REMAINING USEFUL TOOL LIFE PREDICTIONS USING BAYESIAN INFERENCE

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INTRODUCTION

Machining science has seen tremendous gains in process modeling. Predictive model capture the physical laws governing the process. However, the model predictions are uncertain due to the inherent uncertainties in the inputs, underlying assumptions in developing the model, which may include approximations, and/or lack of information. The global marketplace has placed a premium on reducing production time and cost without sacrificing quality so model accuracy is critical. In this work, the limitation to machining productivity imposed by tool wear is addressed using Bayesian inference techniques. A new approach that establishes an estimate of the remaining useful life (*RUL*) for a selected tool based on flank wear width (*FWW*) measurements is described. Although *FWW* measurements may have limited scope in an industrial setting, the proposed method can be applied to any metric used to detect tool wear, such as spindle power or acoustic emissions during machining.

Taylor first defined an empirical relationship between tool life and cutting speed using a power law [1]:

$$VT^{n} = C \tag{1}$$

where V is the cutting speed in m/min, T is the tool life in minutes, and n and C are constants which depend on the tool-workpiece combination. The constant C is defined as the cutting speed required to obtain a tool life of 1 minute. Tool life is typically defined as the time required to reach a predetermined *FWW*, although other wear features (such as crater depth) may also be applied depending on the nature of the tool wear.

BAYESIAN INFERENCE

Bayesian inference models form a normative and rational method for updating beliefs when new information is available. A Bayesian model treats an uncertain variable as a random variable using a probability distribution. Let the prior distribution about an uncertain event, A, be $P(A)$, the likelihood of obtaining an experimental result B given that event A occurred be $P(B|A)$, and the probability of receiving experimental result B (without knowing A has occurred) be $P(B)$. Bayes' rule is used to determine the posterior belief about event A after observing the experiment results, $P(A|B)$, as shown in Eq. 2.

$$P(A\,|\,B) = \frac{P(A)P(B\,|\,A)}{P(B)} \tag{2}$$

The product of the prior and likelihood function is used to calculate the posterior distribution. For multiple measurements, the posterior distribution after the first measurement, or update, becomes the prior for the second, and so on. For this study, the Taylor tool life constants, n and C, are treated as uncertain, which leads to uncertainty in the predicted tool life.

BAYESIAN INFERENCE USING THE RANDOM WALK METHOD

Bayesian inference provides a rigorous mathematical framework for belief updating about an unknown variable when new information becomes available. In this study, the *RUL* of the tool was estimated using Bayesian inference and *FWW* measurements. The tool life was defined as the time required for the tool to reach a maximum *FWW* of 0.3 mm. Tests were performed using an uncoated carbide (inserted) tool to mill AISI 1018 steel. The *FWW* was assumed to increase linearly with time until the end of tool life. In the Taylor tool life model (Eq. 1), there is uncertainty in the values of the exponent, *n*, and the constant, *C*. Subsequently, there is uncertainty in the tool life, *T*. The *FWW* growth curve can be predicted by generating *N* sample *FWW* growth curves, or sample paths, each potentially representing the true *FWW* growth curve with an equal prior probability of 1/*N*. The sample paths generated in this way were used as the prior for Bayesian inference. The prior probability of the sample paths was updated by applying Bayes' rule to experimental *FWW* measurements. For each sample path, Bayes' rule can be written as the following product:

$$P(path = true\ FWW\ growth\ curve|test\ result) \propto P(test\ result|path = true\ FWW\ growth\ curve) \times P(path = true\ FWW\ growth\ curve)$$

where $P(path = true\ FWW\ growth\ curve)$ is the prior probability that a given path is the true *FWW* growth curve. As noted, the probability is assumed to be 1/*N* before any *FWW* measurement is completed since each path is considered equally likely to be the true *FWW* growth curve. Also, $P(test\ result|path = true\ FWW\ growth\ curve)$ is referred to as the likelihood and $(path = true\ FWW\ growth\ curve|test\ result)$ is the posterior probability of the sample *FWW* growth curve given the test result. The product is divided by the normalizing constant $P(test\ result)$. The test result denotes a *FWW* measurement.

