



Enhancing cutting tool sustainability based on remaining useful life prediction

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ABSTRACT

As a critical part of machining, cutting tools are of great importance to sustainability enhancement. Normally, they are underused, resulting in huge waste. However, the lack of reliable support leads to a high risk on improving the cutting tool utilization. Aiming at this problem, this paper proposes an approach to enhance the cutting tool sustainability. A non-linear cutting tool remaining useful life prediction model is developed based on tool wear historical data. Probability distribution function and cumulative distribution function are used to quantize the uncertainty of the prediction. Under a constant machining condition, a cutting tool life is extended according to its specific remaining useful life prediction, rather than a unified one. Under various machining conditions, machining parameters are optimized to improve efficiency or capability. Cutting tool sustainability is assessed in economic, environmental and social dimensions. Experimental study verifies that both material removal rate and material removal volume are improved. Carbon emission and cutting tool cost are also reduced. The balance between benefit and risk is achieved by assigning a reasonable confidence level. Cutting tool sustainability can be enhanced by improving cutting tool utilization at controllable risk.

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1. Introduction

As a critical machining resource, cutting tools are of great importance to sustainability enhancement. Although cutting tool cost is less than 4% of machining cost (Astakhov, 2017), their abnormal states account for 10–40% of the total downtime of machine tools, and indirectly affected up to 30% of total machining cost (Liu et al., 2018). Production of cutting tools needs many types of rare metal, including tungsten, chromium, molybdenum, vanadium, cobalt, etc. In the process of mining, smelting, forging, rolling and machining, great mineral resources and energy are used (Li et al., 2015). Consequently, the more durable and capable a cutting tool is, the more cost, resource and energy could be saved.

Unfortunately, to avoid poor surface quality, shock and vibration

caused by overuse, cutting tools are normally underused, resulting in huge waste. Study showed that only 50–80% of cutting tool life was rationally used (Zhou and Xue, 2018). American companies e.g. Kennametal believed that up to 30% cutting tool life could be saved (Liu et al., 2018). European and Japanese manufacturers used less than or equal to 70% of cutting tool life (Martinova et al., 2012). Inevitably, underuse may lead to cutting tool life reduction, machining cost increment, and cutting tool utilization waste (as shown in Fig. 1). Although a cutting tool has potential utilization, how to unleash it is very tough. The lack of reliable support puts cutting tool life extension, and material removal rate (MRR) or material removal volume (MRV) improvement at a great risk.

Under a certain machining condition (MC), every cutting tool's utilization could be extended further to reduce cutting tool consumption, to save machining cost, and to enhance sustainability (Schultheiss et al., 2013). However, cutting tools' lives vary greatly, even if they are the same type produced by the same manufacturer. Within a single batch, tool life of Russian production may vary widely by 15–40% (Martinova et al., 2012). Moreover, every cutting tool has its unique and dynamic wear curve. Without quantized

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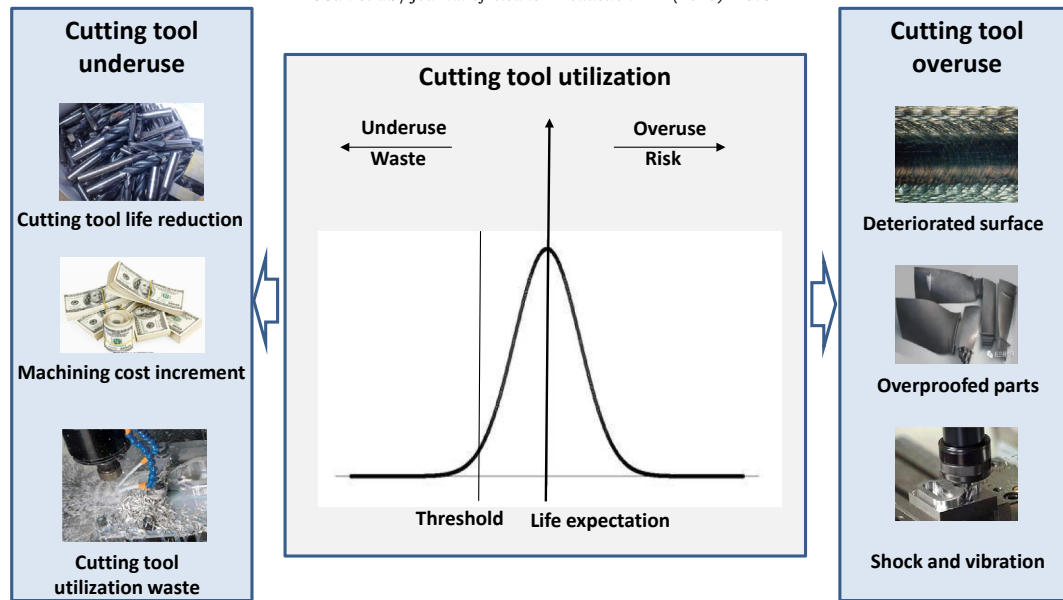


Fig. 1. Paradox in cutting tool utilization.

uncertainty, cutting tool remaining useful life (RUL) prediction is not reliable enough for cutting tool selection or replacement decision-making (Sun et al., 2018).

Under various MCs, cutting tools could be used further by optimizing machining parameters for higher efficiency. Then, fewer cutting tools are needed to finish assigned machining tasks. However, multiple variables affect the cutting tool wear curve. Due to the lack of a reliable basis, machining parameter optimization for higher efficiency faces a huge barrier.

This work aims to enhance the sustainability by making cutting tool more durable and capable. A cutting tool could be used based on its specific RUL prediction. Machining parameters could be optimized to improve cutting tool utilization. Benefit and risk could be balanced by assigning a proper confidence level. Cutting tool sustainability could be improved in economic, environmental and social dimensions.

The rest of this paper is organized as follows. Section 2 presents a brief review of literature related to cutting tool sustainability and RUL prediction. Section 3 proposes the sustainability improvement approach based on RUL prediction. Several sub-sections are included to address some key issues, respectively. An experimental study is presented in Section 4, which is followed by concluding remarks in Section 5.

