Cutting tool life prediction using symptom reliability and vibration signals in milling process of ST-52-3 steel

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Abstract
Tool wear during machining is inevitable since it is inherent to any cutting process because of high level of stresses, friction and temperature to which the tool is subjected. However, machining with a worn tool may not only affect the tolerances, but also the machine tool. The tool wear leads to undesirable vibration and it influences tool change strategies, dimensional quality of product and productivity. It has been shown that tool failure contributes on average up to 6.8% to breakdown time in machining centers. Tool wear monitoring by indirect methods offers possibilities of successful on-line implementation. The use of vibration based monitoring has its success conditioned on the definition of features able to capture the evolution of tool condition. This work aims to estimate residual life of cutting tool in milling as a function of a well defined vibration symptom (feature). The concept of symptom reliability is used to predict the tool life during a milling process based on vibration measurement. .

1 Introduction

The cutting tools are subjected to very high surface stresses, high temperatures, chip sliding on the cutting surface and sliding of the main relief surface on the machined surface. These conditions lead to mechanical and thermal damage, i.e to tool wear. Working with a worn out tool has negative impact on the quality of machined worpiece in terms of surface roughness and dimensional accuracy. Tool wear also leads to high cutting force and undesirable vibration which can contribute to the surface quality deterioration; in the worst case, it can result in tool breakage [1]. It has been shown that tool failure contributes on average up to 6.8% to breakdown time in machining centers [2].

Whatever the machining technique used, when examining tools of different compositions (high-speed steel, carbides, cermets, ceramics, etc.), one notes a wide range of wear facies. Some are broken (edge breaks), others are chipped. Most have a geometry that evolved almost continuously (worn tools). Apart from the ruins of tools by chipping and micro-chipping, it can be observed that each of these cases gives rise to more or less rapidly three typical facies of damage (figure 1):

1. formation of a crater on the rake face, the maximum depth of which is commonly referred to as KT; The strength of the tool decreases as KT increases;

2. a flat frontal wear area on the main flank face, the average height of which is commonly indicated by the symbol VB. As VB increases, the cutting edge moves back and the dimensions deviate from the target value;

3. formation of a grooves on the flank faces at the edge of the cutting zone. The condition of the machined surface is all the more deteriorated as these grooves are more developed.

In order to decide whether the tool is used or not, quantitative criteria must be established. Two approaches are possible:

- one can choose to link these criteria to the dimensional degradation of the parts and the quality of their surface. A state of wear is then declared if one moves away from a certain tolerance zone for the dimensions and the surface roughness. This approach requires measuring the dimensions and surface condition of each workpiece;
- the second approach defines criteria related to wear measured directly on the tool.

The second approach is often preferred to the first. The most commonly used criterion is based on the measurement of flank wear (VB), because it is the type of wear that most influences the quality of the generated surface. A standard measure of tool life as proposed by the NF E66-505 and ISO 3685 standards is the time required to develop an average VB wear of 300 μm when wear is relatively uniform and easy to measure, therefore mainly caused by abrasion. On the other hand, when the wear presents an irregular profile, the average flank wear is no longer a tool life criterion, VBmax = 600 μm is used (Figure 1).

However, other sources argue that fixing the maximum wear to a given VB can lead to serious economic mistakes, because some tools used for roughing pass and having large cutting edge dimensions can support VB up to 1 mm while remaining within a permissible operating mode [3]. Unlike flank wear, the crater does not influence the finish of the surface. It may, however, under certain thermal conditions, result in a sudden failure of the tool. A KT crater depth of 0.05 mm to 0.1 mm is considered as an end-of-tool criterion (Figure 1).

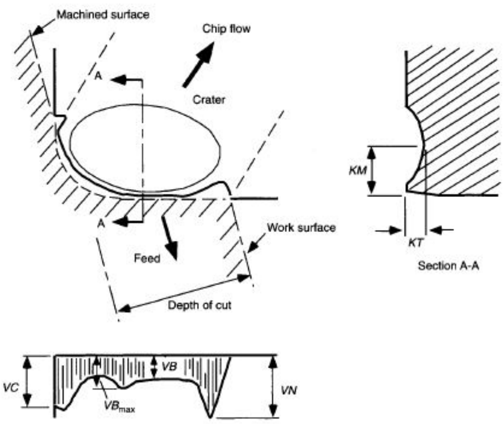

Figure 1: Wear pattern for a carbide tool ([3])

It is obvious that direct measurement of tool wear in production environment is as not feasible as the systematic check of surface quality of machined part. That is the reason why in mass production, a simple approach based on the number machined parts is often used.

