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Authors: **S. Laddada [(1),(3)], T. Benkedjouh [(2)], M. O. Si- Chaib [(1)] , R. Drai[(3)]**
Affiliations:
[(1)] Solid Mechanics and Systems Laboratory (LMSS), University Mhamed Bougara Boumerdes, Algeria
[(2)] Laboratoire Mécaniques des Structures, Ecole Militaire Polytechnique, Bordj Elbahri Algiers, Algeria
[(3)] Research Center in Industrial Technologies CRTI P.O.Box 64, Cheraga 16014 Algiers, Algeria

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Laboratory of Signals and Systems
Address : IGEE (Ex-INELEC), Boumerdes University, Avenue de l'indépendance, 35000, Boumerdes, Algeria
Phone/Fax : 024 79 57 66
Email : lss@univ-boumerdes.dz ; ajsyssig@gmail.com

Remaining useful life prediction of cutting tools using wavelet packet transform and extreme learning machine

S. Laddada [(1),(3)*], T. Benkedjouh [(2)], M. O. Si- Chaib [(1)] , R. Drai[(3)]
[(1)] Solid Mechanics and Systems Laboratory (LMSS), University MhamedBougaraBoumerdes, Algeria
[(2)] Laboratoire Mécaniques des Structures, Ecole Militaire Polytechnique, Bordj ElbahriAlgiers,Algeria
[(3)] Research Center in Industrial Technologies CRTI P.O.Box 64, Cheraga 16014 Algiers, Algeria
[*]Corresponding author laddadas@gmail.com

Abstract: Online tool wear prediction is a determining factor to the success of smart manufacturing operations. The implementation of sensors based Prognostic and Health Management (PHM) system plays an important role in estimating Remaining Useful Life (RUL) of cutting tools and optimizing the usage of Computer Numerically Controlled (CNC) machines.
The present paper deals with health assessment and RUL estimation of the cutting tool machines based on Wavelet Packet Transform (WPT) and Extreme Learning Machine (ELM). This approach is done in two phases: a learning (offline) phase and a testing (online) phase. During the first phase, the WPT is used to extract the relevant features of raw data computed in the form of nodes energy. The extracted features are then fed to the learning algorithm ELM in order to build an offline model. In the online phase, the constructed model is exploited for assessing and predicting the RUL of cutting tool. The main idea is that ELM involves nonlinear regression in a high dimensional feature space for mapping the input data via a nonlinear function to build a prognostics model.
The method was applied to real world data gathered during several cuts of a milling CNC tool. The performance of the proposed method is evaluated through the accuracy metric. Results showed the significance performances achieved by the WPT and ELM for early detection and accurate prediction of the monitored cutting tools.

Keywords: Feature extraction, Prognostic, ELM, WPT,RUL.

1. INTRODUCTION

With the rapid development of manufacturing processes, machine tools have become more and more complex in response to the need for higher production quality. Applying a robust monitoring systems and intelligent maintenance is becoming more crucial to maximize the operational availability and safety of the target system, and better manage their health.
Condition monitoring based on fault detection and diagnosis is limited to predicting failure. Many applications of diagnosis can be found in[1],[2].Therefore, PHM is a contemporary maintenance strategy which anticipates the failure of degrading tools. In general, prognostic approaches can be categorized into model-based approaches, data-driven approaches and hybrid approaches [3].
The data-driven prognostic is more widely employed in recent years due to its quick implementation, deployment and no system knowledge is required, etc.
Feature extraction step is a commonly used technique applied before prognosis. The goal is to define a mapping from the raw monitoring data provided by the sensors into a lower-dimensional space [4].
Wavelet Transform (WT) is considered to be powerful to analyze non-stationary signals. In its continuous form, the information obtained is excessive and often redundant. In other hand,Discrete Wavelet Transform(DWT) suffer from the drawback of losing high-frequency contents. For overcoming these drawbacks, wavelet packet transform can further decompose the detailed information of the signal in the high-frequency region [5].
There are applications of WPT in tool condition monitoring. In [6] WPT has proven to be a robust method for real-time monitoring of the surface roughness in CNC turning operations.

