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SURROGATE MODELLING FOR RELIABILITY ASSESSMENT OF CUTTING TOOLS

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ABSTRACT

Currently, cutting tool life for machining operations is correlated to process parameters through the widely applied Taylor functions. The latter are valuable expressions in established practice however their generalised nature does not allow accurate prediction of the tool's service life or optimization of the manufacturing process due to effects of uncertainties in various input variables. These variables should be treated in a stochastic way in order to avoid employment of safety factors for quantification of uncertainty. This paper documents a procedure that allows derivation of analytical expressions for cutting tools performance employing advanced approximation methods and concepts of reliability analysis. Due to the complexity of manufacturing processes surrogate modelling (SM) methods are applied, starting from a few sample points obtained through lab or soft 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.

Keywords: Kriging, surrogate modelling, manufacturing tool reliability.

1 INTRODUCTION

Performance degradation of cutting tools is an aspect of major importance towards optimization of manufacturing processes. Flank and nose wear, crater formation, and built-up edge are only a few unwanted tool wear mechanisms that can have a significant impact on the surface finish of manufactured components yielding a need for costly reworks due to waste of raw material or classification as un-acceptable. The latter case may lead to production delays due to the additional work introduced and hence it has been established as current practice to replace tools even though the still retain 20-50% of extra service life (Wiklund 1998).

Hard and brittle materials, which perform in a way that a local defect propagates rapidly and hence with sever effects are characterized as "difficult to machine" and therefore demand an even greater understanding of the conditions of cutting tools which illustrate high wear rates on both the flank and the face of the tool.

Although fabrication of cutting tools follows processes of high quality, their performance (also considering the interaction with the cutting surface) is characterized by stochasticity, constituting deterministic approaches to prediction as insufficient. To this extend and considering that tooling cost in flexible manufacturing accounts for a quarter of the total machining costs (Shakarov et al. 1990); more systematic methods should be employed in order to accurately quantify the effect of uncertainties. Concepts of structural reliability has widely been applied in cases of critical systems in aspects of frequency or consequence of failure; nuclear (Ellingwood 1998), aviation (Liu and Moses 1994), offshore (Kam 1988), and critical infrastructure (Micic et al. 1990) to name a few. Therefore the applicability of such methods in estimating cutting tool reliability is considered in the present paper.

This paper aims to adopt such practices for the probabilistic prediction of the cutting tool fatigue life starting from a limited number of experimental data, and following by using surrogate modelling as an approximation methods construct an implicit expression linking flank wear to feed rates and cutting speeds over time. The latter can then be combined to existing reliability analysis methods expressing the probability of failure (or reliability) of a cutting tool under stochastic inputs.

2 PERFORMANCE OF CUTTING TOOLS

Performance degradation of cutting tools is characterized by a number of different wear modes and mechanics, such as flank wear and crater development. The various wear mechanisms essentially depend on the cutting conditions and on the tool and part materials. 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 (El Wardany and Elbestawi 1997):

- 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.

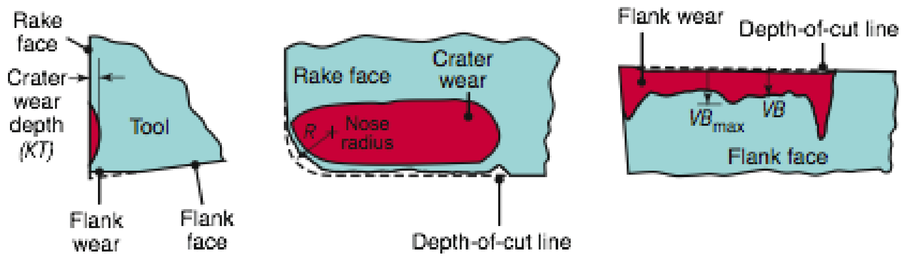

Figure 1: Wear characteristics (Kalpakjian and Schmid, 2008)

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.

3 CONCEPTS OF STRUCTURAL RELIABILITY

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". 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 $X = \{x_1, x_2, x_3, \dots x_k\}$ using a Limit State Function as:

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

Where L is the limit and V the actual value of the limited variable.

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: $P_f = P[g(X) < 0]$. Hence the probability of failure can be rewritten as:

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

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 P_f (Choi et al., 2007).

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.

4 RELIABILITY ANALYSIS OF CUTTING TOOL LIFE USING SURROGATE MODELING TECHNIQUES

4.1 Approximation Methods

Complexity of engineering problems often demands reduction of system through appropriate approximations, formulating expressions that explicitly represent the relationship between inputs and outputs. Available techniques distinguish Response Surface (RSM) and Surrogate Modelling methods (SM). Both methods start from a limited number of $\{Y_i, X_i\}$ points, the first category attempting to find an interpolating fit through those points (best fit) while the second one, through more numerically intensive procedures build models that can accurately reproduce the initial points (passing through). In the RSM, polynomial regression techniques (MPR) and generalised linear models (GLM) can be identified while in SM techniques such as kriging and radial basis functions (RBF) (Khuri 2001). Approximating the system under analysis using such expressions facilitates analysis allowing both optimization and reliability analysis since objective and Limit State functions can be approximated with such techniques. Response surface methods, in particular SRSM, have already been employed successfully both in optimization and reliability analysis (Queipo et al. 2005), as well as kriging (Forrester et al., 2006).

