Evaluation of Tool Life Equation of Single-Point Cutting Tool by Accumulation Model

A. V. Antsev, N. I. Pasko and A. V. Khandozhko

Abstract The effective use of modern machines with numerical control is impossible without a stable cutting process. An unexpected tool failure leads to high production costs. Various models are proposed to predict the wear value and tool life of the cutting tool. In this paper, the tool life equation is understood as a set of the law of distribution of the tool life and the parameters of the law, depending on the cutting mode. It is assumed that the spread of the tool life is associated with the spread of hardness and the allowance for the machining of workpieces. The case of asymptotically normal wear distribution for a given operating time is considered. The method of the assessment of the tool life equation parameters by the maximum likelihood method by statistics "speed-feed-depth-operating time-wear" is offered. The average intensity of the wear depends on the parameters of the cutting mode in the form of an exponent from the polynomial which is not higher than the third power of the logarithms of the noted parameters of the cutting mode. The method is illustrated by a numerical example with the statistics "speed-feed-operating time-wear". It is shown that the average tool life calculated by the proposed method differs from the mathematical expectation by an amount of 0.4–5%, so in practical calculations, you can use a simpler formula to calculate the mathematical expectation of the tool life.

Keywords Tool life · Wear · Cutting tool · Tool life equation · Wear rate · Normal distribution · Maximum likelihood method

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A. A. Radionov et al. (eds.), *Proceedings of the 5th International Conference on Industrial Engineering (ICIE 2019)*, Lecture Notes in Mechanical Engineering,
https://doi.org/10.1007/978-3-030-22063-1_100

1 Introduction

The development and improvement of metalworking technologies is inextricably linked with the use of numerically controlled machines. Their effective use is impossible without ensuring a stable cutting process, which is evaluated comprehensively on the following criteria: the accuracy, the finished surface quality, and the reliability of the cutting tool.

Modern machine-building enterprises are characterized by a very wide range of used cutting tools [1]. The cutting tool is the most vulnerable link in metal-cutting systems. An unexpected tool failure leads to high production costs due to the increased costs of prevention and maintenance of cutting tools and the increased costs of repairable and irrepairable reject due to the high costs of workpieces for finishing operations, so a large number of papers in the modern literature are devoted to the study of the wear mechanism of cutting tools, the diagnosis of their conditions, and the prediction of their tool life.

When diagnosing the state of cutting tools, the methods which use the machine learning methods [2] are widely used. For this purpose, various indirect parameters of the cutting process are used: acoustic emission [3], vibration [4], temperature [5], cutting force [6], as well as their combinations [7]. The optical control is also used to control the condition of cutting tools [8]. However, despite scientific research, an extensive industry experience in this area and the economic importance of the cutting operations, the cutting process needs in-depth study, which is confirmed by a low predictive ability of the known cutting models and their efficiency only in relatively narrow and constant operating conditions [9].

Various models are proposed to predict the wear value and tool life of the cutting tool. For example, De-Jun Cheng et al. propose an approach for calculating the wear overlap (WO) geometry [10]. Anton Panda et al. use Taylor's equation to predict the cutting tool life [11]. Also there are known approaches using the finite element method (FEM) [12], the partial least-squares regression (PLSR) [13] and a general model of wear [14]. However, these models do not take into account the stochastic nature of the cutting tools wear, which depends on a large number of factors: cutting modes, cutting properties of the tools, type of machining, hardness of machined parts, value of machining allowances, pre-existing mode of deformation, vibration, geometric errors of machine, etc. [15–19].

Therefore, in this paper, the tool life equation is considered in a generalized form as a set of the distribution law of the cutting tool life T and the dependence of the parameters of this law on the cutting mode [20, 21]. When turning the mode parameters are the cutting speed V, the feed S, and the depth of cut h. The tool life is mean time between failures (a dulling or a breakage of the cutting blade). Here, we consider the case when the reason for the spread of the tool life is the spread of hardness, machining allowance, and other parameters of workpieces [20].

2 Materials and Methods

The failure of the cutting tool is considered to have occurred if the wear of the cutting tool Y from the moment of installation after processing a batch of T workpieces for the first time exceeds the maximum permissible value L. If ΔY_i is the increment of the wear after machining of the ith workpiece, then after machining the T workpieces the total wear of the cutting tool is $Y = \sum_{t=1}^{T} \Delta Y_t$. Because of the marked spread, the ΔY_i wears are random variables and their sum after machining t workpieces according to the central limit theorem has an asymptotically normal distribution with the density of distribution

$$f_t(y) \approx \frac{1}{\sqrt{2\pi D_t}} \exp\left[-\frac{(y - \bar{Y}_t)^2}{2D_t}\right]. \tag{1}$$

Formula (1) with practice-relevant accuracy can be used when $t > 10$.

