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# Prediction and Optimization of Tool Life in Micromilling AISI D2 (~62 HRC) Hardened Steel

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**Abstract**

This paper presents a study for the development the first and second order tool life models of micromilling hardened tool steel AISI D2 62 HRC. The models were developed in terms of cutting speed, feed per tooth and depth of cut, using response surface methodology. Central composite design (CCD) was employed in developing the tool life model in relation to independent variables as primary cutting parameters. All of the cutting tests were performed within specified ranges of parameters using ∅0.5 mm TiAlN microtools under dry condition. Tool life and dual-response contours of metal removal rate have been generated from these model equations. Tool life equation shows that cutting speed is the main influencing factor on the tool life, followed by feed per tooth and depth of cut. The results were presented in terms of mean values and confidence levels. The adequacy of the predictive model was verified using analysis of variance (ANOVA) at 5% significant level and found to be adequate.

## 1. Introduction

   Miniaturized parts or features of a few millimetres to micrometer in dimension are gaining ground in such field as medical, transportation, environmental, communication, microfluidic and etc. In order to manufacture these parts in an economical way, replication techniques play a major role for mass production. However, implementation of these techniques depends on the availability of tooling technologies for manufacturing the tools and moulds. Currently, Micro Electro Discharge Machining (μ-EDM) process is mainly used to manufacture the needed moulds or die for microinjection moulding, hot embossing and microforming industries. In such processes the shape of a mould or a die is replicated on the workpiece through plastic or viscoelastic deformations. However, the material removal rate of EDM process is relatively low thus results in long throughput-time and high manufacturing cost. In order to fabricate the net shape of the mould and die, several electrodes have to be made by micromilling. Thus, micromilling could represent the most powerful process in terms of versatility and obtainable shapes and features.

   Tool life is an important aspect in evaluating the performance of the cutting tool in material removal process. In addition, tool life could estimates the corresponding economic analysis in process planning and machining optimisation [1]. In macromilling, tool flank wear was chosen as criteria in assessing the tool life. However due to small diameter microtool with sharp cutting edge, fracture of cutting edge as early stage of micromilling are most dominant before flank wear occur. Moreover, it's difficult to measure the flank wear for every slot milling due to small of microtool, it need to take off from

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spindle and measured under SEM. Thus in order to reduce errors in tool deflection, time consuming in setup and warming up the spindle, thermal growth and consistent in machining process, therefore, it was decided measured width of slot as a relation to tool wear reduction. Thus 30 μm tool diameter reduction was selected as a criteria in tool life in this study. This align to another research work on micromilling X38CrMoV5-1 steel ~53 HRC using ∅0.5 mm CBN microtool with 25 μm tool diameter reduction as tool life criteria [2].

Response Surface Methodology (RSM) is a collection of mathematical and statistical techniques for determining the relationship between various factors and the responses within the desired criteria. In addition, RSM is useful for developing, improving and optimised the process which provides an overall point of view of the system response within the design space [3]. The process modelling using statistical design of experiment is proved to be an efficient modelling tool [4] and seems to be most well-known methodology for tool life prediction. The methodology not only reduce cost and time by reducing number of experiment but also gives the required information about the main and interaction effects of selected parameter study[5]. Many researchers have used RSM for their experimental design and analysis of the results in end milling [6-11], but very few of them used in micromilling [12-13] perhaps due to difficulty in measurement and facilities available. In this study, primary machining variable such as cutting speed, feed per tooth and depth of cut, which are easily controllable, are considered in building the models. This paper presents an approach to develop tool life mathematical models of micromilling AISI D2 using RSM. Tool life and dual-response contours of metal removal rate contour have been generated from these model equations. The optimum cutting conditions is obtained by constructing contours of constant tool life using design expert 6.0 software.

## 2. Experimental Design and methodology

The experiments were done on commercial 3-axis ultra high speed machining centre Matsuura LX-1 with maximum spindle torque 0.7 Nm at 4.5 kW outputs. It can accommodate to maximum spindle speed up to 60k rpm with 1 μm position accuracy. The micro tool was clamped with shrinkage fit tool holder with 20 mm tool over hang. Non contact laser tool setting measurement system by Renishaw-NC3 is used for tool length compensation with repeatability of ±0.15 μm.

The used cutting tools were 4-flute TiAlN coated ∅0.5 mm square carbide endmill, with cutting length is 1.0 mm, the helix angle is $30^0$ with 6 mm shank diameter. The cutting edge radius between 5-7 μm and was checked using Alicona-IFM. In order to avoid quality variation, these endmills were produced from same batch and SEM picture was taken before and after machining. The workpiece material is hardened tool steel D2 with 62 HRC; it's chemical composition is: 1.5% C; 11.5% Cr; 0.8% V; 0.75%Mo [11]. The dimension of the workpiece is 20 X 20 x 90 mm (W×H×L). The surfaces of the workpiece were ground and further face milling with ∅8.0mm in order to archive a good flatness and as machining datum. The entire test was inclusive the warm-up of the spindle for 30 minutes follow by tool length measurement using NC3 in order to minimise/eliminate the spindle thermal growth. All of the experiments were carried out in the dry mode. In order to avoid ramping process, the tool was positioned 20 mm outside the workpiece and then slots were milled with the full tool diameter being engaged.

