



## THE MICRO MILLING OF BIPOLAR PLATES - A TOOL LIFE MODEL

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### ABSTRACT

Tool life is a major cost driver in all micro milling operations, due to the costly and brittle nature of micro end mills. As such, the need exists to be able to predict tool life for the purpose of tool cost estimation. This paper addresses this issue by developing an empirically determined tool life model that characterises tool life in terms of cutting parameters. The model is intended for a specific application; that is, the micro milling of bipolar plates. Further, the model is developed via designed experimentation and multiple-linear regression analysis of the resulting data.



## 1. INTRODUCTION

The world's research efforts towards a hydrogen economy are intensifying and South Africa is at the centre. This is because South Africa has approximately 80% of the world's known Platinum Group Metals reserves, a vital mineral in hydrogen fuel cell operation.

The production cost of hydrogen fuel cells is driven significantly by the manufacture of bipolar plates. This is because bipolar plates are complex in design and account for most of the mass and volume in a fuel cell stack. The need, therefore, exists to find materials and manufacturing techniques that result in cost effective production of these components.

Several techniques exist that could be used for the manufacture of bipolar plates. Micro milling is one such technique that shows promise, especially for small to medium batch sizes. Micro milling is defined as the milling of components with two or more dimensions in the sub millimetre range. This technique is characterised by the ability to manufacture complex three dimensional, free form geometries of small to medium batch sizes cost effectively. Micro milling, therefore, warrants further investigation.

The purpose of this paper is to initiate an investigation into the economic feasibility of the manufacturing of bipolar plates using micro milling. Tool life, is a significant cost driver in all micro milling operations, due to the brittle and costly nature of micro end mills. As such, tool life is the subject of investigation for this paper. An empirical model is built using the Response Surface Methodology (RSM).

### Response Surface Methodology (RSM) and its Applicability

Myers, et al. [4] defines RSM as a collection of statistical and mathematical techniques useful for the design, development and optimisation of products and processes. RSM is especially useful in situations where several input variables potentially influence some or other performance measure or quality characteristic, otherwise known as the response.

## 2. DESIGNING THE TOOL LIFE EXPERIMENTS

This section describes all the practical and academic aspects associated with designing the experiments carried out.

### 2.1 Selecting the Experimental Factors

There are a number of potential factors, which may or may not influence tool life. To test all of these factors through experimentation would not return the appropriate level of insight given the required investment (in both time and money). It is possible, however, to reduce the number of influencing variables by defining the specific machining conditions. These conditions are as follows:

- The workpiece material considered is a polymer-graphite composite. This material shows the most promise for use in bipolar plates in terms of its physical and chemical properties.
- The design of the bipolar plates is such that approximately 70% of the machining is done using one tool size.
- The radial depth of cut is held constant (at a maximum) due to the nature of milling required for the bipolar plate design.



- Further, only one type of tool is considered in terms of material and geometry. This decision comes under recommendation from industry expert, Sven Bornbaum, project manager for fuel cell components at Schunk Kohlenstofftechnik GmbH.

As a result, the only experimental factors that remain are *feed per tooth* ( $\mu\text{m}$ ), *cutting speed* ( $\text{m}/\text{min}$ ) and *axial depth of cut* ( $\text{mm}$ ). Using only these experimental factors is consistent with other experimental based efforts to characterise tool life. See Prakash, et al. [5] and Mayor, et al. [2].

## 2.2 The Experimental Design

The aim of experimental designs is to achieve experimental efficiency. This refers to the amount of information yielded versus the required experimental runs. In addition, it must be possible to fit an empirical second-order function to the resulting data. Second order functions are highly flexible and often yield an estimated response function that is a good approximation of the true response function (Myers, et al. [4]). For this reason, the Central Composite Design (CCD) is used.

