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Research article

Investigation of cutting conditions on tool life in shoulder milling of Ti6Al4V using PVD coated micro-grain carbide insert based on design of experiments

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ABSTRACT

Tool life prediction is generally of great importance in all metal cutting processes, including milling titanium. In this paper, tool life testing was performed based on full factorial design. The cutting speed and width varied between 100 and 120 m/min, and 10 and 70 percent of tool diameter, respectively. All cutting tests were performed in Ti6Al4V under wet conditions using Physical Vapor Deposition (PVD) coated milling inserts. The wear limit was set to 0.2 mm. The data were analyzed using multiple regression analyses, where the method of least squares was applied. A mathematical tool life model was established. Roughly, for each one percent increase in cutting width, tool life decreases on average by one percent, and an increase in cutting speed by a percent leads to a decrease in tool life by four percent. The adequacy of the model was verified using analysis of variance at 95% confidence level. Tool life contour in cutting width and speed was generated from the model. The results can be used for selecting optimum cutting parameters for providing a desired tool life or maximum metal removal rates for a favored tool life.

1. Introduction

Today's manufacturing industry demands higher productivity with preserved or even smaller tolerances. The demand for high productivity leads to increased material removal rate. However, certain combinations of cutting parameters can result in decreased quality, reduced tool life, and in the worst-case tool failure. Tool wear is therefore of great practical interest [1] and tool life predictability is an important factor in modern manufacturing that usually use automated and or un-manned machining operations [2]. In addition to the tool life's strong economic impact in production, prediction of tool wear is important for minimizing material waste for sustainable manufacturing [3].

Many efforts have been made to develop methods for tool life prediction. The most widely used empirical deterministic models are the Taylor tool life model and its modified variations. These models are reviewed in most machinery handbooks and textbooks dealing with metal cutting, tool wear and tool life. However, the accuracy of parameters in Taylor equations is limited to low cutting speeds and more simple machine tools and workpiece [1].

Tool wear rate models can be developed considering the type of wear mechanism and knowledge of temperature and stress distribution on the cutting tool face, which has either to be measured experimentally or to be estimated using finite element analysis [4]. However, these kinds of models are usually limited to orthogonal cutting. In addition, knowledge of temperatures and stresses require extensive tests or non-trivial numerical simulation and calibration cutting tests.

Another way to describe tool wear is to fit mathematical models to a set of experimental data using design of experiments [5, 6, 7]. These models are better suited for selecting optimum cutting conditions for specific applications with more complex machining operations, tools, and workpiece [1]. For example, in Ref. [5] tool life model is established for turning high strength steel using uncoated cemented carbide under dry conditions; in Refs. [6] and [7], tool life is predicted for end milling titanium alloy, also under dry conditions. The used cutting inserts in

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those latter studies ([6] and [7]) were uncoated cemented carbide and polycrystalline diamond (PCD), respectively.

In terms of machinability, titanium alloys are generally known as challenging; they have low thermal conductivity, high hardness and high chemical reactivity with other materials at elevated temperatures [8, 9]. Low thermal conductivity generally results in higher temperatures in the cutting zone, due to the heat concentration on the cutting insert. The built-up heat in the cutting insert and the high reactivity of the titanium alloy contributes to the acceleration of tool wear in uncoated cemented carbide grades [10] and in PCD coated tools [9]. Although PCD tooling seems to provide acceptable performance [7, 9, 11], they are relatively expensive, sensitive to vibration, and usually require high volumes of coolant [12]. When using cutting fluid, different techniques are applied depending on the cutting speed, for example, flood cooling at low cutting speed and high-pressure cooling at high cutting speed [8]. If no cooling technique is used, the cutting speed will be limited due to the risk of high cutting temperatures. Therefore, machining specialist do not recommend dry milling titanium, and in practice, many manufacturing companies do not allow that in the production due to the risk of titanium fire.