2. Literature review

2.1. Cutting tool sustainability assessment

Due to scarcity of natural resources and increasingly strict regulations, sustainable manufacturing has become a hot topic both in academia and industry (Huang and Badurdeen, 2017). Metrics for sustainable manufacturing were investigated in economic, social, and environmental dimensions of the triple bottom line (TBL) concept (Lu et al., 2012; Reich-Weiser et al., 2013; Peralta et al., 2017). Manufacturing sustainability was also evaluated based on the correlation between TBL dimensions and balanced scorecard perspectives (Junior et al., 2018). Cutting tool sustainability is included in manufacturing sustainability, but related research is very limited.

Cutting tools' economic sustainability was normally assessed by using cutting tool cost. However, cutting tool cost accounted for a

small share of machining cost (Zhou and Xue, 2018). On the other hand, the frequency of cutting tool replacement affected downtime of machine tools. Then, machining efficiency was considered in cutting tools' economic sustainability assessment (Astakhov, 2019).

The concept of life cycle assessment (LCA) or life cycle sustainability assessment (LCSA) (Gbededo et al., 2018) was used in cutting tool's environmental sustainability assessment. Production of cutting tools needed both plenty of energy and mineral resources, when huge carbon emission was produced (Yi et al., 2015; Zhou et al., 2017). For example, tungsten is a rare and non-renewable metal. Approximately half of the tungsten in the world was consumed to produce carbide cutting tools (Schultheiss et al., 2013). Tungsten embodied material energy 400 MJ/kg. Production of a carbide insert consumed 1–2 MJ energy on average (Gutowski et al., 2009). If the energy footprint of its material was considered, the energy consumption was 5.3 MJ (Rajemi et al., 2010). Environmental impact rating of cutting tool production was 33.7478 kgCO₂/kg (Hegab et al., 2018). Production of cutting tools consumed huge resource and energy (Loglisci et al., 2013). The more cutting tools were used, the poorer the environmental sustainability was. In the machining process, worn cutting tools were believed to increase energy consumption.

Normally, social sustainability is the ability of a social system, such as a country, to function at a defined level of social well-being indefinitely (Lu et al., 2011). Regarding an enterprise, social sustainability relates to personnel health, operational safety, stakeholder engagement (Huang and Badurdeen, 2017), risk assessment (Reich-Weiser et al., 2013), and so on. To the best of the authors' knowledge, study on social sustainability of cutting tools is rare.

2.2. Cutting tool life estimation and RUL prediction

Cutting tool life extension should be based on accurate life estimation. In the past few years, these topics attracted great attentions. Traditional cutting tool life estimation used statistic models, such as normal distribution, lognormal distribution, and Weibull distribution. In addition, Bernstein distribution function was also used as a practical approach to the cutting tool reliability improvement (Astakhov, 2010).

Normally, cutting tool life was measured in the time dimension. Although many cutting tool manufacturers have developed cutting

tools with longer life at higher cutting speeds, few manufacturers have worked to develop cutting tools that have less variability in life (Black and Kohser, 2007). In a machining process, unpredictable cutting tool failure is extremely costly. Tool life variability may lead to low productivity and high machining cost. Then, cutting tool life variability under a certain MC should be clarified and limited as much as possible (Astakhov, 2014). However, tool wear was no longer considered to be the primary criterion of failure (Astakhov, 2014). Instead, machining accuracy, surface roughness, or machining efficiency might be the primary concern.

The cutting tool utilization was considered to be the ability to achieve the pre-set quality requirements for a given material efficiently. A cutting tool's time-varying utilization can be measured by RUL. In the past few years, a significant amount of research has been done to develop cutting tool RUL prediction models (Lei et al., 2018). For example, by using force, vibration and acoustic emission (AE) signals (Zhou and Xue, 2018), cutting tool RUL was predicted based on the operational reliability assessment and the back propagation neural network (BPNN) (Sun et al., 2016). Cutting tool RUL was also estimated based on neuro fuzzy logic, support vector regression (SVR) (Gokulachandran and Padmanaban, 2018) and hidden Markov model (HMM) (Kumar et al., 2019). By using wavelet packet transform and extreme learning machine (ELM), a nonlinear regression model was built for tool RUL prediction (Laddada et al., 2017). The proportional hazards model and the logical analysis of data were used and compared in cutting tool RUL prediction of titanium metal matrix composites turning (Shaban and Yacout, 2016). Moreover, an adaptive resampling-based particle filtering for cutting tool RUL prediction was proposed to overcome the sample impoverishment problem in sequential importance resampling (Wang and Gao, 2015). However, results of these machining learning-based models were not easy to interpret with compelling physical meanings. There were also challenges in determining thresholds, extracting features, and solving overfitting issues. Although the prediction results may be more accurate, the reliability and interpretability are vague. Without quantized uncertainty, a cutting tool usage decision may be made at unknown risk.

To address the uncertainty of prediction, stochastic process was used to model degradation process and predict RUL. Wiener process, i.e., Brownian motion with a linear drift, was one of the most popular ones (Si et al., 2017; Wang and Tsui, 2018). Due to its excellent mathematical properties and physical interpretations, Wiener process could provide a good description of systems' non-linear, non-monotonic, and dynamic characteristics (Zhang et al., 2018). Wiener process could model a degradation state as an infinitely divisible process. The explicit distribution of the first hitting time (FHT) of a Wiener process could be resolved (Huang et al., 2017). Therefore, a Wiener-based cutting tool wear curve and RUL prediction approach was put forward (Sun et al., 2018). However, the non-linear wear curve was modelled as several segmented linear ones. Although the predicted results approximated the measured ones well, huge absolute errors still existed at the bnnng. A real non-linear cutting tool wear curve is more reasonable.

2.3. Cutting tool utilization improvement

If every cutting tool's utilization could be used precisely, the cost of labour and machine stoppage will be decreased greatly (Astakhov, 2010). In order to make most use of every cutting tool, some decisions should be made prior to the machining process, e.g. whether a cutting tool can finish a machining task with minimum life waste. In industry, life expectation of a group of cutting tools was estimated based on some machining tests. Every cutting tool in

this group was used according to a unified life bound, regardless the differences among them. Then, most cutting tools were used conservatively. In fact, every cutting tool is unique, and every cutting tool wear curve is dynamic and time varying. Such a unified bound is not suitable for smart and sustainable manufacturing.