Prior

The first step in the Bayesian inference approach is to select a prior. The prior distribution of *n* and *C* for the uncoated insert was based on previous experimental results [2]. In a separate study conducted by the authors, the means of the constants *n* and *C* for the given tool-work piece combination were found to be 0.33 and 600 m/min. Based on these values, the priors for *n* and *C* were selected to be uniform distributions with minimum values of 0.3 and 400, respectively, and maximum values of 0.35 and 700, respectively, independent of each other. This is expressed using: *n* = *U* (0.3, 0.35) and *C* = *U* (400,700), where *U* denotes a uniform distribution and the values in the parentheses identify the minimum and maximum values, respectively. The random sample *FWW* growth curves were generated as follows. First, random samples were drawn from the prior joint probability density function (pdf) of *n* and *C* and the Taylor tool life curve was calculated for each {*n*,*C*} pair; this exercise was repeated 1×10^4 times. As noted, the *FWW* was assumed to increase linearly with time until the end of tool life. Second, the linear *FWW* growth curve was generated for all the tool life values calculated from the first step at the selected experimental spindle speed. These growth profiles were the prior random sample paths used for Bayesian inference. Figure 1 shows the prior histogram of tool life at 5000 rpm. Figure 2 shows the prior cumulative distribution function (cdf) of *FWW* as a function of machining time at 5000 rpm. Figure 3 shows the prior probability of *FWW* being less than 0.3 mm (defined as the *FWW* limit) as a function of machining time. From Figure 3, the 95% *RUL* of the tool was 2.7 minutes. This implies that there is a 5% probability that the *FWW* will exceed 0.3 mm at 2.7 minutes.

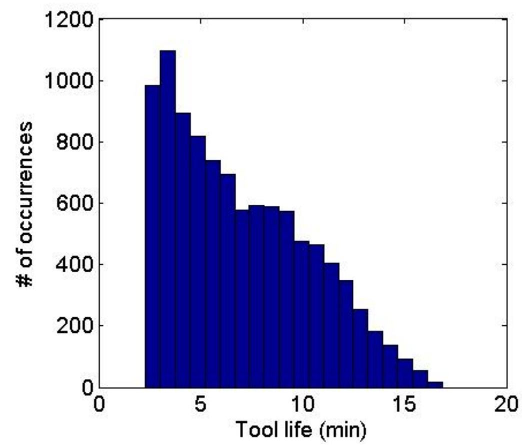

FIGURE 1. Prior histogram of tool life at 5000 rpm.

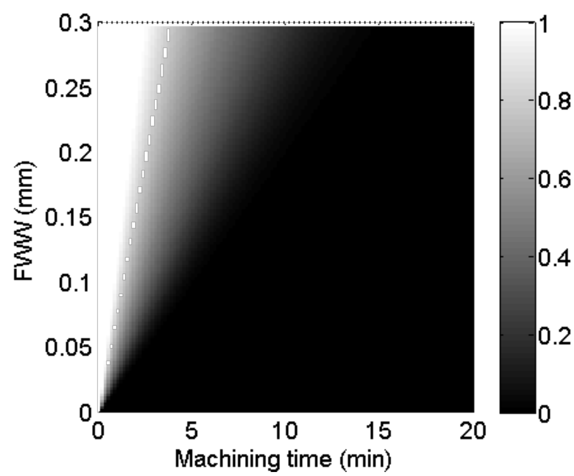

FIGURE 2. Prior cdf of FWW as a function of machining time at 5000 rpm.

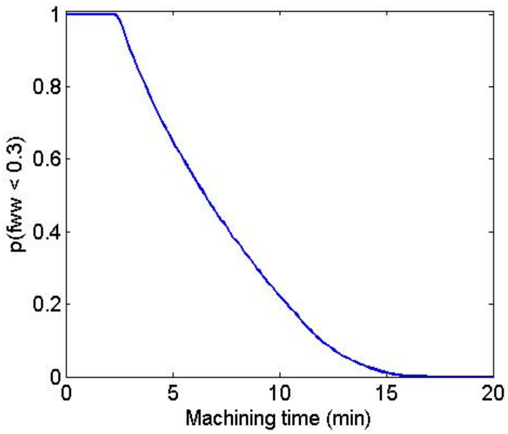

FIGURE 3. Prior probability of FWW being less than 0.3 mm as a function of machining time.