Dearnley and Grearson [13] has shown that (older) coated carbide tools, with coatings of titanium nitride, titanium carbide, aluminum oxide and hafnium nitride, wear more rapidly than uncoated grades during continuous turning tests. But, the newer developed tools and coatings are more effective and nowadays, coated grades are recommended by suppliers of cutting tools and solutions as, for example, specified in [14]. Nevertheless, when a tool is coated, the cutting edge is blunted to some extent, which may be disadvantageous to titanium machining. Machining experts always recommend sharp tools for titanium machining; the sharper the cutter is the less heat that is generated, resulting in longer tool life. Hence, Physical vapor deposionsion (PVD) coatings may be preferred to chemical vapor deposition coatings when higher productivity is in focus. As an example, titanium aluminum nitride coated cemented carbide inserts seems promising regarding titanium turning [15].

Milling titanium alloys is proven more difficult than turning [12] due to the intermittent cutting process and the operations are often carried out at lower cutting speeds. In Reference [16], the tool life of different coated tools in face milling titanium alloys is investigated during cutting speeds between 55 and 100 m/min. In order to enable a better understanding of milling titanium, in stable conditions at medium to high cutting speeds, more data that is experimental is required.

The aim of this work is to increase knowledge about how the combination of cutting speed and radial engagement of the cutter affects the tool wear, and thereby help titanium component manufacturers to maximize the metal removal rate while maintaining sustainable manufacturing. The objective is to establish a mathematical tool life model for PVD coated cemented micro-carbide inserts with sharp cutting edges in shoulder milling titanium alloy Ti6Al4V under wet conditions.

2. Experimental setup and procedure

In the experiments, Titanium Grade 5 Ti–6Al–4V alloy square bars of 170 mm × 170 mm and lengths of 600 mm were used as workpiece material. They were in an annealed condition and had a typical hardness of about 300 HV. The chemical composition are given in Table 1. The producer is Sandvik AB, Sweden.

The cutting tool, a 12 mm diameter square shoulder milling cutter (Sandvik Coromant R390-012A12-07L) was mounted in a tool holder, a Weldon adaptor (A1B20-40 12 050), which, in turn, was mounted in a vertical milling machine, Hermle C40U. The cutting insert chosen for this experiment was a PVD coated cemented micro-grain carbide, namely Sandvik Coromant 390R-070204E-ML, grade S30T. The cutting insert has a ground periphery with a sharp cutting edge and a positive rake angle, and the coating material is titanium aluminum nitride. Figure 1 shows the experimental setup, where a) is machine table, b) vises, c) workpiece, d) shoulder mill, and e) Weldon adapter.

The experiments were performed with only one cutting insert mounted in the milling cutter so that the possible influence of the runout of the cutting edges on the mounted tool is minimized among the trials.

To reduce the risk of tool chipping [12] down milling (also called climb milling) and smooth entry by rolling-into-cut [14] were used.

The cutting conditions depend on the workpiece material, tool, machine, required surface finish, etc. In order to select suitable range of parameters, and their values, preliminary tests were conducted based on tool manufacturer recommendations, and feasible range of parameters for the given cutting tool–workpiece system. The preliminary tests led to following parameters: Maximum chip thickness, h_{ex}, and axial depth of cut, a_p, were fixed to 0.05 mm/tooth and 1.5 mm respectively. The cutting speed, v_c, and the cutting width (also called radial depth of cut), a_e, varied between 100 and 120 m/min, and 1.2 and 8.4 mm, respectively. The cutting width can also be defined relative to the cutting tool diameter, D_c. In our case, the cutting width varied between 10 and 70 percent of D_c. It must be remembered however that milling with a cutting width of 50 percent of the tool diameter is not recommended. The reason for this is that the shock loads at the cutting edge are very high when the centerline of the tool aligns with the workpiece edge [17]. Hence, no cutting tests were performed with cutting widths about 50 percent of the tool diameter. The feed per tooth, f_z, in mm/tooth, is also an important key value in milling but was not a control factor in our design of experiment since it, in turn, depends on maximum chip thickness, cutting tool diameter and cutting width. All cutting tests were conducted under wet conditions using HOCUT 4940 cutting fluid (www.houghtonintl.com).