Moreover, cutting tool replacement decisions should also be made during the machining process, e.g. when a cutting tool's failure is around the corner. Xu and Cao (2015) investigated periodic tool replacement decision-making in the production process to reduce cost, improve production efficiency and energy efficiency. They also proposed a partially observable Markov model for dynamic tool replacement decision-making considering the quality failure probability and cutting energy consumption. However, replacement decision-making should be made for every single cutting tool. In-process conditions should be analysed to improve reliability of tool replacement decision-making (Ren et al., 2019). Considering the stochastic characteristics of tool life in the machining process, a hybrid policy was developed based on the reliability function for optimizing the tool replacement time, which could achieve better results for the costs of the cutting tool replacement, cutting tool failures, machine tool downtime and tool condition monitoring (Zaretabab et al., 2019).

By optimizing machining parameters, cutting tool lives could also be extended. By reducing friction between cutting tools and workpieces considerably, cutting fluid improved surface roughness and cutting tool lives (Debnath et al., 2014). Compared with the traditional flood cooling system, some sustainable techniques, including minimum quantity lubrication (MQL) (Mia et al., 2018), cryogenic cooling, etc., were adopted to improve cutting tool durability (Shokrani et al., 2012). MQL was proved to have lower tool wear and surface roughness value (Sakharkar and Pawade, 2018). However, LCA should be used to prepare a strong database for sustainable manufacturing (Chetan and GhoshRao, 2015). Although optimization of machining parameters, including feed rate, cutting depth and cutting speed, were believed to improve cutting tool sustainability, how to make a trade-off between them was a big challenge.

In summary, cutting tool sustainability could be improved by using every cutting tool according to its specific RUL prediction. In order to balance the benefits and risks, more reliable decisions about cutting tool selection and machining parameter optimization should be made. However, studies regarding its implementation are very limited and insufficient. Some significant topics should be investigated further to enhance cutting tool sustainability. This paper aims to bridge these gaps.

3. Cutting tool sustainability enhancement approach based on cutting tool RUL prediction

The proposed approach to cutting tool sustainability enhancement based on RUL prediction is shown in Fig. 2. The approach includes the following three steps.

- (1) Cutting tool RUL prediction. Based on non-linear Wiener process and historical tool wear data, a cutting tool RUL prediction model is built for every MC. A cutting tool RUL prediction comes with quantized probability distribution function (PDF) and cumulative distribution function (CDF). However, every cutting tool has its unique wear curve. Under a certain MC, a cutting tool's wear trend can be predicted considering its wear history. Its RUL variability can also be predicted under a certain confidence level. Similar cutting tool wear trend and RUL prediction models can also be built for various MCs.

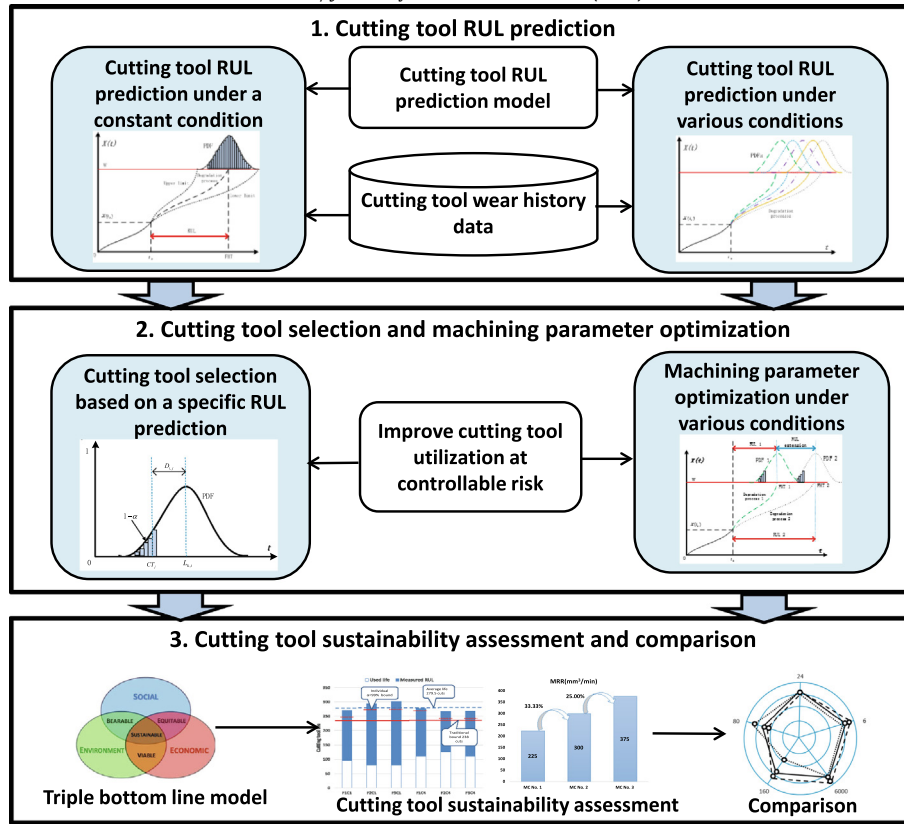


Fig. 2. Approach to cutting tool sustainability enhancement based on RUL prediction.

- (2) Cutting tool selection and machining parameter optimization. In order to use every cutting tool further at controllable risk, a cutting tool can be matched with a suitable machining task according to its specific RUL prediction, rather than a unified one. Machining parameters can also be optimized based on RUL prediction under various MCs. The benefit and risk are balanced by using a confidence level.
- (3) Cutting tool sustainability assessment and comparison. Based on TBL, cutting tool sustainability is assessed in economic, environmental and social dimensions. MRR, MRV, cutting tool cost, carbon emission and risk are evaluated and compared.

Therefore, cutting tool RUL prediction, cutting tool selection decision-making, machining parameters optimization and cutting tool sustainability assessment are vital to this approach. The following sub-sections address these issues in detail.

