Selecting Cutting Data Tests for Cutting Data Modeling Using the Colding Tool Life Model

Johansson, Daniel; Akujärvi, Ville; Hägglund, Sören; Bushlya, Volodymyr; Ståhl, Jan Eric

Published in:
Procedia CIRP

DOI:
10.1016/j.procir.2018.03.035

2018

Document Version:
Early version, also known as pre-print

Link to publication

Citation for published version (APA):

General rights
Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

• Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
• You may not further distribute the material or use it for any profit-making activity or commercial gain
• You may freely distribute the URL identifying the publication in the public portal

Take down policy
If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.
Selecting Cutting Data Tests for Cutting Data Modeling

Daniel Johansson\textsuperscript{a}, Ville Akujärvi\textsuperscript{a}, Sören Hägglund\textsuperscript{b}, Volodymyr Bushlya\textsuperscript{a}, Jan-Eric Ståhl\textsuperscript{a}

\textsuperscript{a}Division of Production and Materials Engineering, Lund University, 221 00 Lund, Sweden
\textsuperscript{b}Seco Tools AB, Fagersta, Sweden

Abstract

An analysis on selecting cutting speed, cutting feed and depth of cut when collecting data for the Colding Tool Life Model based on Woxen’s Equivalent Chip Thickness was performed to achieve the lowest possible model error. All possible combinations of a large data set were evaluated with regard to model error. This work shows that an increase of ratio between the highest and lowest cutting speed, feed, depth of cut and tool life within the five included tool life tests increases the likelihood of an accurate model. Further, to ensure an accurate model, it is not enough to have a large ratio of one single parameter, but a large ratio in all parameters is needed. The paper also presents a suggestion on how to select the cutting data points, derived from the best performing tool life models. It is concluded that one should aim to have one pair of cutting data points with equal equivalent chip thickness while varying cutting speed and three more test points with different equivalent chip thickness.

1. Introduction

The ability to predict tool life and cutting data (cutting speed $v_c$, feed $f$ and depth of cut $a_p$) in metal cutting for a tool engaged with a work piece material is of growing interest. Prediction of cutting data is for example needed since tool manufactures increasingly present more of this type of information to end users on various web based systems. Predicting tool life and cutting data is normally done with exponential functions including a number of model constants. The most common models are the Taylor tool life equation and the Colding tool life equation, where $f$ and $a_p$ are represented by W xen’s equivalent chip thickness $h_e$ in the latter \cite{1,2,3}. The Colding model has proven to work well for prediction of both cutting data and tool life as shown by Johansson \cite{4} and Hägglund \cite{5}, among others, and outperforms the Taylor model. In this study, the Colding model is investigated.

<table>
<thead>
<tr>
<th>Nomenclature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MR</td>
<td>metal removed</td>
</tr>
<tr>
<td>T</td>
<td>tool life</td>
</tr>
<tr>
<td>$a_p$</td>
<td>depth of cut</td>
</tr>
<tr>
<td>$f$</td>
<td>feed</td>
</tr>
<tr>
<td>$h_e$</td>
<td>Woxén chip thickness</td>
</tr>
<tr>
<td>$r_c$</td>
<td>nose radius</td>
</tr>
<tr>
<td>$v_c$</td>
<td>cutting speed</td>
</tr>
<tr>
<td>$\kappa$</td>
<td>major cutting angle</td>
</tr>
<tr>
<td>K, H, M, N0, L</td>
<td>model constants based on curve fitting</td>
</tr>
</tbody>
</table>

The paper also presents a suggestion on how to select the cutting data points, derived from the best performing tool life models. It is concluded that one should aim to have one pair of cutting data points with equal equivalent chip thickness while varying cutting speed and three more test points with different equivalent chip thickness.
When creating a tool life model, a number of tests are necessary for the specific combination of work material and tool grade. Each test comes with a cost of machine time, operator time, work material and tool material. This cost is pushing tool manufactures and researchers to limit the amount of testing, if possible, without increasing the model error. Colding discussed this issue in several papers [6,7] where he investigated the number of model constants needed for a well functioning model while still limiting the number of experimental tests. He concluded that 5 constants are sufficient within a reasonable work load of testing. Johansson et al [8] investigated the importance of including enough tests to create a reliable Colding model and concluded that the model for the test series used in the investigation improved significantly when the number of tests was increased from 5 to 10. In the investigation, the test points were randomly selected from a larger set of test points and it was suggested that greater care should be taken on how to select the test points.

