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To cite this article: Y C Liu *et al* 2019 *IOP Conf. Ser.: Mater. Sci. Eng.* **576** 012021

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**The 17th International Symposium on Solid Oxide Fuel Cells (SOFC-XVII)**  
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# Remaining Useful Life Prediction of Cutting Tools Based on Support Vector Regression

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**Abstract.** Remaining useful life (RUL) prediction of cutting tools is critical to effective condition based maintenance for reducing downtime, ensuring quality and avoiding accidents. In this paper, a RUL prognostic method based on support vector regression (SVR) is proposed for predicting cutting tool's life. The proposed method consists of two main phases: an off-line phase and an on-line phase. In the first phase, the signal features are extracted from raw data, and then the SVR models with considering different length of signals at past times are established to reflect the relationship between monitoring data and tool life. In the second phase, the constructed models are used to predict cutting tool's RUL, and the best signal length for accurate prediction result is obtained. The proposed method is applied on experimental data taken from a computer numerical control (CNC) rotor slot machine in a factory. The result shows the validity and practicability of this method.

## 1. Introduction

As the major equipment in manufacturing system, tool health condition has a great effect on product quality. Tool failure in the machine may lead to unscheduled downtime, quality issues and even serious accidents. It is estimated that about 20% of the downtime is attributed to tool failure, which result in significant economic losses[1]. Thus it is necessary for prognostic and health management (PHM) of cutting tools.

The main task of cutting tool prognostics is to estimate its remaining useful life (RUL), which is defined as the length from the current service time until it fails[2]. Most of the existing RUL prediction models can be divided into two main categories: physics-based models and data-based models[3]. The physics-based models are more accurate than others, but they require a complete understanding of the mechanistic knowledge and theories and are therefore very difficult to build for practical applications. The data-driven models attempt to derive models directly from historical condition monitoring (CM) data instead of building complicated models, and it is widely used in many fields. The data-driven methods mainly include: artificial neural network, Markov models, and support vector machine (SVM) et al. SVM is widely used for RUL prediction. Gokulachandran[4] compared two soft computing techniques, neuro fuzzy logic technique and SVR technique for cutting RUL prediction. Benkedjouh[5] and Shen [6] proposed the RUL prediction method based on SVR to assess bearing's degradations.



Benkedjouh[7] predicted the amount of wear and calculated the RUL of cutting tools by using SVR. Wu[8] predicted the RUL of aero-engine based on SVR.

Generally, the above approaches have achieved accurate RUL prediction results, which focused on establishing the relationship between the current monitoring data and machine health states. However, in reality, the machine health state is not only related to the current monitoring data, but also to the past times. Thus in this paper, a SVR based method with considering different length of signals at past times is proposed for RUL prediction. It consists of two main phases: an off-line phase and an on-line phase. In the first phase, the signal features are extracted from raw data, and then the SVR model with considering information at past times is established. In the second phase, the constructed models are used to predict cutting tool's RUL and the best signal length for accurate prediction result is obtained. The proposed method is validated by the experimental data taken from a computer numerical control (CNC) rotor slot machine in a factory.

## 2. RUL prediction model of cutting tools

### 2.1. SVR model

SVM is divided into two main categories: support vector classification (SVC) and support vector regression (SVR). SVR is the most common application form of SVMs. It has been proposed in 1997 by Vapnik[9]. The main objective of SVR is to map the data into a higher dimensional feature space and to estimate a relationship between input and output random variables under the assumption that the joint distribution of the variables is completely unknown.

Given a data set  $X = \{(x_i, y_i), i = 1, 2, \dots, l\}$ , where  $x_i \in R^N$  is the signal feature vector of the  $i$ th cutter,  $y_i \in R$  is the RUL of the  $i$ th cutter,  $l$  is the sample size. The regression function can be expressed as

$$y = f(x) = w\phi(x) + b \quad (1)$$

where  $\phi(x)$  denotes the high dimensional space transformation of AE features,  $w$  and  $b$  are the coefficients. The coefficients are estimated by minimizing the following regularized risk function:

$$R_{SVM} = \frac{1}{2} \|w\|^2 + C \frac{1}{N} \sum_{i=1}^N L(d_i, y_i) \quad (2)$$

$$R_{SVM} = \frac{1}{2} \|w\|^2 + C \frac{1}{N} \sum_{i=1}^N L(d_i, y_i) \quad (3)$$