In this study, an orthogonal first-order design with three factors consisting of 12 experiments has been used to develop the first order model. These 12 tests consist of 8 corner points located at the vertices of the cube and a centre point repeated four times [10]. As first order models are typically only valid/reliable over a narrow range of variables, the experimental matrix was further expended with 6 axial points at 1.68 argument length ($\alpha = (n_f)^{1/4}$: α- argument length, $n_f$ – number of experiment) for correlation of variable factor responses to second order (quadratic) models, see Figure 1. Experiments were performed in a random order with Table 1 showing the full test matrix ($L_{18}$ experimental design) of the RSM design.

The relationship between the response factor (tool life) and process independent variables can be represented by Equation 1[3];

$$T = C(V_c^{\,l}, f_t^{\,m}, d^n)\varepsilon \tag{1}$$

where T is the tool life in minutes, $V_c$, $f_t$, and $d$ are the cutting speed (m/min), feed per tooth (μm/tooth), and depth of cut (μm) respectively while C, l, m, n are constants and $\varepsilon$ is a random error. Equation 1 can also be expressed in the following logarithmic form, see Equation 2;

$$In\ T = In\ C + l\ In\ V_c + m\ In\ f_t + n\ In\ d + In\ \varepsilon \tag{2}$$

A first-order linear model based on of Equation 2 can then be represented as shown in Equation 3;

$$\hat{y}_1 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 \tag{3}$$

where, $\hat{y}_1$ is the estimated response based on the first-order equation and $y$ is the measured tool life on a logarithmic scale; $x_0 = 1$, is a dummy variable; $x_1$, $x_2$, $x_3$ are logarithmic transformations of cutting speed, feed per tooth and depth of cut respectively, while $b_0$, $b_1$, $b_2$, $b_3$ are the parameters to be estimated.

The transformation equations for each of the independent variables are defined in Equations 4 to 6:

$$x_1 = \frac{\ln V_c - \ln 35}{\ln 50 - \ln 35} \qquad (4)$$

$$x_2 = \frac{\ln f_t - \ln 1.5}{\ln 2.0 - \ln 1.5} \qquad (5)$$

$$x_3 = \frac{\ln d - \ln 35}{\ln 50 - \ln 35} \qquad (6)$$

Following the formulation of the first order model, second order relationship can then be derived according to Equation 7;

$$\hat{y}_2 = y - \varepsilon = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_3 x_3 + b_{11} x_1^2 + b_{22} x_2^2 + b_{33} x_3^2 + b_{12} x_1 x_2 + b_{13} x_1 x_3 + b_{23} x_2 x_3 \qquad (7)$$

where, $\hat{y}_2$ is the estimated response based on the second order models. In the second order response equation, the influence of single factors, quadratic terms and their interaction effects are all considered, and therefore are generally expected to provide more accurate predictions. A 'lack of fit' test for the estimated coefficients was carried out using ANOVA to verify the models and model predictions were tested at the 5% significance level.
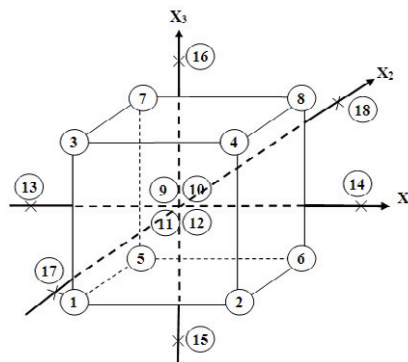