The tool wear criteria (wear limit) was selected to 0.2 mm based on previous experience. Milling operation was stopped to examine the tool at different machining length intervals, depending on the tool wear rates and the cutting conditions. The greater the cutting width, the shorter the machining interval was chosen. The tools were examined and the wear was measured using a microscope equipped with a scale. When notch wear was evident, the number of cutting passes between each inspection were reduced to an interval of five to one passes. Each cutting pass correspond to a machining length of 163 mm. The tool life in minutes (the response) was obtained when the measured tool wear had reached a notch wear of 0.2 mm.

Based on tool life data from our preliminary tests, a replicated full factorial design [18] with four and three levels was selected. Four levels in cutting width and three levels in cutting speed. Each experiment was done duplicate resulting in twenty-four responses. In the 4×3 factorial design, the variables were coded as follows: cutting width (A) and, cutting speed (B). Table 2 shows the factors with their real levels.

The data were analyzed by regression analysis, using MatLab software.

3. Results and statistical analysis

Table 3 shows all values of tool life, T, together with the full factorial design matrix. The measured tool life gets a significantly different value depending on the selected factor levels. The corresponding optical microscope images for the cutting insert edges that have reached the tool wear criteria in Table 3 are shown in Figure 2.

Table 1. Chemical composition of the Ti–6Al–4V alloy (%).

Alloy	Al	V	Fe	O	C	N	H	Ti
Ti–6Al–4V	6	3.8	0.16	0.18	0.01	<0.01	<0.005	Balance

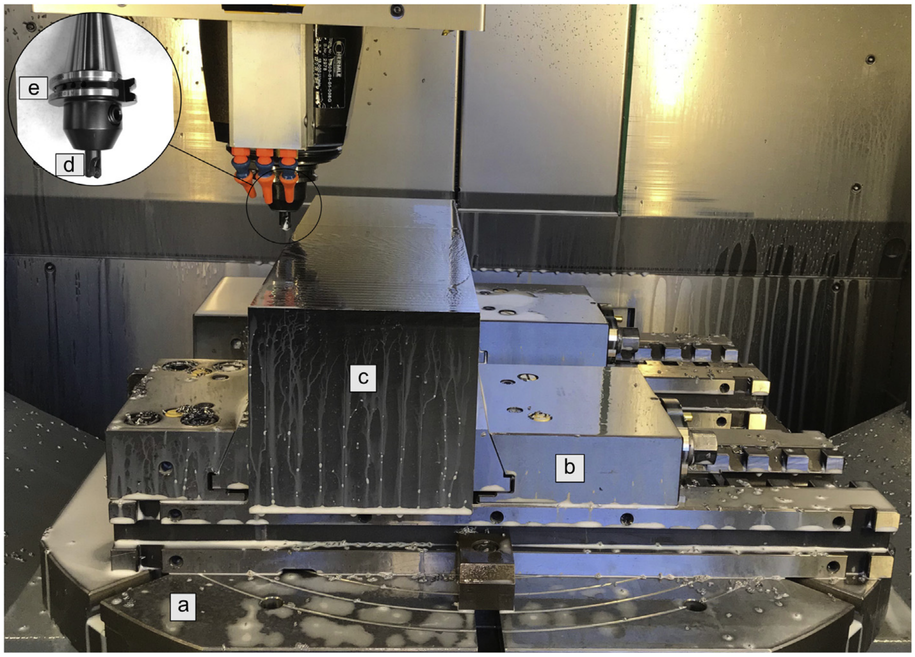

Figure 1. Shows the experimental setup, where a) is machine table, b) vises, c) workpiece, d) shoulder mill, and e) Weldon adapter.

Table 2. Cutting parameters and their levels.