### Central Composite Design (CCD)

The CCD is the most popular class of second-order designs. That is, designs for fitting second-order functions. It was first introduced by Box and Wilson in 1951 (Myers, et al. [4]). Much of the popularity of the CCD comes from the fact that the design components can be executed sequentially as the need is presented.

The CCD consists of:

- $F$  2-level factorial points, where  $F = 2^k$  and  $k$  is the number of experimental factors
- $2k$  axial points and
- $n_c$  centre runs

Myers, et al. [4] described the roles of the three components as follows:

- The  $F$  2-level full factorial runs contribute to the estimation of linear terms and are the sole contributors to the estimation of the two factor interaction terms.
- The  $2k$  axial points contribute to the estimation of the second order terms.
- The  $n_c$  centre runs also contribute to the estimation of the second order terms, but more importantly, provide an internal estimate of statistical error (pure error).

### Selecting the Design Parameters

The flexibility of the CCD comes from the selection of the design parameters  $a$  and  $n_c$ , the axial distance from the design centre and the number of centre runs respectively (Myers, et al. [4]). Note that experimental design parameters ( $a$  and  $n_c$ ) should not be confused with experimental factors ( $v$ ,  $f_t$  and  $d$ ). The selection of these design parameters is closely related to design rotatability. Montgomery, et al. [3] say that a rotatable design is one in which the standard deviation of the predicted response  $\hat{y}$ , is constant at all points that are the same distance from the design centre. This is intended to create stability in that the response is predicted with equal precision for all points that are equal distance from the centre. This is despite the fact that the precision decreases with increasing distance from the centre.

A CCD may be made rotatable through the proper selection of the axial spacing  $a$ . General guidelines exist for the selection of  $a$ . Myers, et al. [4] say that rotatability is achieved by

using  $\alpha = \sqrt[4]{F}$  where  $F$  is the number of factorial points. In the case of the tool life experiments,  $F = 2^3 = 8$  factorial points, which results in  $\alpha = \sqrt[4]{8} = 1.682$ . Further, Myers [3] recommend using 3 to 5 centre runs for a CCD with  $k = 3$ .

For the purpose of these experiments, the design parameters of  $\alpha = 1.682$  and  $n_c = 4$  were selected. Further, following the CCD structure, 18 experimental runs are completed. This consists of  $2^3 = 8$  factorial runs,  $2 \times 3 = 6$  axial runs and 4 centre runs.

### Selecting Experimental Factor Ranges

It is further necessary to select the range of values for each of the experimental factors. That is an upper and lower bound for each of the cutting parameters. Before doing so, it is necessary to consider the *region of interest* and the *region of operability* for the situation at hand.

The *region of interest* is a geometric region characterised by lower and upper limits on experimental factor combinations that are of interest to the experimenter. The *region of operability*, on the other hand, describes the lower and upper limits of experimental factors that can be operationally achieved with acceptable safety and that will output a testable product. These regions are considered in the following way:

- The region of interest is characterised by the bipolar plate design features and by typical ranges for cutting parameters, as used in industry.
- The region of operability is limited to the capability of the machine used i.e. the achievable feed rates and rotational speeds. The maximum achievable feed rate was *1654 mm/min* while the rotational speed limit placed no constraint on the experimental factors.

After considering the regions of interest and operability, the following cutting parameters, as shown in Table 1, were selected. The micro tools used were 0.7112mm, 2-flute, solid carbide flat end mills from Performance Micro Tool.

Coded Values	$-\alpha$	-1	0	1	$\alpha$
	Natural Values				
Cutting Speed (m/min)	47.5	56.621	70	83.379	92.5
Feed per Tooth ( $\mu\text{m}$ )	10	13.040	17.5	21.960	25
Axial Depth of Cut (mm)	0.2	0.5649	1.1	1.6351	2

Table 1: Experimental Factor Ranges

## 3. EXECUTING THE EXPERIMENTS

This section describes the practical aspects involved in executing the experiments and recording the data.