Equation 1 gives the Colding equation and equation 2 gives Woxén equivalent chip thickness.

\[ v_c = e^{\left(\frac{-(ln h_e)^2}{\epsilon M} - \frac{(N0 - L\cdot ln(h_e)) \cdot ln(T)}{\epsilon} \right)} \]  

(1)

\[ h_e = \frac{a_p f}{\sin \theta \cdot \frac{1}{\epsilon} \cdot \frac{r_e + f}{2}} \]  

(2)

A matlab script was created to pick 5 tool performance points out of 22 possible points and then to use the built in curve fitting tool [10], to calculate the Colding model constants K, H, M, N0 and L. No upper or lower limits were applied on the constants. The calculated model was thereafter tested on the full 22 tests series and the RMS error of the model was calculated. This procedure was then carried out for all 26 334 possible combinations of tool performance points and a total of

### 2. Test setup

A total of 22 experimental tests were used for the data presented in table 1. Tool life was recorded when machining C45 E (SS 1672) in longitudinal turning according to ISO 3685:1993 [9] using industry standard coated cemented carbide inserts. No cooling was applied. A wear criterion was set to maximum flank wear 0.3 mm or maximum crater wear 0.5 mm. When reaching this stage, the tool was considered worn out and the tool life was recorded.

The 22 data points (table 1) are defined as:

- cutting data point - a test point based on \( v_c \), \( f \), and \( a_p \)
- tool performance point - a tested point for a defined \( v_c \), \( f \) and \( a_p \) with a corresponding tool life \( T \).

Table 1. The 22 tool performance points used.

<table>
<thead>
<tr>
<th>Test No.</th>
<th>Depth of cut (mm)</th>
<th>Feed (mm/rev)</th>
<th>Cutting speed (m/min)</th>
<th>E. Chip thickness (mm)</th>
<th>Tool life (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>3.5</td>
<td>0.5</td>
<td>260</td>
<td>0.416</td>
<td>7.65</td>
</tr>
<tr>
<td>2</td>
<td>3.5</td>
<td>0.5</td>
<td>245</td>
<td>0.416</td>
<td>9.51</td>
</tr>
<tr>
<td>3</td>
<td>3.5</td>
<td>0.5</td>
<td>230</td>
<td>0.416</td>
<td>13.17</td>
</tr>
<tr>
<td>4</td>
<td>3.5</td>
<td>0.5</td>
<td>215</td>
<td>0.416</td>
<td>17.55</td>
</tr>
<tr>
<td>5</td>
<td>3.5</td>
<td>0.5</td>
<td>200</td>
<td>0.416</td>
<td>20.34</td>
</tr>
<tr>
<td>6</td>
<td>3.5</td>
<td>0.5</td>
<td>185</td>
<td>0.416</td>
<td>30.24</td>
</tr>
<tr>
<td>7</td>
<td>3.5</td>
<td>0.5</td>
<td>170</td>
<td>0.416</td>
<td>33.85</td>
</tr>
<tr>
<td>8</td>
<td>3.5</td>
<td>0.5</td>
<td>150</td>
<td>0.416</td>
<td>71.03</td>
</tr>
<tr>
<td>9</td>
<td>2.0</td>
<td>0.35</td>
<td>355</td>
<td>0.266</td>
<td>10.05</td>
</tr>
<tr>
<td>10</td>
<td>2.0</td>
<td>0.15</td>
<td>490</td>
<td>0.119</td>
<td>12.24</td>
</tr>
<tr>
<td>11</td>
<td>2.0</td>
<td>0.25</td>
<td>410</td>
<td>0.194</td>
<td>14.34</td>
</tr>
<tr>
<td>12</td>
<td>1.5</td>
<td>0.20</td>
<td>455</td>
<td>0.146</td>
<td>14.17</td>
</tr>
<tr>
<td>13</td>
<td>3.0</td>
<td>0.20</td>
<td>430</td>
<td>0.169</td>
<td>18.70</td>
</tr>
<tr>
<td>14</td>
<td>2.0</td>
<td>0.25</td>
<td>420</td>
<td>0.194</td>
<td>9.06</td>
</tr>
<tr>
<td>15</td>
<td>2.0</td>
<td>0.35</td>
<td>365</td>
<td>0.266</td>
<td>7.00</td>
</tr>
<tr>
<td>16</td>
<td>1.5</td>
<td>0.30</td>
<td>405</td>
<td>0.214</td>
<td>11.20</td>
</tr>
<tr>
<td>17</td>
<td>2.5</td>
<td>0.40</td>
<td>350</td>
<td>0.317</td>
<td>4.64</td>
</tr>
<tr>
<td>18</td>
<td>2.0</td>
<td>0.25</td>
<td>420</td>
<td>0.194</td>
<td>9.66</td>
</tr>
<tr>
<td>19</td>
<td>2.0</td>
<td>0.35</td>
<td>365</td>
<td>0.266</td>
<td>10.65</td>
</tr>
<tr>
<td>20</td>
<td>1.5</td>
<td>0.30</td>
<td>405</td>
<td>0.214</td>
<td>13.45</td>
</tr>
<tr>
<td>21</td>
<td>2.5</td>
<td>0.35</td>
<td>330</td>
<td>0.279</td>
<td>13.29</td>
</tr>
<tr>
<td>22</td>
<td>2.5</td>
<td>0.40</td>
<td>330</td>
<td>0.317</td>
<td>10.74</td>
</tr>
</tbody>
</table>