$$L(d_i, y_i) = \begin{cases} |d_i - y_i| - \varepsilon & \text{if } |d_i - y_i| \geq \varepsilon \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where  $\frac{1}{2} \|w\|^2$  is the regularized term,  $L(d_i, y_i)$  is the  $\varepsilon$ -insensitive loss function,  $\varepsilon$  is the tube size of SVM, and  $C$  is the regularization constant determining the trade-off between the empirical error and the regularized term. Two variables  $\xi$  and  $\xi^*$  are introduced to representing the distance from desired values to the corresponding boundary values of the  $\varepsilon$ -tube, and the Eq. (2) can be rewritten as:

$$R_{SVM} = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^l (\xi_i + \xi_i^*)$$

$$s.t. \begin{cases} y_i - w^T \phi(x) - b \leq \varepsilon + \xi_i \\ w^T \phi(x) + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, i = 1, 2, \dots, l \end{cases} \quad (5)$$

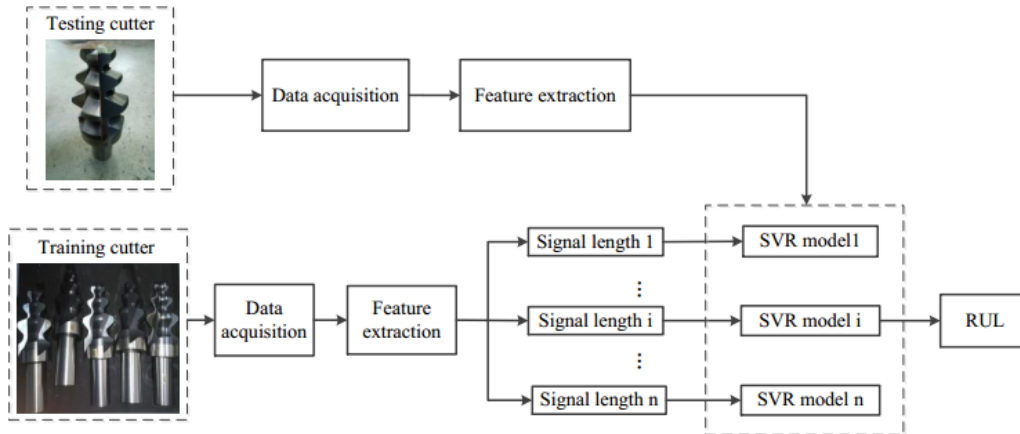
By introducing Lagrange multipliers and kernel function  $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ , the dual Lagrange form of Eq. (4) is given by:

$$R(a_i, a_i^*) = \frac{1}{2} \sum_{i=1}^l \sum_{j=1}^l K(x_i, x_j) (a_i - a_i^*) (a_j - a_j^*) - \sum_{i=1}^l y_i (a_i - a_i^*) + \sum_{i=1}^l \varepsilon (a_i - a_i^*)$$

$$s.t. \begin{cases} a_i, a_i^* \in [0, C], \quad i = 1, 2, \dots, l \\ \sum_{i=1}^l (a_i - a_i^*) = 0 \end{cases} \quad (6)$$

Finally, the regression function Eq. (1) is transformed into:

$$y = f(x) = \sum_{i=1}^l (a_i - a_i^*) K(x_i, x_j) + b \quad (7)$$



**Figure 1.** The framework for RUL prediction.

## 2.2. The Framework for RUL Prediction.

The framework for RUL prediction of cutting tools is shown in Figure 1. The principle of the proposed method relies on two main phases: an off-line phase and an on-line phase. In the first phase, the signal features are extracted from raw monitoring data, and then the SVR models with considering different length of data at past times are established to reflect the relationship between monitoring signals and tool life. In the second phase, the constructed models are used to predict cutting tool's RUL, and the best signal length for accurate prediction result is obtained.