### 3.1 The Experimental Setup

The machine used for these experiments was the Minitex 12528 from Minitex Machine Corporation. The physical setup of this machine was relatively straightforward for this purpose. Flat polymer-graphite composite plates, obtained from Schunk Kohlenstofftechnik GmbH, were fixed to the worktable using mechanical clamps. This provided sufficient machining tolerance for this purpose. The cutting path was generated



using N-Code. For each experimental run, a new tool was used and cutting parameters were held constant until the tool life had expired. A vacuum device was attached to the machine setup to extract the resulting dust and no lubrication or cooling was required.

### 3.2 Measuring Tool Life

Recording the tool life data, in this case, is complicated by the nature of tool failure and the way in which tool life is defined.

#### Deciding on Criteria for Tool Life

Tools typically fail in two ways. Either they fail catastrophically and suddenly or they fail gradually.

Catastrophic failure is characterised by tool breakage. This is an extreme failure mechanism and can occur for two main reasons, as identified by Tansel, et al. [7], namely chip clogging and fatigue.

Gradual failure is characterised by wear to the extent that the tool no longer functions sufficiently for its intended purpose. This can mean that the tool no longer produces a satisfactory surface finish or that the diameter of the tool is reduced below the lower tolerance limit of the part design. Micro end mills are known to wear over the whole length of shaft immersed in the workpiece material. Owing to the small size and challenges with respect to visual inspection, the reduction of the starting diameter is often used to quantify tool wear. This is unlike conventional machining where flank and rake wear are traditionally used to quantify tool wear.

Filiz, et al. [1], conducted similar experiments. They used the changing diameter of their micro end mills as an indication of tool wear. Further, instead of measuring the tool itself, they used the channel widths as the actual measure of tool wear. This is because channel widths are more easily measurable under a microscope. The Society of Manufacturing Engineers (SME) defines this method of judging tool failure as size failure. That is, the occurrence of a change in dimension of the finished part by a certain amount. The convenience of this method is that the position along the cutting path acts as a time-stamp, allowing almost continuous estimation of tool wear over time. This method was chosen for the purpose of these experiments. Further, it was necessary to define the point at which tool wear is considered excessive.

#### Deciding on the Critical Amount of Tool Wear

The critical amount of tool wear is defined as the maximum allowable reduction in tool diameter that maintains satisfactory performance. This implies that the resulting channel width must remain within tolerance limits, while maintaining an acceptable surface finish. These two criteria represent conflicting objectives. On the one hand, maximum tool life is desirable, but on the other, an acceptable surface finish is required.

In order to account for both objectives, a conservative approach was taken in defining the critical amount of tool wear. Making liberal assumptions about the tolerable tool wear can compromise the integrity and usefulness of the tool life model. The tolerable wear, for the purpose of this model, was decided to be 100µm worth of wear. In other words, end of tool life was defined as the point at which there was a 100µm reduction in nominal tool diameter.

## Recording Tool Life

For the purpose of these experiments, both catastrophic and gradual failure mechanisms were considered. The tool life after each experimental run was recorded as the length of cut, up to the occurrence of the earliest failure mechanism.

Photographs of the channels were taken at certain points along the cutting path, under an optical microscope with 102x optical zoom. Measurements of the channel widths were then taken from the photographs using calibrated computer software. It was further necessary to interpolate along the measured points to identify the point where 100 $\mu$ m of wear was evident.

## Results

The results of the experiments are presented in the table below.

