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Reliability assessment of cutting tool life based on surrogate approximation methods

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Abstract

A novel reliability estimation approach to the cutting tools based on advanced approximation methods is proposed. Methods such as the stochastic response surface and surrogate modelling are tested, starting from a few sample points obtained through fundamental experiments and extending them to models able to estimate the tool wear as a function of the key process parameters. Subsequently different reliability analysis methods are employed such as Monte Carlo Simulations and First and Second Order Reliability Methods. In the present study these reliability analysis methods are assessed for estimating the reliability of cutting tools. The results show that the proposed method is an efficient method for assessing the reliability of the cutting tool based on minimum number of experimental results. Experimental verification for the case of high-speed turning confirms the findings of the present study for cutting tools under flank wear.

Keywords

Tool wear, flank wear, structural reliability, approximation methods, kriging, SRSM

1. Introduction

Cutting tool life is the time a tool can be reliably and efficiently used for cutting before it must be discarded or repaired. This is important in machining since considerable time is lost whenever a tool is replaced and reset. Tool wear such as flank and nose wear, crater formation, built-up edge directly affects machined part quality, in term of the surface finish, dimensional accuracy, etc. The overall process reliability, quality and capability of the machining process are affected by cutting tool reliability. 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. It has been reported that 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 accurate prediction of its performance is quite difficult. The application of reliability techniques can allow the calculation of tool life treating uncertainties systematically 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. Patino Rodriguez and Souza [7] developed a reliability-based method combined with process planning for estimating the optimum cutting tool change time. Their approach takes into consideration that each cutting tool is used for a number of different operations and was validated for the case of drilling. However, they estimate the reliability of the

manufacturing process in total, taking into consideration besides the cutting tool condition, the operator and the machine. Vagnorius et al. [8] having the same goal as the previous ones, i.e. developing an "age replacement model" as they characterize it, considered both the case of steady state wear of cutting tools through Weibull distributions and the unlikely case of premature failure through Poisson distribution.

Within the present paper a probabilistic approach for the assessment of the tool life performance is presented that is based on a minimum number of fundamental experimental data for cutting speeds and feed rates. The methodology developed and adopted, accounts for construction of an approximation model, both implicit and explicit using a response surface and a surrogate method, for the representation of flank wear as a function of cutting speed and feed rate, 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). The benefit of the proposed method is that it can account for consideration of multiple stochastic variables further to cutting speeds and feed rates, providing an even more robust probabilistic model.

2. Cutting tool wear

Reliable prediction of tool life is always a concern for machining processes. The first model for cutting tool life is Taylor's equation. A simple relationship derived from experimental observation was established for the cutting speed (V) and tool life (T): $vT^n = C$, where n and C are constants. Constants n and C depend on feed, depth of cut, work material and tooling material. However typical values can be found in the literature for various combinations of workpiece and tool material, for example for the case of use of cemented carbides for machining steel workpiece, n has a typical value of 0.25 and C equals 900 m/min [9]. However, this model has limited usefulness, since it does not take into account all cutting parameters and the amount of wear. As a result of this limitation, Taylor's equation was extended to numerous forms when considering other parameters in cutting, such as $VT^nf^md^p=C$ where V is the cutting speed, T is the tool life, f is the feed rate and d the depth of cut. Constants n, m, p and C depend on the characteristics of the process and are experimentally derived.

Tool life is directly related to the wear behaviour of the cutting tool. Tool degradation appears under various wear modes and mechanisms, such as flank wear and crater development. Of these two, flank wear is often considered as most important and used

to define the end of effective tool life. Tool wear at the cutting edge can be also observed as nose wear and chipping [9].

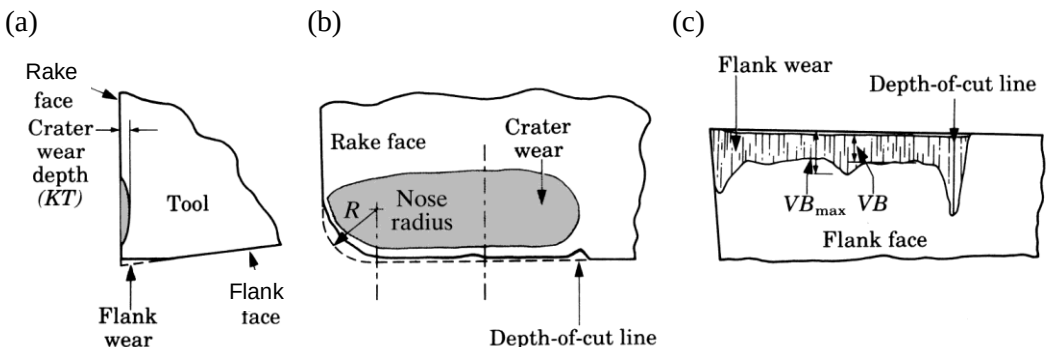

Figure 1. Wear characteristics [9]

A number of different types of wear mechanisms can be observed depending on the cutting conditions such as abrasion, adhesion, oxidation, diffusion etc. (Figure 2). On most occasions, these wear mechanisms operate simultaneously in a machining processes. The dominant wear mechanism will depend on the cutting conditions and tool / workpiece materials. El Wardany and Elbestawi [10] correlated the prevailing wear mechanisms with the cutting parameters. A common understanding nowadays link crater wear with dissolution and diffusion mechanisms [11], [12] and flank wear with adhesive wear [13].