3.1. Cutting tool RUL prediction

Without loss of generality, flank wear (VB) is considered to be the primary criterion of cutting tool failure in this work. Normally, a cutting tool's life ends when its VB value exceeds the predefined wear criterion w . Cutting tool wear is a non-linear stochastic process $\{X(t), t \geq 0\}$ regarding time t . RUL of a cutting tool at time t_k is denoted by T_k . According to the definition of FHT, it is the duration between time t_k and the time that VB value exceeds w for the first time, as shown in Eq. (1).

$$T_k = \inf\{t : X(t+t_k) \geq w | X(t_k) < w, t > 0\} \quad (1)$$

The CDF $P_T(t)$ gives the area under the PDF $f_T(t)$ from 0 to time T , and can be calculated by Eq. (2).

$$P_T(t) = \int_0^T f_T(t) dt \quad (2)$$

By using historical data, the wear curve of a cutting tool type under a certain MC can be modelled (Sun et al., 2018). As shown in Fig. 3, RUL regarding state $X(t_k)$ can also be estimated with quantized PDF and CDF. Under a specific confidence level α , the upper bound and the lower bound can be resolved.

Similarly, wear curves, RULs, PDFs and CDFs under various MCs (shown in Fig. 4) can also be modelled or calculated. The more data are used, the more reliable the RUL prediction results are.

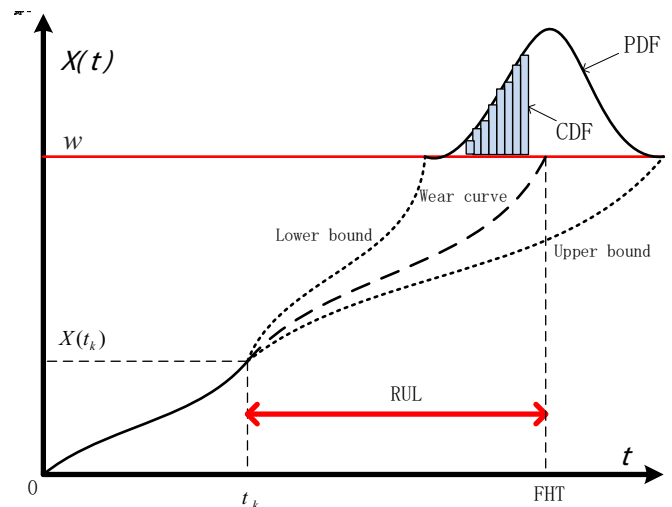


Fig. 3. A wear curve under a certain MC.

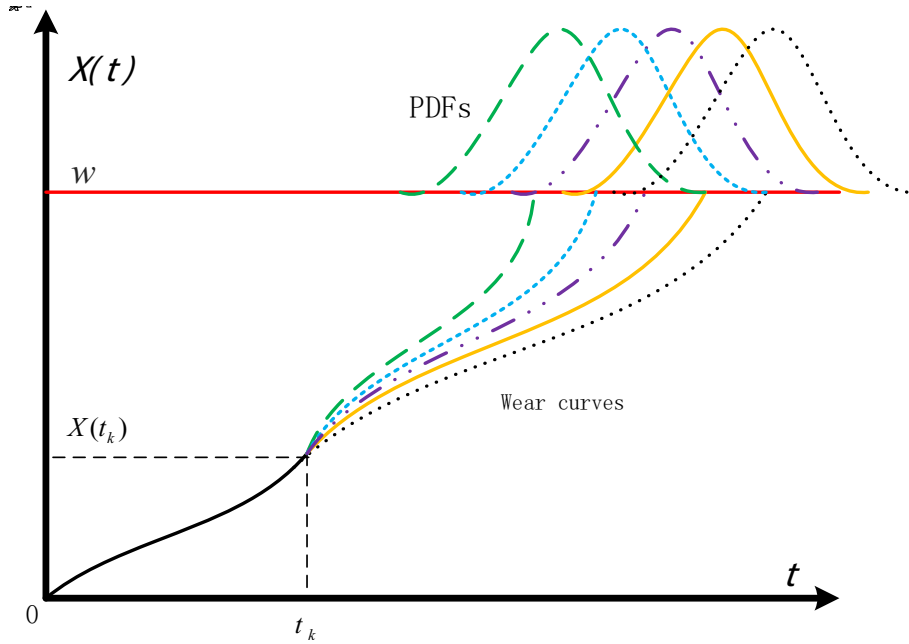


Fig. 4. Wear curves under various MCs.

3.2. Cutting tool selection based on a specific RUL prediction

Prior to a machining task, a right cutting tool should be selected according to its specific RUL. Some cutting tools of the pre-defined types with different conditions and RULs are candidates. A reliable decision could be made based on cutting tool RUL prediction. In order to maximise the use of every cutting tool at controllable risk, the confidence level α is used. To finish machining task j , CDF of cutting tool i regarding CT_j , denoted by $P_{T_{k,i}}(CT_j)$, should satisfy the following constraint.

$$P_{T_{k,i}}(CT_j) = \int_{t_k}^{t_k+CT_j} f_{T_{k,i}}(t) dt \leq 1 - \alpha \quad (3)$$

Here, CT_j is time duration of task j . $T_{k,i}$ is RUL of cutting tool i at time t_k . The difference between CT_j and $T_{k,i}$, denoted by $D_{i,j}$, stands for the margin. Then, the risk of a cutting tool selection decision is calculable. RUL waste of a cutting tool is also measurable and controllable. By minimizing $D_{i,j}$ and satisfying Eq. (3), every cutting tool is matched with a right task. Interrelationship among α , CT_j and $D_{i,j}$ is shown in Fig. 5. Obviously, PDF affects the margin greatly. The benefit and risk can be balanced by adjusting the confidence level α .