Run	Coded Experimental Factors Values			Natural Experimental Factor Values			Machine Parameters		Tool Life (mm)
	Cutting Speed	Feed/tooth	Depth	Cutting Speed (m/min)	Feed/tooth ( $\mu$ m)	Depth (mm)	RPM	Feed Rate (mm/min)	
1	-1	-1	-1	56.621	13.040	0.565	25342	660.941	12886.497
2	1	-1	-1	83.379	13.040	0.565	37318	973.276	5144.530
3	-1	1	-1	56.621	21.960	0.565	25342	1112.992	5570.790
4	1	1	-1	83.379	21.960	0.565	37318	1638.951	9636.601
5	-1	-1	1	56.621	13.040	1.635	25342	660.941	13466.417
6	1	-1	1	83.379	13.040	1.635	37318	973.276	15036.808
7	-1	1	1	56.621	21.960	1.635	25342	1112.992	10873.640
8	1	1	1	83.379	21.960	1.635	37318	1638.951	9713.592
9	-1.6818	0	0	47.500	17.500	1.100	21259	744.081	19410.052
10	1.6818	0	0	92.500	17.500	1.100	41400	1448.999	20902.941
11	0	-1.6818	0	70.000	10.000	1.100	31330	626.594	11237.564
12	0	1.6818	0	70.000	25.000	1.100	31330	1566.486	29299.892
13	0	0	-1.6818	70.000	17.500	0.200	31330	1096.540	7950.618
14	0	0	1.6818	70.000	17.500	2.000	31330	1096.540	13739.308
15	0	0	0	70.000	17.500	1.100	31330	1096.540	17400.874
16	0	0	0	70.000	17.500	1.100	31330	1096.540	17347.656
17	0	0	0	70.000	17.500	1.100	31330	1096.540	20320.245
18	0	0	0	70.000	17.500	1.100	31330	1096.540	21211.358

Table 2: Experimental Results

#### 4. ANALYSIS OF THE EXPERIMENTAL DATA

This section details all of the practical and academic aspects involved in the analysis of the experimental data.

##### 4.1 Approximating a Tool Life Response Function

The relationship between tool life ( $L_T$ ) and the cutting parameters can be formalised as follows:

$$L_T = f(f_t, v, d) + \varepsilon \quad \dots 1$$

where  $f_t$  = feed per tooth ( $\mu\text{m}$ ),  $v$  = cutting speed (m/min),  $d$  = axial depth of cut (mm) and  $\varepsilon$  = statistical error on the measured response.

The true response  $f(f_t, v, d)$  is unknown. The term  $\varepsilon$  is included to account for effects such as measurement error and inherent sources of variation (Myers, et al. [4]). The term  $\varepsilon$  is thus treated as a statistical error that follows the standard normal distribution with a mean of zero and variance of  $\sigma^2$ . If the expected value of  $\varepsilon$  is zero, then

$$\begin{aligned} E(L_T) &= E(f(f_t, v, d)) + E(\varepsilon) \quad \dots 2 \\ &= f(f_t, v, d) \end{aligned}$$

The variables  $v$ ,  $f_t$  and  $d$  are known as the natural variables, because they are expressed in natural units of measurement (Myers, et al. [4]).

The true form of the response function must be approximated using a regression model. The second order model is most widely used for this purpose because it is highly flexible and often finds a good approximation of the true response surface (Myers, et al. [4]).

The general form of a second order model is shown below.

$$L_T = \beta_0 + \sum_{j=1}^k \beta_j x_j + \sum_{j=1}^k \beta_{jj} x_j^2 + \sum_{i < j}^k \sum_{j=2}^k \beta_{ij} x_i x_j \quad \dots 3$$

The coefficients of regression  $B$ 's are estimated using the method of least squares as it forms part of linear regression analysis. The flexibility of the second order model is demonstrated by the number of possible terms, which may or may not be included in the final model.

##### Multiple Linear Regression Analysis and the Method of Least Squares

A linear regression model can be thought of as an empirical model where some response function is related to  $k$  independent or regressor variables. Multiple linear regression analysis is a generalised case where  $k > 1$ .

The regression coefficient  $\beta_j$  in the equation above represents the expected change in the response  $L_T$  per unit change in  $x_j$ , provided that all remaining regressor variables  $x_i$ , for  $i \neq j$ , are held constant. The least squares estimate of parameters is used to estimate the regression coefficients  $\beta_j$ .