Control Factor	Quantity	Symbol	Unit	Level 1	Level 2	Level 3	Level 4
A	Cutting width	a_e	mm % of D_c	1.2 10	2.4 20	4.2 35	8.4 70
B	Cutting velocity	v_c	m/min	100	110	120	

Table 3. Design matrix with response.

Exp. No	Control factor					Response: Tool life	
	Coded value		Real world unit value			Main trails	Replicates
	A: a_e	B: v_c	A: a_e [mm]	[% of D_c]	B: v_c [m/min]	T [min]	
1	1	1	1.2	10	100	216	177
2	2	1	2.4	20	100	97	96
3	3	1	4.2	35	100	53	35
4	4	1	8.4	70	100	34	26
5	1	2	1.2	10	110	121	127
6	2	2	2.4	20	110	79	58
7	3	2	4.2	35	110	37	30
8	4	2	8.4	70	110	21	20
9	1	3	1.2	10	120	98	92
10	2	3	2.4	20	120	49	45
11	3	3	4.2	35	120	25	20
12	4	3	8.4	70	120	13	13

Figure 3 shows the relation between measured tool life and cutting width for different cutting speed. The data points implies curved graphs; the tool life seems to decay exponentially with respect to cutting width. Hence, a regression model is used after logarithmic transformation of both independent and dependent variables to estimate the effects of each factor.

Preliminary analysis for a second-order model [6, 7] showed that interaction terms and square terms were statistically insignificant. The model applied to our factors becomes:

$$\ln(T) = b_0 + b_1 \ln(a_e) + b_2 \ln(v_c) \tag{1}$$

where b_i is coefficient estimates for the regression. The coefficients are estimated by the method of least squares [18]. This method computes the unique plane that minimizes the sum of squared distances between the measured data and that plane. The actual values of b_i are shown in Table 4 together with their corresponding standard error (SE), test statistic from t-test (t statistic) [18] and probability value (p-value) [18]. Both t statistics and p-values are for testing significance of regression