For fault diagnosis of rolling bearing, Jun Ma et al. [7] used the wavelet packet-energy, entropy method to extract efficient features.
Next, the extracted features are transformed into relevant model. Different regression models have been proposed in the literature which has addressed the health assessment and RUL prediction. In [8], the authors proposed a new tool condition monitoring approach based on Mel-frequency Cepstral coefficients and support vector regression. The experimental results show that the health indicator can reflect effectively the tool wear degradation. In [9], the authors proposed a data-driven approach for estimating RUL using principal component and instance learning. The principal component analysis (PCA) is used to reduce the dimensions of the statistical features of the measured signals. Then, the health indicators (HI) curves can be obtained by using weighted Euclid distance (WED), and regressed by the data-driven methods. At last, the method based on instance learning is employed to estimate the RUL of the turbofan engine.
Tobon-Mejia et al. [10] proposed wavelet packet decomposition technique, and the mixture of Gaussians hidden Markov models for RUL estimation of bearings. Mossalem et al. [11] proposed a data driven method for RUL prediction based on a Bayesian approach which has been applied to turbojet engines and lithium-ion batteries. The results obtained showed the performance of the proposed approach.
Recently, Huang et al. [12] proposed a new learning algorithm for Single Layer Feed forward Neural Network (SLFN) architecture called Extreme Learning Machine (ELM). The advantages of using ELM are: low computational cost, better generalization ability, and ease of implementation.
Moreover, this algorithm is capable to solve the problems caused by gradient descent based algorithms such as Back propagation applied on Artificial Neural Networks (ANNs).
Nowadays, many applications of ELM have been done in solving the real problems of RUL prediction.
Javed et al. [13] proposed a data-driven prognostic approach, called enhanced multivariate degradation based prognostics. This approach integrates two new algorithms, Summation Wavelet-Extreme Learning Machine and Subtractive- Maximum Entropy Fuzzy Clustering. It is used to monitor the evolution of the machine degradation through simultaneous predictions, state estimations and improving the accuracy of the RUL.
In [14], a novel method based on ELM is carried out to estimate roughness of machined surface. It was shown that the predictive accuracy and capability of generalization could be achieved more accurate by the ELM than genetic programming and ANNs.
There are no published studies on the use of the WPT transform and ELM methods using vibration signals for remaining useful life prediction of cutting tools.
In this study, we propose a data-driven prognostic method based on the use of the WPT and the ELM (WPT-ELM). This approach is done in two phases: offline and online phase. In the first phase, the raw data provided by the accelerometer are processed by using WPT to extract reliable and useful features, which can better reflect the tool degradation. The extracted features are then fed to the learning algorithm ELMto build an offline model. In the online phase, the constructed model is exploited for assessing and predicting the RUL of cutting tool.

2. RUL ESTIMATION BASED ON WPT AND ELM

The main steps of the proposed data-driven prognostic method are shown in Fig. 1.

A. Feature extraction based on WPT: In tool condition monitoring, it is difficult to define vibration signals from raw data as a degradation feature due to the redundancy and noisy data. In order to extract relevant features that are interpretable, the WPT has obtained significant attention in recent decades.
The WPT method is a generalization of the wavelet decomposition that offers a richer signal analysis [5]. In the WPT decomposition, the original signal S is split into two frequency bands at level L1: an approximation signal A1 and a detail signal D1.
On the next level L2, the approximation signal A1 is recursively decomposed into approximation signal AA2 and a detail signal DA2; the detail signal D1 is split into approximation signal AD2 and detail signal DD2, and this procedure can be repeated for the 3rdlevel and over as shown in Fig. 2.
The approximation and detail coefficients generated at each level are called packets.Each packet is composed of $N \times 2^{-j}$ coefficients defined as:

$$A_{j+1}[n] = \sum_{k=-\infty}^{\infty} H[2n-k] A_j[k] \quad (1)$$

$$D_{j+1}[n] = \sum_{k=-\infty}^{\infty} G[2n-k] D_j[k] \quad (2)$$

where:

N: number of original signal samples
j: number of transformation levels with *j* = 1, 2, …
k: number of filter coefficients
n: number of packet coefficients with *n* = 1, 2, …, $N \times 2^{-j}$
G: coefficients of high-pass filter
H: coefficients of low-pass filter

At each level, when the signal is filtered, the signal must be decimated by a factor of 2.

