Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 101 (2021) 106–109

www.elsevier.com/locate/procedia

9th CIRP Conference on High Performance Cutting (HPC 2020)

Logistic classification for tool life modeling in machining

Jaydeep Karandikar[a,*], Tony Schmitz[a,b], Scott Smith[a]

[a]Energy and Transportation Science Division, Oak Ridge National Laboratory, Oak Ridge, TN 37830, USA
[b]University of Tennessee, Knoxville, 1512 Middle Dr., Knoxville, TN 37996, USA

* Corresponding author. Tel.: +1-865-574-4641; fax: +1-865-241-3955. *E-mail address:* karandikarjm@ornl.gov

Abstract

This paper describes the application of logistic classification for tool life modeling and prediction in an industrial setting using shop floor data. Tool life is treated as a classification problem since tool wear can only be measured at the time of tool replacement in a production environment. Laboratory tool wear experiments are used to simulate shop floor wear data by two states: not worn (class 0); and worn (class 1). To incorporate non-linearity in logistic classification, a log-transformation of input features is performed. The logistic classification approach, results, and interpretability of the logistic model are presented.

Keywords: logistic classification; machine learning; tool wear;

1. Introduction

Tool life is one of the significant limitations to machining productivity. Tool life is traditionally defined as the time required for the tool wear to reach a pre-determined wear limit (flank, notch, or crater depth), where tool wear is the loss of material from the tool cutting edge during operation due to interaction with the workpiece material [1].

Nomenclature

g	linear model of input features
k	number of input features
m	number of data points
n	Taylor tool life coefficient
p	probability
x	logistic model input
t	tool replacement time
t_m	mean value of tool life from experimental data
t_s	standard deviation of tool life from experimental data
y	logistic model output
C	Taylor tool life coefficient
T	tool life
V	cutting speed
θ	logistic model parameters

There have been many attempts in the literature at modeling and predicting tool life. The models are empirical, such as Taylor-type tool life equations or response surface methodology [1-4], or physics-based, including analytical and finite element methods [5-7]. The challenge for the practical implementation of existing models is that they require extensive experimentation to calibrate the model coefficients;

This manuscript has been authored by UT-Battelle, LLC under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes. The Department of Energy will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan.2212-8271

10.1016/j.procir.2021.03.125

this is expensive and time-consuming for many tool-material combinations and, therefore, can be infeasible in a production environment. To address the problem of tool life prediction in a production environment, this paper presents the application of logistic classification for tool life modeling using shop floor tool wear data. The concept is to treat production parts as tool wear experiments and use the available tool wear data for modeling tool life. However, in a production environment, tool wear is typically only measured at the time of tool change resulting in a single data point on the tool wear-cut time curve. Therefore, tool life is considered as a classification problem instead of a regression problem, where two classes are defined: tool not worn (class 0); and tool worn (class 1) based on the measured tool wear level. If the tool wear is less than the pre-defined wear limit, the tool is not worn (class 0); otherwise, it is worn (class 1). Tool life is the classification decision boundary in time which separates the two classes. The remainder of the paper is organized as follows. Section 2 describes the procedure to simulate wear data from the shop floor using laboratory experiments. Section 3 describes the logistic classification method and application to tool life modeling. A discussion on model interpretability is provided in Section 4 followed by conclusions in Section 5.

2. Experimental results

To simulate shop floor tool wear data, tool wear experiments were completed using a 19.05 mm diameter, single insert Kennametal endmill in down milling. The insert was a 9.53 mm square uncoated carbide Kennametal insert (107888126 C9 JC) with zero rake and helix angles and a 15° relief angle. Tool wear tests were performed at 149.6 m/min (2500 rpm), 299.2 m/min (5000 rpm), and 448.9 m/min (7500 rpm). The feed per tooth was 0.06 mm/tooth and the axial and radial depths of cut were 3 mm and 4.7 mm (25% radial immersion), respectively. The insert wear status was measured at regular intervals using a handheld microscope (60× magnification). Tool life, T, was defined as the time required for the insert to reach a maximum flank wear width of 0.3 mm (no crater wear was observed during the tests). Three tests were completed at each cutting speed, V. Table 1 shows the results. As seen from Table 1, there is uncertainty in tool life results due to the stochastic nature of tool wear and tool-to-tool performance variation. Taylor first defined an empirical relationship between tool life and cutting speed using a power law [2]:

$$VT^n = C \quad (1)$$

In Eq. 1, n and C are coefficients which depend on the tool-workpiece combination. The constant C is defined as the cutting speed required to obtain a tool life of 1 min. Figure 1 shows the Taylor-tool life model fit to the experimental tool life data shown in Table 1. The Taylor tool life constants were determined as $n = 0.363$, and $C = 675.7$ m/min. The tool life at the experimental spindle speeds was modeled as a normal distribution. The mean, denoted by t_m, and the standard deviation, denoted by t_s, was calculated from the three experimental test results at each speed shown in Table 1.

The experimental results were used to simulate shop floor data as follows. First, the tool life value at the selected cutting speed was sampled from the normal distribution determined from the three experimental test results shown in Table 1. Second, the tool replacement time for wear measurement was generated by a uniform random sample from the interval $[t_m - 3\times t_s, t_m + t_s]$. The upper limit for the interval was limited to one standard deviation above the mean tool life because tool change in a production environment is typically conservative, where the tool is replaced before tool wear exceeds the threshold wear limit. Third, the tool life sample was compared to the tool replacement time sample. If the tool replacement time was less than the tool life, the tool was considered not worn (class 0). Otherwise, the tool was worn (class 1). Figure 2 shows 30 data points (10 at each test spindle speed), where blue denotes class 0 and red denotes class 1. As seen in Fig. 2, the data has more points where the tool is not worn (21) than when the tool is worn (9). This is representative of data collected from the production environment. The simulated data is not perfectly separable because the class 0 and class 1 data points overlap. This accounts for the tool life uncertainty observed in Table 1.

Table 1. Experimental tool life results.

Test #	149.6 m/min (2500 rpm)	299.2 m/min (5000 rpm)	448.9 m/min (7500 rpm)
1	50.1 min.	8.5 min.	2.6 min.
2	68.5 min.	11.5 min.	3.2 min.
3	72.0 min.	9.5 min.	3.3 min.

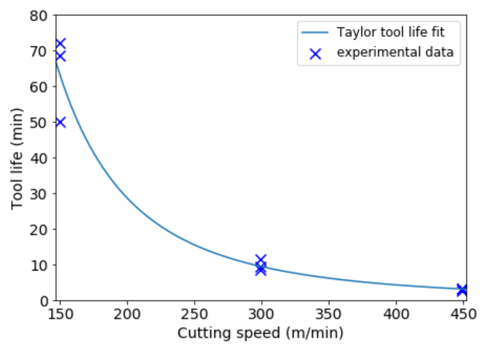

Figure 1. Taylor tool life fit to the experimental tool life data.

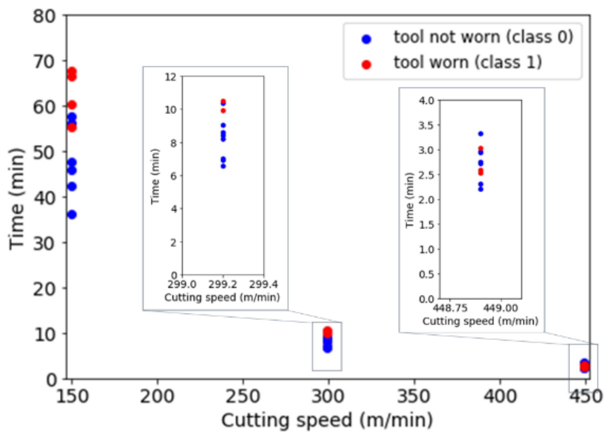

Figure 2. 30 simulated data points; blue denotes tool has not worn (class 0) and red denotes tool is worn (class 1).