3.3. Machining parameter optimization considering various MCs

Cutting tool wear curves vary greatly under different MCs. Machining parameters could be optimized to extend a cutting tool's life. Without loss of generality, some factors, such as machine tool, workpiece material and cutting fluid, are regarded as constants. Feed speed ($f/\text{mm} \cdot \text{min}^{-1}$), cutting width (a_e/mm), cutting depth (a_p/mm), etc., are considered as key machining parameters in this work. Here, an MC means a combination of them. As Fig. 6 shows, at time t_k , two MCs result in different cutting tool wear curves, FHTs, RULs and PDFs. Compared with MC 1, cutting tool life could be extended greatly by MC 2. Then, the wear curve 2 is better than wear curve 1 under the same confidence level α . However, cutting tool life extension may lead to lower machining efficiency. To

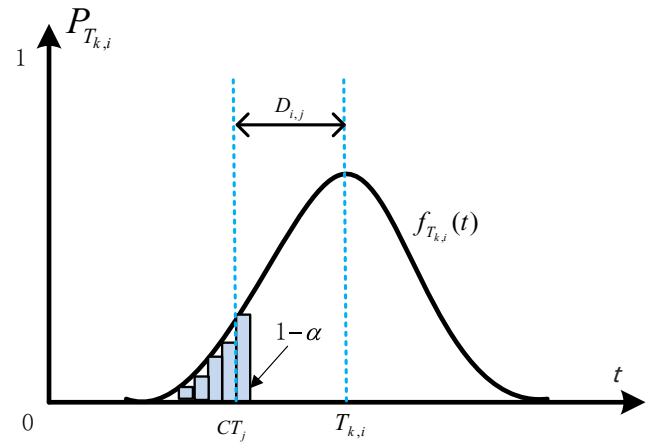


Fig. 5. Pre-task RUL prediction and probability.

improve the benefit systematically, an MC should be evaluated according to the sustainability assessment metrics.

3.4. Cutting tool sustainability assessment and comparison

According to the TBL, cutting tool sustainability can be assessed in economic, environmental and social dimensions.

(1) Economic sustainability assessment

The economic sustainability is assessed by cutting tool life and cost. Compared with traditional mode, cutting tool selection based on a specific RUL prediction is liable to maximise the use of every cutting tool. Due to life extension, fewer cutting tools are used to fulfil the same machining time requirement and cutting tool cost could be reduced. Moreover, cutting tool life extension leads to less cutting tool replacement, which means more machining time. The equipment utilization ratio can be increased too.

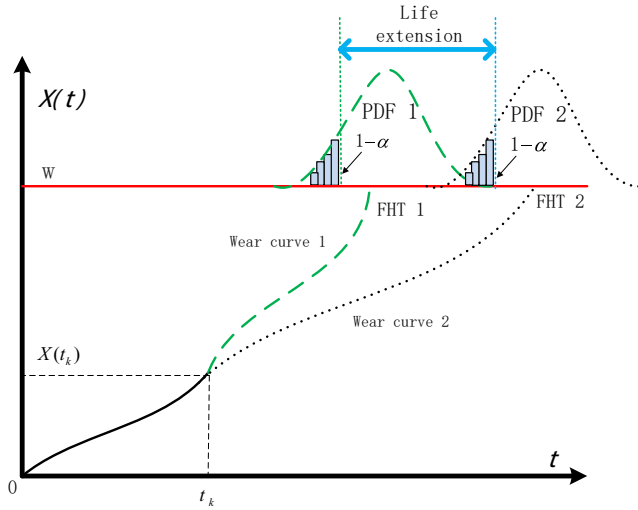


Fig. 6. Cutting tool wear curves under different MCs.

Cutting tool life varies under different MCs. Machining parameter optimization may extend or shorten a cutting tool's life. It can also change MRR, a measurement of machining efficiency. Under a certain MC, MRR can be calculated by Eq. (4).

$$MRR = f \cdot a_e \cdot a_p \quad (4)$$

Cutting tool life and MRR affect a cutting tool's utilization, which can be evaluated by MRV. As to cutting tool i , within time duration of machining task j , MRV is calculated by Eq. (5).

$$MRV_{ij} = MRR_j \cdot CT_j \quad (5)$$

Cost of cutting tool i can be shared by material it removes as in Eq. (6)

$$CC_i = Cost_i / MRV_i \quad (6)$$

where CC_i is cost sharing of cutting tool i , $Cost_i$ is cost of cutting tool i , and MRV_i is the total MRV of cutting tool i .

(2) Environmental sustainability assessment

The environmental sustainability is assessed by carbon emission, which was calculated by using weight of cutting tool material (Rajemi et al., 2010; Li et al., 2015; Hegab et al., 2018). Carbon emission of cutting tool i is shared by its total life as in Eq. (7)

$$CE_i = F_{ce} W_i / L_i \quad (7)$$

where CE_i is carbon emission sharing of cutting tool i , F_{ce} is the carbon emission factor, W_i is the mass of cutting tool i , and L_i is life of cutting tool i . If a cutting tool's life is extended, carbon emission per machining time could be decreased.

Carbon emission in the production process of cutting tool i can also be shared by material it removes as in Eq. (8)

$$CE_i = F_{ce} W_i / MRV_i \quad (8)$$

If MRV of cutting tool i is improved by machining parameter optimization, carbon emission per material volume could be decreased. Therefore, cutting tool environmental sustainability could be improved by enhancing cutting tool durability and capability.

(3) Social sustainability assessment

The social sustainability is assessed by social development and life quality of the employees. Traditionally, operators select cutting tools based on experience at their own risks. It is quite conservative and arbitrary to some extent. Cutting tool life extension increases the uncertainty and the risk. Fortunately, cutting tool selection based on a specific RUL prediction comes with a quantized confidence level α , which makes the cutting tool usage decision-making more reliable. Machining quality could be guaranteed at controllable risk without artificial factors. Operators are free from cutting tool selection decision-making. Moreover, cutting tool life extension reduces cutting tool replacement frequency, which also decreases operators' workload. Then, non-productive time can be reduced, and cutting tools can be used precisely to avoid unexpected downtime and scrapped components.

In summary, cutting tool sustainability could be improved by cutting tool selection based on a specific RUL prediction and machining parameter optimization considering various machining parameters. In order to assess and compare cutting tool sustainability, some significant metrics are selected and listed in Table 1.