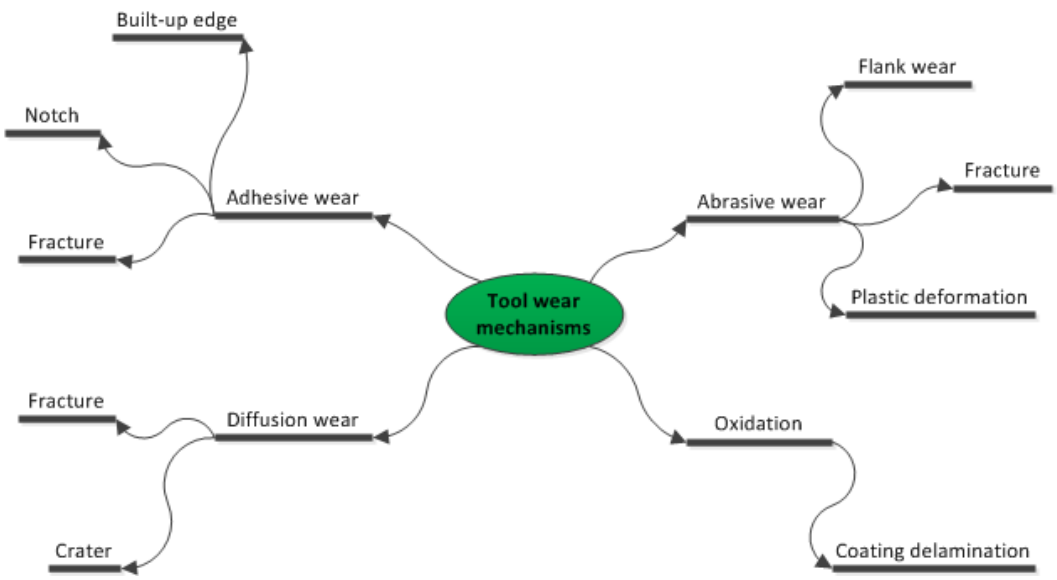

Figure 2. Tool wear mapping

The most reliable and accurate way of assessing the cutting tool wear is through visual inspection using an optical microscope. However, such an approach in not practical as it intermits the process and is associated with high costs and delays. Indirectly, the tool wear can be identified through a number of consequences, for example for the case of finishing processes either increased surface roughness or deviation from tolerances is an evidence of tool wear. For the case of roughing processes, tool wear affects the machining dynamics, and can be monitored by measuring cutting forces or cutting temperature. Tool life criteria in practice are presented in table 1.

Table 1: Tool life criteria in practice

Tool life criteria
1. Complete failure of cutting edge 2. Visual inspection of flank wear (or crater wear) by the machine operator 3. Fingernail test across cutting edge 4. Changes in sound emitted from operation 5. Chips become ribbony, stringy, and difficult to dispose of 6. Degradation of surface finish (e.g. surface roughness exceeding a critical value) 7. Increased power 8. Workpiece count 9. Cumulative cutting time

It is evident that the industrial practice is on the conservative side with regards the expected tool life. As already mentioned less than 80% of the expected tool life is used [1]. The lack of theoretical models for the prediction of tool life is also an issue. Traditional tool life models do not take into account the variation inherent in metal cutting processes. Taylor model which is still used for assessing the tool life considers tool life to be deterministic in nature. As a consequence, the real tool life rarely matches the predicted values due to the inherent variation of the machining processes [14].

3. Reliability Background

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 inherent sources of uncertainty. 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 is defined as "the ability of a system to fulfil its design functions under designated operating and environmental conditions for a specified period of time" [15]. 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). Theoretically reliability is defined as the complementary to 1 of the probability of failure. The probability of failure can be seen as the probability for which a limit state for a system is exceeded. This can be expressed for a multi-variable system $\mathrm{X} = \{\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, \ldots \mathrm{x}_\mathrm{k}\}$ using Limit State Functions formulated as the difference between the supply and demand:

$$\mathrm{g(X) = L(X) - V(X)} \tag{1}$$

Where L is the allowable (permitted) limit, often determined by design standards and practices, and V the actual value of the response variable, i.e. stress range or displacement, each or both as a function of the stochastic variables.

The n-dimensional vector X expresses the design variables which each has a known continuous joint distribution $f_X(X)$. Thus each functional requirement must necessarily be expressed by $g_j(X)$, the 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 [16].

According to the definition of the Limit State Function given above, the probability of failure can be mathematically defined as the probability for the limit state condition to be unsatisfied: $\mathrm{P_f = P[g(X) < 0]}$. Hence the probability of failure can be rewritten as:

$$\mathrm{P_f = \int_{-\alpha}^{0} f_g dg = \int_{g(X)<0} f_g dg} \tag{2}$$

The solution of this integral is in most cases very difficult, if not impossible, to be analytically derived hence approximation methods are often employed characterised by different computational requirements and accuracy.

First and Second Order Reliability Methods (FORM/SORM) employ second order Taylor expansions formulating easy to model algorithms for computation of $\mathrm{P_f}$. Further to analytical, stochastic methods such as Monte Carlo simulations are widely used due to the fact that they do not require much knowledge and statistical understanding of the problem. The algorithm is easy to implement and consists of launching several times the deterministic model with different inputs and checking each time if one or more thresholds are exceeded or not. Disadvantage of the method is that it is not suitable for

low probabilities of failure as it becomes computationally demanding. Further description of the methods and their mathematical formulation can be found in [16].

4. Approximation methods for estimating cutting tool wear reliability

Input stochasticity brings uncertainty in the process and some randomness on the output. The output is often reasonably limited and an assessment regarding limit exceedance is difficult to perform. Lack of knowledge on the behaviour of the system also forces to frequent inspection and maintenance action which is often unneeded and impose a further cost.

Systematic probabilistic assessment of complicated systems is possible but conventional deterministic approaches are so well established that novel ones face several barriers towards their application, such as the need of more complicated analytical tools to account for system variability. The problem can be treated in a more mathematically intensive way through intrusive formulation (i.e. embedding in the analysis codes the stochastic variability of the system) or in a simpler way through non-intrusive formulation (i.e. keeping codes as black boxes and dealing with system response surfaces). In the first group Stochastic Galerkin FEM or Spectral Stochastic FEM are included; in the second one SRSM and Probabilistic Collocation Method are [17].

Complexity of engineering problems often demands reduction of system through appropriate approximations, formulating expressions that implicitly or explicitly represent the relationship between inputs and outputs.