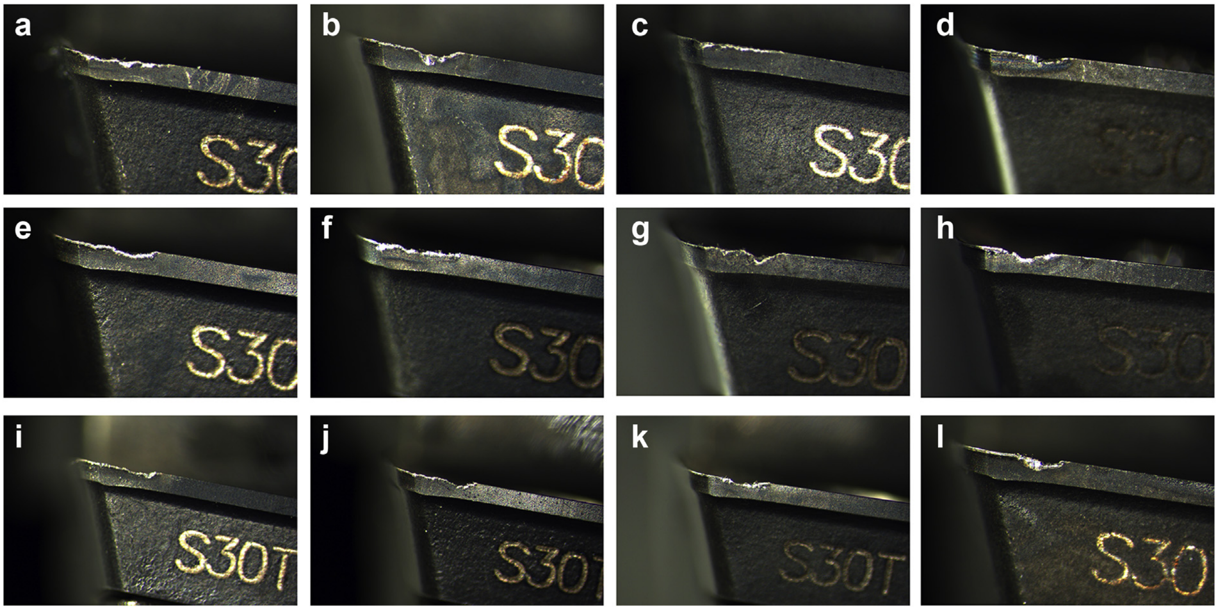

Figure 2. Optical microscope images of the worn cutting inserts for main trails. (a) Exp. No. 1, (b) Exp. No. 2, (c) Exp. No. 3, (d) Exp. No. 4, (e) Exp. No. 5, (f) Exp. No. 6, (g) Exp. No. 7, (h) Exp. No. 8, (i) Exp. No. 9 (j) Exp. No. 10 (k) Exp. No. 11 (l) Exp. No. 12.

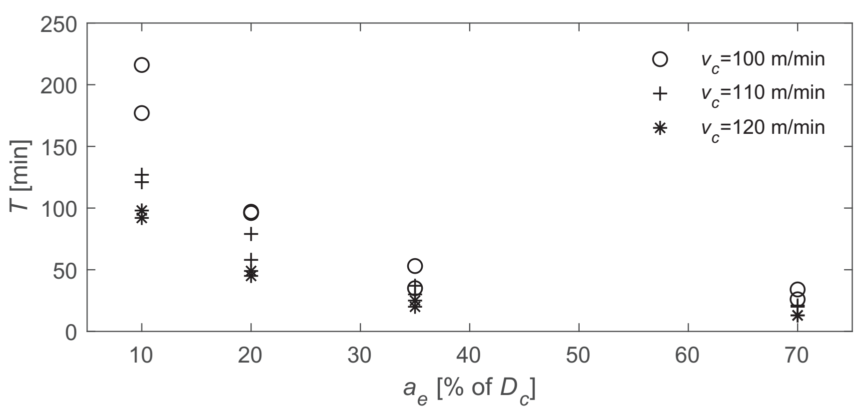

Figure 3. Tool life vs. cutting width at various cutting speeds.

Table 4. Estimated Coefficients and t statistics.

	Estimate	Standard error	t Statistic	p-value
b_0	25.9887	1.9266	13.49	<0.001
b_1	-1.0001	0.0425	-23.51	<0.001
b_2	-4.0076	0.4090	-9.799	<0.001

coefficients. The t statistic is t calculated for each coefficient to test the null hypothesis that the corresponding coefficient is zero against the alternative that it is different from zero, given the other predictors in the model. The t are calculated using the formula [18].

$$t_i = \frac{b_i - (\text{hypothesized value})}{SE \text{ of } b_i} \tag{2}$$

i.e. the coefficient divided by its standard error. For example, the t-statistic for b_0 is $25.9887/1.9266 = 13.49$. With 21 error degrees of freedom and 95% confidence level, this value of t is highly significant since it is greater than the tabulated critical value of 2.080 from the Student's t distribution. The probability values, p-values, are significance level of the t calculated.

The estimated coefficients are all significant because their p-values (provided by MatLab's Statistics and Machine Learning Toolbox) are less than the significance level 0.05.

Greater cutting width and a higher cutting velocity generally result in lower tool life.

The analysis of variance, ANOVA, for the regression model is shown in Table 5. The F statistic is a test statistic from the ANOVA hypothesis test, F-test, where F are calculated as ratio of two variances, “mean squares” [18]. For example, the F statistic for regression is $7.219/0.0223 = 324.36$. The p-values are calculated from the corresponding F statistic values following the F-distribution. The p-value for the regression is less than the significance level 0.05 and indicate that a significant linear relationship exists between the transformed response ln (T) and the

Table 5. Analysis of variance for the regression model.