4. Experimental study

4.1. Cutting tool sustainability assessment under a constant machining condition

In order to assess cutting tool sustainability under a constant MC, the dataset provided by the 2010 PHM Data Challenge (PHM, 2010) is used. The experimental setup is given in Table 2.

Cutting tools used in this case are named C1, C2, C3, C4, C5 and C6 respectively. Every cutting tool was used for about 315 cut cycles under the same machining condition. VB values of cutting tool C1, C4 and C6 were recorded after every cut cycle. Each flute is regarded as a specific one. Flute 2 of cutter C1 is named F2C1, and other flutes are named similarly. The carbon emission factor of cutting tool production was 29.6 kgCO₂/kg (Li et al., 2015). Carbon emission for a flute production is 266.4 g, because the average weight of a flute is 9g (Rajemi et al., 2010).

Regarding flutes F1C1, F2C1, F3C1, F1C4, F2C4 and F3C4, the maximum life, average life and minimum life are 302 cuts, 279.500 cuts and 266 cuts, respectively. In order to use cutting tools at controllable risk, 85% of average life (238 cuts) is set as the wear criterion for all flutes, according to engineering experience. If this unified bound is used, the sustainability is assessed as follows.

- (1) Economic sustainability assessment: The total RUL is 825 cuts. The total MRV is 2229 mm³.
- (2) Environmental sustainability assessment: Carbon emission sharing is 1.121 g/cut.
- (3) Social sustainability assessment: To some extent, the wear criterion is arbitrary. Cutting tools may be used conservatively.

Table 1
Cutting tool sustainability assessment metrics.

	Cutting tool selection based on a specific RUL prediction	Machining parameter optimization considering various machining parameters
Economic sustainability	<ul style="list-style-type: none"> • Cutting tool RUL • Cutting tool cost sharing • MRV 	<ul style="list-style-type: none"> • Cutting tool RUL • Cutting tool cost sharing • MRR • MRV
Environmental sustainability	<ul style="list-style-type: none"> • Carbon emission per machining time 	<ul style="list-style-type: none"> • Carbon emission per material volume
Social sustainability	<ul style="list-style-type: none"> • Risk control 	/

Table 2
Experimental setup A.

Name	Description/content
Machine tool	Röders Tec RFM 760 CNC machine
Workpiece	stainless steel (HRC52)
Cutting tool	three-flute tungsten carbide cutters
Spindle speed	10400 RPM
Feed speed (f)	1555 mm/min
Cutting width (a_e)	0.125 mm
Cutting depth (a_p)	0.2 mm
Cutting cycles	315 cuts
Cutting length	108 mm/cut
MRR	38.875 mm ³ /min (2.7 mm ³ /cut)
Wear criterion	$VB \geq 0.15$ mm

If every cutting tool is used based on its specific RUL prediction, the situation is different. Under the confidence level $\alpha = 99\%$, the upper bound of every cutting tool life is obtained and given in Table 2. The sustainability is assessed as follows.

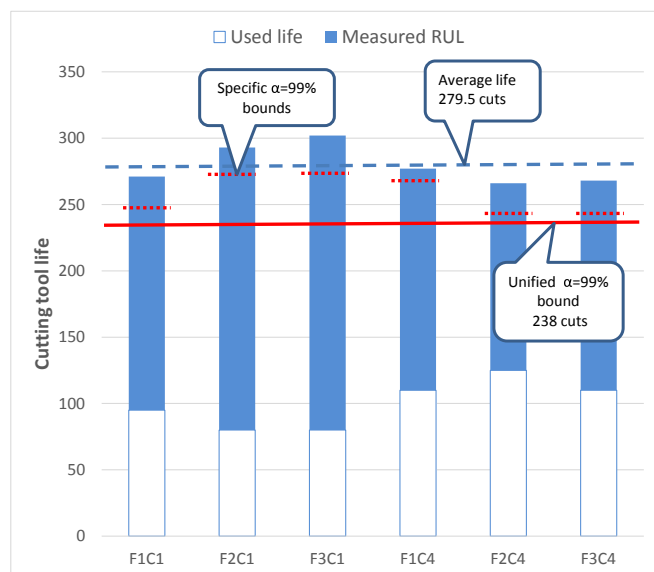
- (1) Economic sustainability assessment: The total life and total RUL are 1556 cuts and 956 cuts, respectively. The total MRV is 2581 mm³.
- (2) Environmental sustainability assessment: Carbon emission sharing is 1.027 g/cut.
- (3) Social sustainability assessment: Every cutting tool is used under the confidence level $\alpha = 99\%$. Cutting tools could be used further at measurable and controllable risk.

Detailed comparison between a unified bound and some specific bounds is given in Fig. 7 and Table 3.

In Fig. 8, a radar diagram is used to compare two situations vividly. To present in “the higher the better” manner, the reciprocal of carbon emission (cut/g) is used in the diagram. It can be seen that cutting tool selection based on the specific bounds is more sustainable than the unified bound.

4.2. Cutting tool sustainability assessment considering various machining conditions

In order to assess cutting tool sustainability under various MCs, a series of machining experiments are carried out. The experimental setup is given in Table 4.

**Fig. 7.** Life and RUL comparison.**Table 3**
Detailed information of every flute.

- (1) As to economic sustainability, the total RUL is improved from 825 cuts to 956 cuts. The total MRV is improved from 2229 mm³ to 2581 mm³ by 15.81%.
- (2) As to environmental sustainability, carbon emission for a flute production is decreased from 1.21 g/cut to 1.027 g/cut by 8.39%.
- (3) As to social sustainability, cutting tools are used further at precisely controlled risk.

	F1C1	F2C1	F3C1	F1C4	F2C4	F3C4	Total
Life Used (cuts)	95	80	80	110	125	110	600
Traditional bound (cuts)	237.6	237.6	237.6	237.6	237.6	237.6	1426
Available RUL (cuts)	142.6	157.6	157.6	127.6	112.6	127.6	825
Measured RUL (cuts)	176	213	222	167	141	158	1077
Predicted RUL (cuts)	172	210	211	195	142	157	1087
$\alpha = 99\%$ bound (cuts)	151	194	193	162	120	135	956
The specific bound (cuts)	246	274	273	272	245	245	1556
MRV (mm ³)	409	524	521	437	325	365	2581

Obviously, better sustainability is achieved by using each cutting tool according to its specific RUL prediction.