The proposed method herein (Figure 3) predicts the reliability of cutting tools based on a minimum number of tool wear experiments. Measuring the flank wear under different (but typical) process parameter combinations is common when first testing new cutting tools. Such measurements can allow the estimation of the reliability of the tool. However, in order to use equation 2 for estimating the probability of failure, the limit state function needs to be determined. The actual value of the limited variable in that case needs to be determined from the experimental results. Therefore, two different approximation methods are used for estimating the actual value function V(X), response surface and surrogate (kriging) modelling methods. Afterwards, and based on the limit value L(X), the probabilistic analysis can be performed using either FORM/SORM or Monte Carlo simulations for the estimation of the probability of failure. In the following sections all these different discrete tools/methods are explained in more detail, and the mathematical basis is presented.

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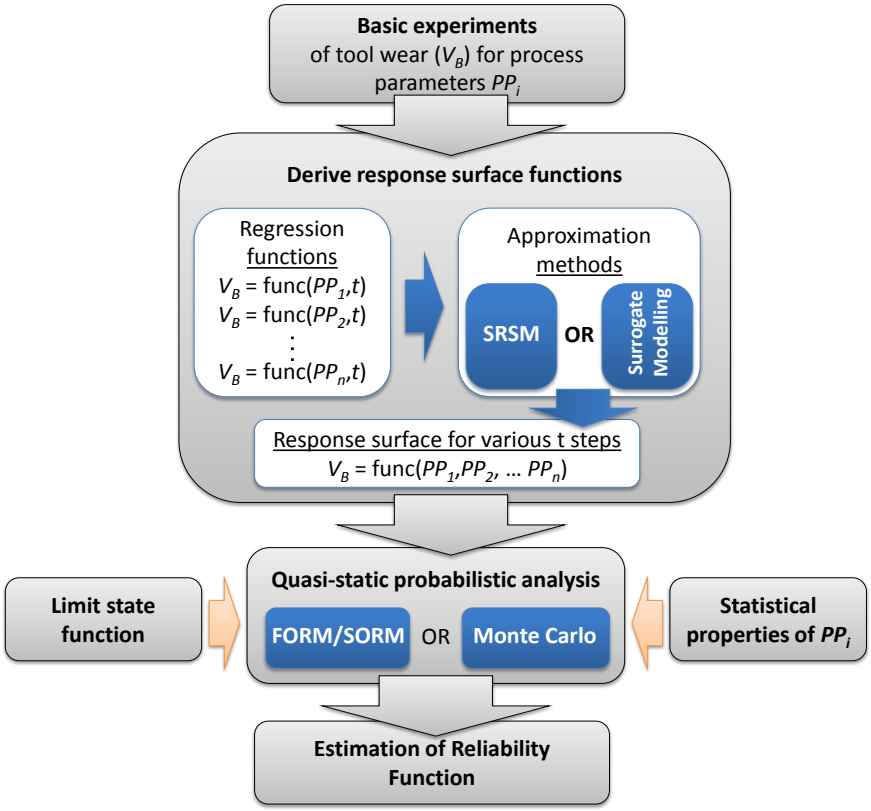

Figure 3. Analysis procedure block diagram

4.1. Deriving approximation models

The value function V(X) describing the actual flank wear can be estimated from the basic experimental results. Available techniques for estimating a function from a minimum number of experimental points distinguish Response Surface (RSM) and Surrogate Modelling methods (SM). Both methods start from a limited number of {Xi, Yi} points, the former one attempting to find an interpolating fit through those points (best fit) while the second one, through more numerically intensive procedures build non explicit models that can accurately validating the initial points (passing through each of them). In the RSM, polynomial regression techniques (MPR) and generalized linear models (GLM) can be identified while in SM, techniques such as kriging and radial basis functions (RBF) [18]. Approximating the system under analysis using such expressions facilitates analysis allowing both optimization and reliability analysis since objective functions and Limit State functions can be expressed through such reduction techniques.

4.1.1. Stochastic Response Surface Method (SRSM)

In cases of linear response of a system to stochastic inputs, a response surface method can provide accurate results approaching the 'real' limit state function 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.

One of the drawbacks of this method is the lack of accuracy in cases of strongly non-linear limit-state functions to be approximated. Gavin and Yau [19] investigated how the use of higher order polynomials or the relocation of the sample points in second-order polynomials provides significant benefits. In the present work, quadratic polynomial functions will be employed.

Mainly two factors affect the accuracy of such approximation, which is typically not highly accurate for complicated response surfaces. First of all the shape of the function is assumed before performing any analysis on the system and so it is independent of the real shape of the response surface. Secondly this is a non-interpolating technique for which smoothing and averaging of the original surface happens [20]. Some other methods, based on weighted regression (e.g. Adaptive Response Surface Method) are available [21] and guarantee higher accuracy because different weights are given to the samples closer to the limit state function so that they contribute more to the regression approximation, they demand however a dynamic sampling procedure that is not applicable in the case that results from real experiments, rather than numerical simulations, are taken into consideration. The order of the polynomial necessary to well approximate the system can be found through statistic residuals tests.

Following a common Least Square Method (LSM), the unknown coefficients can be determined solving a system of equations:

$$\mathrm{Y} = \mathrm{X}\alpha \tag{3}$$

Where Y represents the vector of responses, X the matrix of input sets and α the vector of unknown coefficients. Solution techniques for this system of equations are well known and will not be reported here [22].

Few studies have been presented that uses RSM for studying the cutting tool wear [23], [24], without however considering the stochasticity of the parameters.

4.1.2. Surrogate Modelling Methods – Kriging

Surrogate Modelling methods include a group of functions that try to approximate the response surface by means of combination of simple functions. Such functions are called basis function and have various shapes [25]. An evolution of simple Gaussian radial basis functions (where radial refers to the symmetrical functions, centred around a set of

points) is represented by kriging, which was first developed by mining engineer Danie Krige to predict the concentration of minerals [26].

