levels of AE signal (cutter C4).

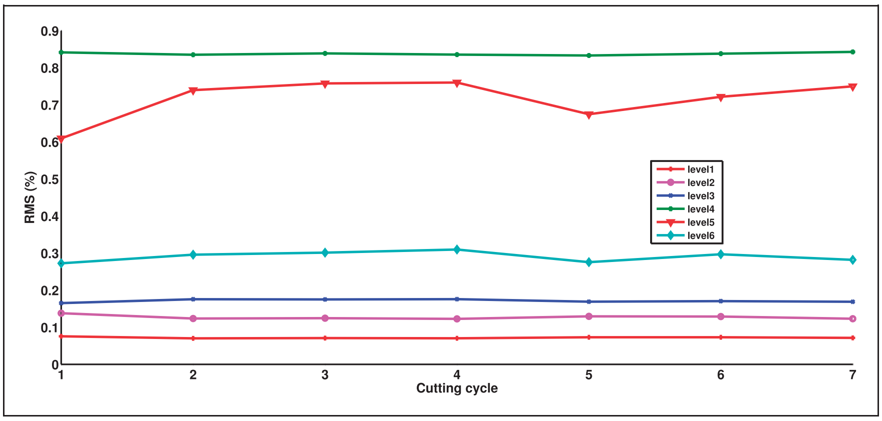

Figure 10. RMS (real)/ RMS (image) coefficients extracted from six levels of AE signal (cutter C15).

and produces the better generalization performance. For improving the computational robustness, Benkedjouh and Rechak [34]used the extended complete orthogonal decomposition method to solve the computational problem in ELM weights computing. Then, IELM was applied for nonlinear regression to approximate the function for RUL estimation of cutting tool.

For a set of N arbitrary distinct training samples with $(x_i, t_i) \in \Re^n \times \Re^m (i = 1, 2, \ldots, N)$, the output vector t_j of SLFN is mathematically expressed as

$$\sum_{i=1}^{\tilde{N}} \beta_i f_i(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i f(a_i . x_j + b_i) = t_j \qquad j = 1, 2 \ldots, N \tag{3}$$

where $\tilde{N}$ is the hidden nodes and $f(x)$ is an activation function. The ith hidden nodes and the input nodes are connected by the weight vector a_i, $a_i = [a_{i1}, a_{i2}, \ldots, a_{in}]^T$. b_i represents the bias of the ith hidden nodes.

The jth hidden nodes and the output nodes are connected by the weight vector β_i, $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}]^T$. $(a_i . x_j)$ is the inner product between a_i and x_j. The compacted format of equation (3) can be expressed as $H\beta = T$, where

$$H = \begin{bmatrix} f(a_1 . x_1 + b_1) & \ldots & f(a_{\tilde{N}} . x_1 + b_{\tilde{N}}) \\ . & \ldots & . \\ . & \ldots & . \\ f(a_1 . x_N + b_1) & \ldots & f(a_{\tilde{N}} . x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}},$$

$$\beta = \begin{bmatrix} \beta_1^T \\ . \\ . \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m} \text{ and } T = \begin{bmatrix} t_1^T \\ . \\ . \\ t_N^T \end{bmatrix}_{N \times m}$$

The output weights β can be calculated from $\hat{\beta} = H^{\dagger} T$. $H^{\dagger}$ denotes the Moore–Penrose generalized inverse of the hidden layer output matrix H.[9]

In this work, our contribution is to enhance the performances of ELM in terms of accuracy. As known, when solving a linear system or least squares problem, the double inverse is a fast and accurate replacement for inverse or pseudo-inverse. Then, an improvement has been suggested by inverting the

Moore–Penrose generalized inverse of the hidden layer output matrix. The IELM algorithm can be implemented as follows:

First, the parameters of hidden nodes (a_i, b_i) are generated randomly for $i = 1, \ldots, \tilde{N}$. Second, determining the output matrix of H. Last, the output weight matrix β is calculated by $\beta = inverse(H^{\dagger})T$.

Results and discussion

Based on the key steps highlighted in 'RUL estimation based on CCWT and IELM' section, the extracted features are injected into the learning algorithm IELM for building the prognostic models describing the cutting tool's degradation behavior. Note that, training is performed with cutters C15, C14, C5, C8, C3 and C13, while testing is performed with cutters C4, C9, C8, C16, C2 and C12 respectively. The output result represents the health indicator, as shown in Figure 11 for cutters C4 (left) and C9 (right). The proposed IELM algorithm and the ordinary ELM algorithm are compared together in terms of RMSE testing. Table 3 shows that the RMSE testing in IELM is less than in the ELM algorithm because the double inverse of the hidden layer output matrix is a more accurate replacement compared to the pseudo-inverse.

From the obtained health indicator, the predicted RUL can be estimated. During the experiments, in each case, the flank wear (in mm) was measured as a function of cutting cycle. From real wear curve, the real RUL can be established.

