

Reliability assessment of cutting tools life based on advanced approximation methods

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Abstract

Cutting tools' reliability influences the whole manufacturing efficiency. However, in most cases the same cutting tool may be used for different operations with different processing parameters, making thus difficult to estimate the remaining life of the tool precisely. The present study proposes a new reliability estimation approach to the cutting tools based on advanced approximation methods. Reliability-based design/operation is a technique extensively employed for problems of structural reliability, assessing the performance of critical infrastructure under stochastic design parameters. Due to the complexity of machining processes which involve a significant number of hidden or difficult to statistically model variables, advanced approximation methods, such as response surface or surrogate modelling methods may be applied, starting from a few sample points obtained through fundamental experiments and extending them to models able to predict/estimate the values of control values/indicators as a function of the key design variables, often referred to as limit states. Having constructed such models, and according to the level of probability that need to be measured, different reliability analysis methods can be employed such as Monte Carlo Simulations or First Order Reliability Methods (FORM). In the present study these two reliability analysis methods are assessed for estimating the reliability of cutting tools.

INTRODUCTION

The reliability and quality of the various machining processes is affected by cutting tool reliability. Tool wear such as flank and nose wear, crater formation, built-up edge, can have a negative affect on the surface finish of the produced components and can be the cause of costly rework. The quality of parts is significantly affected by the condition of the cutting tools used in the machining processes. Tool fracture can lead to scrapping of the part being machined due to chipping for example. Additionally, it can result in expensive equipment stalling, even bringing down the whole production line. To avoid failures and related consequences, tools are often replaced well before the end of their useful lifetime. Only 50–80% of the expected tool life is typically used [1].

The wear of the cutting tools is even more significant when machining hard and brittle

materials, that are in general characterized as “difficult to machine”. The processing of such materials can result in very high wear rates on both the flank and the face of the tool. In practice, the tooling cost in the case of flexible manufacturing systems represents approximately 25% of the total machining cost [2].

In general tool life is characterized by stochasticity and its accurate prediction is quite difficult. The application of reliability techniques can allow the calculation of tool life by taking into account the experimentally observed distribution of the operating times to failure.

A number of papers have been presented on the reliability of cutting tools under different cutting conditions. Carlson and Strand [3] presented a statistical model for the prediction of tool life as part of a control strategy. The basis of their modelling was the extended Taylor equation. Wang et al. [4] developed a

reliability-dependent failure rate model as to predict the reliability of a cutting tool. Klim et al. [5] proposed a reliability model taking into account both the flank and the face wear on the cutting tool. Ding and He [6] studied the cutting tool reliability through a proportional hazards model.

The present paper aims to present a probabilistic approach to the assessment of the tool life performance based on fundamental experimental data for cutting speeds and feed rates. The methodology developed and adopted, accounts for construction of a response surface (RSM) for the representation of flank wear (V_B) as a function of cutting speed (V_c) and feed rate (f), formulate a relevant limit state function and together with appropriate statistical representation of stochastic variables provide input to bespoke probabilistic assessment techniques such as Monte Carlo Simulations (MCS) and First Order Reliability Methods (FORM).

CUTTING TOOL WEAR

Tool degradation appears under various wear modes and mechanisms, such as flank wear and crater development. The various wear mechanisms essentially depend on the cutting conditions and on the tool and part materials. They can generate different statistical distributions of the operating time to failure such as the normal, the log-normal or the Weibull distributions. To evaluate the reliability of cutting tools in both variable and constant feed machining process, a mathematical model based on the theory of probability is necessary. This stochastic model is related to the random variable associated with the operating time to failure of the cutting tool.

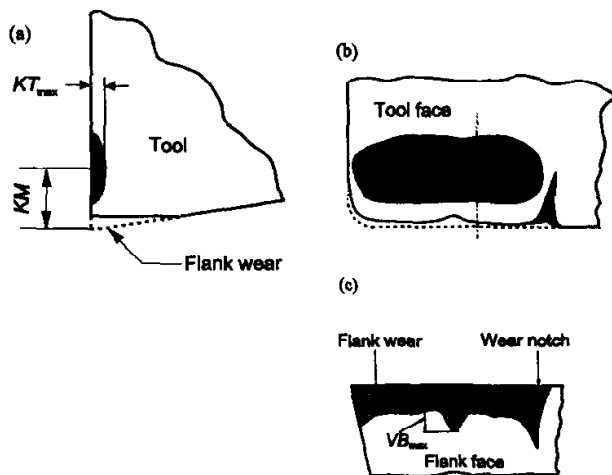


Figure 1: Wear characteristics [5].