The basis function used to approximate the original one is:

$$corr[Y(x^{(i)}), Y(x^{(l)})] = e^{-\left(\sum_{j=1}^{k} \theta_j |x_j{}^{(i)} - x_j{}^{(l)}|^{p_j}\right)} \quad (4)$$

Which represents the correlation between two sample points (i-th and l-th). The two parameters that differentiate this basis function from the Gaussian radial basis one are the smoothness coefficient p_j that represents how fast the function is and how quickly tends to infinite and zero and θ_j which stands for the "activity or width parameter" and contains information about the level that the output is affected by the corresponding input. The prediction at a new point is assumed to follow the same correlation. Finding the parameters values is a procedure done maximizing the likelihood of the sample set which is partially achieved through analytical differentiation and partially by direct search (e.g. genetic algorithms, simulated annealing etc). The predictor is expressed as:

$$y^*(x) = \hat{\mu} + \psi^T \Psi^{-1}(y - 1\hat{\mu}) \quad (5)$$

Where ψ is the correlation vector between the samples and the prediction point, Ψ is the correlation matrix, $\hat{\mu}$ the MLE estimate of the mean of the sample responses and y the sample responses.

Kriging also incorporates a procedure to eliminate noise in the sample set [25]. Sampling and tuning are also of key importance for kriging. Sampling can be successfully achieved through Latin Hypercube Sampling (LHS) and tuning strategies can be found in literature.

In actual applications the limit state is mostly represented by a second order polynomial in k variables. Kriging parameters obtained though kriging approximations performed on the reference system can be used to directly work out the limit state expressing through the kriging predictor. What can be obtained from second term of the predictor is a single value that represents the deviation from the mean value $\hat{\mu}$. In the expression of this matrix multiplication one part of the formula dependent on the new prediction point, which is ψ^T and a second part independent from this, $\mathcal{G} = \Psi^{-1}(y - 1\hat{\mu})$ can be distinguished. $\mathcal{G}$ is a nx1 matrix where each line can be expressed as:

$$\mathcal{G}(i,1) = \Psi^{-1}(i,1)(y_1 - \hat{\mu}) + \Psi^{-1}(i,2)(y_2 - \hat{\mu}) + \cdots + \Psi^{-1}(i,n)(y_n - \hat{\mu}) \quad (6)$$

The multiplication $\psi^T \mathcal{G}$ can be expressed as

$$\psi^T\mathcal{G} = \psi^T(1,1)\mathcal{G}(1,1) + \psi^T(1,2)\mathcal{G}(2,1) + \cdots + \psi^T(1,n)\mathcal{G}(n,1) \quad (7)$$

Where, $\psi^T(1,i) = e^{-\{\theta_1|x_{1,i}-x_1|^2+\cdots+\theta_1|x_{k,i}-x_k|^2\}}$ and stands for the expression of the Limit State.

4.2. Quasi-static probabilistic analysis

Having formulated a useful expression limit state function, two methods can be employed to quantify probability of failure through reliability index, through a localised search of the optimum design point to the design domain.

4.2.1. First and Second Order Reliability Methods (FORM/SORM)

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:

$$\mathrm{Zj} = \frac{\mathrm{X_j} - \mu_{\mathrm{X_j}}}{\sigma_{\mathrm{X_j}}} \quad (8)$$

An efficient FORM method is the one proposed by Hasofer and Lind [27] that is composed by six steps. In cases of non-Gaussian variables, two of various available methods for conducting transformations to the normalized space should be employed [28]. Second Order Reliability Methods are often employed for more complicated limit states where the response surface is approximated through a second order Taylor expansion [29].

4.2.2. Monte Carlo Simulations (MCS)

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 $g(X_i)<0$. Generating a set of random inputs according to corresponding variables distributions the response is evaluated and compared with the limit. Repeating this procedure for a large number of runs and summing up the number of times that the limit has been exceeded the probability of failure can be estimated as

$$\mathrm{P_f} = \frac{\mathrm{N_{failures}}}{\mathrm{N_{runs}}} \quad (9)$$

Random input sets can be generated through relevant algorithms using the inverse function method [30] [ref] where first a random number in the range [0, 1] is generated and then, knowing the shape of the density function (Probability Density Function, PDF or Cumulative Density Function, CDF) the corresponding variable value can be found.

A minimum number of runs is required to get accurate results. It is common practice to set the minimum sample as the inverse of two orders of magnitude the expected order of the failure probability to be estimated [16], constituting its direct implementation as computationally costly. 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.

4.3. Limit State Function and Statistical Properties of Process Parameters

The statistical properties of the process, i.e. the statistical distribution that both the process parameters and the outcome of the process follow, have been debated extensively over the last 50 years. Vagnorius et al. [8] recently summarized the state of the art on the statistical characteristics of the tool life. Early researchers considered that the tool life present normal distribution for complete tool failure [14], [31]. Kwon et al. [32] recently used Gaussian distribution as well. However normal distribution can predict negative tool life values [8], and experimental data show that some tool lives are very long, indicating that a non-symmetric distribution skewed at higher durations (tail effect) should probably better describe the reality [14]. Based on these observations, it has been suggested that either the lognormal or the Weibull distribution may better represent the data. Both these two distributions have been tested extensively by the researchers. Rausand and Høyland [33] have argued that the use of lognormal distribution is not a realistic distribution to be used for cutting tool life prediction due to its failure rate function shape, which increases for a certain time, but then starts decreasing and approaches zero. Weibull distribution, due to its inherent flexibility, seems to be the most appropriate choice, as the proper selection of distribution parameters can represent most of the failure rate function shapes [33].

For the needs of the present study the distribution of wear life is one of the factors to be assessed. Therefore all three aforementioned distributions were assessed (Normal, lognormal and Weibull). The probability density functions of the life distribution of tool wear f(t) are listed in table 2.

Table 2. Probability density functions for various distributions

Distribution type	Probability density function (PDF)	Equation No
Normal	$f(t;\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{t-\mu^2}{2\sigma^2}\right\}$	(10)
Lognormal	$f(t;\mu,\sigma)=\frac{1}{t\sigma\sqrt{2\pi}}\exp\left\{-\frac{(\ln t-\mu)^2}{2\sigma^2}\right\},\ t>0$	(11)
Weibull	$f(t;\lambda,k)=\begin{cases}\frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1}\exp\left(-\left(\frac{t}{\lambda}\right)^{k}\right), & t\geq 0\\ 0, & t<0\end{cases}$	(12)
Where μ is the mean and σ is the standard deviation for each distribution type. For the case of Weibull distribution k is the shape parameter and λ is the scale parameter (both values can only be positive).		

