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Selecting Cutting Data Tests for Cutting Data Modeling

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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

Nomenclature

MR	metal removed
T	tool life
a_p	depth of cut
f	feed
h_e	Woxén chip thickness
r_ε	nose radius
v_c	cutting speed
κ	major cutting angle

K, H, M, N0, L are model constants based on curve fitting

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 Woxen's equivalent chip thickness h_e in the latter [1,2,3]. The Colding model has proven to work well for prediction of both cutting data and tool life as shown by Johansson [4] and Hägglund [5], among others, and outperforms the Taylor model. In this study, the Colding model is investigated.

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.

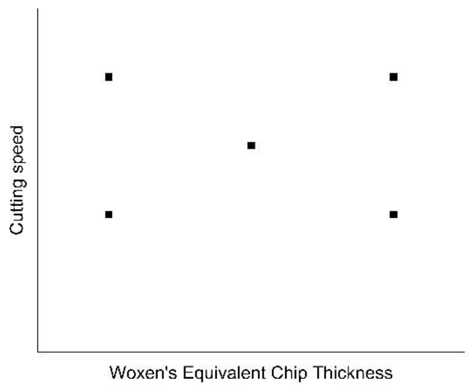

Fig 1. Colding's suggestion of locating the test points.

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.

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.

Test No.	Depth of cut (mm)	Feed (mm/rev)	Cutting speed (m/min)	E. Chip thickness (mm)	Tool life (min)
1	3.5	0.50	260	0.416	7.65
2	3.5	0.50	245	0.416	9.51
3	3.5	0.50	230	0.416	13.17
4	3.5	0.50	215	0.416	17.55
5	3.5	0.50	200	0.416	20.34
6	3.5	0.50	185	0.416	30.24
7	3.5	0.50	170	0.416	33.85
8	3.5	0.50	150	0.416	71.03
9	2.0	0.35	355	0.266	10.05
10	2.0	0.15	490	0.119	12.24
11	2.0	0.25	410	0.194	14.34
12	1.5	0.20	455	0.146	14.17
13	3.0	0.20	430	0.169	18.70
14	2.0	0.25	420	0.194	9.06
15	2.0	0.35	365	0.266	7.00
16	1.5	0.30	405	0.214	11.20
17	2.5	0.40	330	0.317	4.64
18	2.0	0.25	420	0.194	9.66
19	2.0	0.35	365	0.266	10.65
20	1.5	0.30	405	0.214	13.45
21	2.5	0.35	330	0.279	13.29
22	2.5	0.40	330	0.317	10.74

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

$$v_c = e^{\left[K - \frac{(ln(h_e)-H)^2}{4 \cdot M} - (N0 - L \cdot ln(h_e)) \cdot ln(T)\right]} \quad (1)$$

$$h_e = \frac{a_p \cdot f}{\frac{a_p - r(1-cos\kappa)}{sin\,\kappa} + \kappa \cdot r_\varepsilon + \frac{f}{2}} \quad (2)$$

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

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 he, 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.

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

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

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

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.

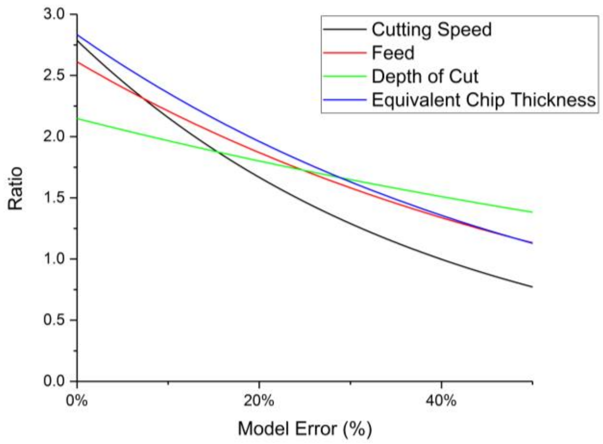

Fig 2. Model error in relation to the average ratio of v_c , f, a_p and h_e.

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 (●).