The average wear after machining t workpieces is

$$\bar{Y}_t = u \cdot t, \tag{2}$$

and the dispersion of the wear, if the increments ΔY_i are statistically independent, is

$$D_t = \sigma^2 t, \tag{3}$$

where u is the average wear on one workpiece (wear rate), a σ is the standard deviation of the wear on one workpiece. If there is a correlation between the increments, then the dependence of D_t on t is more complicated and the formula (3), in this case, must be considered as an asymptotic formula for t.

Taking into account the formulas (2) and (3), we obtain that

$$f_t(y) = \frac{1}{\sqrt{2\pi\sigma^2 t}} \exp\left[-\frac{(y - u \cdot t)^2}{2\sigma^2 t}\right]. \tag{4}$$

The probability of non-failure operation during the operating time, that is, the probability that $Y(t) < L$ is

$$P(t) = \int_0^L \frac{1}{\sqrt{2\pi\sigma^2 t}} \exp\left[-\frac{(y - u \cdot t)^2}{2\sigma^2 t}\right] \mathrm{d}y = \Phi^*\left(\frac{L - u \cdot t}{\sigma\sqrt{t}}\right) - \Phi^*\left(\frac{-u \cdot t}{\sigma\sqrt{t}}\right), \tag{5}$$

where $\Phi^*(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp(-x^2/2)\mathrm{d}x$ is the cumulative distribution function of the normal distribution. When $t > 10$ you can use the approximation $P(t) \approx \Phi^*\left(\frac{L - u \cdot t}{\sigma\sqrt{t}}\right)$.

The mathematical expectation $\bar{T}$ and the coefficient of tool life variation K_T are calculated using the following formula

$$\bar{T} = \int_0^\infty P(t)\mathrm{d}t, \quad K_T = \sqrt{2\int_0^\infty P(t)t\mathrm{d}t - \bar{T}^2}/\bar{T}. \tag{6}$$

Along with the mathematical expectation of the tool life $\bar{T}$, the average tool life, which is calculated by the formula (7), may be of practical interest:

$$\breve{T} = L/u. \tag{7}$$

It should be noted that $\bar{T}$ and $\breve{T}$ are close in value, but do not coincide. When optimizing the cutting modes in the case of tool replacement on failure, we should use the value $\bar{T}$ since the costs per unit in this case are directly dependent on $\bar{T}$.

Since the tool life T is a random variable, then to determine the tool life equation, we must also know in addition to the distribution law T the dependence of the parameters of this distribution on the cutting modes. In this case, you should know the dependence of the parameters σ and u on the cutting mode parameters $V,\ S,\ h$.

The coefficient of wear variation during machining one workpiece

$$k = \sigma/u, \tag{8}$$

depends on the coefficient of variation of the workpiece hardness and the coefficient of variation of the machining allowance, but it does not depend on the cutting modes. As for the wear rate u, it essentially depends on the cutting modes and mainly determines the tool life equation.

3 Assessment of Tool Life Equation Parameters

To assess the parameters of the tool life equation from tests, we use the statistics $(t_i, V_i, S_i, h_i, Y_i), i = 1, \ldots, N$, where t_i is the number of the machined workpieces when the cutting mode parameters are V_i, S_i, h_i, and Y_j is the total wear during the time of machining t_i workpieces. i is the test number with the cutting mode parameters V_i, S_i, h_i, N is the number of tests. For the tests adequacy, it is necessary that at each test, the values of the cutting mode parameters are changed, for example, as in a two-level factorial experiment.

We will look the wear rate as a function of the cutting mode parameters in the form of power dependence, for example, of this type:

$$u(V, S, h) = \exp\left[b_0 + b_1 \cdot \ln V + b_2 \cdot \ln^2 V + b_3 \cdot \ln^3 V + b_4 \cdot \ln S + b_5 \cdot \ln^2 S + b_6 \cdot \ln V \ln S + b_7 \cdot \ln h\right], \tag{9}$$

where $b_0, \ldots, b_7$ are the required coefficients to be estimated using the statistics noted above. The number of components in the formula (9) may vary depending on the available statistics, the factors taken into account, and the required accuracy of the dependence (9). To estimate the coefficients $b_0, \ldots, b_7$, let us use the maximum likelihood method based on the distribution (4) with taking into account (8). The optimal values of the parameters $b_0, \ldots .b_7$ and k maximize the likelihood function

$$\Pr(b_0, \ldots, b_7, k) = \prod_{i=1}^{N} \frac{1}{\sqrt{2\pi t_i} k u_i} \exp\left[- \frac{(Y_i - u_i t_i)^2}{2k^2 u_i^2 t_i} \right] \tag{10}$$

