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Superalloy Machining Tool Wear: State Estimation and Alternative Path Planning for Mitigation

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Abstract: End-product quality is the driving factor for all machining processes. This consideration is particularly important when machining high strength materials such as gamma-prime strengthened alloys. High ultimate strength, poor thermal conductivity and rapid work hardening accelerate tool wear and tool change intervals, and reduce overall productivity. Worn tools also deteriorate surface finish, dimensional integrity, and induce undesired residual stress to the workpiece. By better managing the tool wear rate in the machining of Ni-based alloys these negative effects can be mitigated. Alternative path planning methods such as trochoidal milling and a more recently introduced technique termed variable depth milling have been shown to improve tool life. This work characterizes the combined impacts of these tool paths on tool wear, end-product quality and dimensional accuracy. Moreover, monitoring the tool condition during the process is of great importance. In this work, a model-based Kalman Filter and data-driven Bayesian Neural Network methods are introduced and compared for tool condition monitoring of Ni-based alloys. Results of the data-driven method show greater than 50% error reduction as compared to the model-based methods; however, with model-based methods estimated parameters represent actual physical phenomena in the process, and therefore can be used to drive process improvement.

Keywords: *Tool Wear, Ni-based alloys, Trochoidal Milling, Variable Depth Milling, Kalman Filter, Neural Network*

1. INTRODUCTION

Understanding and controlling the wear of cutting tools in nickel-based alloy material machining is critical in order to provide consistent-quality output of high value components from the machining process. Unexpected tool wear introduces unwanted variation to the surface quality (both form and underlying stress), and to the dimensional performance of the process. These variation sources can lead to variation in assembly and functional performance of the outgoing product.

It is with this motivation that we examine the topic of information generation in the machining process, particularly estimation of tool wear, and the effect of alternative tool path planning to improve consistency in tool wear when machining these materials. The alternative tool paths also mitigate a particular form of notch wear that causes inconsistent failures in these processes.

2. MECHANISMS OF TOOL WEAR IN NICKEL-BASED ALLOYS

There are several wear failure mechanisms observed in research articles in milling, turning and drilling of Ni-based alloys with different inserts and cutting conditions. Several researchers have reviewed these mechanisms comprehensively. According to the state of the art papers by Zhu *et al*. and Akhtar *et al*., wear failure mechanisms in Ni-based alloys are classified as abrasive, adhesive, diffusion, oxidation (chemical), and debonding failures [1-2]. Existence of each wear failure mechanism is highly dependent on the workpiece material; insert geometry, and cutting conditions. In some cases, the wear progress is only dependent on one particular mechanism; in other cases multiple wear mechanisms progress together, or sometimes tool wear starts with a particular mechanism (abrasive wear) and will evolve by the nucleation of adhesion and diffusion until failure occurs.

The SEM images of a 08M-PM 1030 coated Sandvik insert used in this study for end-milling of Rene-108 in addition to CNGG12-04-04-SGF1105 insert used for turning INC718 are shown in Figures 1 and 2. The parallel grooves on the flank face of the inserts represents abrasive wear, the high percentage of elements Ni and Co represents excessive diffusion, in addition to chipping and built-up edge that were observed at the macro level in the turning process.

Due to the existence of different sources of uncertainty in machining, a stochastic estimation view is necessary to be able to quantify the machining operation.

