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Extended Kalman Filter for Stochastic Tool Wear Assessment in Turning of INC718 Hard-to-Machine Alloy

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Abstract
An Extended Kalman Filter (EKF) is employed in this work for tracking tool flank wear area in wet-turning of Inconel 718 (INC718) Nickel-based alloy in variable feed condition. The tool wear area evolution is modeled with a 3\textsuperscript{rd} order polynomial empirical function and an analytical solution for discrete state space system is derived. The state uncertainty was found to decrease up to 200-250\,µm of average flank wear length and then increase abruptly with an increase in tool wear. Therefore, the tool wear uncertainty was modeled with failure probability density, \textit{i.e.} the bathtub function. While a constant uncertainty was considered for the measurement signal (spindle power). The root mean square error (RMSE) and the mean absolute error (MAE) were calculated in estimation of the tool wear area with experimental results and it was shown that the EKF was able to estimate the tool wear area with less than 0.05 mm\textsuperscript{2} RMSE but did not perform well in estimating the rate of the tool wear area.

Keywords: Extended Kalman Filter, Nickel-based alloy, Estimation, Uncertainty

1 Introduction

Monitoring the cutting tool performance during machining operations is a critical factor since the quality of the end-product and productivity rate are highly dependent on the functional state of the tool. A worn-out tool can deteriorate surface quality and causes high tensile residual stress which increases the possibility of micro-crack nucleation and early failure. Ni-based alloys are a class of hard-to-machine materials that exhibit a combination of maintaining high strength at elevated temperature and corrosion/creep resistance. These features make them a suitable candidate for high...
temperature/load environments such as power generation industry. Nevertheless, the same features making them appealing candidates for such industries, give them a poor machinability features in terms of high tool wear rate and frequent tool change. As an example, in seven hours rough and fine cutting of a Ni-based blade, more than 40 cutting tools are needed to complete the process (Zhu et al., 2013). Therefore, monitoring the state of the tool in machining Ni-based alloys are significantly important to increase the productivity rate and reduce the machining downtime.

One of the challenges in tool wear monitoring is the complexity of its dynamics and quantifying the effect of various variables such as tool coating, tool geometry, material structure, lubrication, tool run-out and initial residual stress. Since controlling all these parameters are impossible, they act as the sources of uncertainties in machining. Therefore a stochastic based method is required for analyzing the state of the tool. One of the early works in this field is the work of Schmitz et al. on stochastic estimation based on mesh grid method for identification of unknown parameters in 2-D Merchant model. The identified parameters then fed into the model for predicting cutting force and its uncertainty and experimentally validated on turning AISI-1045 steel (Schmitz et al., 2011). In another effort by Karandikar et al., they used the mesh grid method and Markov Chain Monte Carlo (Metropolis algorithm) for Bayesian parameter inference on Taylor’s tool life and extended Taylor’s life in milling of AISI-4137 steel. They compared the results with deterministic approach (maximum likelihood estimation) and showed that by using Bayesian method and combining the prior knowledge to the likelihood function, less experiments were required for parameter inference (Karandikar et al., 2014a; Karandikar et al., 2014b). The performance of Bayesian inference and its superiority over deterministic approaches when limited information is available was also investigated on mechanistic tool wear model in milling Ren-108 Ni-based alloys (Akhavan Niaki et al., 2015b). Online stochastic estimation with the Kalman filter and the Particle filter was also studied on the same material by the same authors. They showed that with using the random sampling-based method such as the Particle filter; a more informative prior can be selected for online parameter inference (Akhavan Niaki et al., 2015a). An alternative stochastic approach for tool wear studies is based on reliability and injury theory. Salonitis and Kolios investigated the applicability of using Monte Carlo simulation and first order reliability method for characterizing the probability of tool failure in different feed and cutting speed (Salonitis and Kolios, 2013). In an interesting work by Braglia and Catellano and Braglia et al., they derived the distribution of the tool life based on progressive behavior of the tool wear with diffusion theory and Fokker-Plank equation. They calculated the average and the uncertainty of progressive tool wear which were in agreement with experimental results (Braglia and Castellano, 2014; Braglia et al., 2014). While diffusion theory is successful in tracking progressive tool wear, it cannot be used for chipping or breakage detection and this will limit the applicability of their method.