Indirect tool monitoring methods, in contrast to the direct methods, proceed by evaluating the wear on the basis of the parameters measured during the cutting process: cutting forces, acoustic emission or vibrations. Indirect methods are usually online methods. Online ability to monitor the tool state and to predict its residual life is important, on the one hand for a rational management of production time and on the other hand to guarantee the quality of the parts machined in term compliance with tolerances and surface condition. There is therefore a real need for methods to detect the occurrence of wear and to monitor its evolution as part of a "just-in-time" tool change policy [4, 5]. Tool wear monitoring by indirect methods offers possibilities of successful online implementation, and can enable the implementation of such a policy. Among the indirect monitoring techniques, vibration monitoring are cheap to implement, but its successfull use is conditioned on the definition of good and relevant features able to capture the evolution of tool condition.

In general, feature-based monitoring compares the feature values to predefined thresholds to decide on the state of the monitored process. The prediction of future state is based on the time when a projected feature trajectory hits the threshold level. It comes that threshold definition is a crucial step in a such approach.

This work exposes a threshold-free approcach based on symptom reliability to online assess the residual life of a cutting tool.

2 Symptom reliability

2.1 The concept

The traditional concept of reliability is based on the statistics of failure time. Another approach to the reliability concept was introduced by Natke and Cempel [7, 8] by making it follow from the theory of the energy model of mechanical systems damage. Under this approach, the energy balance of a mechanical system can be written as

$$N_i = N_u + N_d \tag{1}$$

where N_i is the input power, N_u the usable power and N_d the total dissipated power. This latter power is due to the variation of two energy quantities E_d and V and which are respectively internal and external dissipation. The internal dissipation E_d results in damage to the system (wear, for example), while the external is expressed by observable symptoms S (vibration, temperature, noise, ...).

If θ is the system lifetime and θ_b the breakdown time, by adopting a linear model of damage one defines the dimensionless cumulated damage as

$$D = \frac{\theta}{\theta_b} \tag{2}$$

so that the damage $D = 0$ at the beginning and $D = 1$ at breakdown.

The residual life at a time $t = \theta$ is estimated by $\theta_b - \theta$ leading to the dimensionless damage capacity ΔD,

$$\Delta D = 1 - D = 1 - \frac{\theta}{\theta_b} \tag{3}$$

The mechanical system monitoring can be based on comparing the symptom $S(\theta)$ to a limit S_l, not necessarily equal to $S_b = S(\theta_b)$ the symptom value at breakdown. As long as the inequality $S < S_l$ is verified, the system can be considered as in "good condition", otherwise there is a failure.

In [9], the authors define the symptom reliability $R(S)$ as the probability that a system characterized by $S < S_l$, i.e. classified as in good condition, will be operational. It comes that

$$R(S) \equiv P(S_b > S | S < S_l) \equiv P_G(S_b > S) \tag{4}$$

This definition can be justified by assuming that measurements $\{S_i\}$ at different dates θ_i are available for a set similar equipments. One assumes also that all the limitations imposed to the definition are respected. At a time increment $\delta\theta$, the measured symptom becomes $S_i + \delta S_i$ with $\delta S/S << 1$, and some of the equipments can experience a failure, i.e d $S + \delta S \geq S_b$. Thus, following its definition, the symptom reliability at $S + \delta S$ can be written as the conditional probability, given $S < S_b$:

$$\begin{aligned} R(S+\delta S) &\equiv P_G(S+\delta S \leq S_b | S < S_b) \\ &= P_{GG}(S+\delta S < S_b | S < S_b) + \\ &\quad P_{GF}(S+\delta S \geq S_b | S < S_b) \end{aligned} \tag{5}$$

with $P_{GG}(.)$ the proability the system doesn't fail after the time increment δS, and P_{GF} the failure probability when the symptom is increased by δS. The probability of failure can be assessed as follows:

$$\begin{aligned} P_{GF}(S+\delta S \geq S_b | S < S_b) &= \frac{P(S < S_b \leq S+\delta S)}{P_G(S < S_b)} \\ &= \frac{P_G(S) - P_G(S+\delta S)}{P_G(S)} \\ &= \frac{R(S) - R(S+\delta S)}{R(S)} \\ &= h(S)\delta S - ... \\ &\cong h(S)\delta S \end{aligned} \tag{6}$$