A number of different types of wear mechanisms can be observed depending on the cutting conditions (figure 1). Typically tool failure modes are dictated by the following types of wear mechanisms [7]:

- Gradual wear (flank and nose wear), observed at low feed, speed, and depth of cut
- For higher values of depth of cut, the dominant failure mechanism is the depth of cut notch on the tool rake and flank faces
- For high cutting speeds and relatively high feed speeds, catastrophic failure due to tool breakage occurs. The time and severity of tool breakage depends on the speed.
- In finishing processes, depth of cut notches and secondary grooves are the causes of tool failure since the former causes chipping of the tool and the latter spoils the quality of the workpiece surface.

Chemical wear is also one of the main causes of tool failure. The adhered workpiece material always removes small particles of the tool when it breaks away and causes tool chipping.

Within the present paper, the basic wear mechanism considered is the flank wear. It has been experimentally identified as the most dominant mode of wear and is a function of cutting conditions (cutting speed V_c , feed rate f and cutting time t), workpiece and cutting tool material, kind and type of coolant, etc. Experimental data available from the literature indicate that exponential relationship exist between the average flank wear and the cutting conditions, and can be described with the following equation:

$$V_B = cV_c^{b_1}f^{b_2}t^{b_3} \quad (1)$$

where c , b_1 , b_2 and b_3 are experimentally determined constants. However, the effort required for estimating these factors is increased and their applicability is limited, since these exponents are also depending on the cutting conditions as well [8].

RELIABILITY MODEL OF CUTTING TOOLS

The distribution of wear life obeys a normal distribution [9], [10], and thus the probability density function of the life distribution of tool wear $f(t)$ can be expressed as:

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{-\frac{t-\mu^2}{2\sigma^2}\right\} \quad (2)$$

where μ is the mean and σ is the standard deviation of the wear life distribution.

The damage probability (cumulative distribution function $F(t)$) is:

$$F(\tau < t) = \int_0^t f(\tau) d\tau \quad (3)$$

The reliability function $R(t)$ can be expressed thus from equation:

$$R(t) = 1 - F(t) \quad (4)$$

APPROXIMATION METHODS

Traditionally, the methods used in practice for the assessment of structures and components are based on safety factors, partial or global, usually derived from the experience gained on the field, and do not take systematically into account the total uncertainty on the model. A probabilistic approach, on the contrary, can overcome this deficiency including different types of uncertainties through a methodological procedure, characterizing with a degree of confidence the level that the design specifications are met.

Reliability Analysis allows the estimation of the joint probability of non-fulfilment for each of the functional requirements mathematically expressed through corresponding limit states (difference between allowable and actual values of variables). It is assumed that design variables are expressed by an n -dimensional vector X , which has a known continuous joint distribution $f_X(X)$. Each functional requirement must necessarily be expressed by $g_j(X)$, called limit-state function, which associates a negative value if the state identified by the variables results in failure, a positive for safe and a null value for the critical limit condition [11]. The probability of failure P_f is the likelihood that the variables satisfy or not each of the limit-states, and is given by:

$$P_f = \text{Prob}\{g(X) < 0\} = \int_{g(X) < 0} f_X(x) dx \quad (5)$$

2.1 Stochastic Response Surface Method (SRSM)

Complicated failure mechanisms can impose significant difficulties on the derivation of an explicit expression of corresponding limit states. Towards this and depending on the nature of the limit state, the Stochastic Response Surface Method (SRSM) can be employed in order to provide an effective and precise estimate of the reliability of a structure. According to this method, the real limit-state function is estimated by a simpler mathematical function, such as polynomial quadratic, obtaining an approximated limit-state function, constructed by using some designated sample

points, where the response surface is suited to the limit-state.

Once the approximation has taken place, P_f and all the other quantities can be evaluated with both stochastic and analytical methods, such as FORM, SORM or MCS.