The objective of this work is first to understand how uncertainties of the tool wear evolve over machining time and how to quantify these uncertainties. Second is to accurately estimate the progressive tool flank wear in the presence of uncertainties in turning a Ni-based alloy. The organization of this work is as follows. The theoretical background of the stochastic-based estimation method used in this work will be discussed in section 2, following by experimental setup in Section 3. In section 4, uncertainty quantification in the state and the measurement models are addressed. And finally, results and conclusion are discussed in Sections 5 and 6.

2 Theoretical Background

Using the Bayes rule, Rudolf Kálmán introduced a method of estimation where a Gaussian model is assumed for the states of stochastic events (Kalman, 1960). For state estimation, the Kalman filter uses a closed-form discrete state space equation for linear systems and an approximation solution for nonlinear systems known as Extended Kalman filter. In the EKF, the nonlinear state or measurement model is linearized first and then the Kalman filter is applied for updating the mean and variance of
the states. Depending on the system’s degree of nonlinearity, the EKF might not be accurate. In this case, deterministic sampling methods such as Unscented Kalman Filters (UKF) (Wan and Van Der Merwe, 2000) or random sampling methods such as Particle Filters (PF) (Arulampalam et al., 2002) are proposed.

Assuming a discrete nonlinear state and measurement functions as \( f \) and \( g \), the state space representation of the system can be written as Equations 1 and 2; where \( k \) is the time step, \( x \) is the state’s vector, \( u \) is the inputs, \( w \) is the state noise, \( v \) is the measurement noise and \( y \) is the vector of measurements. In the context of machining, \( x \) will be the tool wear, \( y \) will be the sensor measurement, and \( u \) can be the feed.

\[
x_{k+1} = f(x_k, u_k, w_k) \\
y_{k+1} = g(x_k, v_k)
\]

(1) \hspace{1cm} (2)

The states and measurements models \( f \) and \( g \) can be approximated by the 1st order Taylor’s expansion into Equations 3 and 4, where \( \hat{x} \) and \( \hat{y} \) are the approximations of the states and measurements, \( \hat{x} \) is a posterior estimate of the state \( x \), \( A \) and \( G \) are Jacobians of functions \( f \) and \( g \) with respect to state \( x \) and \( W \) and \( V \) are Jacobians of functions \( f \) and \( g \) with respect to \( w \) and \( v \). These Jacobians are shown in Equations 5 to 6.

\[
x_{k+1} \approx \hat{x}_k + A(x_k, -\hat{x}_k) + W_k \\
y_{k+1} \approx \hat{y}_k + G(x_k, -\hat{x}_k) + V_k \\
A_y = \frac{\partial f}{\partial x_j}(\hat{x}_k, u_k, 0) , \hspace{0.5cm} W_y = \frac{\partial f}{\partial w_j}(\hat{x}_k, u_k, 0) \\
G_y = \frac{\partial g}{\partial x_j}(\hat{x}_k, 0) , \hspace{0.5cm} V_y = \frac{\partial g}{\partial v_j}(\hat{x}_k, 0)
\]

(3) \hspace{1cm} (4) \hspace{1cm} (5) \hspace{1cm} (6)

Using the linear Equations 3 and 4, Kalman filter can be applied as described by time update (Equations 7-8) and measurement update (Equations 9-11).

**Time Update:**

\[
\hat{x}_{k+1} = f(\hat{x}_k, u_k, 0) \\
P_{x_{k+1}} = A_k P_k A_k^T + W_k Q W_k^T
\]

(7) \hspace{1cm} (8)

**Measurement Update:**

\[
K_k = P_k H_k (H_k P_k H_k^T + V_k R V_k^T)^{-1} \\
\hat{x}_k = \hat{x}_k + K(z_k - h(\hat{x}_k, 0)) \\
P_k = (I - K_k H_k) P_k
\]

(9) \hspace{1cm} (10) \hspace{1cm} (11)