##### Model Building

Consider the general form of a second order model, seen in Equation 3. The final model can take on any finite combination of first order, second order and/or interaction terms. Strictly speaking, if there are  $K$  candidate regressor variables, then there are  $2^K - 1$  possible

regression equations. For this reason, a good approximation of the true response surface can often be found with a second order model.

One approach to variable selection, as described by Montgomery, et al. [3], is to consider all possible regressions. This requires that the analyses fit all possible regression equations. The regressions are then evaluated according to some universal criteria and the 'best' model is selected. A commonly used criterion to evaluate the fit of a model is *adjusted R<sup>2</sup>* ( $R^2_{adj}$ ). The  $R^2_{adj}$  statistic is a measure of the amount of variability in the data accounted for by the response function. In this regard, it is a measure of the quality of fit of the function to the actual data. The  $R^2_{adj}$  also guards against over-fitting by penalising a model for adding terms that are not useful.

### Selection of Regressor Variables

There are 9 candidate regressor variables for the purpose of this second order model. These include 3 first order main effects ( $v$ ,  $f_t$ ,  $d$ ), 3 second order main effects ( $v^2$ ,  $f_t^2$ ,  $d^2$ ) and 3 interaction effects ( $v*f_t$ ,  $v*d$ ,  $f_t*d$ ). In effect  $2^9 - 1 = 511$  combinations of regressor variables exist. The approach taken for the purpose of the tool life model was to evaluate all of the possible regressions using the  $R^2_{adj}$  statistic. It was therefore necessary to code a short program using Matlab™ that evaluated all possible regressions in this way. The regression model with the highest  $R^2_{adj}$  value was selected as the 'best'.

Tool life can further be defined in terms of *cutting length (mm)*, *cutting time (min)* or total *volume of material removed (mm<sup>3</sup>)*. There is some discrepancy in literature regarding the correct way to define tool life. See Mayor, et al. [2] and Prakash, et al. [5]. This disparity provides grounds for considering all three definitions. The Matlab™ program mentioned previously was used to determine the highest possible  $R^2_{adj}$  value for each definition of tool life considering all possible regression models. The results are shown in Table 3 below.

	Cutting Length (CL)	Volume of Material Removed (VMR)	Cutting Time (CT)
Maximum $R^2_{adj}$	0.3222	0.6330	0.5697

Table 3: Maximum Adjusted R Square for Different Definitions of Tool Life

It can be seen that the highest  $R^2_{adj}$  value is achieved when tool life is defined in terms of VMR.

However, the low  $R^2_{adj}$  value is cause for concern. This suggests that the initial model is not a sufficient representation of the data. A normal probability plot of the regression model is shown in Figure 1 below. The normal probability plot tests the normality assumption in linear regression analysis. That is, the assumption made that the data follow a normal distribution. If the normal probability plot follows approximately a straight line, then the data are assumed normally distributed. Visual inspection of Figure 1 shows distinct curvature in the shape of the graph, indicating a possible violation of the normality assumption. Myers, et al. [4] suggests that when this plot indicates a problem with the normality assumption a transformation of the response variable should be considered as a remedial measure.

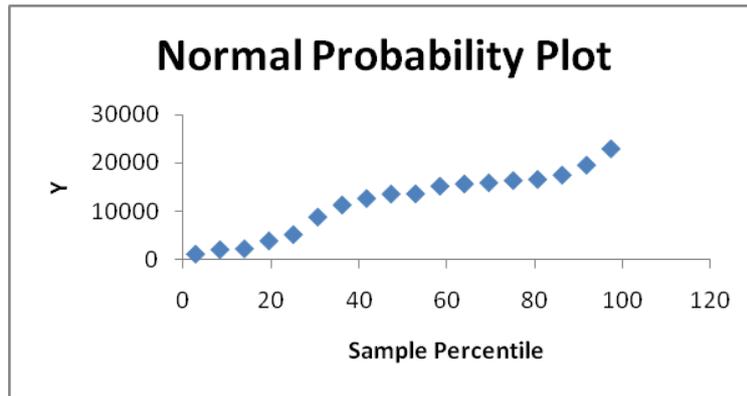


Figure 1: Normal Probability Plot for Non-Transformed Analysis

It was therefore decided to transform the response variable. The most commonly used transformation is to take the natural logarithm of the response variable. The new relationship between the input variables and response function can now be formalised as follows:

$$\ln(L_T) = f(v, f_t, d) + \varepsilon \quad \dots 4$$

or by making  $L_T$  the subject of the formula,

$$L_T = e^{f(v, f_t, d) + \varepsilon} \quad \dots 5$$

The same procedure, as that for the non-transformed analysis, was followed. The Matlab™ program mentioned previously was used to determine the highest possible  $R^2_{adj}$  value for each definition of tool life considering all possible regression models. The results are shown in Table 4 below.

	Tool Life		
	$\ln(CL)$	$\ln(VMR)$	$\ln(CT)$
Maximum $R^2_{adj}$	0.3619	0.8405	0.5697

Table 4: Maximum Adjusted R Square for Different Transformed Definitions of Tool Life

The table above indicates vastly improved results when the natural logarithm of the response variable was taken. It was reaffirming to note that the maximum  $R^2_{adj}$  value occurs when tool life was defined in terms of  $VMR$ , as was consistent with previous analysis.

The normal probability plot of the transformed data, in Figure 2, indicates an improved adherence to the normality assumption. This is indicated by the 'straightness' of the graph and validates the decision to transform the response variable.

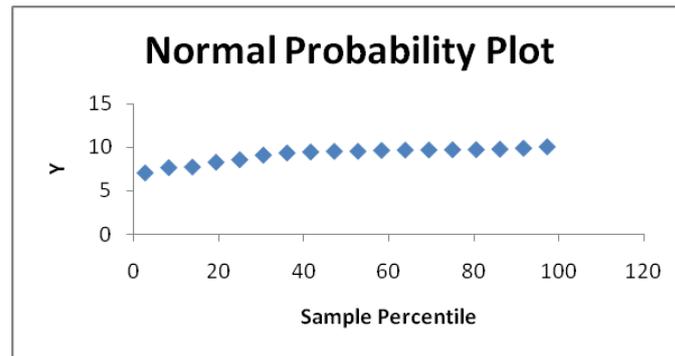


Figure 2: Normal Probability Plot for Transformed Analysis

Further transformation of either the response or input variables was ill advised. In a situation of the-simpler-the-better, further transformations would only complicate the model, making interpretations more difficult and less intuitive. It was therefore decided to accept the model as shown below.

### Regression Results

Regression analysis was done using MS Excel™. The critical regression statistics are presented in Table 5 below.

Multiple R	0.9420
$R^2$	0.8874
$R^2_{adj}$	0.8405
Standard Error - $\sigma$	0.3556
Variance - $\sigma^2$	0.1265
Observations	18

Table 5: Regression Summary Statistics

$R^2_{adj}$  indicates that 84.05% of the variation in the observed data is accounted for by the model. The variance  $\sigma^2$  is an unbiased estimator of the true variance  $\sigma^2$  of the error term  $\epsilon$ . The regression results are presented in Table 6 below.

	<i>Coefficients</i>	<i>Standard Error</i>	<i>t Stat</i>	<i>P-value</i>	<i>Lower 95%</i>	<i>Upper 95%</i>
Intercept	5.84236	0.50716	11.51969	0.00000	4.73735	6.94738
$d$	5.27527	0.77244	6.82932	0.00002	3.59226	6.95828
$v^2$	-0.00035	0.00020	-1.71682	0.11169	-0.00079	0.00009
$f_t^2$	-0.00506	0.00317	-1.59501	0.13669	-0.01197	0.00185
$d^2$	-1.72381	0.34146	-5.04830	0.00029	-2.46780	-0.97983
$v*f_t$	0.00270	0.00158	1.71410	0.11220	-0.00073	0.00614

Table 6: Regression Results

The results above show the combination of regression terms that result in the best 'fitting' model. They indicate a strong influence from the depth of cut parameter  $d$ . Further, several second order terms are indicated in the model, validating the decision to fit a second order model.