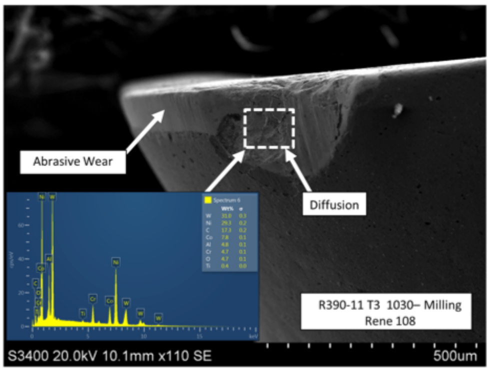


Fig. 1: SEM image of the insert in milling Rene-108 with elemental analysis

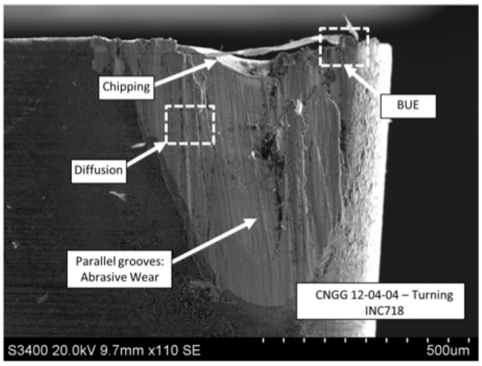


Fig. 2: SEM image of the insert in turning INC718

3. ALTERNATIVE PATH PLANNING STRATEGIES

Wear uncertainty is affected by the macro approach undertaken in machining path planning. As described previously, one of the major motivations of this research is the extension of tool life while milling these alloys. The tool wear occurs at a rapid rate resulting in increased manufacturing costs when compared to other metallic materials. While previous researchers have identified that tool material and geometry can have positive impacts on tool life [3], the research discussed here focuses solely on the influence of the milling tool path.

3.1. Trochoidal Milling

An alternative tool path that has been found to extend tool life in the milling of steel and aluminium is trochoidal milling [4]. The trochoidal tool path is described as a linear feed motion superimposed on a uniform circular motion about the linear feed, as shown in Fig. 3. This method of milling has been shown to reduce tool loads and cutting temperature [5], resulting in reduced and more consistent tool wear. This idea is reinforced by the findings that nickel-based alloys thermally harden [6], leading to an increase in tool wear, so keeping cutting temperatures low is of great importance.

There has been a limited amount of work investigating this type of tool path in the machining of nickel-based alloys. Previous work by the authors [7] showed that the trochoidal tool path in Inconel 738 had a much lower material removal rate when compared with end milling, due to the incremental engagement of the tool, but greatly extended the tool life. The trochoidal method was able to remove at least six times more material than end milling for the same amount of tool wear.

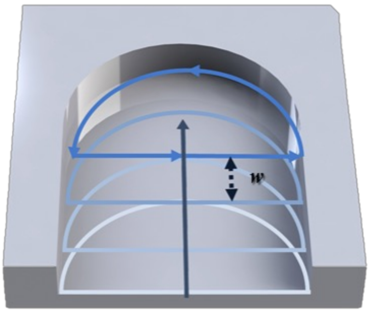


Fig. 3: Trochoidal tool path

While the trochoidal tool path extended the tool life, it was found that at depths of cut exceeding 5mm, significant notch wear would develop on the carbide inserts at the depth of cut line which as shown in Fig. 4. This wear was the result of chip hammering and smearing, and was captured using high-speed videography, a frame of which is shown in Fig. 5.

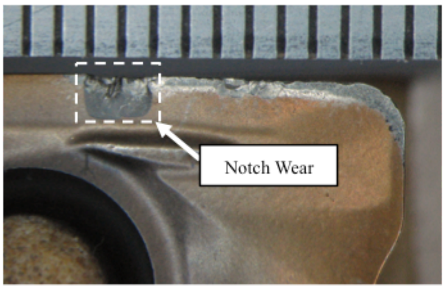


Fig. 4: Notch wear from trochoidal milling

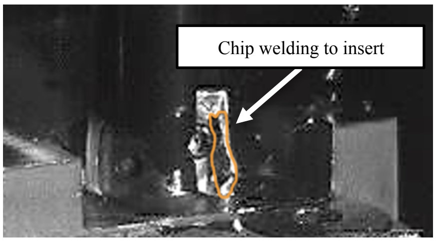


Fig. 5: Chip welding to insert for multiple rotations

The manifestation of notch wear when milling nickel-based alloys leads directly to catastrophic tool failure, an unpredictable and costly phenomenon. In extreme cases, this also results in damage of the workpiece. With notch wear development identified in trochoidal milling, the authors set out to investigate an additional alternative tool path to reduce its development.

3.2. Variable Depth Milling

The variable depth milling tool path is a direct solution to reduce the manifestation of notch wear in the milling of difficult to machine materials. Using this milling strategy, the tool moves at a constant feed rate across the material while continuously varying the axial depth of cut (see Fig. 6). The tool makes two passes, with the first pass starting at the desired depth of cut and decreasing axial depth over the length of feed, followed by a second pass at a constant height, with cutting depth decreasing over the length of cut.