Likelihood

The probability of the sample *FWW* growth curves was updated using *FWW* measurements and Bayes' rule. The likelihood function incorporates the uncertainty in tool wear and the assumed linear *FWW* growth model. A non-normalized Gaussian distribution was used as the likelihood in his study shown in Eq. 3:

$$l = e^{-\frac{(fww - fww_m)^2}{k}} \tag{3}$$

where l is the likelihood value, fww_m is the measured *FWW*, *fww* is the *FWW* value for a sample curve at the experimental spindle speed, and k depends on the tool wear uncertainty. Because the likelihood function is expressed as a non-normalized normal distribution, $k = 2\sigma^2$, where σ is the standard deviation of *fww*; it represents the uncertainty in tool wear and the linear *FWW* growth model. The likelihood function describes how likely is the given the *FWW* measurement result, at a particular machining time, given that the sample *FWW* growth curve is the correct curve. Figure 4 shows the likelihood function for a measured *FWW* of 0.1 mm after 5 minutes. If the *FWW* growth curve value is near the measurement result, then the likelihood value is high. Otherwise, it is low. The likelihood function can be interpreted as assigning weights from 0 to 1 to the sample curves; 0 implying not likely at all and 1 implying most likely. As shown in Figure 4, increased uncertainty (higher σ) widens the likelihood function so that comparatively higher weights are assigned to sample curves far from the experimental result. Subsequently, larger uncertainty yields a more conservative estimate of tool life.

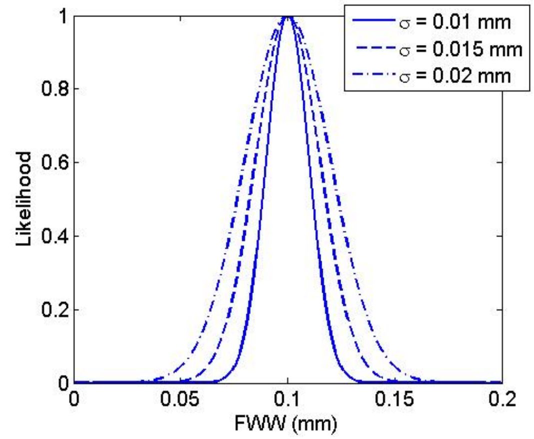

FIGURE 4. Likelihood values for various uncertainty levels for a measured FWW of 0.1 mm after 5 minutes of machining.

Bayesian updating

According to the Bayes' rule, the posterior probability is the product of the prior and the likelihood and normalized so that the sum is equal to unity. The prior probability for each path is 1×10^{-4} and the likelihood value is determined using Eq. 3; the value of σ was taken as 0.01 mm. The updated probabilities of the sample paths, calculated as the product of the prior and likelihood and normalized such that the sum is equal to unity, were used to determine the posterior *FWW* cdf. Figure 5 shows the updated cdf of *FWW* given a measurement of 0.1 mm *FWW* at 5 minutes. Figure 6 shows the posterior probability of FWW being less than 0.3 minutes. The 95% *RUL* was 7.4 minutes; note that the measurement was taken after 5 minutes.

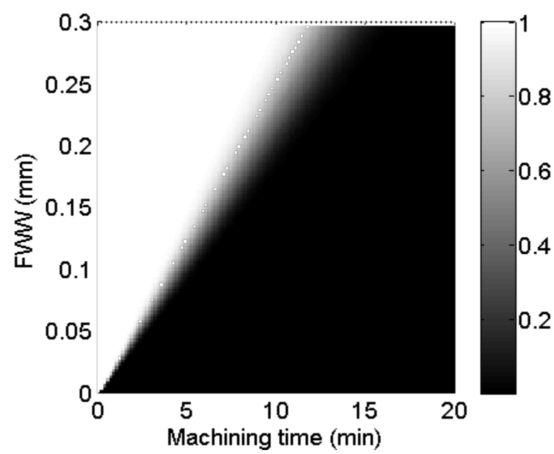

FIGURE 5. Posterior cdf of FWW as a function of machining time at 5000 rpm.

