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EFFECT OF UNCERTAINTY ON PREDICTION OF TOOL LIFE FOR MILLING ULTRAHIGH STRENGTH STEEL

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Abstract. Ultrahigh strength steel belongs to difficult-to-machine material. The wear of the tool can affect surface quality of the workpiece and frequent tool changing leads to low machining efficiency. Tool life of milling ultrahigh strength steel is thus an important indicator in manufacturing. However, in traditional method to predict tool life, it doesn't consider the uncertainties existed in experiments which are for getting data and procedure of developing models of tool life. In this paper, we investigate two distributions of milling variables and coefficients in exponental model developed by least square method on prediction by exponential model to find the effect of uncertainty. The results show that variations of variables and coefficients of variables following random distribution obviously affect prediction of tool life. To variables and constant in the model following the random distribution, prediction of tool life is not affected.

1 INTRODUCTION

Ultrahigh strength steel is used extensively in aerospace, biomedicine, heavy machinery and automotive industries, owing to its high strength-to-weight ratio, retention of strength at elevated-temperature and high corrosion resistance. Despite of having outstanding machinery, it is extremely difficult to machine because of its low thermal conductivity, low modulus of elasticity and strong chemical reactivity with cutting tool materials at higher temperature.

Severe tool wear, leading to low machining efficiency, occurs during the milling operation because of their low thermal conductivity, high chemical activity, and large friction coefficient and so on. Thus tool life is an essential aspect considered in evaluating the performance of cutting ultrahigh strength steel. Moreover, estimation of tool life and evaluation of corresponding cost are very important for processing planning and machining optimization. Prolonging tool life can reduce manufacturing cost and time of tool changing which intend to increase productivity. Estimation of tool life avoids operation with worn tool and makes sure integrity and quality of surface of work piece. The productivity, cost and surface quality are strongly depending on tool life. Estimation and prediction of tool life thus become crucially important for cutting ultrahigh strength steel. Therefore, it is very important to predict tool life for ultrahigh strength steel. The traditional method is developing model of tool life using Response Surface Methodology (RSM) or model-based approach. These models assume that tool life is deterministic [1]. RSM using approximation idea is very effective and popular for predicting tool life so that many researchers have done many works on this. Tsai et al [2] use abductive network to predict too life for milling SKD61 steel, and prediction error is less than 10%. Ojha and Dixit [3] compared neural networks and multiple regressions for estimating tool life and showed the superiority of the former. Natarajan et al [4] used artificial neural network (ANN) to predict tool life. Yang et al [5] developed a numerical model by a third-order polynomial function and compared the results of experiment and commercial finite element. Benkedijouh [6] presented a method based on nonlinear feature reduction and support vector regression for life prediction. Khamel et al [7] established the quadratic model of cutting forces, tool life and surface roughness by fitting with experimental results. Kadirgama [8] used response surface method (RSM, exactly, the method is linear regression and quadratic regression in this paper) to develop the prediction model of tool life. Lajis et al [9] also used least square method to obtain the coefficients of first or second models developed using RSM. These works provides well a theoretical foundation for prediction tool life.

However, there are many uncertainties existed in the experiments which are for getting data. In addition, inherent uncertainties exist in the empirical constants. And tool life is generally considered a stochastic process because variation is inherent in every cutting process [10]. This work thus focuses on the effect of uncertainty of milling variables and contents of models on prediction of tool life for milling ultrahigh strength steel.

2 METHODS AND PROCEDURE

The main parameters which control the quality and the efficiency of the NC machining process are depth of cut d_p (mm), width of cut d_e (mm), feed rate f (mm/min) and spindle speed N (rpm). Expression of tool life is obtained by least square method from previous work of authors [11]. In previous work, the variables sets were determined by the four-level orthogonal designs of experiments. Five tests were performed for the same experiments. At last, the mean value was taken as the final variable. The model of tool life was given after the coefficients were identified by the least square method. The material used in experiments was ultrahigh strength steel (40CrNi2Si2MoVA) with high tensile strength (around 53 *HRC*). In addition, this formula (1) is successfully used in reliability-based design optimization of NC machining operations of ultrahigh strength steel.

$$T = \left(\frac{19650}{Nf^{0.25}dp^{0.15}de^{0.1}}\right)^5 \tag{1}$$

In order to investigate the uncertainty of each variables and contents of models on prediction of tool life, here given point is [1100, 450, 3.5, 9.5] while T=111.2810 (mins). The number of trails is 10^5.