3 Experimental Setup

The work was conducted on INC718 Ni-based alloys contained 53.8% Ni, 18.44% Cr, 17.33% Fe, 5.31% Nb+Ta, 0.97% Ti, 0.58 Al and less than 0.1% of other elements with 44 HRC hardness. The OKUMA CNC lathe was used for turning 50 mm of an INC718 bar in a wet cutting condition. The
The insert used was Sandvik CNGG 12 04 04 SGF PVD coated insert shown in Figure 1. To investigate the effect of variable cutting conditions on the process, feed was changed between 0.05 mm/rev to 0.15 mm/rev while cutting speed and depth of cut were kept constant at 80 m/min and 0.1 mm as recommended by Sandvik. A Design of Experiment (DoE) table used in this work is shown in Table 1. 4 replications of feeds 0.05, 0.1 and 0.15 mm/rev were used for model development and uncertainty quantification while other feeds were used for validation purposes.

<table>
<thead>
<tr>
<th>Cutting Speed (m/min)</th>
<th>Feed (mm/rev)</th>
<th>Depth of cut (mm)</th>
<th>Replications</th>
</tr>
</thead>
<tbody>
<tr>
<td>80</td>
<td>0.050</td>
<td>0.1</td>
<td>4</td>
</tr>
<tr>
<td>80</td>
<td>0.100</td>
<td>0.1</td>
<td>4</td>
</tr>
<tr>
<td>80</td>
<td>0.150</td>
<td>0.1</td>
<td>4</td>
</tr>
<tr>
<td>80</td>
<td>0.063</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>80</td>
<td>0.088</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>80</td>
<td>0.113</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td>80</td>
<td>0.138</td>
<td>0.1</td>
<td>1</td>
</tr>
</tbody>
</table>

Each replication starts with a sharp insert and the tool wear on the flank side was measured after each experiment (cutting 50mm length) under optical microscope. It was decided to continue the operation beyond the 300µm tool wear length suggested by ISO-8688 to investigate the effect of excessive tool wear on surface quality, dimensional integrity and residual stress. Spindle power consumption was collected from an Hall effect sensor with 100 Hz sampling rate using the NI-cRIO9103. Then the mean value of the signal between 85%-95% of the cutting length was calculated as measurement signal ($y$).

### 3.1 Tool Flank Wear Metric

It is accepted in the academia to report the tool flank wear with its average length. Usually the wear length is measured at a certain pre-defined distances and the mean of the measurements is reported. However, there are some difficulties that make this method prone to inaccurate results. First, is the irregular shape of the tool wear area which can be misleading as shown in Figure 2(a), where the average wear length measured at 4 locations is equal to 163 µm. However, one of the pick points were missed in the measurement and the actual average wear length is 178 µm. Second, is the effect of chipping or build up edge shown in Figure 2(b) where no guidelines exist in ISO-8688 for considering them as the tool wear. Considering these factors as well as the human error makes tool wear length measurement an objective task which can lead to some unrealistic outputs as shown in Figure 3, where tool wear length decreases for some measurements which does not happen in reality.

To compensate and reduce these effects it was decided to measure the tool wear area on the flank face instead. Since the tool wear rate in machining Ni-based alloys is relatively high compared to other materials, the change in the area on the flank face is high and therefore irregular shapes and human errors can be reduced. The results of the tool wear area and spindle power measurement for all the replications of the feeds 0.05, 0.1 and 0.15 mm/rev is shown in Figure 4 to Figure 6. The lowest variation in the tool flank wear area belongs to the lowest feed (0.05 mm/rev) and the largest variation belongs to the mid-feed (0.1 mm/rev) where significant departure observed after the reaching the area of 0.1mm² (approximately 200µm of average tool wear length).
Figure 2: Tool wear measuring methods, (a) 4-location measurements in irregular shape of the flank wear, (b) Chipping of the tool wear

Figure 3: Tool wear length measurements for different feeds, circles represent unrealistic measurements

Figure 4: Tool wear area (left) and Spindle power (right) for feed of 0.05mm/rev
4 Stochastic State and Measurement Models