4.2 Surrogate Modelling - Kriging

Kriging is an evolution of Gaussian radial basis functions using the following basis function to approximate the original one:

$$corr[Y(x^{(i)}), Y(x^{(l)})] = e^{-\left(\sum_{j=1}^{k} \theta_j \left| x_j^{(i)} - x_j^{(l)} \right|^{p_j}\right)} \tag{3}$$

Which represents the correlation between two sample points. 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 gives information about how much 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:

$$y^*(x) = \hat{\mu} + \psi^T \Psi^{-1}(y - 1\hat{\mu}) \tag{4}$$

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 $\mathbf{y}$ the sample responses.

Having formulated the above expression, FORM is employed to quantify probability of failure through reliability index, through a localised search of the optimum design point to the design domain. 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 (Casali et al. 2012):

$$\mathcal{G}(i,1) = \Psi^{-1}(i,1)(y_1 - \hat{\mu}) + \Psi^{-1}(i,2)(y_2 - \hat{\mu}) + \cdots + \Psi^{-1}(i,n)(y_n - \hat{\mu}) \tag{5}$$

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

$$\psi^T\mathcal{G} = \psi^T(1,1)\mathcal{G}(1,1) + \psi^T(1,2)\mathcal{G}(2,1) + \cdots + \psi^T(1,n)\mathcal{G}(n,1) \tag{6}$$

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. The relevant algorithm is shown in Figure 2.

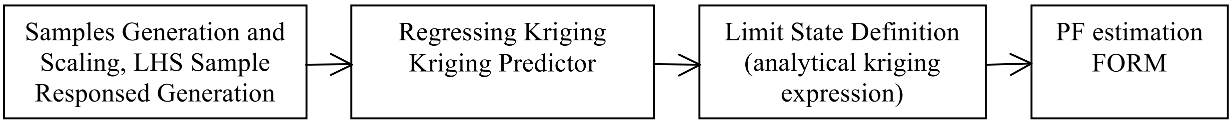

Figure 2: Analytical Kriging - FORM algorithm.

5 ILLUSTRATIVE EXAMPLE

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. 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.

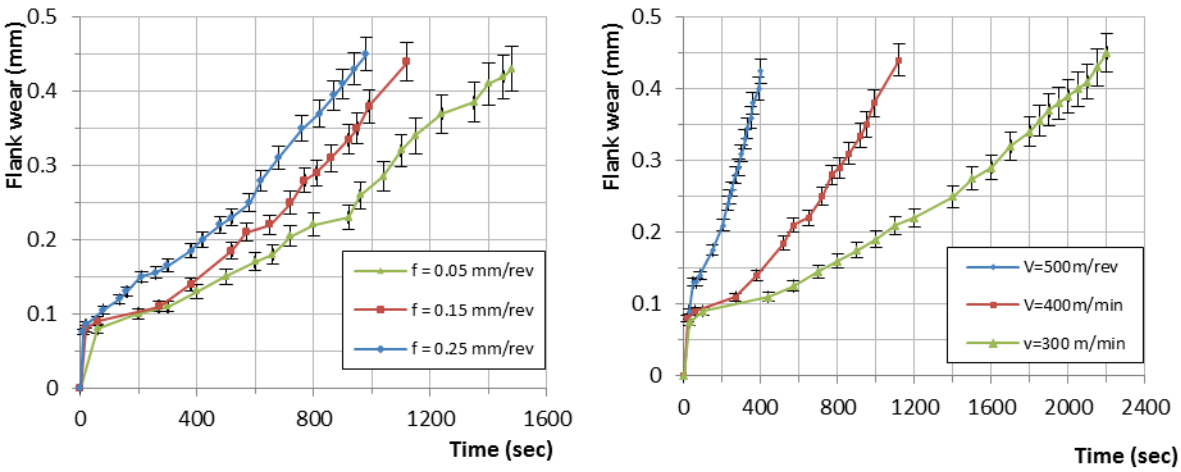

Figure 3: Tool flank wear (left) for different feed rates with V_c = 400 m/min and (right) for different cutting speeds with f = 0.15 mm/rev. In both cases cutting depth is a_e = 0.8 mm)

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. 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. Figure 3 present the measured flank wear for different feed rate and cutting tool speed.

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. (1979) and Wager and Barash (1971) who have observed that the cutting tool life can be represented by the statistical normal distribution. The tool life criterion (limit state definition) was set to be 0.3 mm.

Following the analysis outlined in section 4, the reliability and probability of failure for the cutting tools were estimated. In Figure 4, typical analysis results are presented for a specific cutting setup. 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. 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. This is in agreement to the authors findings using the combination of Response Surface modelling to Mode Carlo simulations and First Order Reliability Methods (Salonitis and Kolios, 2013).