Fig. 1: Central composite design for three factors

Table 1: Design matrix RSM

| Test No. | Location in CCD | Independent parameters | | | Coded | | | Responses | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | $V_c$ (m/min) | $f_t$ (μm/tooth) | d (μm) | $X_1$ | $X_2$ | $X_3$ | Tool Life T (min) | Material Removed MR (mm$^3$) | Rate of Removal MR/T (mm$^3$/min) |
| 1 | Factorial | 20.00 | 1.00 | 15.00 | -1.00 | -1.00 | -1.00 | 4.71 | 1.8 | 0.38 |
| 2 | Factorial | 50.00 | 1.00 | 15.00 | 1.00 | -1.00 | -1.00 | 1.42 | 1.4 | 0.95 |
| 3 | Factorial | 20.00 | 2.00 | 15.00 | -1.00 | 1.00 | -1.00 | 2.77 | 2.1 | 0.76 |
| 4 | Factorial | 50.00 | 2.00 | 15.00 | 1.00 | 1.00 | -1.00 | 1.10 | 2.1 | 1.91 |
| 5 | Factorial | 20.00 | 1.00 | 55.00 | -1.00 | -1.00 | 1.00 | 3.14 | 4.4 | 1.40 |
| 6 | Factorial | 50.00 | 1.00 | 55.00 | 1.00 | -1.00 | 1.00 | 0.95 | 3.3 | 3.47 |
| 7 | Factorial | 20.00 | 2.00 | 55.00 | -1.00 | 1.00 | 1.00 | 1.19 | 3.4 | 2.86 |
| 8 | Factorial | 50.00 | 2.00 | 55.00 | 1.00 | 1.00 | 1.00 | 0.55 | 3.9 | 7.00 |
| 9 | Centre | 32.00 | 1.42 | 29.00 | 0.00 | 0.00 | 0.00 | 1.90 | 3.1 | 1.63 |
| 10 | Centre | 32.00 | 1.42 | 29.00 | 0.00 | 0.00 | 0.00 | 1.70 | 2.9 | 1.71 |
| 11 | Centre | 32.00 | 1.42 | 29.00 | 0.00 | 0.00 | 0.00 | 1.70 | 2.9 | 1.71 |
| 12 | Centre | 32.00 | 1.42 | 29.00 | 0.00 | 0.00 | 0.00 | 1.90 | 3.1 | 1.65 |
| 13 | Axial | 14.77 | 1.42 | 29.00 | -1.68 | 0.00 | 0.00 | 2.64 | 2.0 | 0.76 |
| 14 | Axial | 68.30 | 1.42 | 29.00 | 1.68 | 0.00 | 0.00 | 0.68 | 2.6 | 3.85 |
| 15 | Axial | 32.00 | 0.78 | 29.00 | 0.00 | -1.68 | 0.00 | 2.16 | 2.0 | 0.93 |
| 16 | Axial | 32.00 | 2.50 | 29.00 | 0.00 | 1.68 | 0.00 | 0.92 | 2.6 | 2.84 |
| 17 | Axial | 32.00 | 1.42 | 10.00 | 0.00 | 0.00 | -1.68 | 3.12 | 1.7 | 0.54 |
| 18 | Axial | 32.00 | 1.42 | 85.00 | 0.00 | 0.00 | 1.68 | 1.56 | 7.3 | 4.68 |

## 3. Results and discussion

Figure 2 shows progression of diameter tool reduction versus cutting time under test cessation where 30 μm diameter tool reduction was chosen as a criterion for tool life. In general tool life ranged from 0.5 to 4.7 minutes, with Test 1 ($V_c$=20m/min, $f_t$=1μm/tooth, $d$=15μm) showing the longest tool life (4.7 minutes) and correspondingly Test 8 ($V_c$=50m/min, $f_t$=2μm/tooth, $d$=55μm) giving the shortest (0.5 minutes). Understandably, the highest operating parameters led to the shortest tool life (Test 8) due to the greater tool wear, albeit with the highest material removal rate. In contrast, Test 18 which employed the 'preferred' combination of cutting parameters ($V_c$=35m/min, $f_t$=1.5μm/tooth, $d$=68.6μm), achieved the highest volume of material removed (7.3mm$^3$). A comparison between tool life (mins), material removed (mm$^3$) and material removal rate (mm$^3$/min) following the extended central composite design (CCD) testing is shown in Figure 3.