The tool wear area in the Figure 4 to Figure 6 can be represented by an empirical 3rd order polynomial function with more than 95% $R^2_{adj}$ as goodness of fit as in Equation 12, where $MR$ denotes material removed, $a$, $b$ and $c$ are the polynomial coefficients that change with the feed and $VB_a$ is the flank wear area. By taking derivative of this function the $VB_a$ rate can be found as 2nd order polynomial as Equation 13. However, to write the state space model, the trajectory of the state $VB_a$ is required, i.e. the parameter $MR$ should be eliminated from the Equation 12 and 13 and the rate of $VB_a$ should be written as $VB_a$.

$$VB_a = aMR^3 + bMR^2 + cMR$$  \hspace{1cm} (12)

$$VB_a' = 3aMR^2 + 2bMR + c$$  \hspace{1cm} (13)

In the 16th century, Gerolamo Cardano found a solution for solving cubic functions. Using the Cardano’s formula, a closed-form solution for Equation 12 was found and plugged into the Equation...
13. After some simplifications Equations 14 to 16 can be derived as the continuous function of \( VB_a \) rate and \( VB_a \). In these equations, \( w \) represents the added normally distributed noise.

\[
VB'_a = 3a\left( \frac{2}{3} \alpha^3 + \beta^3 \right) - 2aA + c - \frac{b^2}{3a} + w 
\]

\[
\alpha = \frac{B}{2} + \sqrt{\frac{B^3}{4} + \frac{A^3}{27}}, \quad \beta = \frac{B}{2} + \sqrt{\frac{B^3}{4} + \frac{A^3}{27}} 
\]

\[
A = \frac{c}{a} - \frac{b^3}{3a^2}, \quad B = \frac{-VB_a}{a} + \frac{2b^3}{27a^3} - \frac{bc}{3a^2} 
\]

Writing the \( VB_a \) rate in Equation 14 as \( \frac{VB_a(k) - VB_a(k-1)}{\Delta MR} \), the discretized nonlinear state function can be written as in Equations 17. The last step is linearizing this equation by taking the Jacobian of the nonlinear function \( f \). This is shown in Equation 18 to 19.

\[
VB_a(k) = \Delta MR\left( 3a\left( \frac{2}{3} \alpha^3 + \beta^3 \right) - 2aA + c - \frac{b^2}{3a} \right) + VB_a(k-1) + \Delta MRw_i 
\]

\[
= f(VB_a(k-1)) + \Delta MRw_i 
\]

\[
A = \frac{\partial f}{\partial VB_a} = 2a \cdot \Delta MR\left( \alpha^{\frac{1}{3}} \alpha' + \beta^{\frac{1}{3}} \beta' \right) + 1 
\]

\[
\alpha' = \frac{1}{2a} \left[ 1 - \frac{B}{2} \left( \frac{B^3}{4} + \frac{A^3}{27} \right)^{\frac{1}{2}} \right], \quad \beta' = \frac{1}{2a} \left[ -1 - \frac{B}{2} \left( \frac{B^3}{4} + \frac{A^3}{27} \right)^{\frac{1}{2}} \right] 
\]

The next step is developing the relationship of the tool wear area and the spindle power. A linear function is selected to describe the measurement model. The slope of this function was considered constant equal to average slope of spindle power versus tool wear area curves. The offset from y-axis was considered to be feed dependent. This offset represents the amount of power required to cut the material when using a sharp insert. To find the relationship, 4 replications of tests with sharp inserts in 5 different feeds were conducted and a linear model with 93% \( R^2 \) was fitted to the data accordingly. The measured results are shown in Table 2 and Figure 7. The measurement model is described in Equation 20.