It is easier to find the maximum of the likelihood function's logarithm, that is, the maximum

$$\ln(\Pr(b_o, \ldots, b_7, k)) = \sum_{i=1}^{N} [-\ln(\sqrt{2\pi}) - \ln(k) - \ln(u_i) - \ln(t_i) - \frac{(Y_i - u_i t_i)^2}{2k^2 u_i^2 t_i}]. \tag{11}$$

In the formulas (10), (11), the notation is accepted $u_i = u(V_i, S_i, h_i)$. The maximum of the function (11) in our example is searched by the differentiation method together with the random search. From the equation $\frac{\partial \ln(\Pr(b_0, \ldots, b_6, k)}{\partial k} = 0$ we obtain that

$$k^2 = \frac{1}{N} \sum_{i=1}^{N} \frac{(Y_i - u_i \cdot t_i)^2}{u_i^2 \cdot t_i}. \tag{12}$$

Taking into account (12), the expression (11) will be simplified and take the form:

$$\ln(\Pr(b_o, \ldots, b_6, k)) = -N[\ln(\sqrt{2\pi}) - \frac{1}{2N} \sum_{i=1}^{N} \ln(t_i) - \ln(k) - \frac{1}{N} \sum_{i=1}^{N} \ln(u_i) - \frac{1}{2}]. \tag{13}$$

We are searching for the maximum of function (13) for $b_0, \ldots, b_7$ using a random search method. Random search is implemented as follows. The parameter value options $b_0, \ldots, b_7$ are generated by the formula

$$b_j = b'_j + (b''_j - b'_j) \cdot \text{random}, \quad j = 0, \ldots, 7, \tag{14}$$

where b'_j, b''_j are the search boundaries, which are defined from a priori considerations, *random* is a function generating each time a pseudorandom number uniformly distributed in the interval from 0 to 1.

The parameter value options $b_0, \ldots, b_7$ are generated in the search cycle. For each option, the value of $\ln(\Pr(b_0, \ldots, b_7, k)$ is calculated by (12) and (13). The best option parameters $b_0, \ldots, b_7, k$ and the maximum achieved $\ln(\Pr(b_0, \ldots, b_7, k))$ will be stored in the computer memory.

4 Illustration of the Method

Now let us consider a specific example of the calculation of the tool life equation on statistics $(t_i, V_i, S_i, Y_i), i = 1, \ldots, N$. Such statistics are shown in Table 1. The statistics was gathered during test with material steel 1X18H9T, cut depth 0.5 mm, tool material hard alloy T30K4, and maximum wear 0.4 mm.

The wear rate function will be searched in the form similar to (9), but with the feature that the cut depth h during the tests did not vary, so the dependence for the wear rate on h is not included, that is, $u_i = u(V_i, S_i)$. In addition, we will check ten options of this function as $u(V, S)$ according to the likelihood ration test. The simplest form for $u(V, S)$ is option 1, where the maximum powers at $\ln V$ and $\ln S$ are 1 and 1, which is indicated in the Table 2 as 1 1. Hereby, $u(V, S) = \exp(b_0 + b_1 \ln V + b_4 \ln S)$. In option ten, these powers are 2 and 2 and besides there is a member $\ln V \cdot \ln S$, which is indicated in Table 2 as 2 2 1*1. This means that $u(V, S) = \exp(b_0 + b_1 \ln V + b_2 \ln^2 V + b_4 \ln S + b_5 \ln^2 S + b_6 \ln V \ln S)$. Similarly, other dependency options $u(V, S)$, marked in the Table 2, are defined. The option based on $u(V, S)$ with the maximum likelihood $\Pr(b_0, \ldots, b_6)$ is considered preferable. The calculation results for all ten options are summarized in Table 2.

Table 1 Experimental data: speed-feed-operating time-wear ($V - S - T - Y$)

V	S	T	Y		V	S	T	Y		V	S	T	Y
37	0.1	41	0.4		170	0.15	6	0.4		110	0.3	27	0.4
70	0.1	45	0.4		210	0.15	1.8	0.4		120	0.3	25	0.4
100	0.1	62	0.4		37	0.2	45	0.4		210	0.3	1.2	0.4
150	0.1	25	0.4		70	0.2	54	0.4		45	0.4	44	0.4
200	0.1	2.5	0.4		100	0.2	37	0.4		70	0.4	65	0.4
37	0.15	55	0.4		140	0.2	14	0.4		100	0.4	60	0.4
70	0.15	75	0.4		210	0.2	1.8	0.4		110	0.4	31	0.4
100	0.15	80	0.4		45	0.3	37	0.4		155	0.4	5	0.4
135	0.15	70	0.4		70	0.3	60	0.4		210	0.4	0.9	0.4
150	0.15	13	0.4		95	0.3	27	0.4					