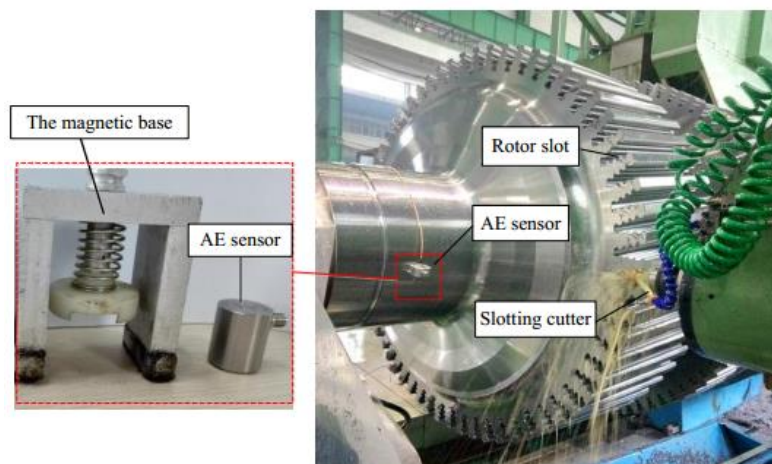
### 3. Application and results

#### 3.1. Experiment Setup.

The experiment was carried out on a special turbine rotor slotter of a factory, as shown in Figure 2. The workpiece material was high strength low alloy structural steel 30Cr2Ni4MoV and the material of J1-formed 4-flute slotting cutter was powder metallurgy high speed steel (PM HSS) M42-4. The experiment data were obtained under constant conditions. The cutting parameters were: the spindle speed of the slotting cutter was 200 rpm and the feed rate was 15mm/min.

The PCI-2 based AE system was adopted in this experiment and it was fixed on the rotor through the magnetic base, as show in Figure 2. Though it maybe a litter far away from the machining position than fixed on the machine tool, it can avoid the interference of external factors such as machine tool vibration, the impact of cutting fluid, and get more useful information.

The operating frequency of the sensor is from 100 to 450 KHz and the sampling frequency was set at 1 MHz. The flank wear value was measured at the end of each cutter's life by using an optical microscope XDC-10A-E630. The mean wear of the four flutes was considered as the wear status of slotting cutter. In this paper, a total of 7 J1-formed slotting cutters were used during the experiment. Among them, cutter no.3 is used to verify the proposed method. The wear threshold is set as 125 $\mu$ m considering the actual experience of the factory.



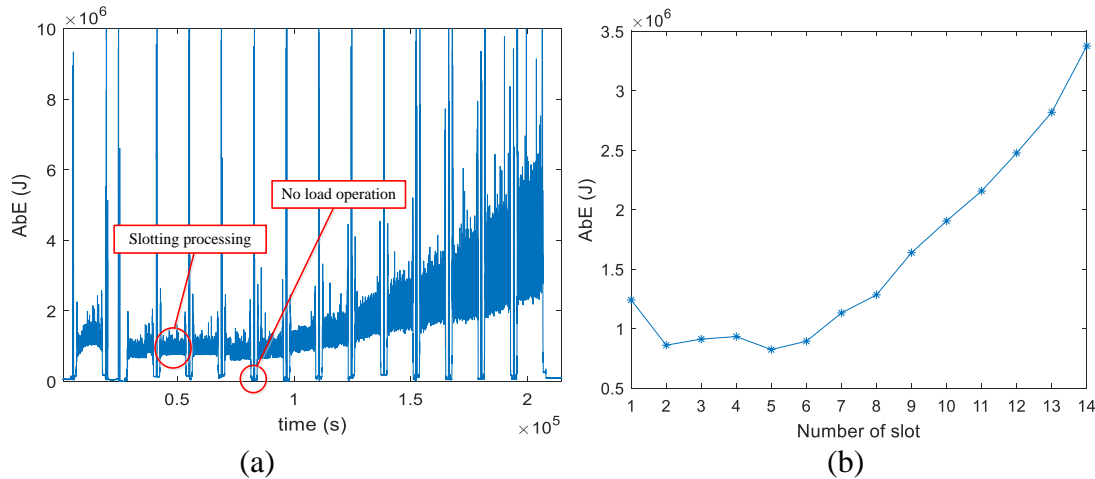
**Figure 2.** Experimental setup for RUL prediction of slotting cutter.

#### 3.2. Signal Analysis.

AE is one of the most effective signals for tool wear monitoring, especially for the industrial applications. It can avoid the interference of external factors because the frequency of AE signals is much higher than that of machine vibration and environmental noises [10, 11]. Previous studies [12-14] have shown some AE features can indicate tool wear, in this work, 14 features are extracted: rise time(RT), counts(C), energy(E), amplitude(A), average frequency(AF), root mean square(RMS), average signal level(ASL), Counts To Peak(CTP), Reverberation Frequency(RF), Initiation Frequency(IF), Signal Strength(SS), Absolute Energy(AbE), Frequency Centroid(FC), and Peak frequency(PF).