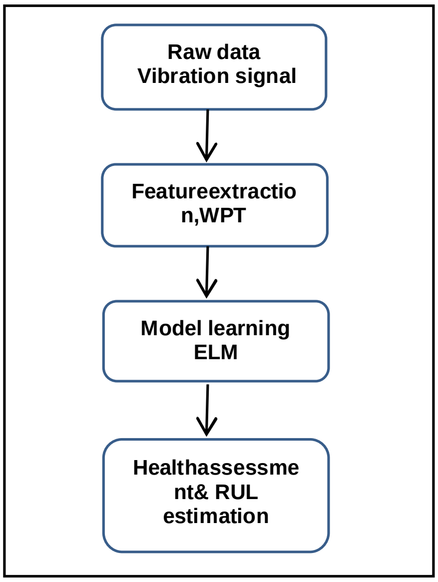


Fig. 1 The main steps of the data-driven prognostic method.

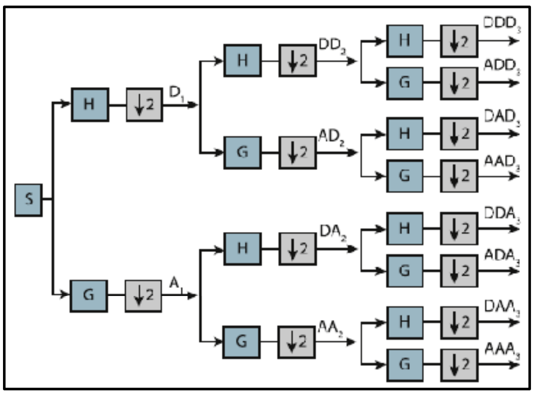


Fig. 2 Three level wavelet packet decomposition.

B. Feature extraction based on WPT: The ELM for a single (SLFNs) is composed of three fully connected layers, namely, the input layer, the hidden layer and the output layer [12]. It randomly chooses the input weights and analytically determines the output weights of SLFN, and shows that hidden nodes can be randomly generated.

For N arbitrary distinct samples $(x_i, t_i) \in R^n \times R^m \left(i = 1, 2, \ldots\ldots, N \right)$, the output of SLFN with $\tilde{N}$ hidden nodes and an activation function $f(x)$, are mathematically expressed as:

$$\sum_{i=1}^{\tilde{N}} \beta_i f_i(x_j) = \sum_{i=1}^{\tilde{N}} \beta_i f(a_i \cdot x_j + b_i) = t_j \quad (3)$$

where $j = 1, 2...., N$, t_j is the output vector of the SLFN.

$a_i = [a_{i1}, a_{i2}, \ldots\ldots, a_{in}]^T$ is the weight vector connecting the i th hidden node and the input nodes, and b_i is the threshold of the i th hidden node. $\beta_i = [\beta_{i1}, \beta_{i2}, \ldots\ldots, \beta_{im}]^T$ is the weight vector connecting the jth hidden nodes and the output nodes. $(a_i . x_j)$ represents the inner productof a_i and x_j.

The above Equation (3) can be written compactly as $H \times \beta = T$.

whereH is called the hidden layer output matrix of the hidden layer.

We can calculate the output weights b from $\hat{\beta} = H^{\dagger} T$, where $H^{\dagger}$ is the Moore–Penrose generalized inverse of H.

ELM algorithm can be implemented in three steps:

- Step 1: Randomly assign the parameters of hidden nodes (a_i, b_i), $i = 1, \ldots\ldots, \tilde{N}$;
- Step 2: Calculate the output matrix of the hidden layer H;
- Step 3: Find the output weight matrix β: $\beta = pinv(H^{\dagger}) \times T$.

C. Feature extraction based on WPT:

The data driven prognostic approach requires performing the estimation of current health status and future conditions of the monitored cutting tools to calculate the remaining useful life before failure (RUL).

The RUL can be obtained by estimating the time between the current time t_c and the time t_f related to the failure threshold, as shown in Fig. 3 and the formula is given by

$$RUL(t) = t_f - t_c \quad (4)$$

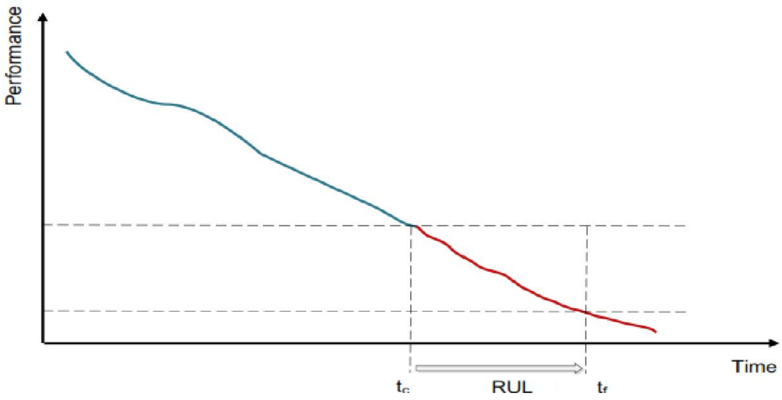


Fig. 3 RUL illustration.