Table 2 Results of the calculation

№	Structure $U(V,S)$	b_0	b_1	b_2	b_3	b_4	b_5	b_6	k	Pr
1	1 1	−9.52	1.175	0	0	0.087	0	0	5.015	0.0003
2	2 1	−0.19	−3.42	0.533	0	−0.02	0	0	5.273	0.0332
3	2 1*1	−0.19	−3.42	0.533	0	0	0	−0.02	4.77	0.0462
4	3 1	−3.96	8.54	−4.17	0.49	−0.01	0	0	2.341	1791
5	3 1*1	−3.96	8.54	−4.17	0.49	0	0	−0.01	2.323	953
6	3 2	−15.1	8.913	−2.50	0.242	0.461	−0.06	0	3.356	0.018
7	3 1 1*1	−5.62	6.243	−2.91	0.345	−0.60	0	0.08	2.731	2.143
8	3 2 1*1	−4.24	6.326	−3.11	0.405	−1.57	1.074	1.151	2.510	0.379
9	2 2	−1.747	−2.75	0.425	0	−1.47	−0.53	0	4.987	0.016
10	2 2 1*1	0.795	−3.97	0.665	0	−1.38	0.585	0.662	4.106	0.032

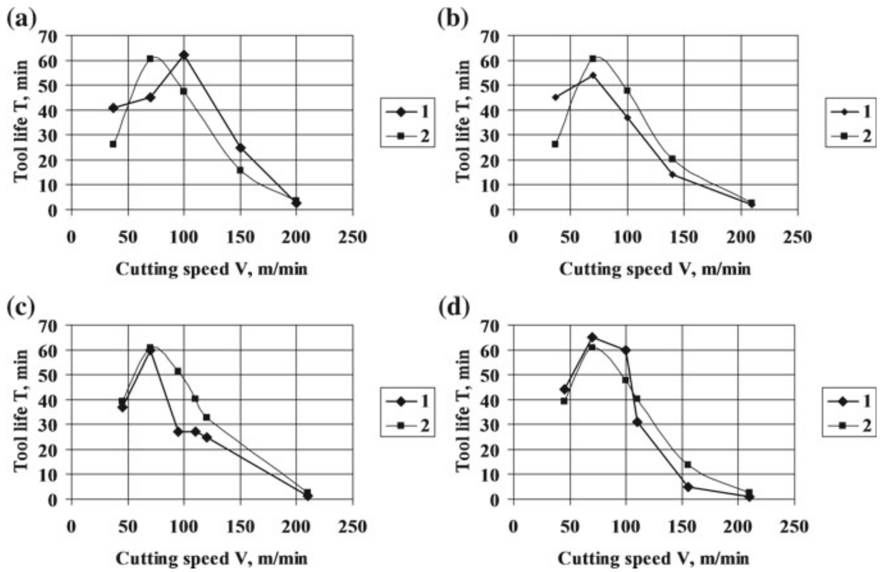

Fig. 1 Graphs of tool life dependence on the cutting speed at different feeds. 1—experimental values, 2—mathematical expectations. **a** $S = 0.1$ mm/rev; **b** $S = 0.2$ mm/rev; **c** $S = 0.3$ mm/rev; **d** $S = 0.4$ mm/rev

It follows from Table 2 that option four is preferable in terms of likelihood. In this case, the wear rate is

$$u(V,S) = \exp\left(-3.96 + 8.54 \cdot \ln V - 4.17 \cdot \ln^2 V + 0.49 \cdot \ln^3 V - 0.01 \cdot \ln S\right). \tag{15}$$

As it follows from the analysis of Table 2, the agreement of the actual wear distribution with the theoretical one can be judged by a simpler indicator calculated by the formula (12). The graphs shown in Fig. 1 are constructed using the dependence (15). The mathematical expectation of the tool life $\bar{T}$ was calculated by the formulas (5), (6).

5 Conclusion

The proposed tool life equation as a set of the distribution law of the cutting tool life T and the dependence of the parameters of this law on the cutting mode can accurately predict tool failure taking into account the stochastic nature of the cutting tools wear. The average tool life $\breve{T}$, calculated by the formula (6) using the expression for $u(V, S)$ (15), differs from the mathematical expectation of the tool life by an amount of 0.4–5%. The difference between $\bar{T}$ and $\breve{T}$ is not big and in practical calculations, you can use the approximation $\bar{T} \approx \breve{T}$ and a simpler formula (7) to calculate $\bar{T}$.

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