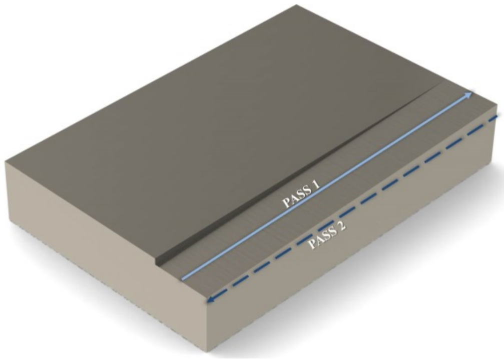


Fig. 6: Variable Depth Milling tool path

This tool path was first investigated by the authors for machining Ni-based alloys in [8] and was found to greatly reduced the occurrence of notch wear at the depth of cut line. When compared with a traditional end milling strategy, using the same cutting parameters, yet a single depth of cut pass, it was found that variable depth milling exhibited lower resultant forces than in end milling with a corresponding improvement in surface roughness, producing a surface that was 9% smoother than end milling; notch wear was also reduced and in some cases eliminated.

4. BAYESIAN PARAMETER INFERENCE

Bayesian inference is a powerful tool for parameter inference when limited observations are available. Unlike maximum likelihood estimation where only the observations are utilized, Bayesian inference enables us to use the initial probability density in addition to likelihood probability. This difference is illustrated in Fig. 7.

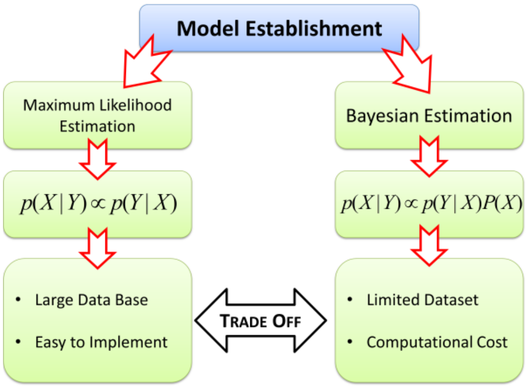


Fig. 7: Difference between Bayesian and MLE estimation methods

To demonstrate the applicability of the Bayesian estimation, 8 tests with 2 replications were conducted for end-milling Rene-108 nickel-based alloy. The feed and cutting speed were varied and the model of Shao *et al*. was selected (Fig. 8) to relate the tool wear (VB) to the spindle power consumption (P) [9] in addition to random-walk Metropolis method for inference on the unknown parameters. As shown in Fig. 9, the initial uncertainties in parameters K_1 and K_2 were quantified and reduced after running the algorithm. The distribution of the unknown parameters was identified as well. The detail of this method is described in [10].

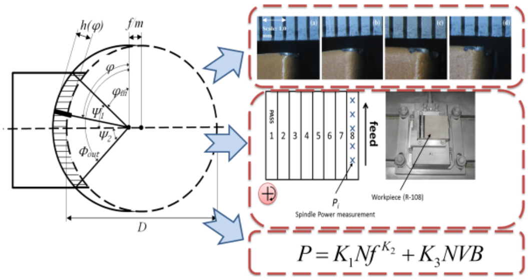


Fig. 8: Milling schematic [9], measured tool wear and experimental setup

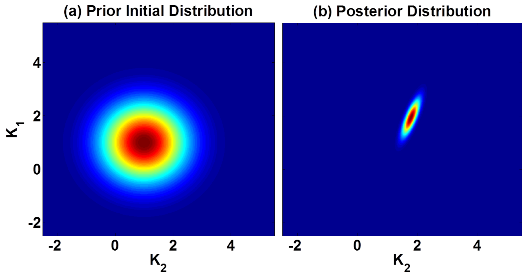
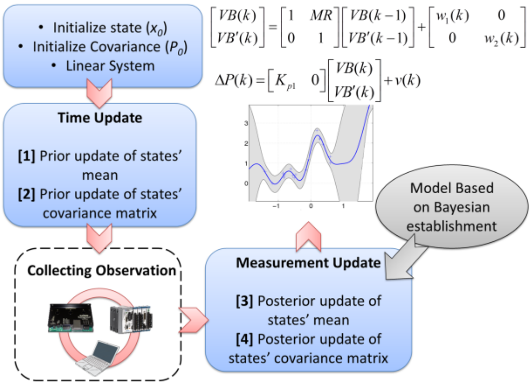