3. EXPERIMENTAL SETUP

The data set represents experiments from runs on a high speed milling machine under various operating conditions [15]. There were six individual 3-flute cutters (C1, C2, C3, C4, C5 and C6). Each cutter made 315 cuts over an identical work piece for a face milling job. The spindle speed of the cutter was 10400 RPM; feed rate was 1555 mm/min; Y depth of cut (radial) was 0.125 mm; Z depth of cut (axial) was 0.2 mm. During the cutting operation, three types of sensors are used for collecting the data: accelerometers, forces and acoustic emissions. The data were recorded at a frequency of 50 kHz/channel. Fig. 4 shows the experimental setup.

In this study,we focus only on vibration signals; the cutters C4/C1, C6/C4 and C1/C6 are made for training/testing. Figs. 5, 6 and 7 show the maximum wear of three flutes of C1, C4 and C6 which are used to calculate the real RUL of each cutter and validating the results.

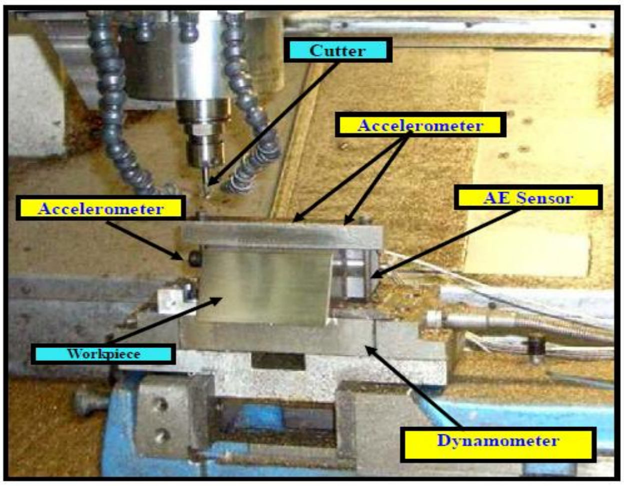


Fig. 4 Experimental setup.

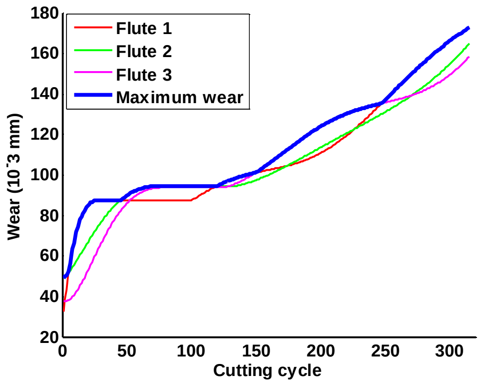


Fig. 5 A sample wear pattern on three flutes of a cutter C1.

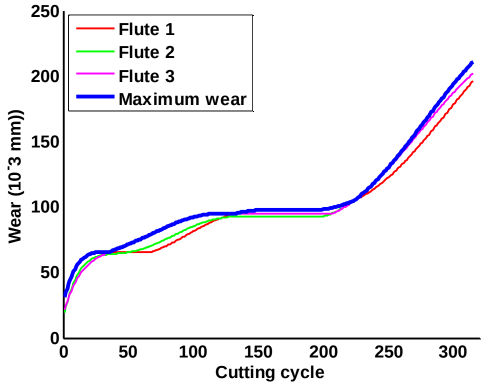


Fig.6 A sample wear pattern on three flutes of a cutter C4.

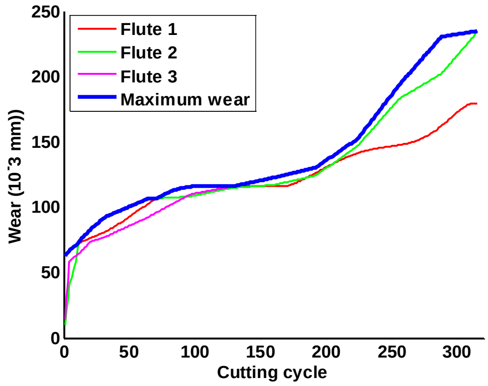


Fig. 7 A sample wear pattern on three flutes of a cutter C6.