The predicted RUL obtained from ELM and IELM, real RUL and the failure threshold for the tested cutters C4, C9, C8, C16, C2 and C12 is shown together in Figure 12(a) to (f), respectively. In this contribution, according to the standard ISO 3685, the failure threshold of flank wear is considered to be 0.3 mm.[35] In RUL curves, the obtained results were normalized. The authors considered the failure threshold of flank wear equals to 0.3%. When the degradation level reaches this threshold (critical value), the RUL can be evaluated. Then, the necessary action should be done before the occurrence of failures. It can be clearly seen from these comparative figures that the predicted RUL using IELM fits better to the real RUL as compared to ELM.

In order to evaluate the prognostic performance of the proposed method and the improvement offered by the IELM for tool wear prediction, relative accuracy (RA), mean absolute percentage error (MAPE), and RMSE metrics are implemented. RA should be closer to 1 for the best performance and 0 for the worst; MAPE and RMSE should be minimum for the best performance. The results are given in Table 4 and a clear explanation of the implemented metrics can be found in Saxena et al.[36] It is apparent from Table 4 that, for each case, the obtained values of MAPE and RMSE of IELM are smaller than those of ELM. In terms of RA, IELM is more accurate than ELM for tool wear prediction. Finally, IELM performs better

Table 3. Model performances of ELM and IELM.

Train cutter	Test cutter	Activation function	Hidden nodes	RMSE testing ELM	RMSE testing IELM
C15	C4	Radbas	20	0.003366	0.001184
C14	C9	Radbas	20	0.007984	0.005603
C5	C8	Radbas	20	0.001488	0.000718
C8	C16	Radbas	20	0.006821	0.006567
C3	C2	Radbas	20	0.003216	0.002521
C13	C12	Radbas	20	0.016376	0.004161

IELM: improved extreme learning machine; ELM: extreme learning machine.

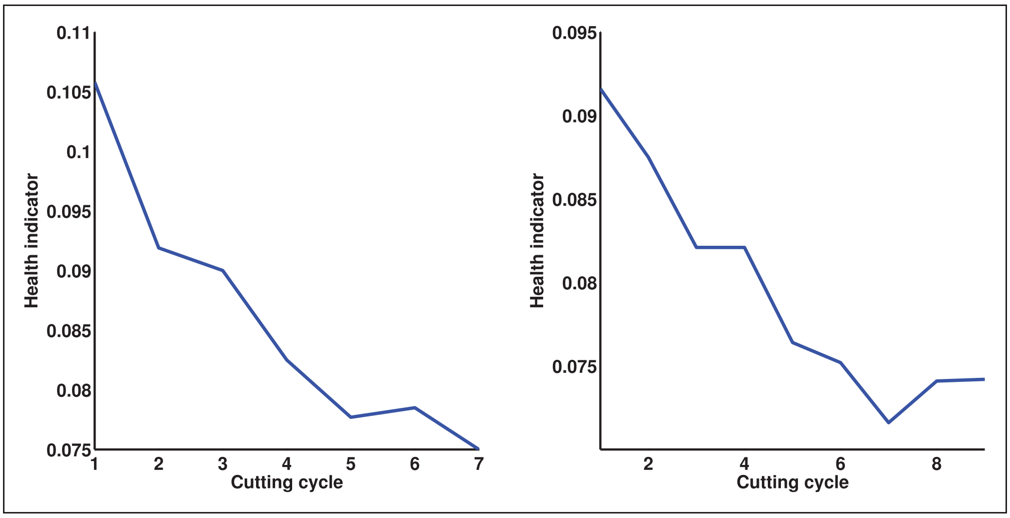

Figure 11. Health indicators using IELM: Cutter C15 for training/cutter C4 for testing (left) and cutter C14 for training/cutter C9 for testing (right).