Fig 1. Colding’s suggestion of locating the test points.

In his work, Colding suggested one possible way of selecting the cutting data points where the data points represent a large window of cutting data. As presented in Fig. 1, 5 points should be selected in two pairs of equivalent chip thickness \( h_e \) and cutting speed \( v_c \) plus one additional center point to enable for simple calculation and a reliable model [6]. However, selecting test points according to Colding’s suggestion is not always sufficient due to the fact that several of the test points can be outside applicable cutting data, allowing for phenomena like built up edges, vibration, poor chip breaking, plastic deformation or economically insufficient tool life.

The aim of this work is thus to investigate how the 5 test-point locations should be selected in regard to \( v_c \), \( f \) and \( a_p \) to minimize the risk of a poor tool life model. Moreover, the location of the test points tested should help to avoid undesired phenomena due to cutting data selected outside of the applicable cutting data range. An improved methodology of selecting the locations of the test points will limit the amount of experimental testing and hence, limit the cost of creating tool life models with low model errors.
26 334 Colding models with respective model constants and error were created and evaluated.

For each model, the ratio of cutting speeds $v_c$, feeds $f$, depth of cuts $a_p$, equivalent chip thicknesses $h_e$, tool life $T$, and metal removed $MR$ of the included tool performance points were calculated as equation (3), where $x$ can be substituted for any previously mentioned parameter. The total testing time (4) and the total amount of metal removed from the work piece (5) was also calculated for each Colding model, as these are the driving factor of costs in tool life testing.

$$\text{ratio}(x) = \frac{x_{\text{max}}}{x_{\text{min}}}$$ (3)

$$T_{\text{model}} = T_1 + T_2 + T_3 + T_4 + T_5$$ (4)

$$MR_{\text{model}} = MR_1 + MR_2 + MR_3 + MR_4 + MR_5$$ (5)

3. Result and Discussions

3.1. Influence of parameters

Fig. 2 shows the exponential fit of the increase of error when the average ratio decreases. It can be noted that the ratio of $v_c$ has a bigger influence on model error than the ratio of $h_e$, and that the ratio of $f$ has a more significant influence on the model error than the ratio of $a_p$. Fig 3 shows the exponential fit of the increase of error when the average ratio decreases for $v_c$, $h_e$ and $T$. As shown, the ratio of tool life $T$ is more significant than the ratio of $v_c$. It is important to notice that the ratio of the different parameters, i.e. the highest and the lowest $v_c$ compared to the highest and the lowest $h_e$, varies and one should therefore be careful when comparing the data. What can be concluded is that the ratio of all parameters influences the model error.