Taken AbE as an example, the signal changes with time is shown in Figure 3 (a). It can be seen that The AbE values increase along with time, and each slotting processing cycle consists of two stages: slotting processing stage and no-load operation stage. For the convenience of analysis, the mean values

of the above features change over each slot processing stage were calculated by using Matlab software. The feature AbE changes with the number of processed slots is shown in Figure 3 (b).



**Figure 3.** AbE of AE signal features.

Although the above mentioned features are indicative of tool wear from different aspects, they have different important degrees. Some features are salient and closely related to the wear, but others are not. Thus, it is necessary to select the important and discard the irrelevant features. Correlation coefficient between two vectors  $x$  and  $y$  can be calculated by equation

$$\rho(x, y) = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2} \sqrt{\sum (y - \bar{y})^2}} \quad (8)$$

where  $\bar{x}$  and  $\bar{y}$  are the mean values of  $x$  and  $y$ , respectively. The value of  $\rho$  ranges between  $-1$  and  $+1$ . The larger the absolute value of  $\rho$ , the higher the degree of correlation.

According to Eq. (10), the correlation coefficient between the above 14 features and tool wear when the cutting tools were replaced are calculated and displayed in Table 1.

**Table 1.** Correlation coefficients between AE features and tool wear.

AE feature	Correlation coefficients	AE feature	Correlation coefficients
RT	0.1148	CTP	0.1640
C	0.1582	RF	0.2890
E	0.7566	IF	0.3111
A	0.6672	SS	0.7164
AF	0.2235	AbE	0.7089
RMS	0.8483	FC	0.2247
ASL	0.6689	RF	0.2507

It can be seen that these 6 features E, A, RMS, ASL, SS, and AbE is significant correlated with tool wear. They compose the input vector  $X = [E, A, RMS, ASL, SS, AbE]$  of the ARMA and SVR model. The extracted features are normalized to  $[0.1, 0.9]$  by the follow equation:

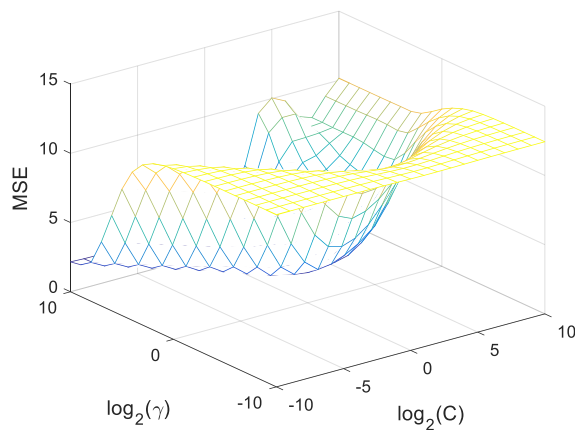
$$y = 0.1 + \frac{(0.9 - 0.1)}{(x_{\max} - x_{\min})} \times (x - x_{\min}) \quad (9)$$

where  $x$  is the feature vector to be normalized;  $x_{\min}$  is the minimum value of  $x$ ;  $x_{\max}$  is the maximum value of  $x$ ;  $y$  is the normalization result.

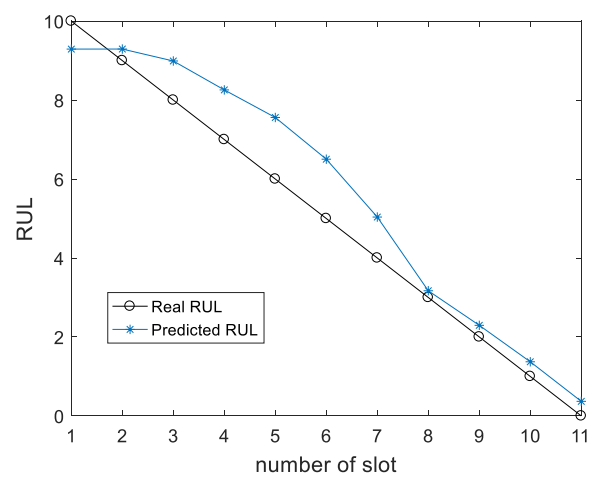
### 3.3. RUL Prediction

In this paper, cutter no.3 is used to verify the proposed method, and the other six cutters are used for modeling. Assuming the RUL of cutting tools is only related to the condition monitoring signal of current slot. The AE features extracted from the six cutters during their whole working life compose the input vector  $X = [E, A, RMS, ASL, SS, AbE]$  of SVR model. Then the RUL of tool life-cycle are the output of this model.