<table>
<thead>
<tr>
<th>Replication (Watt)</th>
<th>0.05</th>
<th>0.075</th>
<th>0.1</th>
<th>0.125</th>
<th>0.15</th>
</tr>
</thead>
<tbody>
<tr>
<td>P1</td>
<td>33.6</td>
<td>38.6</td>
<td>59.2</td>
<td>48.0</td>
<td>113.8</td>
</tr>
<tr>
<td>P2</td>
<td>24.5</td>
<td>55.6</td>
<td>74.4</td>
<td>71.7</td>
<td>91.7</td>
</tr>
<tr>
<td>P3</td>
<td>39.2</td>
<td>41.1</td>
<td>59.1</td>
<td>83.1</td>
<td>122.9</td>
</tr>
<tr>
<td>P4</td>
<td>40.9</td>
<td>71.7</td>
<td>84.1</td>
<td>81.4</td>
<td>83.1</td>
</tr>
<tr>
<td>Average</td>
<td>34.56</td>
<td>51.73</td>
<td>69.22</td>
<td>71.07</td>
<td>102.87</td>
</tr>
</tbody>
</table>

| Standard Deviation | 7.39  | 15.29 | 12.26| 16.16 | 18.59 |
4.1 Uncertainty Quantification for the State and Measurement Models

Since the variation in the spindle power is relatively constant throughout the whole process (Figure 4 to Figure 6), the maximum standard deviation of the measured power of the 4 replications of each feed was calculated equal to 40 Watts. On the other hand, a different strategy should be taken to find the uncertainty for the state $VB_a$. Considering Figure 8(a) which shows the standard deviation in different feeds, an interesting fact was emerged. The uncertainties in the tool wear area decreases at the beginning of the process and reaches a relatively constant value around $VB_a = 0.15$ mm$^2$ (equivalent to nearly 200µm of the average tool wear length). Then it starts to increase with an increase in the tool wear area which explains the large variation and departure of the tool wear curves after 0.3 mm$^2$. The uncertainties behavior which represents the bathtub failure probability curve can be modeled with a closed form function shown in Equation 21. Considering this equation and after normalizing the tool wear area to be within 0 to 1, an unconstrained optimization method based on simplex search algorithm was chosen to find the unknown coefficients (Table 3). The state model uncertainty was then calculated based on the bathtub curve model and is shown in Figure 8(b).

$$q_k = c_1 + c_2 \left( \frac{VB_a (k)}{0.65} \right)^{c_4} + c_4 \left( 1 - \frac{VB_a (k)}{0.65} \right)^{c_4}$$  \hspace{1cm} (21)
Figure 8: Uncertainties propagation (a) different feeds and (b) Modeled bathtub curve for state uncertainty function

Table 3: Identified coefficients of bathtub function based on simplex search algorithm

<table>
<thead>
<tr>
<th>Model</th>
<th>( q_k = c_1 + c_2 \left( \frac{V_B_a(k)}{0.65} \right)^{c_3} + c_4 \left( 1 - \frac{V_B_a(k)}{0.65} \right)^{c_5} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( C_i )</td>
<td>( C_1 )</td>
</tr>
<tr>
<td>Value</td>
<td>-2.1E-05</td>
</tr>
</tbody>
</table>

The state space representation of the system is summarized as Equations 22 to 25. Note than in Equation 22, \( V_{B_a}(k-1) \) is embedded in \( \alpha \) and \( \beta \) parameters as well.

State Model \( \rightarrow \) \( V_{B_a}(k) = MR \left[ 3a \left( \alpha^2 + \beta^2 \right) - 2aA + c - \frac{b^2}{3a} \right] + V_{B_a}(k-1) + MRw_k \)  (22)

\( w_k \sim N(0, q_k^2) \) where \( q_k = \left( -2.1 + 5.9 \left( \frac{V_B_a(k)}{0.65} \right)^{1.028} + 6.3 \left( 1 - \frac{V_B_a(k)}{0.65} \right)^{2.43} \right) \times 10^{-5} \)  (23)

Measurement Model \( \rightarrow \) \( P(k) = 655V_B_a(k) + 655f + v_k \)  (24)

\( v_k \sim N(0, r_k^2) \) where \( r_k = 40 \)  (25)

5 Results and Discussion

To test the performance of the EKF in estimating the tool flank wear area, first its performance was tested on all the 4 replications for feeds 0.05, 0.1 and 0.15 mm/rev. The initial value of \( V_{B_a} \) is chosen as \( 0.04 \) mm\(^2\) with the initial variance of \( 0.007 \) mm\(^4\) for all the estimations. The resulting estimated mean (black curve) and uncertainty (red curve) for the tool flank are shown in Figure 9 to Figure 11.
Figure 9: Estimated tool wear area for feed 0.05 mm/rev, (a) Replication 1, (b) Replication 2, (c) Replication 3 and (d) Replication 4