Fig. 4 shows the relationship between model error and the ratio of $v_c$ and $h_e$ and fig. 5 shows the relationship between the ratio of $v_c$, $h_e$, and $T$ and the model error. Each Colding model is represented with (●) and an exponential curve fit of the average ratio for any specific model error is represented with (●).

Fig 3. Model error in relation to the average ratio of $v_c$, $h_e$ and $T$.

Fig 4. Model error in relation to $v_c$ and $h_e$. Each Colding model is represented with (●) and an exponential curve fit of the average ratio for any specific model error is represented with (●).

Fig 5. Model error in relation to $v_c$ and $h_e$ and $T$. Each Colding model is represented with (●) and an exponential curve fit of the average ratio for any specific model error is represented with (●).
The main cost driving factor in tool performance testing is the time used for testing and the material consumed by testing. Fig. 6 shows the model error in relation to total time of testing, eq. 4, and fig. 7 shows the model error in relation to total amount of work piece material used, eq. 5, where (●) represent Colding models.

Fig 6. Model error in relation to total time used for testing: Each Colding model is represented with (●) and an exponential curve fit of the average tool life for any specific model error is represented with (●).

Fig 7. Model error in relation to the amount of work piece material used. Each Colding model is represented with (●) and an exponential curve fit of the material used for any specific model error is represented with (●).

The most cost efficient way of collecting data for any Colding tool life model is to aim for the models found in the lower left corner of fig. 6 and fig. 7, which require short testing time or low material usage. The result of this study shows that when testing with low total test time or low material use, the risk of potential error increases. It can be noted, though, that if these models are studied closely, it is not possible to find reasons why some models have high accuracy and some have poor accuracy for cutting data prediction based on the selection of the initial cutting data points creating the specific model.

3.2. Optimal selection of test points

This study shows that the ratio the parameters \(v_c\), \(h_e\) and \(T\) all influence the model error. An increase of ratio in any of the parameters lowers the risk of creating an inaccurate tool life model. However, a large ratio of one single parameter alone will not guarantee for an accurate tool life model. Only when the ratio of \(v_c\), \(h_e\) and \(T\) combined are as large as possible is the risk of creating an inaccurate model reduced.

According to fig 5, the highest ratio of \(v_c\), \(h_e\) and \(T\) is 6.1. A total of 172 combinations of cutting data points and Colding models were created with this highest ratio with a model error from 3.24 % to 19.24%. An analyze of these models shows that the following selections of cutting data points should be avoided:

- Different \(h_e\) in each cutting data point.
- More than one pair of \(h_e\) in the test series.
- Three or more cutting data points with the same \(h_e\) value.

Based on this conclusion we suggest the following selection of cutting data points:

- Maximize the range of cutting speed.
- Maximize the range of equivalent chip thickness.
- Maximize the range of tool life.
- Include two cutting data points using the same equivalent chip thickness.

To fill these criteria but avoid issues like plastic deformation and build up edges, a suggestion of placing the five test points is presented in fig. 8 and selected with the following criteria:

1. Smallest possible \(h_e\) within working range and high \(v_c\).
2. Aiming for economical tool life and equivalent chip thickness.
3. Minimum tool life and relative high \(h_e\).
4. Maximum \(h_e\) within working range and economical tool life.
5. Maximum $h_s$ within working range, low cutting speed and long tool life.

Further, a suggestion of how to place the cutting data points is presented, derived from the best performing tool life models with a high total ratio. It is concluded that one should aim to have on pair of cutting data points with equal equivalent chip thickness while varying cutting speed and three more cutting data points with different equivalent chip thickness. This conclusion contradicts the work of Colding [5] suggesting the cutting data points to be selected in a square placing the cutting data points in each corner as shown in fig. 1 and then adding one cutting data point in the center of the square.

Acknowledgements

This work was co-funded from the European Union’s Horizon 2020 Research and Innovation Program under Flintstone2020 project (grant agreement No 689279) and is also a part of the Sustainable Production Initiative cooperation between Lund University and Chalmers. The authors wish to acknowledge the valuable contributions made by Seco Tools AB.

References