One of the drawbacks of this method is the lack of accuracy in cases of limit-state functions to be approximated being strongly non-linear. It has been investigated in [12] how the use of higher order polynomials or the relocation of the sample points in second-order polynomials provides significant benefits. Present work will employ quadratic polynomial functions that can match the tail curvature of response surface with good approximation and also restrict the number of required simulations [13].

The real limit-state function $g(X)$ is approximated by $\tilde{g}(X)$ that usually is a k -th order polynomial function having unknown coefficients:

$$\tilde{g}(X) = a + \sum_{i=1}^n b_i \cdot X_i + \sum_{i=1}^n c_i \cdot X_i^2 \quad (6)$$

where the coefficients a , b_i and c_i are the $(2n + 1)$ unknowns that can be found solving a set of equations obtained by some sample points from $g(X)$.

2.2 Analytical Reliability Methods

Among available methods for the approximation of the reliability values, First and Second Order Reliability Methods (FORM/SORM) are proven to be efficient by transforming the stochastic variables in a multidimensional U -space and using Taylor series expansions of the corresponding order, modifying the problem to that of finding the shortest distance from the origin to the intersection of the transformed set of axes. The transformation of the basic variables $\{X\}$ in standard and normal uncorrelated Gaussians $\{Z\}$ is [11]:

$$Z_j = \frac{X_j - \mu_{X_j}}{\sigma_{X_j}} \quad (7)$$

An efficient FORM method is the one proposed by Hasofer and Lind [14] that is composed by six steps. The reader can refer to [11] for detailed presentation of relevant methods. In cases of non-Gaussian variables, one of various available methods for conducting transformations to the normalized space should be employed [15]. Second Order Reliability Method are often employed for more complicated limit states where the response surface is approximated through a second order Taylor expansion [16].

Further from existing analytical methods the Monte Carlo Simulation (MCS) is often employed involving the random generation of values for each of variables X_i according to their statistical distribution. Then P_f is estimated simply by the frequency with which $g(X_i) < 0$. Its direct implementation is computationally very costly, since in order to estimate sufficiently accurate results the number of iterations to be generated is of the order of $10^2 \div 10^1$ times the inverse of the probability of failure to be computed. Furthermore, in MCS, the design point is not calculated. This is the reason why the method is not always suitable for optimization problems in its general case.

TOOL WEAR EXPERIMENTS

In order to apply and validate the proposed method for tool wear reliability calculation, dry cutting tests were carried out on a high speed CNC turning machine tool. The workpiece material was C55 (EN10083-2) high carbon steel, whereas the cutting tool inserts used were made of tungsten carbide (ISO TNMG 160408SG). The flank wear V_B was measured periodically during the machining processes using an optical microscope. For each measurement, five sample measurements were taken. The wear flank value reported is the average value of these five measurements.

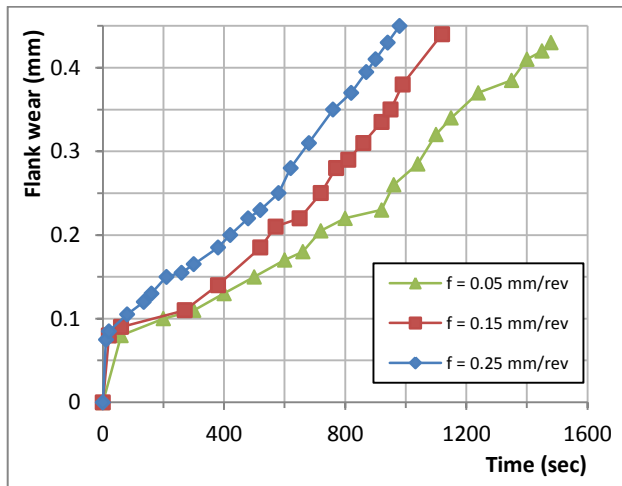


Figure 2: Tool flank wear for different feed rates ($V_c = 400$ m/min and $a_e = 0.8$ mm).