In rough machining, material should be removed as much as possible. MC No. 1 is designed according to the real MC in factory. Three cutting tools are used in the machining experiments. According to above discussion, in-process data is collected to build the degradation model and predict RUL under MC No. 1. As shown in Table 5, although the spindle speed (4000 RPM) is relatively high, a low feed speed (150 mm/min) balances the MRR which is 225 mm³/min. Under the $\alpha = 99\%$ confidence level, cutting tool RUL is 47.07 min, which leads to 10113.75 mm³ MRV. Carbon emission and cutting tool cost are 0.105 g CO₂/mm³ and 0.024 CNY/mm³, respectively.

To improve machining efficiency, the feed speed is increased from 150 mm/min in MC No. 1–200 mm/min in MC No. 2. To extend cutting tool life, spindle speed is decreased to 2000 RPM. As shown in Fig. 9, MRR is increased to 300 mm³/min by 33.33%. During the machining, the data obtained by using three cutting tools is adopted to build the cutting tool wear curve and predict RUL. Under the $\alpha = 99\%$ confidence level, RUL is extended to 62.39 min by 38.80%. MRV is extended to 18717 by 85.06%. Carbon emission is decreased to 0.057 by 45.96%. By optimizing machining parameters, cutting tools becomes more capable and durable.

Moreover, machining efficiency can be improved further. Regarding MC No. 3, feed speed is increased up to 250 mm/min. Because spindle speed is increased to 3000 RPM, MRR is increased to 375 mm³/min by 25.00%. According to the cutting tool wear curve based on three cutting tools, RUL is decreased to 50.88 min by 18.45% under the $\alpha = 99\%$ confidence level. Compared to MC No. 1,

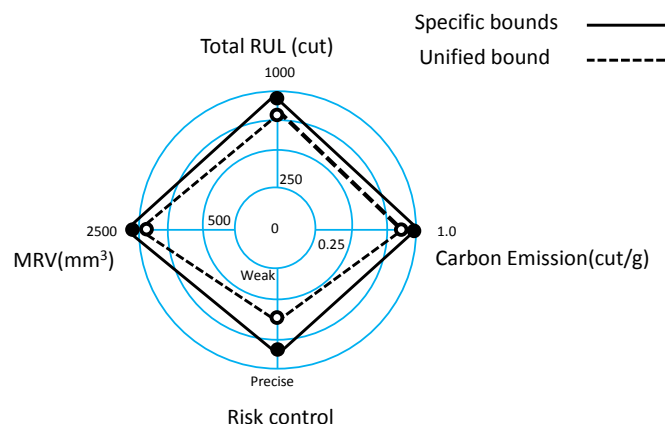
**Fig. 8.** Sustainability assessment and comparison.

Table 4
Experimental setup B.

Name	Description	Memo
Machine tool	JDCT1200E_A12S	3-axis, max power 10kw
Cutting tool	S4-GH1022075-Ø10*25*75	Φ10mm, flat-end, 4 edges, CNY 240 each
Workpiece	45 (ASTM 1045)	70 mm*50 mm*50 mm, HB200
Tool microscope	CW0505	5 + L/20 μm

Table 5
Experiments for rough machining.

	MC No.1	MC No. 2	MC No. 3
Cutting depth (mm)	1.5	1.5	1.5
Spindle speed (RPM)	4000	2000	3000
Feed speed (mm/min)	150	200	250
MRR (mm ³ /min)	225	300	375
α = 99% RUL bound (min)	47.07	62.39	50.88
MRV under α = 99% bound (mm ³)	10113.75	18717	19080
Carbon emission sharing (g CO ₂ /mm ³)	0.105	0.057	0.056
Cutting tool cost sharing (CNY/mm ³)	0.024	0.013	0.013

cutting tool RUL is still extended by 8.09%. MRV is increased to 19080 by 1.94%. Carbon emission sharing and cutting tool cost sharing is decreased by 1.90%. As a result, better sustainability is achieved, despite of decreased cutting tool RUL.

Their sustainability is also compared as shown in Fig. 10. To present in “the higher the better” manner, the reciprocals of cutting tool cost sharing and carbon emission sharing are used in the diagram. It can be seen that MC No. 3 scores the highest marks in almost all cutting tool sustainability assessment metrics, except cutting tool RUL. Considering a 3%–5% share of cutting tool cost out of machining cost, it is reasonable to make such a trade-off for a better sustainability.