The variation of depth of cut d_p is due to non-uniformity of cast iron workpieces and the uncertainties factors in the casting process. Spindle speed N and feed rate f depend on the variation of machine tools. Width of cut d_e is ignored in much work because it is determined by the diameter of tool or experience of worker. In this work, it is given as a parameter because we want to know its effect on tool life. Based on casting process, depth of cut d_p are assumed following random distribution (the range is [2, 5]) and normal distribution (μ_{dp}=3.5, σ_{dp}=0.005) respectively. Width of cut d_e is assumed following normal distribution (μ_{de}=9.5, σ_{de}=0.005). While others one are determined and normal distribution (μ_N=1100, σ_N=5; μ_f=450, σ_f=2).

The sets to be investigated of each variable following different distribution are shown in Table 1. Firstly depth of cut d_p is given random distribution and normal respectively while the others variables are given determined (express as '-'). Then all the variables following normal distribution will be studied.

Table 1: The sets of distributions of each variable

	K	N	f	d_p	d_e
1	-	-	-	random	-
2	-	-	-	normal	-
3	-	normal	normal	random	normal
4	-	normal	normal	normal	normal

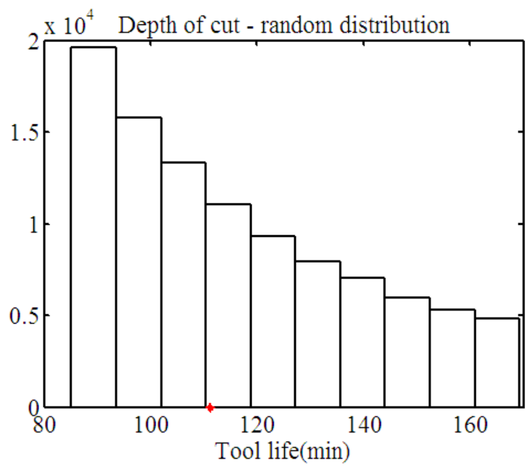
The uncertainties exist in empirical relationship due to the factors that are unknown or not included in the model. In addition, spindle speed N is most significant effect tool life [2]. The coefficient of spindle speed N is investigated in this work. Coefficient of spindle speed N is assumed following normal distribution (μ_{coeN}=-1, σ_{coeN}=0.001) and random distribution (the range is [-1.025, 1.025]). The varation of coefficent K (K=19650) is assumed following normal distributon (μ_{coeK}=19650, σ_{coeK}=3) and random distribution (the range is [19500, 19800]). The sets to be investigated of each coefficient of depth of cut d_p and constant K following different distribution are shown in Table 2.

Table 2: The sets of distribution of coefficients of d_p and constant K

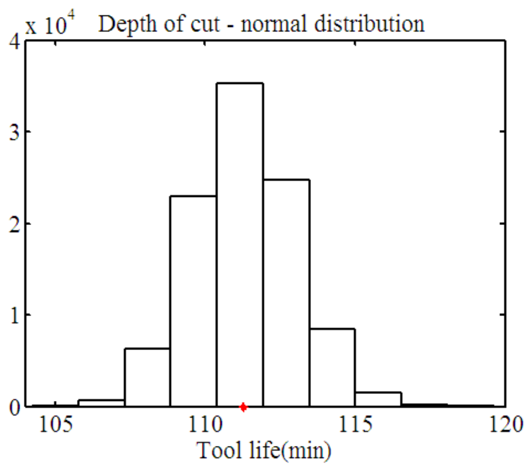
	K	N	f	d_p	d_e
1	-	random	-	-	-
2	-	normal	-	-	-
3	random	-	-	-	-
4	normal	-	-	-	-