Fig. 9: Prior and posterior distribution of the unknown parameters K_1 and K_2

5. STOCHASTIC WEAR ESTIMATION IN MILLING

The model derived based on the Bayesian inference can be used as a measurement model in a stochastic state estimation paradigm such as the Kalman filter Fig. 10 summarizes the steps that need to be taken for estimating the tool flank wear as well as the discrete state space model. For details, refer the previous work of authors [11].



$$\begin{bmatrix} VB(k) \\ VB'(k) \end{bmatrix} = \begin{bmatrix} 1 & MR \\ 0 & 1 \end{bmatrix} \begin{bmatrix} VB(k-1) \\ VB'(k-1) \end{bmatrix} + \begin{bmatrix} w_1(k) & 0 \\ 0 & w_2(k) \end{bmatrix}$$

$$\Delta P(k) = \begin{bmatrix} K_{p1} & 0 \end{bmatrix} \begin{bmatrix} VB(k) \\ VB'(k) \end{bmatrix} + v(k)$$

Fig. 10: The Kalman filter estimation steps and formulation of discrete state space model

A set of replications with constant cutting conditions were carried out for this section. The result of estimation is shown in Fig. 11, where average estimation errors of 11% and 6% were observed for each test replication. To emphasize the performance of the Bayesian parameter inference described in Section 4 to the maximum likelihood estimation (MLE) when the MLE-based model is used as the Kalman filter measurement model, their average error and root mean squared error were compared in Fig. 12. More than 50% reduction in the estimation error shows the advantage of using a Bayesian based model over MLE.

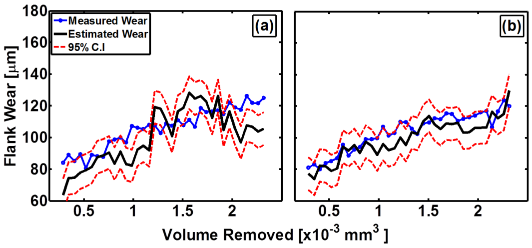


Fig. 11: Estimated error with uncertainties, (a) Replication 1 and (b) Replication 2

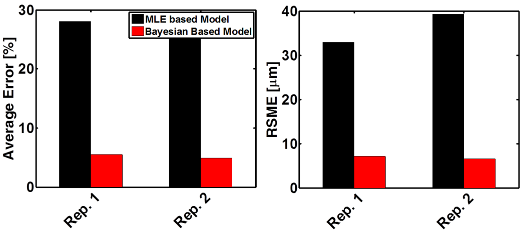
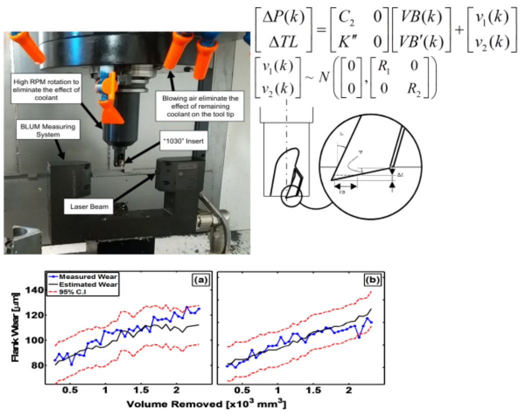


Fig. 12: Average error and RSME comparison of replication 1 and 2 with MLE based measurement model and Bayesian based measurement model

6. FUSING DIRECT AND INDIRECT MEASURING METHODS

As stated in section 2, excessive chipping was observed in milling Rene108, which causes a sudden drop in the spindle power, reflected as a drop in the estimated tool wear in Fig. 11. To increase the accuracy of estimation, a laser-based measuring system was used to gauge the length of the tool before and after each experiment. This way a direct method (laser measurement) in addition to indirect method (spindle power measurement) fused together in the Kalman filter framework. The result of estimation is shown in Fig. 13. Using this method the effect of chipping on estimated tool wear was significantly compensated and the average error reduced to 5.4% and 3.8% for each replication.