The just introduced function $h(S)$ represents the symptom-based risk function. Physically, $h(S)$ can be seen as the failure intensity for a unit increment of the symptom:

$$h(S) \equiv -\frac{d \ln R(S)}{dS} \tag{7}$$

The symptom reliability can then be related to the damage capacity or residual life ΔD:

$$R(S) = 1 - D = \Delta D \tag{8}$$

This theory of mechanical damage is consistent with reliability models described by the following distributions of $R(S)$:

- Weibull, $S > 0$

$$R(S) = \Delta D = exp\left[-\left(\frac{S}{S_0}\right)^{\gamma}\right] \tag{9}$$

- Fréchet, $S > 0$

$$R(S) = \Delta D = 1 - exp\left[\left(-\frac{S}{S_0}\right)^{-\gamma}\right] \tag{10}$$

- Pareto, $S \geq S_0 > 0$

$$R(S) = \Delta D = \left(\frac{S}{S_0}\right)^{-\gamma} \tag{11}$$

where $S_0 = S(\theta = 0)$.

The life curve of an equipment can be expressed as

$$\frac{S}{S_0} = f(D) \tag{12}$$

2.2 Use of symptom reliability for online tool life prediction

When signal-based indirect methods are used, features sensitive to wear must be extracted. The monitoring procedure can use this features with a classifiers trained to recognize specific tool conditions [10, 11]. This implies that historical data should be available to train the classifiers. An alternative option is to define thresholds on the monitoring features and to predict when the feature trajectory will hit the threshold level. The drawback of this approach is the classical difficulty to define reliable thresholds and the dependency of the tresholds on tool and workpiece materials as well as on the cutting parameters.

When symptom reliability method is used, for instance with the Weibull distribution, on can write

$$S_n(\theta) = \left[-\ln\left(1 - \frac{\theta}{\theta_b}\right)\right]^{1/\gamma} + C \tag{13}$$

where $S_n(\theta)$ is the symptom feature at time θ, θ_b is the breakdown time, γ and C are model parameters.

Figures 2 and 3 illustrate a symptom curve and its related damage curve.

The monitoring procedure consists in estimating the reliability model parameters at each time step. The breakdown time θ_b provides information on the remaining life of the tool and correponds to a damage level $D = 1$. The remaining useful life can then be defined as corresponding to a predetermined damage level, for example 0.75.