The common kernel functions used for SVR approaches are linear, polynomial, and RBF. Literature demonstrates that the RBF kernel outperformed the others in most scenarios. Thus in this paper, RBF kernel  $K(x, y) = \exp(-\gamma |x - y|^2)$  is employed to train SVR model. By using grid search method, the optimal values of the parameters are obtained  $\varepsilon = 0.1$ ,  $C = 4$  and  $\gamma = 0.5$ . The grid search result is shown in Figure 4. After being trained, SVR model is used to predict the RUL of cutter no.3, and the prediction result is shown in Figure 5.



**Figure 4.** Grid search result.



**Figure 5.** RUL prediction result.

In order to evaluate the performance of the prediction result, the following prognostic metrics are used in this paper: accuracy, mean absolute error and mean relative error. The three metrics can be expressed as:

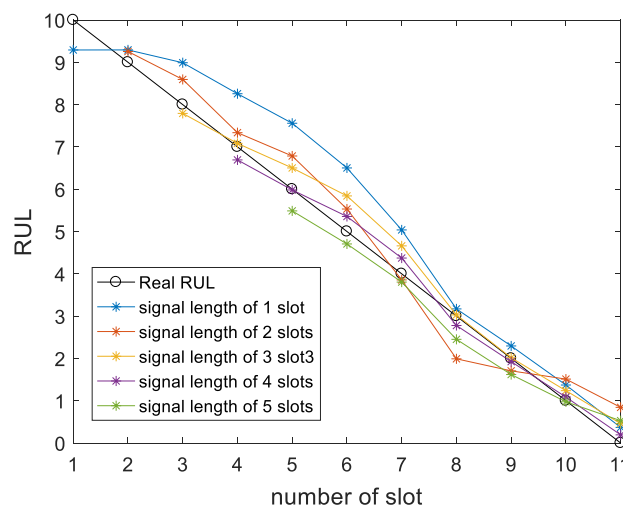
$$\text{Accuracy} = \frac{1}{C} \sum_{c=1}^C e^{-|RUL_{real}(c) - RUL_{estimated}(c)| / RUL_{real}(c)} \quad (10)$$

$$\text{MAE} = \frac{1}{C} \sum_{c=1}^C |RUL_{real}(c) - RUL_{estimated}(c)| \quad (11)$$



$$MRE = \frac{1}{C} \sum_{c=1}^C \left| \frac{RUL_{real}(c) - RUL_{estimated}(c)}{RUL_{real}(c)} \right| \quad (12)$$

It can be calculated that the Accuracy=0.8399, MAE=0.7777 and MRE=0.1802. Similarly, assuming the RUL of cutting tools is not only related to the current slot monitoring signal but also the past N slots machining data. In this paper, the value of N is 0, 1, 2, 3 and 4. Repeat the above procedures, and calculate the RUL of cutter no.3 when N is 1, 2, 3 and 4, respectively. The RUL prediction results of different signal length are shown in Figure 6. The three prognostic metrics were calculated and shown in Table 2.



**Figure 6.** RUL prediction result of different signal length.

**Table 2.** Results of prognostic metrics.

N	Accuracy	MAE	MRE
0	0.8399	0.7777	0.1802
1	0.8635	0.5305	0.1576
2	0.9183	0.3374	0.0887
3	0.9435	0.2039	0.0586
4	0.9079	0.3550	0.0986

It can be seen that when the monitoring data of the past slot machining process is taken into consideration, the RUL prediction results are more accurate than those only used the current slot machining signals. The prediction results are the best when the machining process of the past 3 slots is considered and the best prediction accuracy is 0.9435.

#### 4. Conclusion

In this paper, a RUL prognostic method based on support vector regression (SVR) is proposed to predict cutting tool life. The proposed method consists of two main phases: an off-line phase and an on-line phase. In the first phase, the signal features are extracted from raw data, and then the SVR models with considering different length of signals at past times are established to reflect the relationship between monitoring signals and tool life. In the second phase, the constructed models are used to predict cutting tool's RUL, and the best signal length for accurate prediction result is obtained. The proposed method is applied on experimental data taken from a computer numerical control (CNC) rotor slot machine in a



factory. The best RUL prediction accuracy reaches 94.35%. The result shows the validity and practicability of this method.

Future work will include developing the RUL prediction method with considering different signal length of past times at different machining times, since the cutting tool condition at different times maybe depends on different length of condition monitoring readings. Furthermore, other algorithms like neural network will be investigated to compare with the proposed method.

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## Acknowledgements

This research is supported by National Natural Science Foundation of China (Grant No. 51435009).