$$\begin{bmatrix} \Delta P(k) \\ \Delta TL \end{bmatrix} = \begin{bmatrix} C_2 & 0 \\ K'' & 0 \end{bmatrix} \begin{bmatrix} VB(k) \\ VB'(k) \end{bmatrix} + \begin{bmatrix} v_1(k) \\ v_2(k) \end{bmatrix}$$

$$\begin{bmatrix} v_1(k) \\ v_2(k) \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} R_1 & 0 \\ 0 & R_2 \end{bmatrix} \right)$$

Fig. 13: Fusing direct (laser measuring system) with indirect methods for the tool wear estimation

7. DETERMINISTIC DATA-DRIVEN MODEL WITH WAVELET TRANSFROM

While machine-learning algorithms were widely used for conventional materials such as AISI steels, few researchers have considered them for tracking or classification purposes of Ni-based alloys. In this section a wavelet packet decomposition method with Daubechies wavelet was applied to the two collected signals, *i.e.* spindle power and vibration, and statistical features of the wavelet coefficients were extracted. The scalogram of the power and acceleration for the sharp insert is shown in Fig. 14.

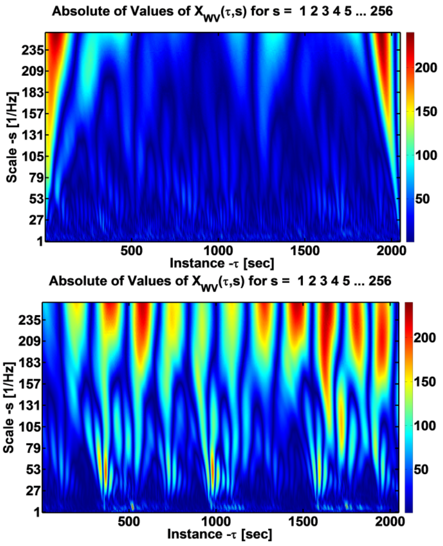


Fig. 14: Scalogram of spindle power (top) and spindle vibration (bottom)

To reduce the cardinality of the features, Principle Component Analysis (PCA) was deployed and six correlated features were selected. A neural network is chosen with Bayesian regularization training algorithm for analysis. This method of training is more robust than backpropagation and can eliminate or reduce the need for a lengthy cross-validation set [12]. This is specifically beneficial when a large dataset is not available for training, as in the case of Ni-based alloys, where high wear rate and short life span of the tool limits the number of experiments before reaching failure. To better enlighten the performance of neural net, its output was also compared to a time series ARMA model and linear regression model. The maximum error of 33% for the linear regression and 17% for the time series model in comparison with 4% error of the neural network model demonstrates the usefulness of neural networks for modeling nonlinear/non-stationary tool wear process (Fig. 15). For a detailed description, please refer to the previous work of authors [13].

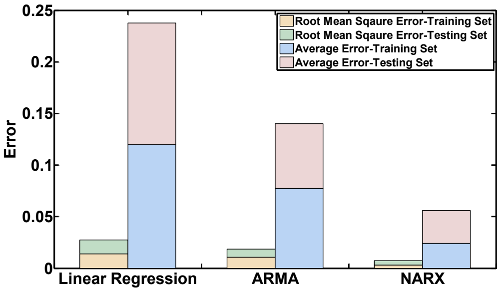


Fig. 15: Error comparison of neural network (NARX) with ARMA and linear regression models

8. DISCUSSION AND CONCLUSIONS

Tool wear in machining nickel-based alloys is estimated using Bayesian parameter influence methods, both from power alone and through sensor fusion with direct tool measurement. Bivariate belief distributions of the wear-dependent power model parameters result in an estimation method with less than 10% error. This is especially beneficial in Ni-based alloys machining, where experimental data sets can be limited.

A wavelet transform modeling approach using scalogram representation is also presented. This method allows for representation of both transient and steady-state phenomena in the time domain, which is especially relevant to the high-wear regime of nickel-based alloy machining. A neural network training approach was demonstrated and found to significantly reduce the estimation error for this sparse data set.

9. ACKNOWLEDGEMENTS

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