3. Logistic classification

When classifying data, the task is to decide class membership y' of an unknown data item x' based on a dataset $D = (x_1, y_1),\ldots,(x_m,y_m)$ of m data points x_i with known class membership y_i [8]. For two classes, y is either 0 or 1. Logistic classification calculates the probability of class membership given input data using the sigmoid function [9-10].

$$p(y = 1|x, \theta) = \frac{1}{1 + e^{-g(x)}}$$

$$g(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots \theta_n x_k \qquad (2)$$

In Eq. 2, p is the probability, k is the number of input features x, y is the class membership, and θ_n are the logistic model parameters, where $g(x)$ is a linear combination of the k input features. The decision boundary between the two classes satisfies the equation $g(x) = 0$ giving $p(y = 1 \mid x, \theta)$ and $p(y = 0 \mid x, \theta)$ equal to 0.5. The logistic model parameters θ are learned using the input data by minimizing the cost function for the logistic model [9-10]. The data shown in Fig. 2 was used to train a logistic classification model; the inputs to the model were cutting speed, V, and tool replacement time, t, and the corresponding labeled class membership for tool wear (0 or 1). In this study, the logistic classification fit was performed in Python using the Scikit-learn library [11-12]. Since the logistic classifier is linear, regularization was not used in training the model. Figure 3 shows the probability of worn tool (class 1) (left) and the decision boundary separating the two classes (right) from the trained logistic model. As seen in Fig. 3, the linear logistic classifier cannot capture the non-linear behavior of tool life with cutting speed. To enable non-linear classification using the logistic classifier, a log-transformation of input features was performed to mimic the behavior of tool life described by the Taylor tool life equation. With this transformation, the classifier's decision boundary is linear in the logarithmic space and non-linear in the original space. Figure 4 shows the non-linear decision boundary resulting from the log-transformation of the input features. Note that since the data is not perfectly separable, the predicted decision boundary finds the best fit for the given dataset.

4. Model interpretability

Machine learning (ML) models are generally considered "black box" where the ML model provides the relationship, but its structure is not interpretable by humans. As noted in Section 3, the input features (cutting speed and tool replacement time) were transformed into the log-space. Recall that tool life is given by the decision boundary between the two classes which satisfies the equation $g(x) = 0$ as shown in Eq. 2. The logistic decision boundary can be rearranged as shown in Eq. 3 and Eq. 4.

$$\theta_0 + \theta_1 \log(V) + \theta_2 \log(t) = 0 \qquad (3)$$

$$\log(t) = -\frac{\theta_1}{\theta_2}\log V - \frac{\theta_0}{\theta_2} \qquad (4)$$

Taking the logarithm of Eq. 1 (Taylor tool life equation) and rearranging the terms gives:

$$\log(V) + n\log(T) = \log(C) \qquad (5)$$

$$\log T = -\frac{1}{n}\log V + \frac{\log C}{n} \qquad (6)$$

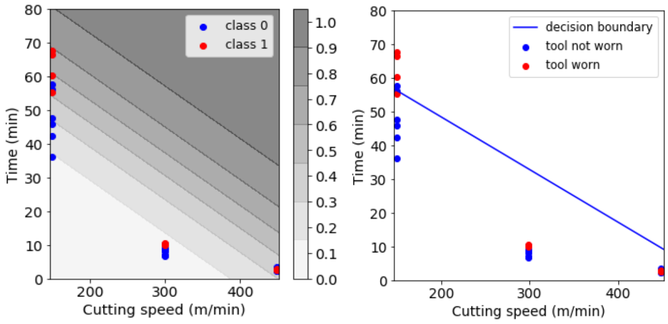

Figure 3. Probability of class 1 (left) and the decision boundary (right) from the logistic classifier model.

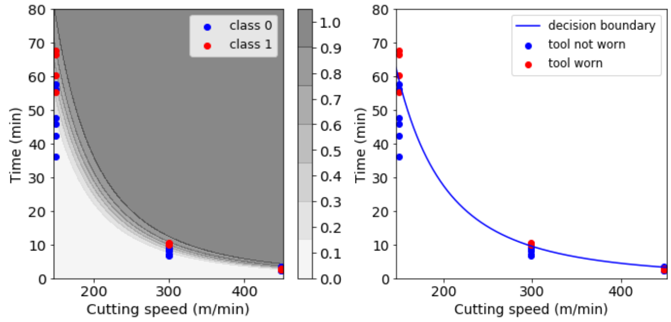

Figure 4. Probability of class 1 (left) and decision boundary (right) from logistic classifier model with log-transformation of the input features.