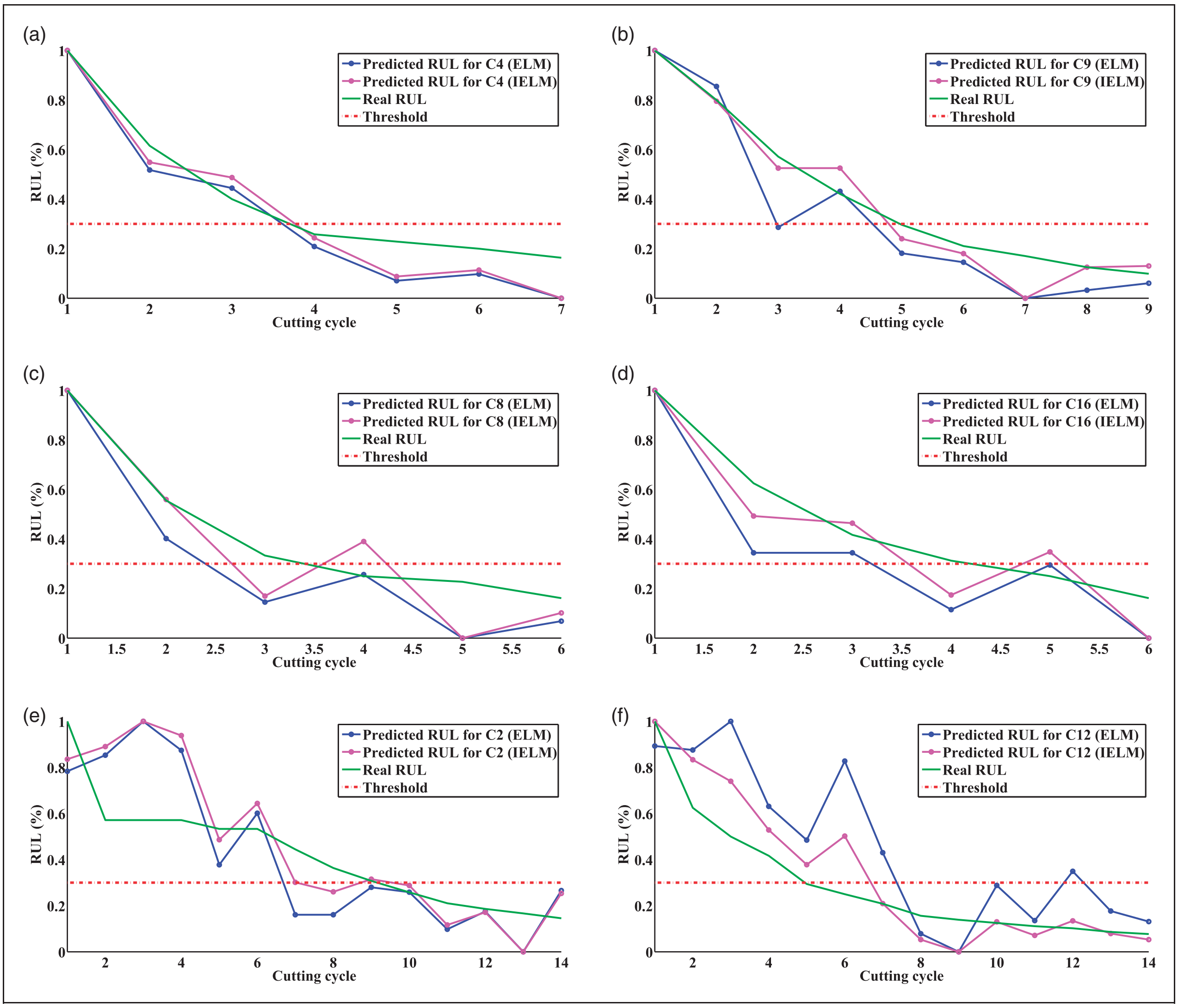

Figure 12. The predicted and the real RUL of the (a) cutter C4 (b) cutter C9 (c) cutter C8 (d) cutter C16 (e) cutter C2 (f) cutter C12.

Table 4. Prognostics performance metrics.

		RA		MAPE		RMSE	
Train cutter	Test cutter	ELM	IELM	ELM	IELM	ELM	IELM
C15	C4	0.8991	0.9097	38.0759	34.7229	0.1043	0.0972
C14	C9	0.8698	0.9444	37.9984	22.0625	0.1251	0.0723
C5	C8	0.8613	0.9020	40.7123	40.4520	0.1410	0.1301
C8	C16	0.8259	0.8880	40.6011	35.9903	0.1587	0.1114
C3	C2	0.6228	0.6646	43.7188	38.7414	0.2084	0.1968
C13	C12	0.5522	0.7950	94.6007	36.7857	0.2555	0.1246

IELM: improved extreme learning machine; ELM: extreme learning machine; RA: relative accuracy; MAPE: mean absolute percentage error.

results by comparison with ELM for the health assessment and RUL estimation of cutting tools.

Conclusion

This paper proposed a new approach based on CCWT and IELM for monitoring the degradation of cutting tools. The method was carried out on data of the real world collected during various cuts of a CNC tool. For improving the computational robustness, the relevant features from the AE signals were extracted by the CCWT, particularly at the six levels of the (Shannon 2–3) wavelet. The RMS of the rapport real and image coefficients for six levels was carried out. These features are continuously injected into the learning algorithm IELM for building the data-driven prognostic model describing the cutting tool's degradation behavior to evaluate its current health condition and predict its RUL. The effectiveness of ELM was further improved by inverting the Moore–Penrose generalized inverse. From the obtained results, it is expected that CCWT-IELM can significantly enhance the accuracy of the estimated RUL for performance degradation assessment.

From the outcome of our investigation, it has been demonstrated that the proposed method is capable of dealing with the non-linearity and the uncertainties of the complexity degradation of the tool wear for a successful decision making.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

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