4.4. Probabilistic assessment methodologies

In this paper three methods have been applied to the tool wear problem under analysis. Their development is documented in this section, highlighting benefits and drawbacks of each of them.

4.4.1. SRSM-MCS

This methodology applies approximation only to approaching the 'real' response surface through a quadratic polynomial for the two independent variables that are considered. The aspect of calculating the probability of failure is not approximated and accuracy of the results is solely dependent on the level of Pf that we seek to calculate. Both modelling SRSM through LSM and the MCS routine are easy, however the computational time required again depends on the level of accuracy considered.

4.4.2. SRSM-FORM

In this methodology approximation is introduced both in the approximation of the response surface as well as in the estimation of reliability index through FORM. The more levels of approximation the greater the expected loss of accuracy in the results. This method is expected to work properly for systems with a limit state presenting high linearity with insignificant curvatures (limited changes in monotony). Benefit of the method is that due to the fact that it is analytical, it demands the same computational resources for the calculation of higher or lower Pfs. Although it is largely employed, results can become unstable and inaccurate (e.g. far from the ones obtained using direct MCS). Concluding this is the most simplified, faster and most approximating technique as will be illustrated in the results.

4.4.3. Kriging-FORM

Reliability approximation can be improved by the adoption of surrogate modelling methods and employment of FORM for the reliability assessment. The latter decision is based on the fact that comparison of the methods combining SRSM with FORM and MCS do not provide significant deviations, revealing the high linearity (continuity) of the system; this can be countersigned by the curves of the original experimental data. Through kriging better accuracy can be obtained since the approximation surfaces passes through all sampling points but the simulation time increases for each iteration of the FORM algorithm.

5. Case study

5.1. 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 C55E (EN 10083-2 - The chemical and mechanical properties are shown in the Tables 3 and 4 respectively) high carbon steel, whereas the cutting tool inserts used were made of tungsten carbide (ISO TNMG 160408SG). The flank wear VB was measured periodically during the machining processes using an optical microscope. For each measurement, five sample measurements were taken in order to minimize statistical errors. The wear flank value reported is the average value of these five measurements. The flank wear was measured according to ISO 3685:1993 standard [34].

Table 3. C55E chemical composition (source: raw material provider)

C%	Si% max	Mn%	P% max	S% max	Cr% max	Mo% max	Ni% max
0.52-0.60	0.40	0.60-0.90	0.030	0.035	0.40	0.10	0.40

Table 4. C55E normalized mechanical and physical properties (source: raw material provider)

Tensile strength (MPa):	600 – 680 (depending on the nominal thickness)
Upper yield strength (MPa):	270 – 370 (depending on the nominal thickness)
Young modulus (GPa):	200
Elongation (%)	8 – 25
Thermal Expansion (10^{-6}/K)	10
Thermal Conductivity (W/m.K)	25

Specific Heat (J/kg.K)	460
Melting Temperature (°C)	1450 – 1510
Density (kg/m^3)	7700
Resistivity (Ohm.mm^2/m)	0.55

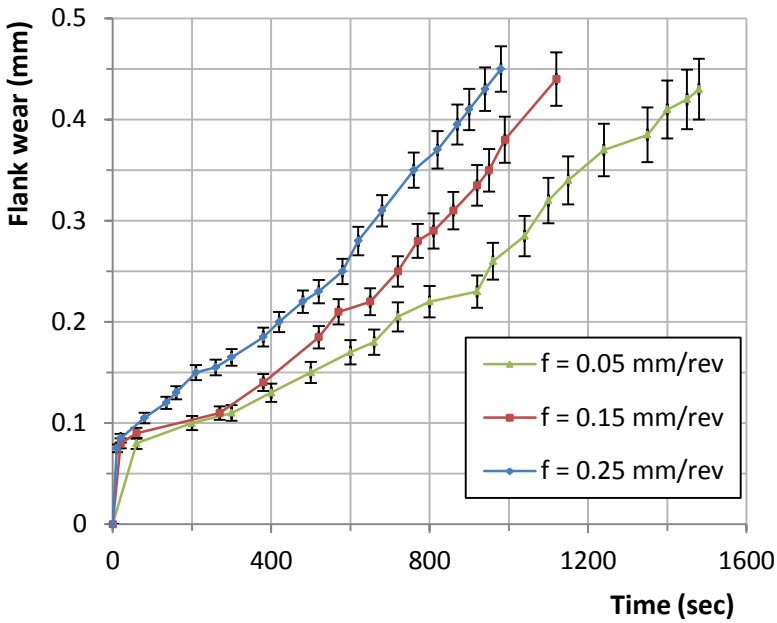

Figure 4. Tool flank wear for different feed rates (V_c = 400 m/min and a_e = 0.8 mm).

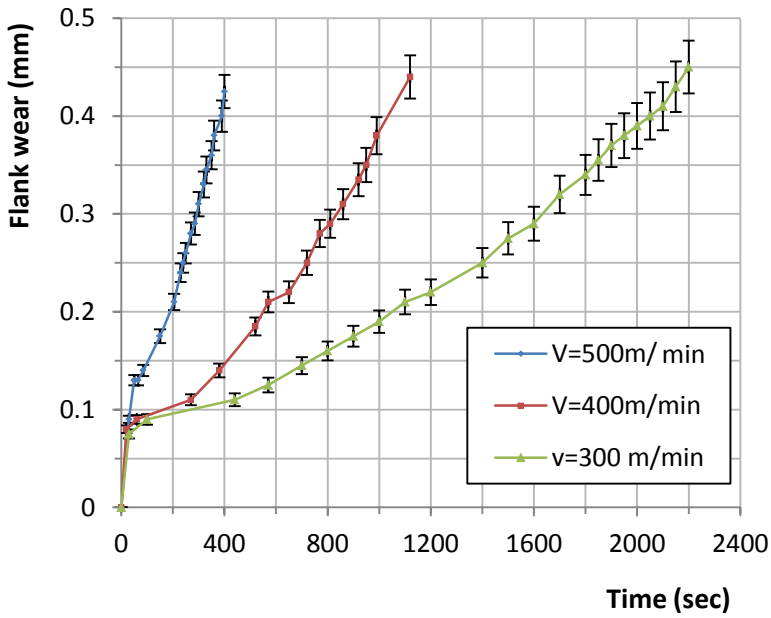

Figure 5. Tool flank wear for different cutting speeds (f = 0.15 mm/rev and a_e = 0.8 mm).