Comparing Eq. 4 and Eq. 6, the logistic classification model parameters may be directly related to the Taylor tool life coefficients. This provides the desired interpretability for the logistic classification model. To illustrate the approach, the logistic model parameters from the fit to the log-transformed features, shown in Fig. 4, were θ_0 = -140.3, θ_1 = 21.4, and θ_2 = 8.1. The logistic model parameters were converted into the equivalent Taylor tool life coefficients using Eq. 4 and Eq. 6 as $n_{logistic}$ = 0.378, and $C_{logistic}$ = 704.0 m/min. Figure 5 shows a comparison between the Taylor tool life fit and the logistic classification decision boundary trained using data shown in Fig. 2.

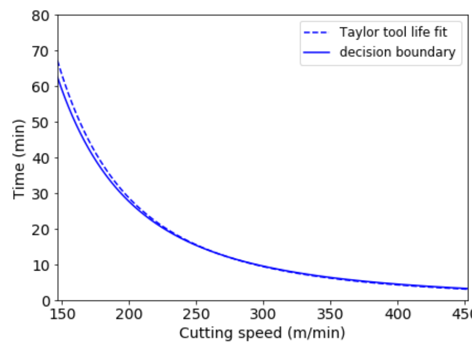

Figure 5. Comparison between the Taylor tool life fit and the logistic classification decision boundary.

The input data shown in Fig. 2 was generated by randomly sampling tool life and the tool replacement time from the experimental results modeled as a normal distribution. To evaluate the influence of input data on logistic classification and the equivalent Taylor tool life coefficients, a Monte Carlo simulation was performed, where 10 input data points at each experimental cutting speed (30 total) were generated multiple times using the procedure described in Section 2. The simulated data was used to learn the logistic model parameters and the equivalent Taylor coefficients from the logistic parameters. Figure 6 shows the histogram of $n_{logistic}$ and $C_{logistic}$ from the Monte Carlo simulations. The distribution of the coefficients implies that the logistic model results are dependent on the nature of the input data. To illustrate, Fig. 7 shows the logistic classification prediction for a sample input data from a single Monte Carlo execution. The equivalent Taylor tool life coefficients are $n_{logistic}$ = 0.312, and $C_{logistic}$ = 628.1 m/min. The logistic model prediction deviates substantially from the Taylor tool life fit at 149.6 m/min. This is because class 1 data points were not recorded at 149.6 m/min. In a production environment, the problem of imbalanced data can be addressed by generating synthetic data using expert opinions, user experience, or extrapolating wear measurements in time. The Monte Carlo simulation was repeated for 20, 50, 100, and 250 measurements at each cutting speed. Table 2 shows the results for mean and standard deviation of the equivalent Taylor tool life coefficients from the trained logistic model parameters. As seen from Table 2, the results converge to $n_{logistic}$ = 0.363, and $C_{logistic}$ = 678.5 m/min, which are different than the least squares Taylor tool life values (n = 0.363, and C = 675.7 m/min) due to the differences in the cost function for the logistic model. As seen from Table 2, the logistic classification approach can be effectively used to model tool life in a production environment with binary information (tool worn and tool not worn).

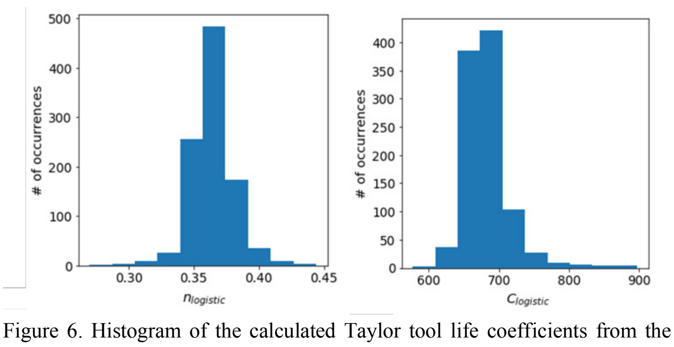

Figure 6. Histogram of the calculated Taylor tool life coefficients from the trained logistic model parameters.