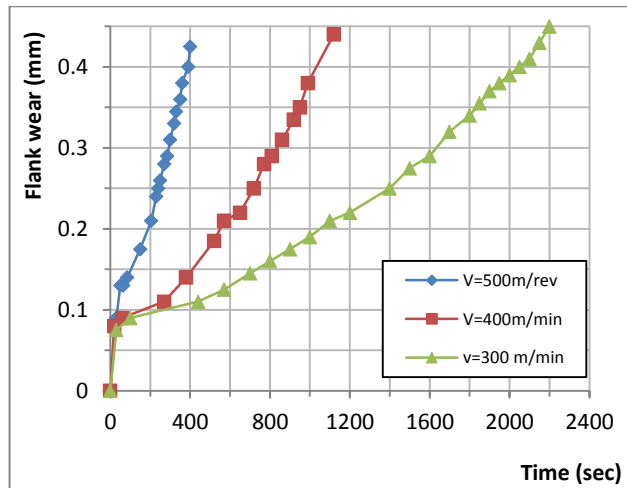


Figure 3: Tool flank wear for different cutting speeds ($f = 0.15$ mm/rev and $a_e = 0.8$ mm).

For the present study, two process variables were considered, the feed rate and the cutting speed. Feed speed values selected were 0.05, 0.15 and 0.25 mm/rev. Cutting speed values selected were 300, 400 and 500 m/min that resemble high speed machining process. In all cases the depth of cut was fixed at 0.8 mm. Figures 2 and 3 present the measured flank wear for different feed rate and cutting tool speed respectively.

RELIABILITY OF CUTTING TOOLS

For the estimation of the reliability of the cutting tools, it was assumed that the tool wear distribution can be represented using a normal distribution. This is in agreement with Hitomi et al. [9] and Wager and Barash [10] who have observed that the cutting tool life can be represented by the statistical normal distribution.

The tool life criterion was set to be 0.3 mm, i.e. when the wear flank reaches this value, the tool life ends:

$$G(V_c, f) = V_{B,crit} - V_{B,act}(V_c, f) \quad (8)$$

The analysis steps can be represented in a block diagram as can be seen in figure 4.

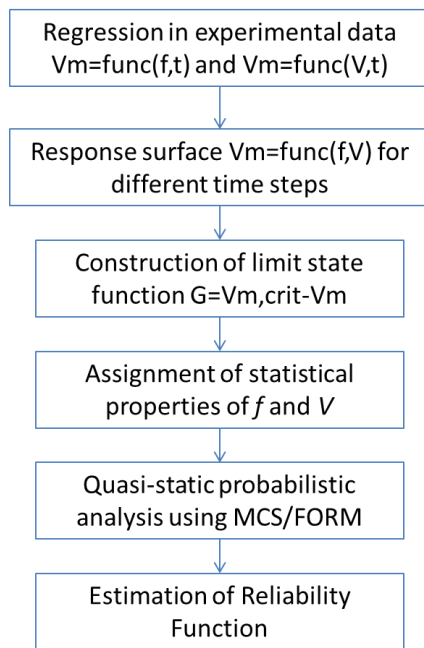


Figure 4: Analysis procedure block diagram.

In Figure 5, typical analysis results are presented for a specific cutting setup. Both the probability of failure due to flank wear and the cutting tool's reliability is presented. The failure probability curve is the probability that flank wear will exceed the critical value subject to the stochastic variables of cutting speed and feed ratio with given statistical parameters at each time step.

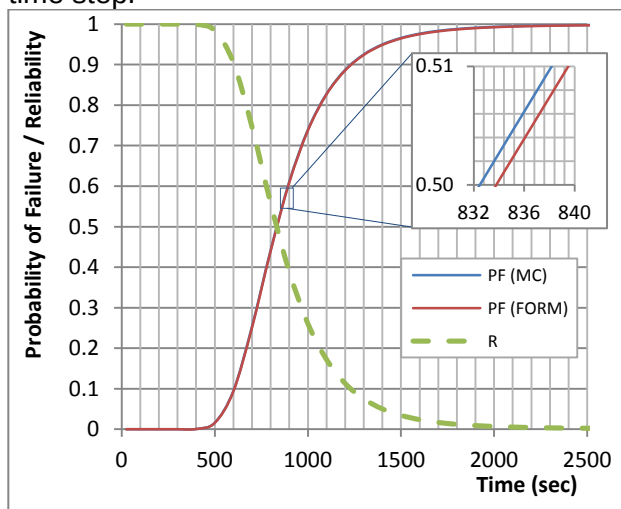


Figure 5: Typical analysis results (PF: probability of failure due to flank wear, R: Reliability of tool – shown here for $f=0.15\text{mm/rev}$, $V_c=400\text{ m/min}$, $a_e=0.8\text{mm}$).