Source	Sum of squares	Degrees of freedom	Mean squares	*F* Statistic	*p*-value
Regression	14.438	2	7.219	324.36	<0.001
Residual	0.4674	21	0.0223		
Lack of fit	0.2228	9	0.0248	1.2147	0.36852
Pure error	0.2446	12	0.0204		
Total	14.9054	23	0.6481		

transformed predictor variables, ln (a_e) and ln (v_c). Furthermore, the ANOVA partitions the residual into the part for the multiple measurements, pure error, and the rest, which is due to lack of fit of the regression model. Since the *p*-value for the lack of fit is larger than the significance level 0.05, we can conclude that there is not enough evidence that there is a lack of fit in the linear regression model. Hence, the regression model is adequate.

The goodness of fit is summarized as follows. The tool life model display satisfactory coefficient of determination, both R^2 and adjusted R^2 are close to one. The R^2 is the proportion of the variance in the dependent variable that is predictable from the independent variables. The R^2 value of 0.969 means the regression model explains about 96.9 % of the total variability in the response. The adjusted R^2 value of 0.966 indicates that the regression model explains 96.6 % of the variability after considering the significant factors. The estimate of the error variance, Mean Squared Error, MSE is 0.0223; the standard error of the regression, which is an estimate of the standard deviation of the random part of the data, Root Mean Squared Error, RMSE is 0.149.

The probability plot in Figure 4 shows how the distribution of the standardized residuals (residuals divided by their estimated standard deviation) compares to a normal distribution. One potential outlier appears on this plot with standardized residual less than -2. Otherwise, the data points are fairly close to the straight dashed line and behave randomly, which suggest that the data fit the model reasonably, but needs more investigation for that individual observation.

The ordinary method of least squares (OLS) produces parameter estimates having smallest variance under the assumption that the independent observations have equal variance [18]. Thus, OLS estimates for regression models are sensitive to outliers. Robust regression provides an alternative to OLS regression that works with less restrictive assumptions such as when outliers are present in the data. In robust regression, instead of minimizing the residual sum of squares the weighted sum of squares is minimized [18]. This method of regression is also called weighted least squares (WLS).

Running the regression analysis without the suspected outlier does not considerably affect the results and the residuals become normally distributed. Moreover, running a robust regression analysis using WLS instead of OLS does not change the results considerably either. The selected robust regression algorithm uses iteratively reweighted least squares with a bisquare weighting function (https://se.mathworks.com). In Table 6, and Table 7, the effect of dropping the suspected observation and using robust regression (keeping that individual observation) is summarized.

Four additional tests without replicate were conducted. The new observations were to check the predictive performance of the regression model when applied to data that were not used in the model estimation. Table 8 shows the experimental conditions and results for the new observations. Also, the predicted response, computed tool life using the regression model, together with the 95% prediction intervals are displayed.

Tool life contour in cutting width (expressed as a percentage of the cutting tool diameter) and cutting speed is shown in Figure 5. Parts of curves near the cutting width of 50 percent of the tool diameter are dashed to indicate that the model not exactly determines their positions and shapes.

4. Summary and discussion

Rather than fitting a higher order polynomial to the curved data, it is preferable for engineers to transform the data and find a simple linear relationship. A linear correlation in a logarithmic transformation domain is shown to be suitable for our measured data. The regression equation for tool life in the transformed domain in the actual values written with standard errors is

$$\ln(T) = \underset{\pm 1.9266}{25.9887} - \underset{\pm 0.0425}{1.0001} \cdot \ln(a_e) - \underset{\pm 0.4090}{4.0076} \cdot \ln(v_c) \tag{3}$$

Obviously, higher cutting speed and width reduce the tool life and according to the model found, the cutting speed has a much greater effect on tool life than the cutting width. Approximately, for each, one percent increase in a_e, T decreases on average by one percent; and an increase in v_c by a percent leads to a decrease in T by four percent. To be precise, an x-percentage increase in one of the predictors (holding the other predictor constant) is associated with a change in the outcome equivalent to multiplying it by$\exp(\ln((100+x)/100)\cdot b)$, where b is the estimated coefficient for the predictor that is changed. For example, a 20 percent increase in cutting speed, while holding the cutting width at a constant level, multiplies the tool life by $\exp(\ln(1.2)\cdot(-4.0076)) = 0.4816$. Therefore, a 20 percent increase in cutting speed reduces tool life by 52 percent.