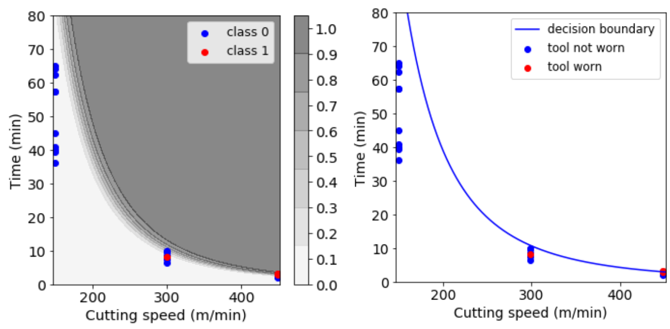

Figure 7. Probability of class 1 (left) and decision boundary (right) from logistic classifier model with log-transformation of the input features.

6. Conclusions

A logistic classification approach for modeling tool life in a production environment using shop floor data was presented. The input data was simulated using tool life experiments and divided into two classes: class 0 for tool not worn and class 1 for tool worn. A logistic classification model was fit to the data, where a log-transformation of input features was performed. A method to transform logistic model parameters into the equivalent Taylor tool life coefficients was presented. This provided interpretability for the logistic classification model.

Table 2. Equivalent Taylor tool life coefficients from logistic model parameters as a function of the number of data points from the Monte Carlo simulation; the values in parenthesis are the mean and standard deviation, respectively.

Data #	$n_{logistic}$	$C_{logistic}$ (m/min)
30	(0.363, 0.0201)	(681.0, 49.0)
60	(0.362, 0.0089)	(676.0, 15.4)
150	(0.364, 0.0058)	(680.4, 10.9)
300	(0.364, 0.0040)	(678.7, 7.5)
750	(0.363, 0.0026)	(678.5, 4.7)

Acknowledgements

This research was supported by the DOE Office of Energy Efficiency and Renewable Energy (EERE), Energy and Transportation Science Division, and used resources at the Manufacturing Demonstration Facility, a DOE-EERE User Facility at Oak Ridge National Laboratory.

References

[1] Tlusty J. Manufacturing Process and Equipment, Prentice Hall, Upper Saddle River, NJ: pp. 463, 2000

[2] Taylor FW. On the Art of Cutting Metals, Transactions of the ASME, 1906; 28:31-248.

[3] Quiza R, Figueira L, Davim JP. Comparing statistical models and artificial neural networks on predicting the tool wear in hard machining D2 AISI steel. The International Journal of Advanced Manufacturing Technology. 2008; 1;37(7-8):641-8.

[4] Alauddin M, El Baradie MA, Hashmi MS. Prediction of tool life in end milling by response surface methodology. Journal of Materials Processing

[5] Usui E, Shirakashi T, Kitagawa T. Analytical prediction of cutting tool wear. Wear. 1984; 100(1-3):129-51.

[6] Xie LJ, Schmidt J, Schmidt C, Biesinger F. 2D FEM estimate of tool wear in turning operation. Wear. 2005; 258(10):1479-90.

[7] Quinto DT. Mechanical property and structure relationships in hard coatings for cutting tools. Journal of Vacuum Science & Technology A: Vacuum, Surfaces, and Films. 1988; May 6(3):2149-57.

[8] Dreiseitl S, Ohno-Machado L. Logistic regression and artificial neural network classification models: a methodology review. Journal of Biomedical

[9] Mitchell TM. Machine learning. 1997. Burr Ridge, IL: McGraw Hill. 1997;45:37:870-877.

[10] Nasrabadi NM. Pattern recognition and machine learning. Journal of Electronic Imaging. 2007 Oct;16:4:049901.

[11] Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, Blondel M, Prettenhofer P, Weiss R, Dubourg V, Vanderplas J. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research. 2011;12(Oct):2825-30.

[12] Buitinck L, Louppe G, Blondel M, Pedregosa F, Mueller A, Grisel O, Niculae V, Prettenhofer P, Gramfort A, Grobler J, Layton R. API design for machine learning software: experiences from the scikit-learn project. arXiv:2013:1309.0238.

This is a resupply of March 2023 as the template used in the publication of the original article contained errors. The content of the article has remained unaffected.