Both FORM and MCS analysis predict similar probability values as it can be seen (detail in Figure 5). Although simpler model numerically, MCS have the drawback of increased computational requirements in cases where low probabilities are to be computed as well as

when dealing with greater number of variables. FORM, although an approximate method, performs uniformly regardless of the number of variables or magnitude of probability under consideration. For the limit state of this study, which is rather simple, both methods perform well; the small variation is due to an error accumulation variable included within the FORM code for computational purposes. However, FORM method can serve more effectively should more process variables are taken into consideration.

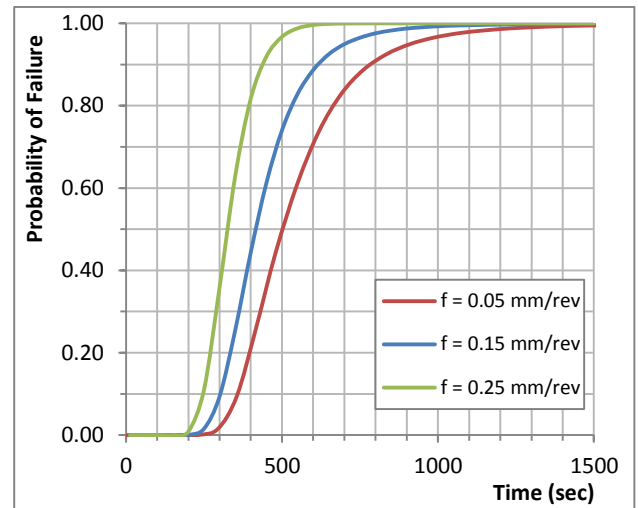


Figure 6: Probability of failure for different feed rates ($V_c = 400\text{ m/min}$ and $a_e = 0.8\text{ mm}$)

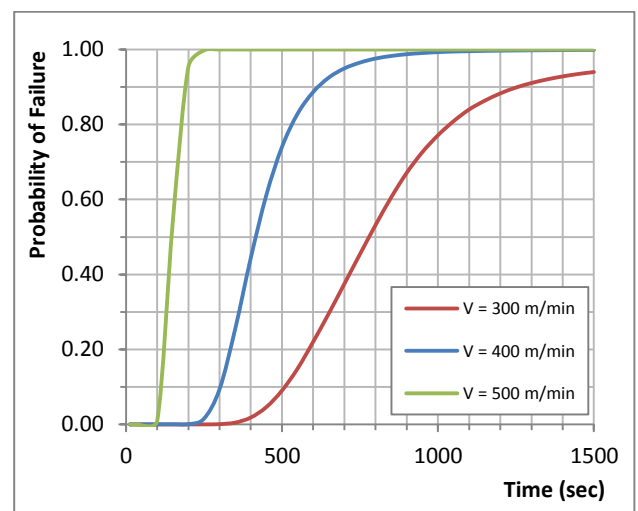


Figure 7: Probability of failure for different cutting speeds ($f = 0.15\text{ mm/rev}$ and $a_e = 0.8\text{ mm}$).

Figures 6 and 7 present the probability of failure for different feed rates and cutting speeds respectively. The effect of feed rate on tool wear failure probability is not so significant compared to cutting speed. It can be seen that tool wear reliability improves with decreasing of feed rate. With regards the cutting speed, as it

decreases, the probability of failure falls, which subsequently results in cutting tool reliability remaining higher for longer times.

CONCLUSIONS

This paper has documented a methodology for the efficient reliability assessment of cutting tool wear based on Stochastic Response Surface Method, Monte Carlo Simulations and First Order Reliability Methods (FORM) for the estimation of reliability indices. Application of the method in a cutting tool wear with indicative statistical values has illustrated its efficiency and simplicity in implementation since each step can be executed individually. The methodology employed herein can be extended to take into account more than two variables (cutting speed V_c and feed rate f in the present paper) increasing the number of variables stochastically modelled. This, together with consideration of more realistic values for the stochastic modelling of key variables, are currently studied by the authors of this paper.

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