3 RESULTS AND DISCUSSION

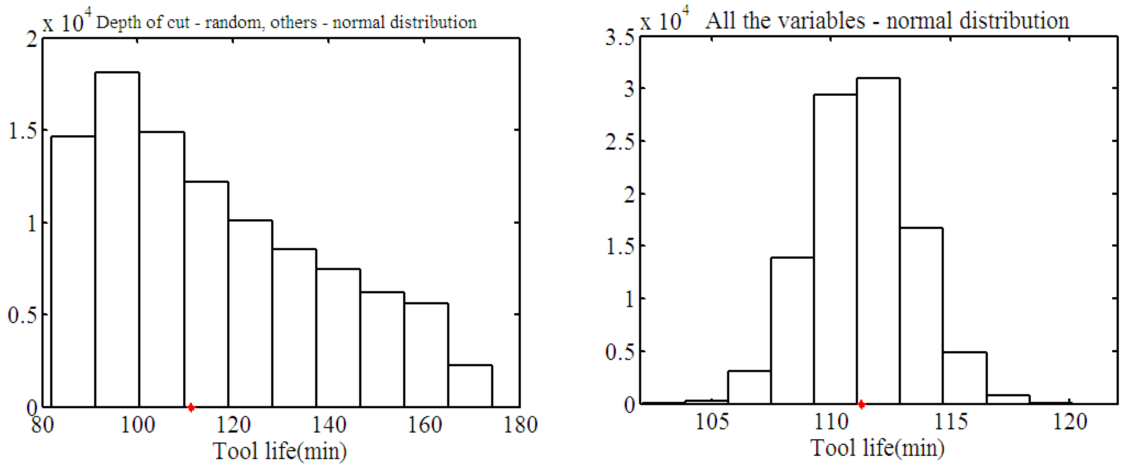
The effects of uncertainty of milling variables (especial depth of cut d_p) on prediction of tool life is shown in Figure 1. We can see that predicted value of tool life is not following random distribution for depth of cut d_p following random distribution (Figure 1 a)). It shows a non symmetric distribution with a rather heavy right 'tail'. It means that tool lives are longer than the life obtained by determined model (red star point '*' in Figure 1). To situation which depth of cut d_p following random and others following normal distribution, tool life shows phenomena liking Figure1 a) (see Figure 1 c)). The tool life is not following the distribution of depth of cut d_p. It tells us that tools can be used longer in this situation. However, for normal distribution of depth of cut d_p or all the variables, tool life follows similar normal distribution (Figure 1 b) and Figure 1 d)).



a)



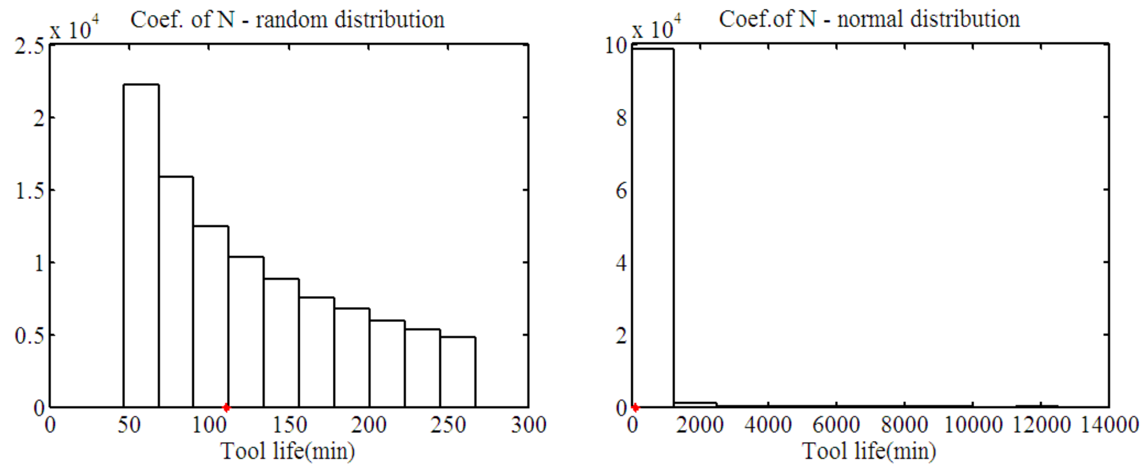
b)



c) d)