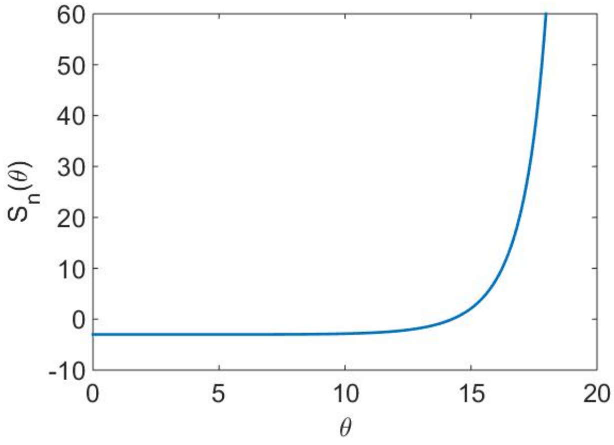

Figure 2: Shape of the symptom trajectory based on Weibul distribution

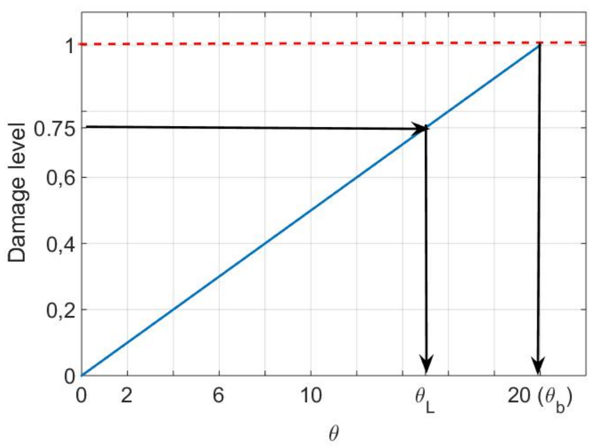

Figure 3: Damage curve

3 Experimental study

3.1 The setup

The data used in this study are acquired during a milling process of the ST-52-3 steel with a high speed cylindrical end mill (diameter 8 mm, 2 flutes, helix angle 30^o), (see Figure 4) [12]. Successive slots are realized in the steel bloc until the tool fails (VB=300μm). The accelerometer is attached to the workpiece and the data are sampled at 25 kHz using NI cDaq 9172 acquisition system. Signal of 10 seconds duration are recorded successively during the process. The cutting conditions are: a spindle speed of 875 rev/min, an axial depth of cut of 4mm, a radial depth of cut of 1mm and a feed rate of 0.04 mm/tooth.

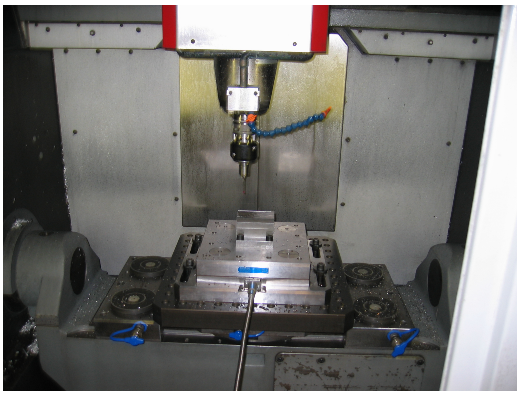

Figure 4: The experimental setup

Figures 5 and 6 show typical signals and their spectra recorded at begining and at the end of life of the tool. In the time signals one can notice events corresponding to when the two teeth enter and exit the material. The global energy of the vibration increases with the wear, however a thorough analysis shows that the difference is mainly coming from the frequency range 2-7 kHz. This suggest to develop features based on filtered signals in this range.

3.2 Definition of the tool wear vibration symptom

Since the initiation of wear is manifested by micro-shocks and its increase induces a general vibrational level increase, we use the crest factor A_{fc} and the rms value A_{rms} in the considered frequency range (2-7kHz) to build wear indicators. In order to take into account the time memory of the tool and the time dependency

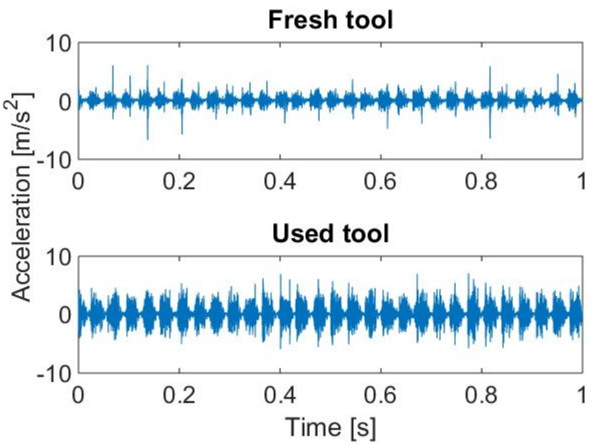

Figure 5: Typical signals relative to fresh and worn tool, respectivelly

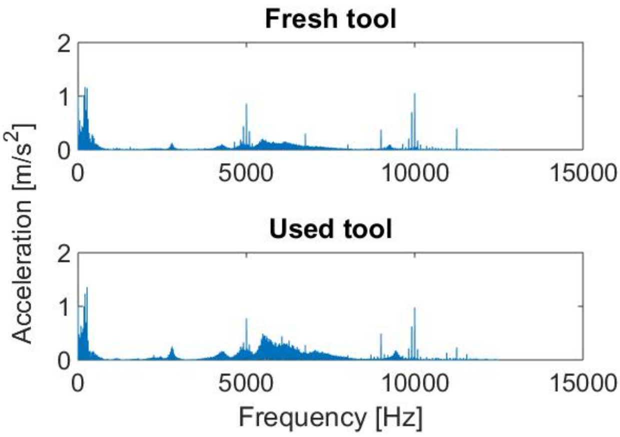

Figure 6: Typical spectra relative to fresh and worn tool, respectivelly

between successive measurements, the running averages of the above mentionned quantities are calculated:

$$Z_{\mathrm{rms}}(t_{\mathrm{i}}) = \frac{1}{i}\sum_{k=1}^{i} A_{\mathrm{rms}}(t_{\mathrm{k}}) \tag{14}$$

$$Z_{\mathrm{fc}}(t_{\mathrm{i}}) = \frac{1}{i}\sum_{k=1}^{i} A_{\mathrm{fc}}(t_{\mathrm{k}}) \tag{15}$$