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. High machining speed leads to high machining efficiency, and subsequently to low production cost. However, high cutting speed can lead to high cutting temperature that accelerates tool wear and shortens tool life.

In all cases the depth of cut was fixed at 0.8 mm, as according to Axinte et al. [35], depth of cut does not have a significant effect on the tool life. Figures 4 and 5 present the measured flank wear for different feed rate and cutting tool speed respectively.

The three typical zones can be identified in figures 4 and 5. Zone A where the initial flank wear is established (break-in period), zone B where wear progresses at a uniform rate (steady-state wear region) and zone C where wear occurs at a gradual increasing rate (failure region). In figure 6, these typical zones are visualized for a specific data set.

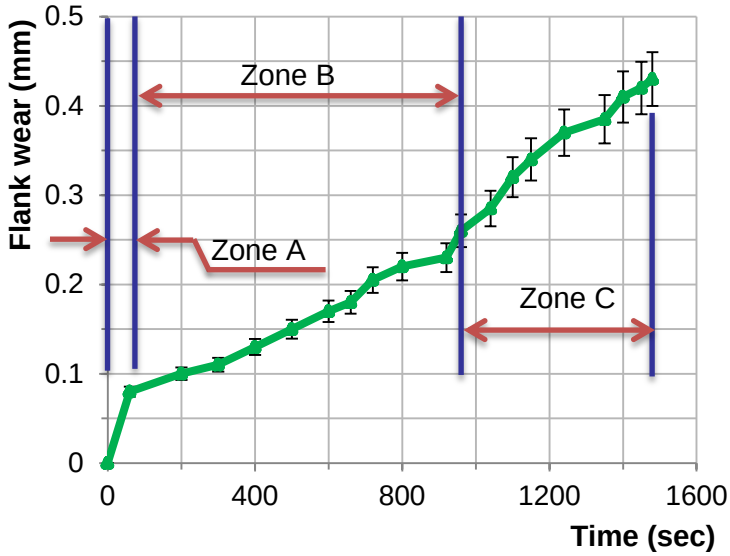

Figure 6. Tool wear progression zones (illustrated for V_c = 400 m/min, f=0.00 mm/rev and a_e = 0.8 mm).

5.2. Methodology implementation

Based on the experimental results, the response surfaces were determined using either SRSM or kriging methodology. The surfaces are characterized by equations in the following form:

$$T = C\,(V^n f^m d^l)\,E \qquad (13)$$

where T is the tool-life in minutes, V, f and d are the cutting speed, feed rate and depth of cut respectively. C, l m, n are constants and E is a random error.

In figure 7, the response surface derived using SRSM, kriging and the experimental points for one of the time steps that have been studied (t=700) are shown for comparison; the solid grey surface represents kriging results, the blue dotted grid the SRSM approximation while the red dots the original points. For this specific case, both SRSM and kriging validate experimental results, since the number of available samples is the minimum that is required for a quadratic SRSM with two variables (2k+1). In a problem where more data would be available, the accuracy of the curve would be significantly higher using kriging.

The response surfaces were calculated quasi-statically through a self-build algorithm for this reason. Although their form follows eq. 13, values C, n, m, l and E are not deterministically determined.

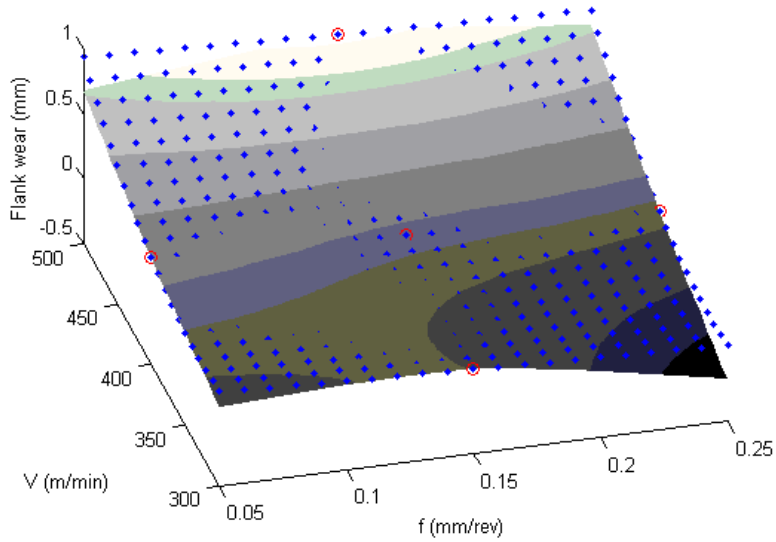

Figure 7. Response surfaces as estimated using SRSM and kriging

For the estimation of the reliability of the cutting tools, all three possible tool wear distributions were considered and assessed. The tool life criterion was set to be 0.3 mm, i.e. when the wear flank reaches this value, the tool life ends:

$$G(V_c, f) = V_{B,crit} - V_{B,act}(V_c, f) \tag{14}$$

The tool life criterion was selected according to ISO 3685:1993 [34] standard for the case of cemented carbide tools where no irregular wear of the flank is observed. As it can be seen in figures 4 and 5, the available tool wear measurements exceeded the tool life

criterion. Although in an experimental setup, the cutting tools can be used up to their total fracture, under operational specifications however the risk of damaging either the workpiece material or the machine limits the use of the tool up to the criterion set by ISO. Nevertheless, all data were used for better prediction of the response surfaces.

6. Approximation methods comparison

In Figure 8, typical analysis results are presented for a specific cutting setup (f =0.15mm/rev, V_c=400 m/min, a_e=0.8mm). 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.