The presented tool life model is obtained using the method of ordinary least squares, which is a well-known and widely used statistical method in regression analysis. The method of weighted least squares used in the robust regression approach was included in the investigation of one suspect data point, only as a part of the validation process of our regression model.

A two-dimensional graphic representation of the model is established (Figure 5 Contour plot). Several combinations of cutting speed and width result in the same tool life. For instance, a cutting speed of 112 m/min with a cutting width of 24% of cutting tool diameter give the same value ($T = 50$ min) as a speed of 106 with a cutting width of 30. It is useful to seek out the cutting data combinations that give a desired tool life or maximum metal removal rate. In general, a larger width of cut leads to a shorter tool life for a certain fixed cutting speed, but also leads to higher metal removal rates and faster machining. To maximize the metal removal rate for a required tool life, one can, therefore, select the cutting width that applies to the lowest cutting speed. For example, with a requirement of 50 min tool life, a cutting speed of 100 m/min and a cutting width of 37% of cutting tool diameter results in a maximum metal removal rate. A variation of the previous example is a case where the cutting width is fixed. If the longest tool life is desired, the lowest cutting speed is selected, but if the maximum metal removal rate is desired, the highest cutting speed is selected (resulting in shorter tool life). The values between these two cutting speeds represent the feasible range for the milling operation. It must be remembered though, that the contour curves are related to the tool life criterion set in the measurements.

The tool life model explains about 97% of the total variations and the individual observation having a large standardized residual does not have any effect on the practical interpretation of the results of the analysis. The scatter and variability in the measurements are acceptable and sources to these variations are variation in the workpiece material, cutting tool geometry, coolant conditions and vibrations [1].

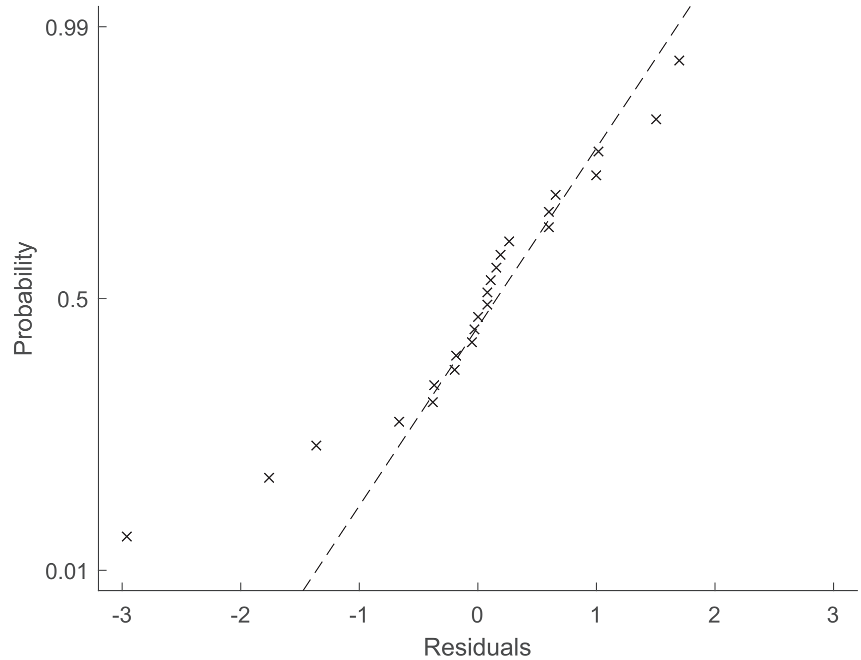

Figure 4. Normal probability plot of standardized residuals.