The running mean rms will have an increasing trend beacause of high vibration energy when wear progresses, and the running mean crest factor will present a decreasing trend. We define the monitoring feature as the ratio of the two

$$\mathrm{Feat}(t_{\mathrm{i}}) = \frac{Z_{\mathrm{rms}}(t_{\mathrm{i}})}{Z_{\mathrm{fc}}(t_{\mathrm{i}})} \tag{16}$$

Figure 7 depictes the march of the monitoring feature for the complete life of the tool. The shape of the curve suggests the use of Weibull distribution for the symptom reliability.

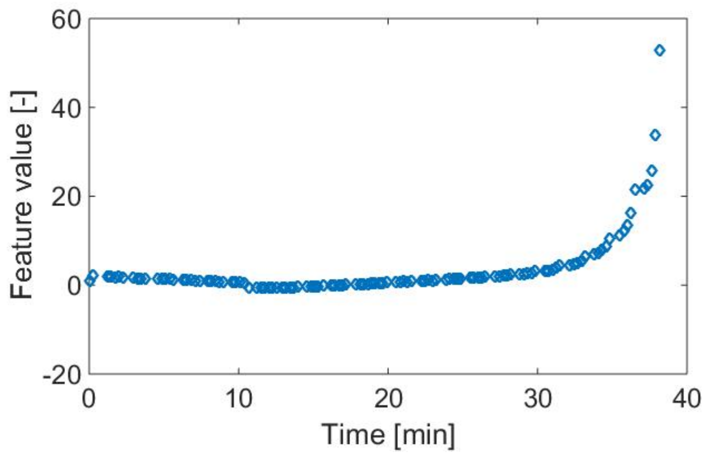

Figure 7: March of the defined feature for the complete life of the tool

3.3 Results and discussion

The model parameters are estimated at each step and the tool end-of-life is predicted (figure 8).

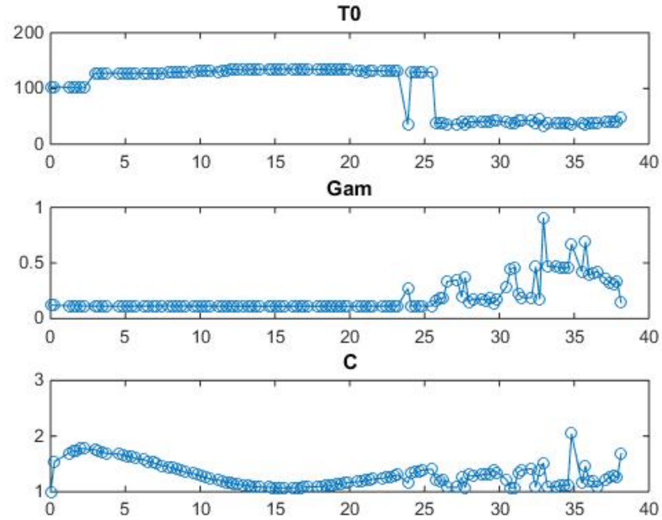

Figure 8: Evolution of estimated parameters at each time step

On figure 9, symptom trajectories are predicted using the already received data points. The represented trajectories correspond to 10, 80, 90, 100 and 117 data points (the run to tool end-of-life comprises 117 data points).

Figure 10 shows the estimated tool damage at each time step. We notice two zones correponding to moderate and high tool wear rate, respectivelly. The second zone is detected 10 minutes prior to the machining test stop. The cutting tool was inspected at the end of the test. One of the cutting tooth presented $\mathrm{VB}_{\max} = 264\mu$m, a value close to the limit of 300 μm indicated in section 1 (see figure11).