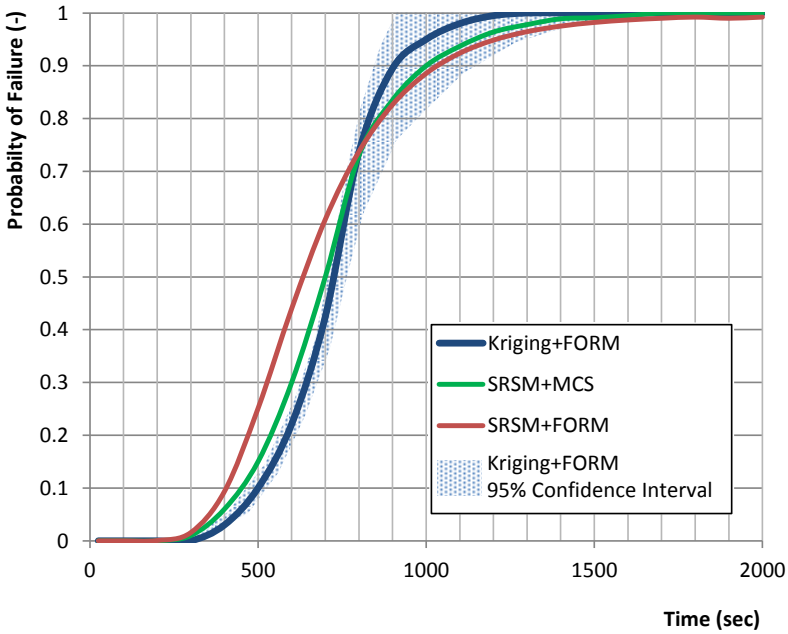

Figure 8. Probability of failure due to flank wear comparison (shown here for f =0.15mm/rev, V_c=400 m/min, a_e=0.8mm - normal distribution considered for all input parameters).

Both FORM and MCS analysis predict similar probability values as it can be seen. Although simpler model numerically, MCS have the drawback of increased computational requirements in cases were low probabilities are to be computed as well as when dealing with greater number of correlated 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.

As it can be seen in figure 9, all methods predictions are close, with kriging being a little bit more conservative towards the end of the life of the cutting tool. However, SRSM predictions for high probability of failure are within 95% confidence interval of kriging prediction.

As mentioned in the section 4.3, flank wear distribution has been considered both as normal, lognormal and weibull type in the past by a number of researchers. Zhou and Wysk [36] argue that the class of probability distribution does not have any significant effect on the choice of the optimal tool life. In figure 9, the sensitivity of the probability of failure on the type of distribution is presented. The characteristics of each distribution were estimated on measurements and observations of the actual process. For example, sigma has been calculated to fit normally the margins of the values in a percentile of 95% whereas the mean value is estimated from the capability of the machine and the experimental setup and/or the measuring instrumentation. It is evident that all three distribution types predict similar results. Therefore the assumption of normal distributions employed above is valid.

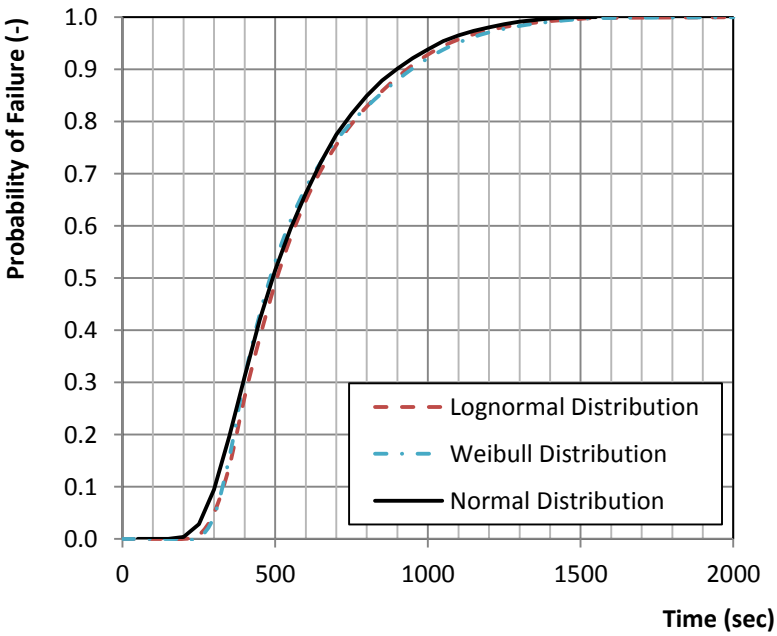

Figure 9. Probability of failure for various distributions of the flank wear (SRSM-MCS approach).

With regards the computational effort for the use of the proposed approaches, it is evident according to figure 10, that kriging method has the highest requirements. The

number of random runs for the Monte Carlo simulation has little effect on the convergence of the results. Indicatively, increasing the number of runs from 100,000 to 10,000,000 runs although the time required for solving the problem is multiplied by almost a factor of ten, the results deviate by less than 0.1%.

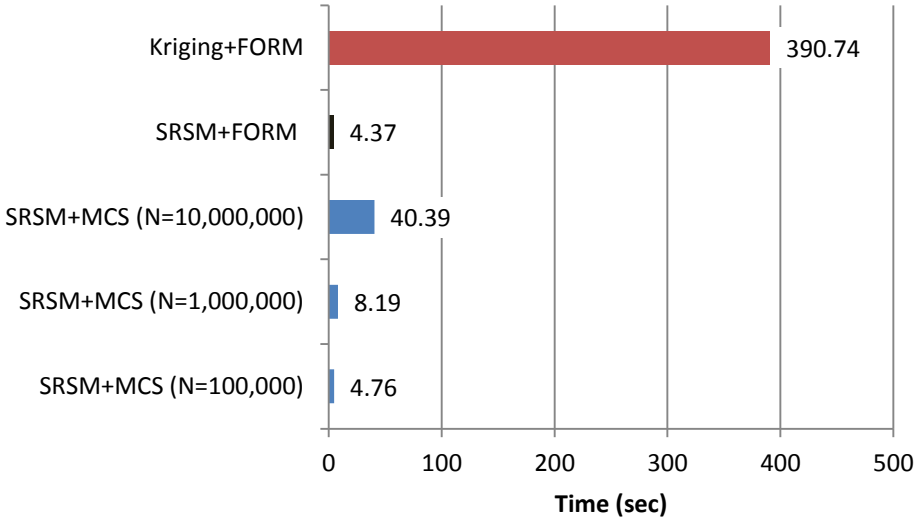

Figure 10. Computational time comparison.