Figure 1 : Histogram of tool life for uncertianty of four variables

Figure 2 shows the effect of uncertainty of contants (coefficent of N and coefficent K of tool-workpiece) in model (1) on tool life. The coefficient of N following random distribution doesn't lead to a random distribution, but non symmetric distribution with a rather heavy right 'tail' (Figure 2 a)). To the coefficient of N following normal distribution, prediction of tool life is totally uncensitive(Figure 2 b)). It means that Uncertainty of coefficent N following normal distribiton doesn't almost affect variation of the tool life. The varation of tool life are same with the variation of coefficent K (Figure 2 c) and Figure 2 d)). The reason is that K is unattached constants in the model developed by least square method.



a) b)

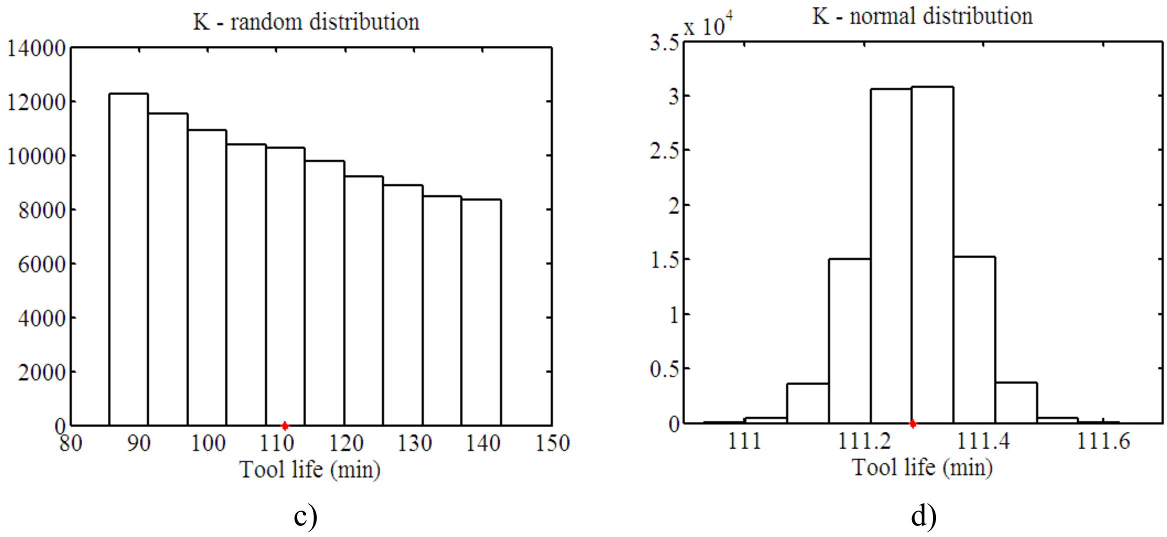


Figure 2 : Histogram of tool life for uncertainty of coefficents in the model

4 CONCLUSIONS

There are many uncertainties existed in experiments which are for getting data. And inherent uncertainties exist in the empirical constants. In addition, tool life is generally considered a stochastic process because variation is inherent in every cutting process. Thus effect of uncertainty of milling variables and contents in exponental model developed by least square method on prediction by exponential model are investigated in this work. The results show:

- The uncertainty of the variables obviously affect prediction of tool life when depth of cut d_p or other variable is following random distribution. However, variation with normal distribution doesn't affect the variation of prediction of tool life.
- To constant K, not matter what distribution, the prediction of tool life is not affected by the variation of the constant. However, to the coefficient of the variables (depth of cut d_p) in the model, prediction values of tool life is affected by the variation of coefficient of the variables.

Therefore, it should pay more attention on the variation of variables and coefficients of variables when using the exponential model for predicting tool life or optimization. Modification coefficients of variables in models by experiments will be the future work.

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