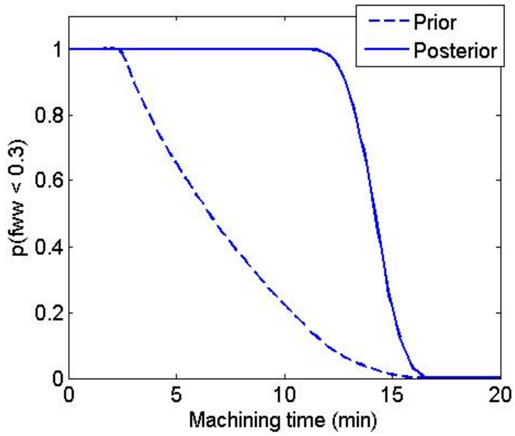

FIGURE 6. Posterior and prior probability of FWW being less than 0.3 mm as a function of machining time.

RUL PREDICTIONS

Tests were performed using uncoated carbide insert and 1018 steel workpiece material. The *FWW* was measured at regular intervals using a portable digital microscope. Figure 7 shows the growth of *FWW* with machining time. The tool life was found to be 11.9 minutes. The measured *FWW* values were then used to update the prior probabilities of the sample *FWW* growth curves using the procedure described previously. The value of σ was assumed to be 0.01 mm. Note that the updated probabilities of sample paths were used to calculate the posterior cdf of *FWW*. From the updated probabilities of the sample *FWW* growth curves, the 95% *RUL* of the tool before the *FWW* reaches 0.3 mm was determined. Each *FWW* measurement updates the *RUL* estimates. Figure 8 shows the 95% *RUL* of the tool after each measurement and the true remaining life calculated from the observed tool life value (11.9 minutes). The *RUL* estimates approach the true remaining life from the conservative side.

CONCLUSIONS

The application of Bayesian inference to *RUL* predictions of the tool was demonstrated using a random walk approach, where the prior probability of *FWW* was generated using sample *FWW* growth curves that represented the true *FWW* growth curve with some probability. This probability was updated using Bayesian inference. Although a linear *FWW* growth model was assumed in this study, a higher order model may also be assumed to describe the three stages of tool wear [3]. The method can be extended to include sensor data such as power or acoustic emission. In addition, uncertainty regarding the threshold value of the sensor, such as percent increase from the nominal, can also be incorporated.

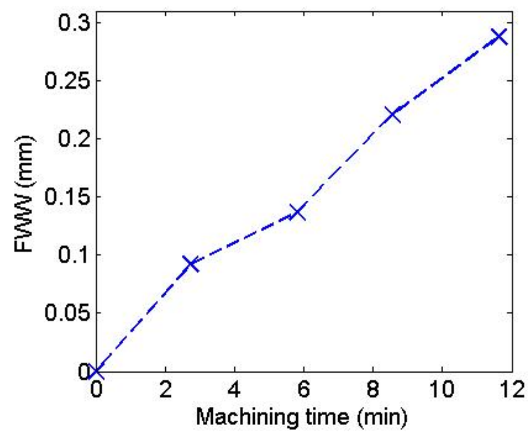

FIGURE 7. Experimental FWW growth with machining time.

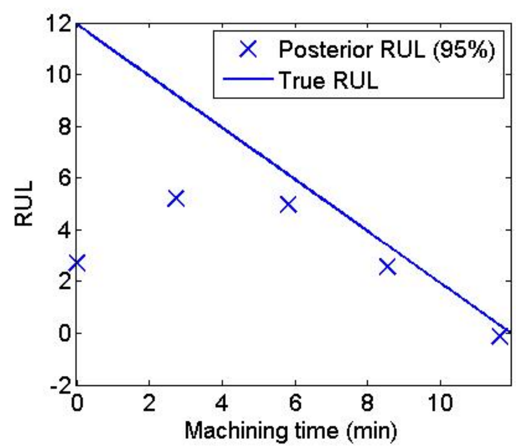

FIGURE 8. 95% RUL predictions.

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