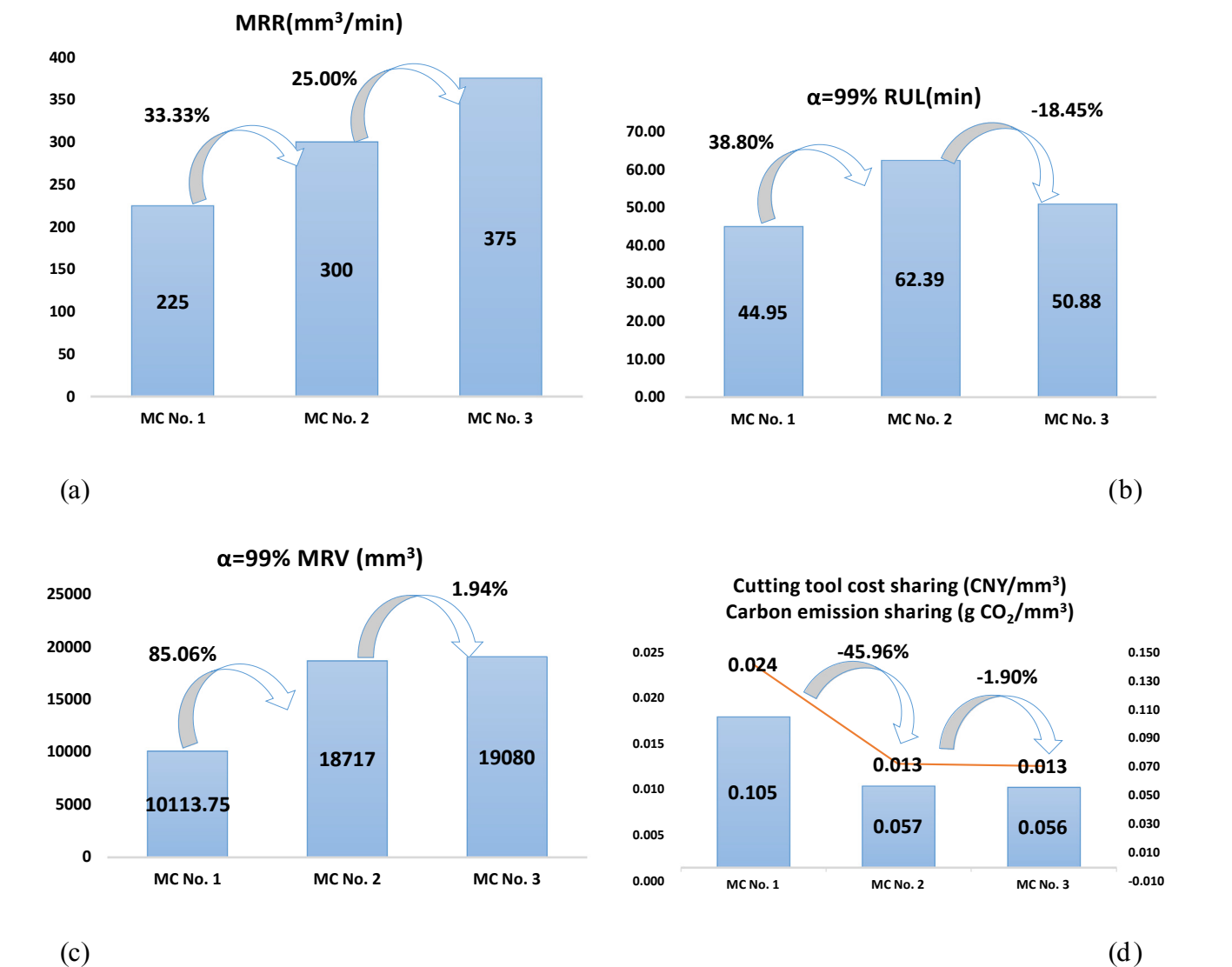


Fig. 9. Detailed sustainability comparison.

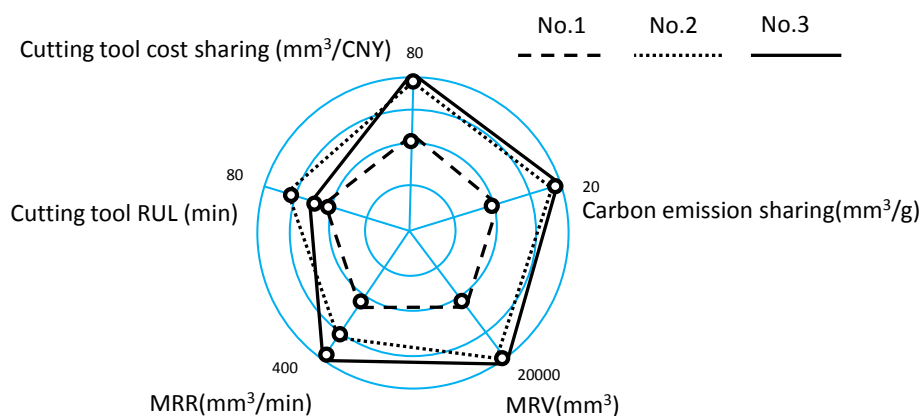


Fig. 10. Sustainability comparison in a radar map.

4.3. Discussions

According to above experimental results, the work shows a great improvement in cutting tool sustainability. Under a constant MC, a cutting tool's life can be extended according to its specific RUL prediction. PDF, CDF and confidence level α contribute to the balance between benefit and risk. In fact, machining sustainability improvement is more than life extension. Based on RUL prediction, machining parameters are optimized to improve MRV, and to reduce cost sharing and carbon emission sharing. As a result, cutting tool sustainability could be enhanced significantly.

However, the feasibility of the proposed method depends heavily on accuracy and reliability of cutting tool RUL prediction. A scattering PDF is meaningless for the consequent decision-making. More efforts should be made to improve the cutting tool RUL prediction model, especially in machining of a high-value component of which quality requirement must be fulfilled. Decision of a RUL extension and an MRV improvement should be carefully made on a more reliable basis.

This work could also be expanded to a wider scope of manufacturing field, such as bearing, battery, and aero-engine overhaul, etc. For example, aero-engine overhaul should be configured for functionality recovery, cost control, environmental sustainability, etc. (Sun et al., 2017). Considering certain flight hours and thrust requirements, whether a part could be reusable is a key issue. If its RUL could be calculated by using similar approach, a selection decision could be made under a certain confidence level. Then, the part could be used further at controllable risk, and the sustainability could be enhanced greatly. However, aero-engine overhaul considers multiple objectives. A part reuse decision should be made with higher reliability. Then, this work is also applicable to decision-making of part reuse in aero-engine overhaul.

5. Conclusions

This paper proposes and verifies an approach to cutting tool sustainability enhancement based on a RUL prediction, and the major contributions are as follows.

- To reduce huge waste of cutting tools in manufacturing industry, cutting tool utilization should be improved considering sustainability. Such a goal can be achieved based on an accurate and reliable cutting tool RUL prediction, by using a historical data driven approach with a quantized uncertainty.

- Under a constant MC, a cutting tool's RUL can be extended according to its specific RUL bound, rather than a unified one. Under various MCs, machining parameters can also be optimized to improve MRR and MRV. Carbon emission sharing and cutting tool cost sharing can also be reduced. Cutting tool sustainability can be enhanced by improving cutting tool utilization at controllable risk.

Although the work enhances cutting tool sustainability, some limitations call for future research. For example, machining accuracy and surface integrity could be considered to improve the cutting tool RUL prediction model's accuracy and reliability. Negative impacts of cutting tool RUL extension should be also included in cutting tool sustainability assessment. More data and cases should be used to improve the approach's feasibility and practicality.

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