The  $t$ -Stat value is a statistic used to test whether the regression coefficients are significant to the model. For a description of the hypothesis to test for significance of the coefficients, refer to Montgomery, et al. [3].

Three out of the six regression parameters show no sufficient evidence exists to reject the null hypothesis. These parameters are  $v^2$ ,  $f_t^2$  and  $v^*f_t$ . Thus, it cannot be concluded that these parameters contribute significantly to the model.

This might be cause for concern. However, the test described here is only a partial or marginal test. This means that the value of the regression coefficients  $\beta_j$  depend on the presence and value of the other regressor variables  $x_i$  ( $i \neq j$ ). For this reason, it cannot be said that the exclusion of any of the above terms would result in a better fit. Further, the combination of regression terms used above yield the highest  $R^2_{adj}$  value out of any combination. Still further, the regression model, as a whole, passes the test for significance of regression with flying colours. An Analysis of Variance (ANOVA) is used to test for significance of regression. The results are shown in Table 7 below.

ANOVA					
	Degrees of Freedom	Sum of Squares	Mean Squares	F0	Significance F
Regression	5	11.9589	2.3918	18.9112	0.000026
Residual	12	1.5177	0.1265		
Total	17	13.4766			

Table 7: Analysis of Variance

It was thus concluded that the response variable was linearly related to at least one regression coefficient at 95% confidence. The test for significance of regression is not an absolute judgement of whether or not a model is a satisfactory representation of the data. However, combined with the statistical evidence presented previously, it is the opinion of the author that the model sufficiently represents the data observed. An interpretation of the model continues in the next section.

$$L_T = e^{5.842 + 5.275d - 0.000348v^2 - 0.00506f_t^2 - 1.742d^2 + 0.00270vf_t} \dots 6$$

### Visual Interpretation

Figure 3 below plots the tool life model in its entirety. It shows the progression of the tool life surface, plotted for *depth of cut* and *feed per tooth*, as *cutting speed* is increased from graph to graph. Tool life (on the z-axis) is in terms of *volume of material removed* ( $mm^3$ ). Some interpretations that can be made from Figure 3 are as follows:

- At low *depth of cut*, a low  $L_T$  is seen. As *depth of cut* increases from 0.2mm to 1.64mm,  $L_T$  increases. This is shown by the rising level of the response surface and is intuitive considering that  $L_T$  is defined as 'volume' of material removed. Such that,

$$L_T = CL \times d \times D$$

where  $CL$  = *length of cut* (mm) and  $D$  = *tool diameter* (mm). Therefore, a high *depth of cut* is expected to result in a correspondingly high  $L_T$ . However, as *depth of cut* increases beyond approximately 1.5mm, the model shows a counterintuitive downward trend in  $L_T$ . This phenomenon has been seen before in literature (see Sreeram, et al. [6]). This emphasises the importance of *depth of cut* in achieving optimal tool life.

- Interestingly, it seems as though the influence of *cutting speed* and *feed per tooth* increases as *depth of cut* is brought towards its optimum. This is shown by increased curvature of the response surface as *depth of cut* tends towards its optimum.

- Another consideration made apparent by Figure 3 is the importance of the combination of *cutting speed* and *feed per tooth*. It appears as though there is interaction between *cutting speed* and *feed per tooth* that results in optimal tool life. At low *cutting speeds*, a low *feed per tooth* yields the best tool life, but at a high cutting speed, a high *feed per tooth* yields the best tool life. This effect is brought about by the inclusion of the  $v \cdot f_t$  term in the regression model.