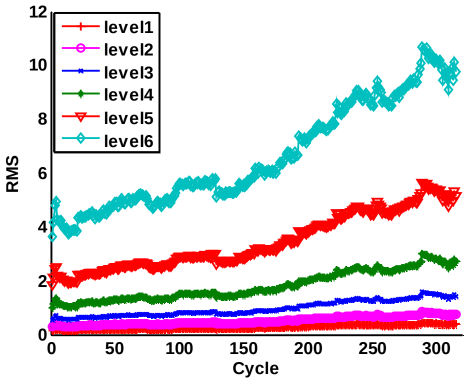


Fig. 8 RMS coefficients extracted from 6 levels of cutter C1.

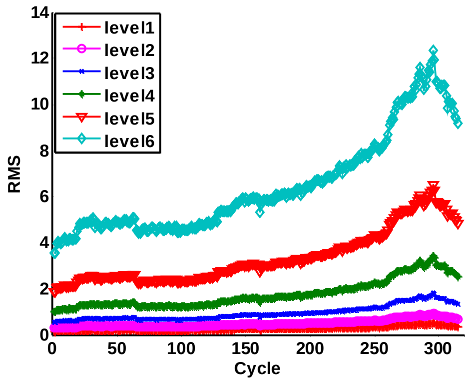


Fig. 9 RMS coefficients extracted from 6 levels of cutter C4.

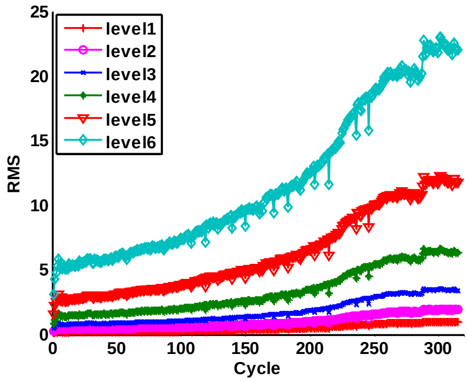


Fig. 10 RMS coefficients extracted from 6 levels of cutter C6.

4. RESULTS AND DISCUSSION

The feature extraction step is performed by using WPT where the vibration signal is decomposed into six levels by using db6. For each level the RMS is computed.

Figures 8, 9 and 10 show RMS coefficients extracted from 6 levels of vibration signals concerning cutters C1, C4 and C6, respectively.

The extracted features are then used as inputs of learning algorithm ELM, which has been considered to be one of the most promising approaches for modeling. Further, ELM involves nonlinear regression in a high dimensional feature space for mapping the input data via a nonlinear function to build a prognostic model of the cutting tool.

The learned model is exploited in online phase. The output result represents the health indicator as shown in Figs. 11, 12 and 13.

The input parameters of ELM are reported in Table 1. Several activation functions have been tested (Radbas, Tribas, Hardlim and Sigmoid). For selecting the best activation function, the RMSE testing was used. From the obtained results, a Sigmoid function is selected with hidden nodes of 20. The predicted RUL is finally obtained from the health indicator. The predicted RUL for the tested cutters C1, C4 and C6 are shown in Figs. 14, 15 and 16. From these figures, it can be seen that the predicted RUL fits better to the real one which is suitable for interventions before the real time of a failure.

The performances of the models are evaluated in terms of Relative Accuracy (RA) [16]. It can be observed from the results in Table 2 that RA is close to 1.

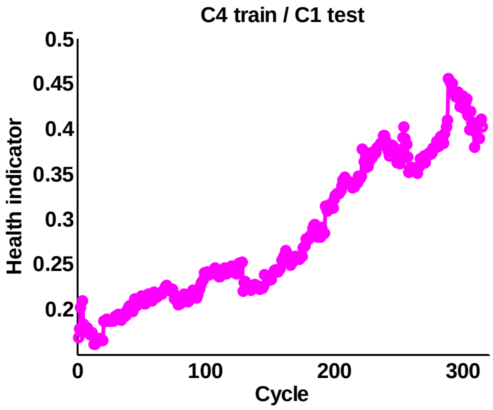
The obtained results show improvement in the performance in terms of accuracy compared to the approaches illustrated in literature [17], [18].