Figure 10: Estimated tool wear area for feed 0.10 mm/rev, (a) Replication 1, (b) Replication 2, (c) Replication 3 and (d) Replication 4
Figure 11: Estimated tool wear area for feed 0.15 mm/rev, (a) Replication 1, (b) Replication 2, (c) Replication 3 and (d) Replication 4

According to the Figure 9, in the 1st replication, the EKF was able to estimate the tool wear area only up to 0.4 mm² and was unable to predict the tool wear area values after that. This is due to the effect of measured power, which reduced abruptly as shown in Figure 4. The Root Mean Square Error (RMSE) of the 1st replication was calculated as 0.06 mm². The largest inaccuracy in estimation occurred in the feed 0.10 mm/rev where in the 2nd, 3rd and 4th replications the EKF failed to have an acceptable accuracy with maximum of 0.14 mm² RMSE. This is due to the large variations that exist in experimental results which make the state model less accurate. Finally, for feed 0.15 mm/rev, the EKF performed well except for the 3rd replication with 0.05 mm² RMSE. In all the other replications the experimental measurement fell in the 95% prediction interval of the filter.

To better assess the performance of the EKF, validation sets was used for estimating the progressive tool flank wear area. Figure 12 to Figure 15 show the results of the estimation. To have a closer look at the performance of the EKF in predicting tool wear and tool wear rate, the trajectory function (meaning tool wear area rate versus tool wear area) and the progressive tool wear function are shown side by side. As can be seen in these figures, the EKF is able to have an accurate estimation for the tool wear area with less than 0.05 mm² RMSE, however there is still inaccuracy in estimating the tool wear area rate specifically after reaching 0.4 mm². The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) of the estimated tool wear area is compared for all the 4 tests in Figure 16.
Figure 12: Estimated tool wear and tool wear rate for feed 0.0625 mm/rev, (a) Estimated tool wear area, (b) trajectory estimation.

Figure 13: Estimated tool wear and tool wear rate for feed 0.0875 mm/rev, (a) Estimated tool wear area, (b) trajectory estimation.

Figure 14: Estimated tool wear and tool wear rate for feed 0.1125 mm/rev, (a) Estimated tool wear area, (b) trajectory estimation.
6 Conclusions

Monitoring the performance of the tool in machining Ni-based alloys is a critical yet challenging task, since various sources of uncertainties exist in the operation. Therefore, a stochastic vision of the estimated tool wear is required. The extended Kalman filter provides a robust framework for estimating states of the system in the presence of noise. This method was deployed in this study and summarized as following:

- Large number of experiments were conducted to quantify the uncertainty function in the tool wear. To increase the accuracy it was decided to measure the area of the flank wear instead of average flank wear length.
- The state and measurement models were found based on 4 replication sets of the feeds 0.05, 0.1 and 0.15 mm/rev. An analytical solution was derived for the nonlinear function of the state model in addition to a linear function for the measurement model.
- It was observed that up to average tool wear length of 200-250µm, the uncertainty decreases following by an increase beyond this value. The uncertainty in the state model
was quantified with a failure probability function, as bathtub curve. While it was considered constant throughout all the for the measurement model.

- The EKF performance was tested in 4 validation tests and less than 0.05 mm$^2$ RMSE was observed for the tool wear area estimation, and all the experimental results fell into the 95% prediction interval of the EKF. However, the EKF did not performed well in estimating the rate of tool wear area.

While monitoring the tool wear is critical in machining Ni-based alloy, its effect on the surface quality or dimensional integrity of the workpiece has not been discussed in the literature. In other words, it is not clear how much damage certain amount of tool wear can cause to the surface roughness and how the uncertainties of the tool wear propagate into that. Therefore, a function representing all these factors leads to a better decision making strategy and provide a better solution on when to change the tool before damaging the quality of the end-product. This function will be introduced in future works.

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