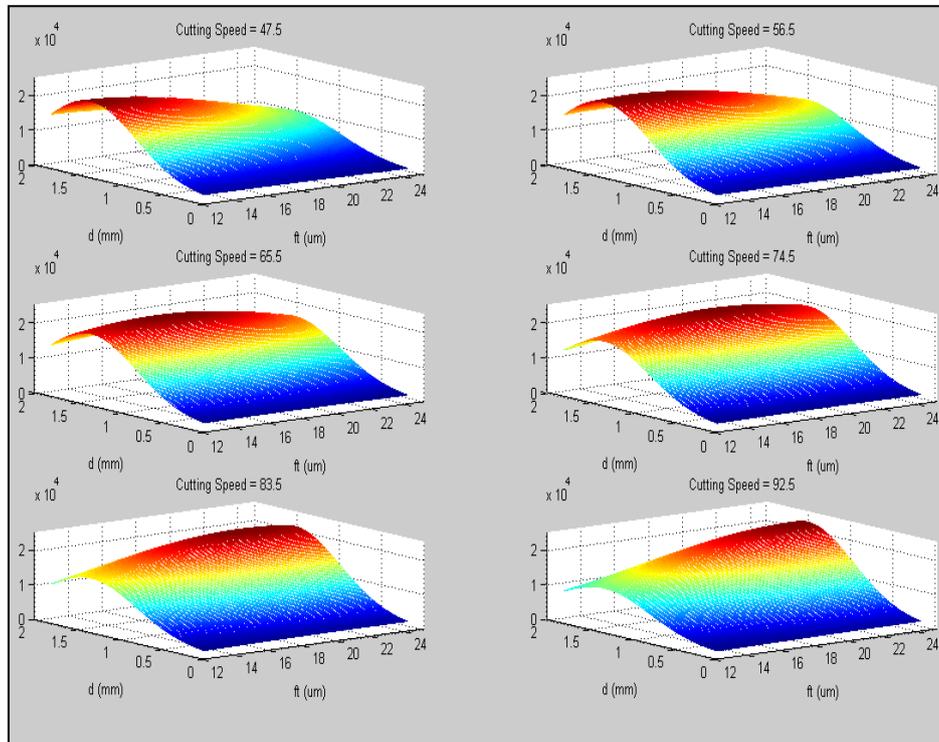


Figure 3: Visual Representation of Tool Life Model

## 5. CONCLUSION

For the purpose of this article, an empirical model was developed that characterised tool life of a micro end mill in terms of its cutting parameters, namely *cutting speed*, *feed per tooth* and *axial depth of cut*. This was done using an empirical model building approach that follows the Response Surface Methodology (RSM). Design of Experiments, multiple linear regression analysis and analysis of variance were the main statistical tools used to build this model.

The initial intention of this tool life model was to predict tool life under certain operating conditions and, in so doing, be able to predict the cost of tools. The tool life model is therefore intended to form part of a higher-level cost model. The model can further be used for the following purposes:

- The tool life can be optimised through selection of the correct machining parameters. This could allow the user to select parameters that would result in the lowest possible tooling cost or achieve an appropriate cost-benefit balance between machining speed and cost.
- The model further provides insight into the true relationship between cutting parameters and tool life, providing groundwork for future investigation into this matter.

In conclusion, some of the limitations of the model should be noted. These include, but are not limited to the following:

- The model represents the *estimated* response of tool life to cutting parameters. In other words, it does not describe the definitive relationship between the input and response variables, but rather serves to provide insight into this relationship.
- The model is bounded by the cutting parameter ranges, as determined in section 2.2. It is possible to extrapolate the response beyond these ranges, but statistical confidence is lost in doing so.
- Finally, the model is constrained to the conditions specified in section 2.1. That is, the model is valid for the material and micro end mills described. Validation outside these conditions requires additional experimentation.

## 6. REFERENCES

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