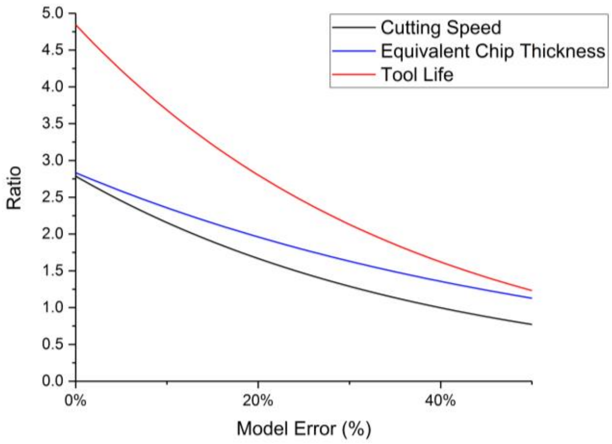

Fig 3. Model error in relation to the average ratio of v_c, h_e and T.

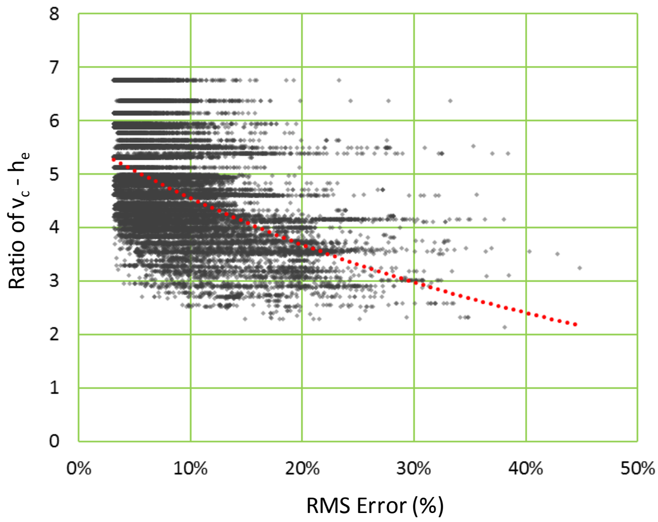

Fig 4. Model error in relation to v_c and h_e. Each Colding model is represented with (●) and an exponential curve fit of the average ratio for any specific model error is represented with (●).

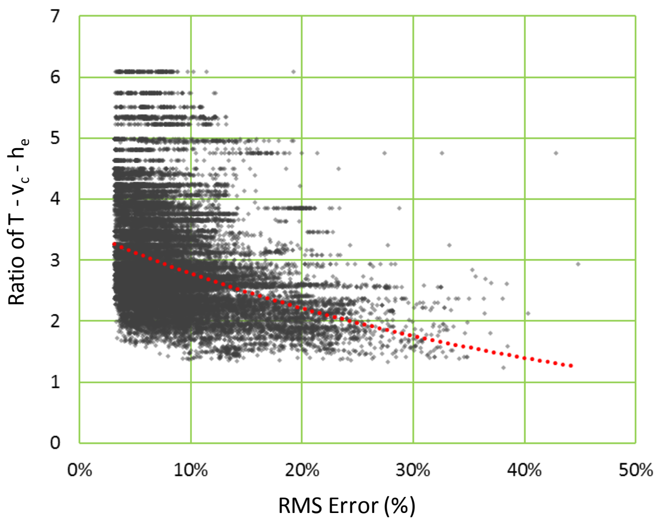

Fig 5. Model error in relation to v_c and h_e and T. Each Colding model is represented with (●) and an exponential curve fit of the average ratio for any specific model error is represented with (●).

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.