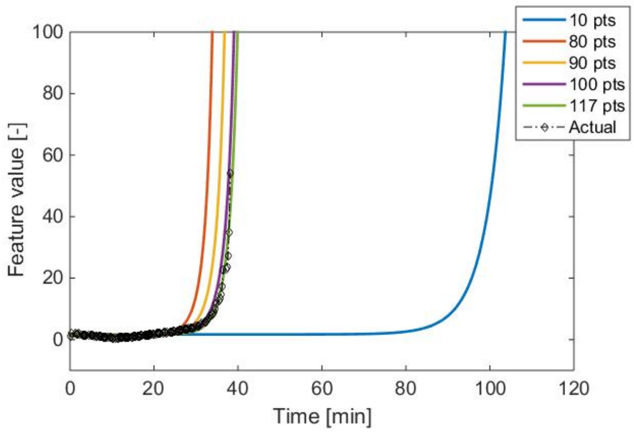

Figure 9: Predicted symptom trajectories

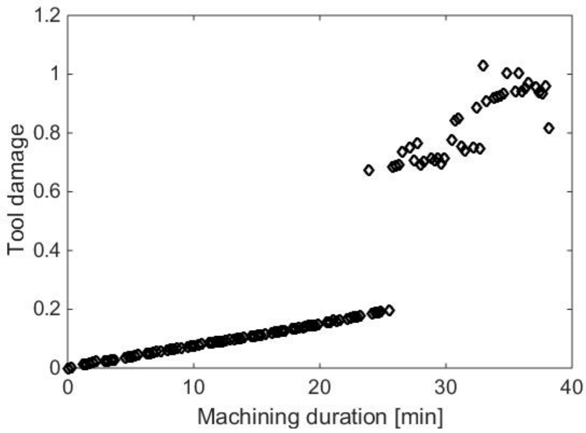

Figure 10: Evolution of estimated parameters at each time step

The remaining tool life is estimated at each time step as $RUL = \theta - \theta_b$. Figure 12 shows also the two zones corresponding to the wear rate. It can also be noted that the tool end-of-life can accuratly be estimated 10 minutes in advance.

4 Conclusion

This paper has demonstrated the use of symptom reliability for tool life prediction using vibration signals. This approach has the advantage of being able to estimate the end of life without needing a predefined threshold. Furthermore, it is independant on the combination tool-material because of its threshold-free character. The end of life is decided based on damage level only rather than on a threshold set on the monitoring feature. A simple

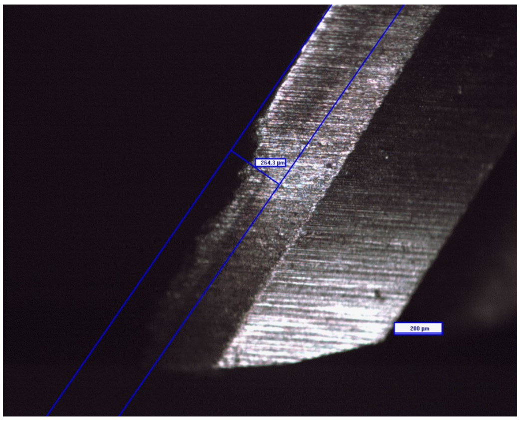

Figure 11: Tool condition at the end of the test

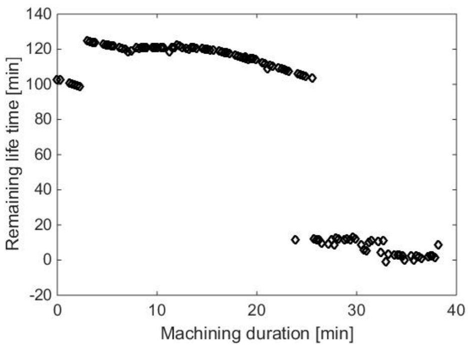

Figure 12: Estimated remaining tool life

usage can consist in changing the tool when a predefined damage level is reached.

The experimental case used in this work showed that weibull distribution was well suited to the defined feature. However, in practice, one can run in parallel different distribution models (weibull, Fréchet or Pareto) to select the one which converges consistently. Although the work presents a single test for a specific combination of tool-material and cutting parameters, the authors think that the approach can be apply to any cutting situation since the reliability model is learning its parameters online based on incoming data. Extensive experiments are planned with different tool-material pairs and cutting parameters to validate the approach.

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