Table 6. Estimated Coefficients for OLS and robust regression.

	b_0	b_1	b_2
OLS regression omitting one outlier	27.5267	-0.9893	-4.3383
Robust regression	26.8895	-0.9898	-4.2025

Table 7. Model summary for OLS and robust regression.

	R^2	MSE	RMSE
OLS regression omitting one outlier	0.982	0.0133	0.115
Robust regression	0.974	0.0180	0.134

Table 8. Experimental conditions and results for new observations together with calculated predicted values and 95% prediction interval for the measured response.

Exp. No	Control factor			Measured Response	Predicted Response	Prediction interval	
						Lower	Upper
	A: a_e [mm]	[% of D_c]	B: v_c [m/min]	T [min]	T_p [min]	PI_L [min]	PI_U [min]
1	7.2	60	105	21	26	18	36
2	3.0	25	115	32	43	31	59
3	3.96	33	113	29	35	25	48
4	2.64	22	117	44	45	33	62
Regression model: $\ln(T) = 25.9887 - 1.0001 \cdot \ln(a_e) - 4.0076 \cdot \ln(v_c)$							

The tool life tests were carried out using only one cutting insert as many other published works, see for example Refs. [6, 7]. In this way, the variation due to cutter runout was minimized among the trials, and the results can be used for comparison between different cutting conditions. To determine tool life for the general case in which the milling cutter contains two inserts, more investigation is needed, were the runout of the cutting inserts have to be included as a control or noise factor. It should, however, be noted that tests with more than one cutting insert may present incoherent results due to more complex dynamics. For example, vibrations due to cutting force variations caused by the chip thickness differences as a result of runout and or of the machined surface produced by preceding cutting edge.

5. Conclusion

It is shown that full factorial design can be successfully used to determine a mathematical model for tool life in shoulder milling of Ti6Al4V under wet conditions and using PVD coated carbide insert.

Approximately, a one-percentage increase in the predictor is associated with a b-percentage change in the outcome. Therefore, for each one percent increase in cutting width, tool life decreases on average by one

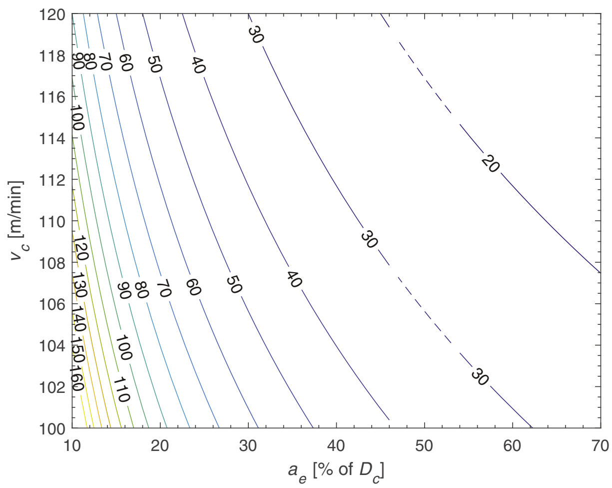

Figure 5. Tool life contour plot of the regression model. The cutting width, a_e, is presented as a percentage of the cutting tool diameter D_c. Dashed curves indicate uncertainty in the region near a cutting width of 50 percent of the tool diameter.

percent; and an increase in cutting speed by a percent leads to a decrease in tool life by four percent.

In spite of all investigations, much is lacking for a complete fundamental understanding of the physics of the tool wear. The results add understanding of how cutting speed and width affect the life of a micro-grain carbide insert with titanium aluminum nitride coating. Developed contour plots can be used to select optimum cutting parameters.

In a planned subsequent paper, the tool ware rates will be studied to investigate the wear mechanisms of PVD coated carbide tools.

Declarations

Author contribution statement

Niklas Andersson: Conceived and designed the experiments; Performed the experiments.

Kourosh Tatar: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Sören Sjöberg: Analyzed and interpreted the data; Wrote the paper.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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