From the analysis documented above, the three methods tested appear to provide similar results in aspects of accuracy for the input data considered, with the combination of kriging and FORM demanding significantly higher computational time when compared to the other two methods. Employment of MCS, even for a sample as high as 10 million simulations, can return good results with low computational requirements. Although for the case of two stochastic variables these results and performance are as expected, in a different case employing more variables or focusing on the upper tail of the cumulative distribution function a different performance would be expected, with kriging and FORM combination demanding the same computational time, while the other two methods demanding greater time than in the baseline case. Especially if the variables modelled stochastically have a highly non-linear behaviour in the response of the system, the results of analysis based on kriging are expected to be more accurate since the produced approximation can approach the 'real' response surface more accurately. By definition surrogate modelling methods like kriging do not pass through the reference points but they can be adequately verified as the constructed surface passes through the points. Due to the fact that these methods do not pre-assume a theoretical shape for the approximation surface (as polynomial regression does) it can approach well very complex, and even non linear surfaces.

7. Reliability of cutting tools

In order to assess the effectiveness of the kriging method, the reliability of the cutting tools was estimated for each of the process parameters combinations.

Figures 11 and 12 present the cutting tool reliability for different mean values for feed rates and cutting speeds respectively. The effect of feed rate on the tool's reliability 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. This is in agreement to the authors' findings using the combination of Response Surface modelling to Mode Carlo simulations and First Order Reliability Methods [37].

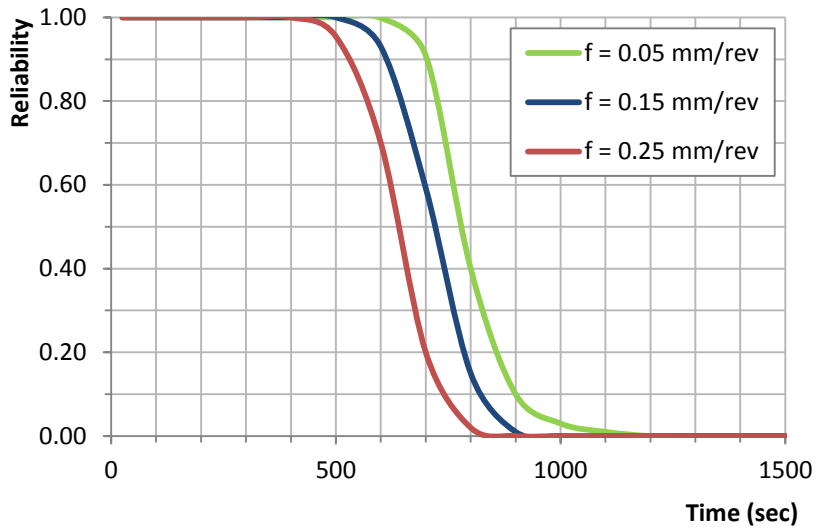

Figure 11. Cutting tool reliability for various mean values of feed rates (V_c = 400 m/min and a_e = 0.8 mm), COV=10%.

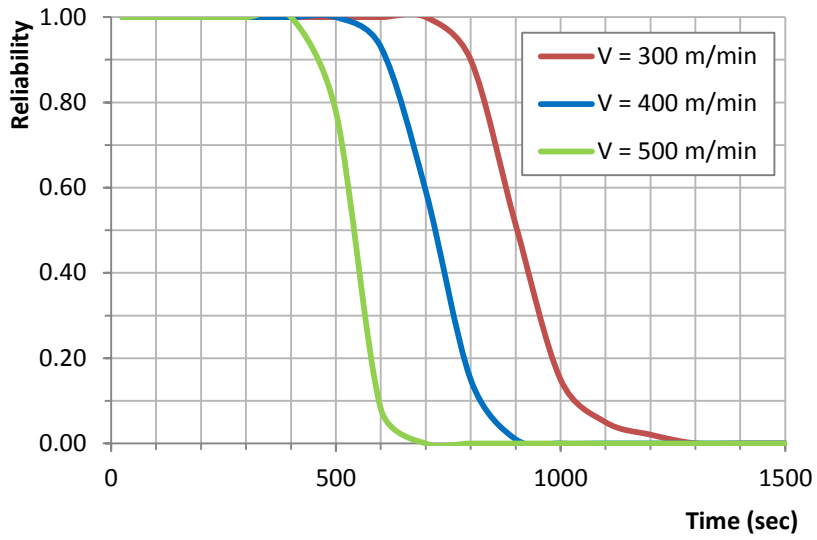

Figure 12. Cutting tool reliability for various mean values of cutting speeds (f = 0.15 mm/rev and a_e = 0.8 mm), COV=10%.

8. Conclusions

This paper has documented a methodology for the efficient reliability assessment of cutting tool wear based on combinations of Stochastic Response Surface and surrogate modelling Methods, coupled with Monte Carlo Simulations and First Order Reliability Methods (FORM) for the estimation of reliability indices. Application of the method in cutting tool wear with indicative statistical values has illustrated its efficiency and simplicity in implementation since each step can be executed individually potentially using specialized tools and incorporating results from experiments.

The methodology employed herein can be extended to take into account more than two variables (cutting speed and feed rate in the present paper) increasing the number of variables stochastically modelled. These are currently studied by the authors of this paper.

The proposed techniques show potential for determining optimal tool lives with reduced experimental testing in comparison to pure empirical methods, however, the resource intensive testing of the machining operations in combination with the machining conditions and work materials still remains.

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