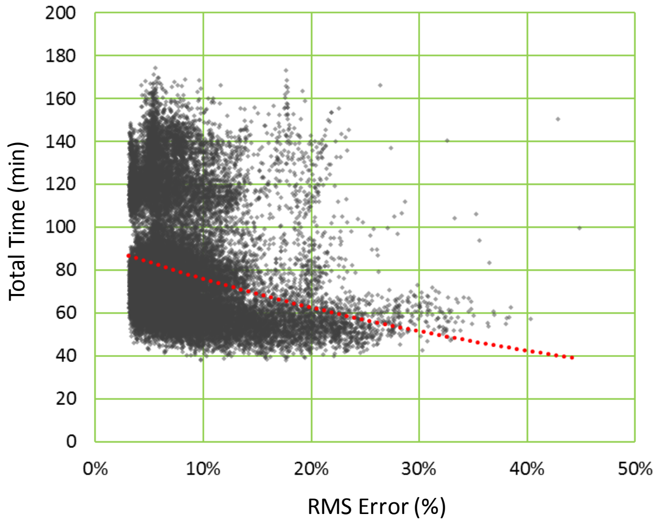

Fig 6. Model error in relation to total time used for testing; Each Colding model is represented with (●) and an exponential curve fit of the average tool life for any specific model error is represented with (●).

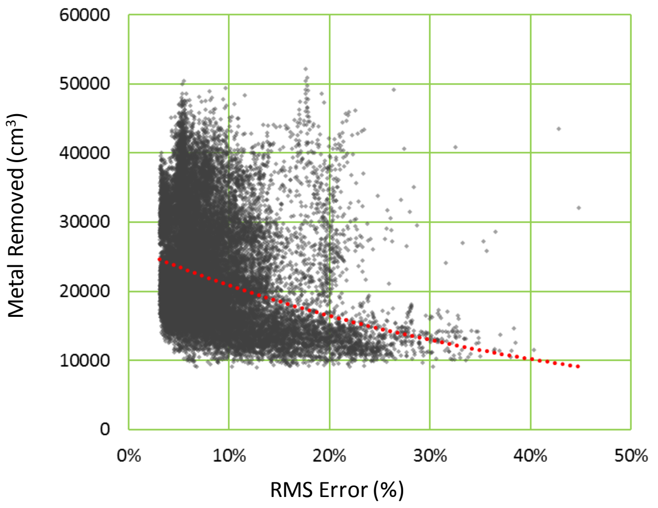

Fig 7. Model error in relation to the amount of work piece material used. Each Colding model is represented with (●) and an exponential curve fit of the material used for any specific model error is represented with (●).

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_e, within working range, low cutting speed and long tool life.

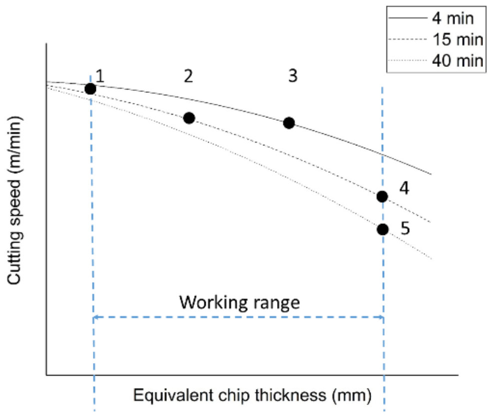

Fig 8. . Suggestion on placement of the cutting data points in a test series of five tests.

In sum, it is clear that the above mentioned method can reduce the amount of time and work material consumed in testing whilst limiting the risk of creating a poor tool life model. Thus, this work offers a cost effective approach for collecting data for tool life and cutting data modeling.

4. Conclusion

A total of 22 tool performance tests from turning C45 E (SS 1672) were used to evaluate the optimal selection of cutting data points to create a Colding tool life model. Five tool performance points were selected, and a tool life model was calculated. This model was then tested on all available data and the model error was recorded. This was done for all 26 334 possible combinations. To reduce cost, time and environmental impact of testing, the aim of this work was to suggest a novel method on select five cutting data points and still creating an accurate model.

The result shows that an increase of ratio between the highest and lowest cutting speed, equivalent chip thickness and tool life within the five tool performance points increases the likelihood of an accurate model. The work also shows that it is not enough to have a large ratio of one single parameter but it is crucial to have a large ratio in all parameters to ensure an accurate model.

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.

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