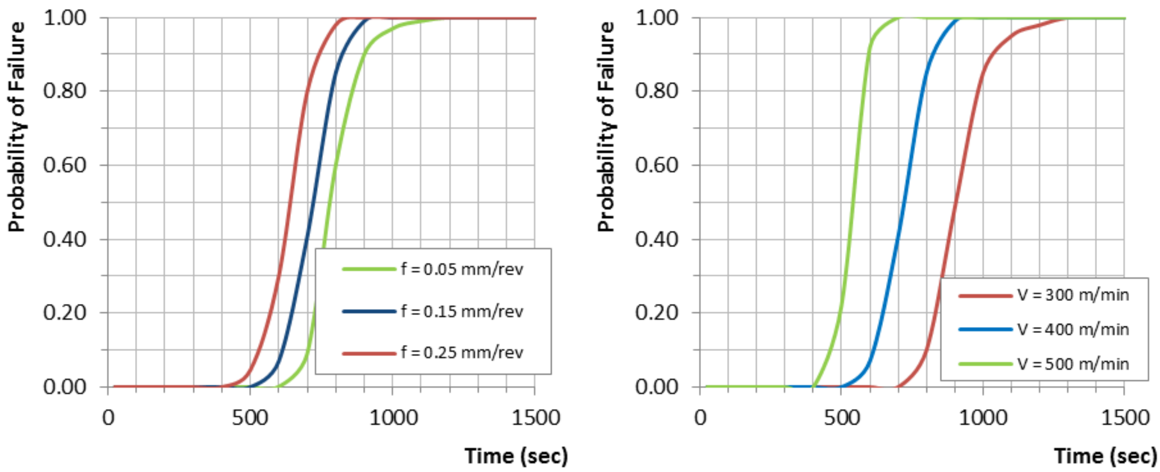

Figure 4: Probability of failure (left) for different feed rates with V_c = 400 m/min and (right) for different cutting speeds with f = 0.15 mm/rev. In both cases cutting depth is a_e = 0.8 mm)

6 CONCLUSIONS

This paper has documented a methodology for the efficient reliability assessment of cutting tool wear based on surrogate modelling (SM) methods, and more specifically kriging, 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. These, together with consideration of more realistic values for the stochastic modelling of key variables, are currently studied by the authors of this paper.

REFERENCES

Casali, D., A.J. Kolios and N. Asproulis, 2012. Uncertainty quantification of pipe flow systems using advanced approximation methods. In: *the Proceedings of the 10th International Probabilistic Workshop*, Stuttgart 2012

Choi, S., R.V. Grandhi, and R.A. Canfield, 2007. *Reliability-based structural design*. Springer, London

El Wardany, T.I., and M.A. Elbestawi. 1997. Prediction of Tool Failure Rate in Turning Hardened Steels, *International Journal of Advanced Manufacturing Technology* 13/1:1-16.

Ellingwood B.R., 1998. Issues related to structural ageing in probabilistic risk assessment of nuclear power plants. *Reliability Engineering and System Safety* 62/3:171–183.

Forrester, A. I. J., A. Sóbester and A.J. Keane. 2006. Optimization with missing data. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 462/2067:935-945

Hitomi, K., N. Nakamura, and S. Inoue, 1979. Reliability analysis of cutting tools. *Journal of Engineering for Industry-Transactions of the ASME* 101:185-190

Kam, J.C.P., 1988. Fatigue reliability assessment of offshore structures. *Quality and Reliability Engineering International* 4:41–48.

Kalpakjian, S., and S.R. Schmid. 2006. *Manufacturing, Engineering & Technology*, 5th Edition, 2006 Pearson Education, Inc., Upper Saddle River, NJ.

Khuri, A.I. 2001. An overview of the use of generalized linear models in response surface methodology. *Nonlinear Analysis* 47:2023-2034.

Liu, Y.W., and F. Moses. 1994. Sequential response surface method and its application in reliability analysis of aircraft structural systems. *Journal of Structural Safety*:6/1–2: 39–46

Micic, T.V., M.K. Chryssanthopoulos, and M.J. Baker, 1990. Reliability analysis for highway bridge deck assessment. *Journal of Structural Safety* 7/2–4:247–254.

Queipo, N. V., R.T. Haftka, W. Shyy, T. Goel, R. Vaidyanathan, R. and P.K. Tucker. 2005. Surrogate-based analysis and optimization, *Progress in Aerospace Sciences* 41/1:1-28.

Sakharov, G.N., V. Ilinykh, Konyukhov, and V. Yu, 1990. Improvement of fastening elements in an assembled cutting tool, *Soviet engineering research*, 10/11:102-103

Salonitis, K., and A. Kolios, 2013. Reliability assessment of cutting tools life based on advanced approximation methods. *Procedia CIRP*, accepted for publication.

Wager, J.G., and M.M. Barash. 1971. Study for distribution of the life of HSS tools. *Journal of Engineering for Industry-Transactions of the ASME* 73/4:295-299.

Wiklund, H., 1998. Bayesian and regression approaches to on-line prediction of residual tool life. *Quality and Reliability Engineering International* 14/5:303-309