Table 1 MODEL PERFORMANCES OF ELM

Train cutter	Test cutter	Activation function	Hidden nodes	RMSE Testing
C4	C1	Sigmoid	20	0.0069
C6	C4	Sigmoid	20	0.0120
C1	C6	Sigmoid	20	0.0323

Table 2 Performance metric of the WPT-ELM based approach

Train cutter	Test cutter	Activation function	RA
C4	C1	Sigmoid	0.9091
C6	C4	Sigmoid	0.8643
C1	C6	Sigmoid	0.8512



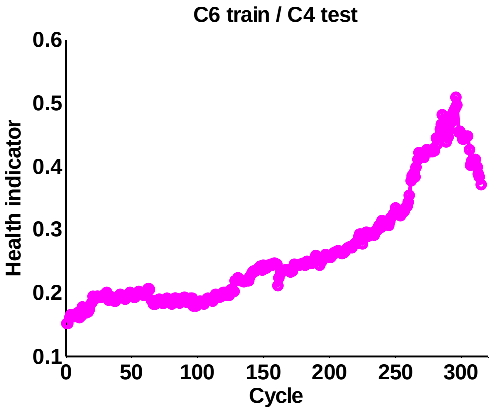


Fig. 11 the health indicator of cutter C1.Fig. 12the health indicator of cutter C4.

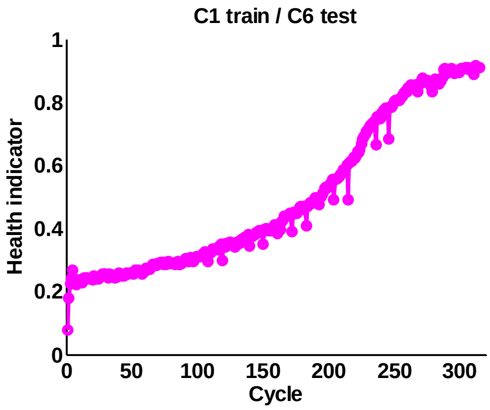
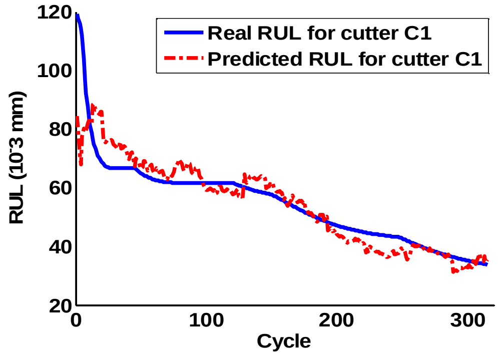


Fig. 13the health indicator of cutter C6.



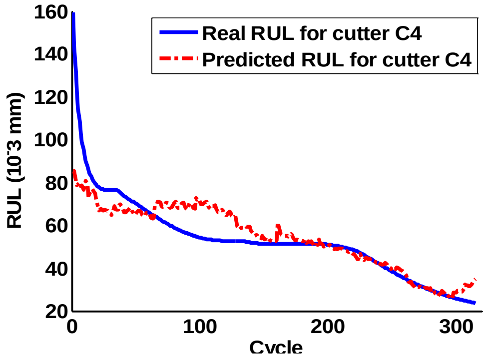


Fig. 14The predicted RUL for the cutter C1.Fig. 15The predicted RUL for the cutter C4.

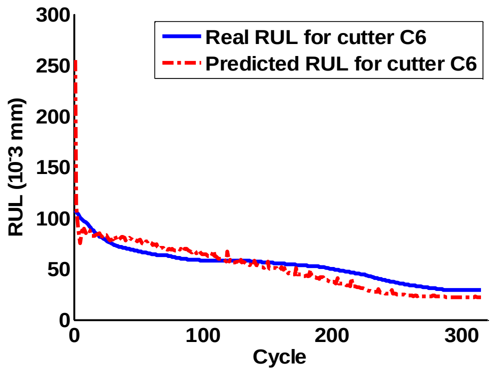


Fig. 16The predicted RUL for the cutter C6.

5. CONCLUSION

This paper presents a new approach based on wavelet packet transform and extreme learning machine for remaining useful life prediction of cutting tools. To enhance the accuracy of ELM model, a robust feature extraction method based on WPT was used. The proposed method is divided into two phases; firstly, the extracted features that reflect the tool degradation are used as inputs of learning algorithms ELM in order to build the model that represent the wear's behavior of the cutting tool. The learned model is finally exploited for health assessment and RUL estimation of the cutting tools. The method was applied and validated with real world data during several cuts of a milling CNC tool. It was found that the proposed approach is highly effective and justified its practical application in real time tool wear condition monitoring.

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