Figure 4 shows the response surface plot presented in logarithmic tool life response as function of cutting speed and feed per tooth at 35μm depth of cut. It is clearly shown, tool life decreases as the cutting speed and feed per tooth increases. Higher cutting speed imposes higher cutting force over cutting edges and higher stress especially as intermittence cutting process thus suddenly chipping the cutting edges, which ultimately reduce the microtool diameter thus shorten the tool life. Furthermore high mechanical impact caused by increasing feed per tooth also results in decreasing tool life.
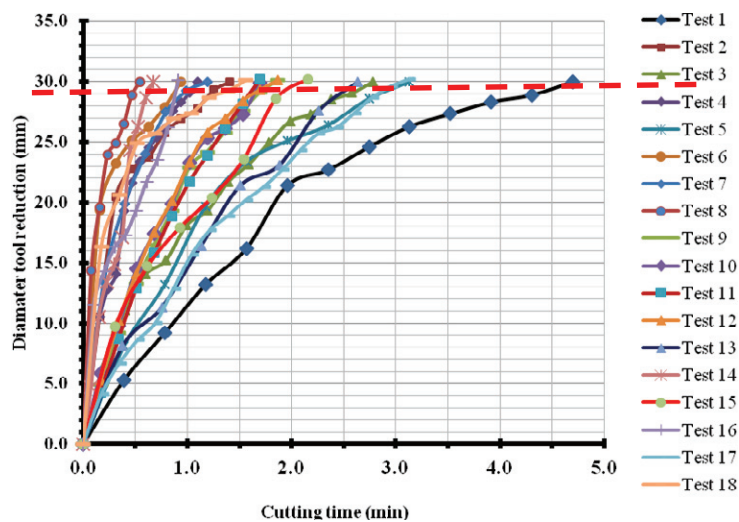
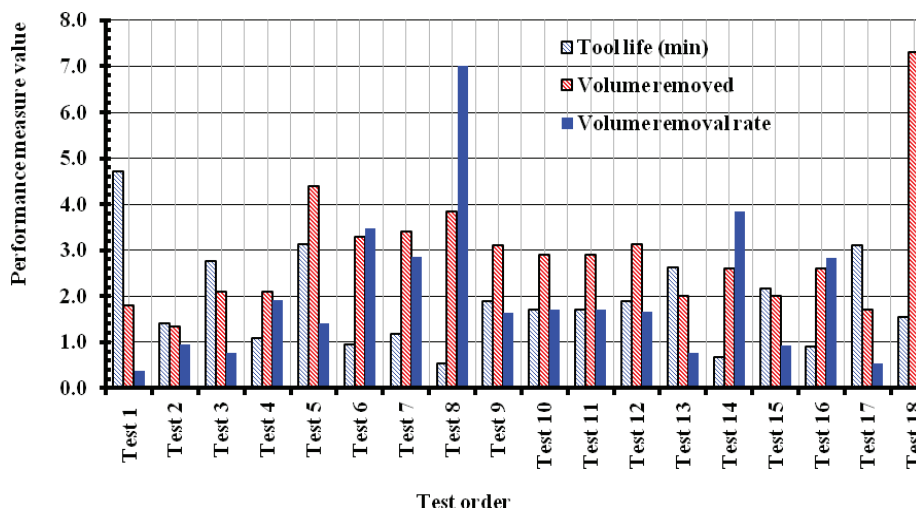Fig. 2: Diameter tool reduction versus cutting time

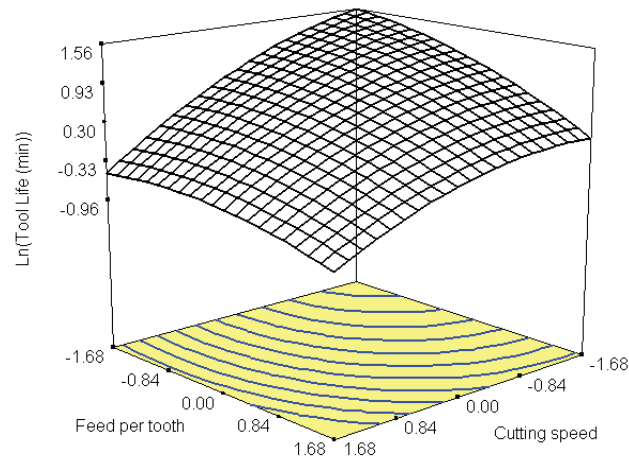Fig. 3: Tool life, volume removed and volume removal rate at test citation

Fig. 4: Logarithm tool life as function of cutting speed and feed per tooth at 35 μm depth of cut

Table 2 shows ANOVA results for tool life based on the linear model ($L_{12}$ array – 12 tests) with estimated effects of each parameter, along with their interactions and standard error. It can be seen that cutting speed, feed per tooth, depth of cut and the interactions between cutting speed × feed per tooth, as well as feed per tooth × depth of cut were significant factors in terms of tool life. Among the variable factors, cutting speed had the largest influence with a contribution of 58%, while feed per tooth and depth of cut showed similar levels at 18% and 20% respectively. The two statistically significant interactions each had very low percentage contributions of 2%.

Table 2: ANOVA results for tool life of linear model (based on $L_{12}$)

| Factor | Sum of Squares | DF | Mean of Squares | F Value | Prob > F | PCR |
|---|---|---|---|---|---|---|
| Cutting speed (A) | 2.0457 | 1 | 2.0457 | 1773.6961 | < 0.0001* | 58% |
| Feed per tooth (B) | 0.6376 | 1 | 0.6376 | 552.8538 | < 0.0001* | 18% |
| Depth of cut (C) | 0.7140 | 1 | 0.7140 | 619.0330 | < 0.0001* | 20% |
| AB | 0.0691 | 1 | 0.0691 | 59.9396 | 0.0015* | 2% |
| AC | 0.0015 | 1 | 0.0015 | 1.3308 | 0.3129 | |
| BC | 0.0751 | 1 | 0.0751 | 65.1091 | 0.0013* | 2% |
| Curvature | 0.0232 | 1 | 0.0232 | 20.0868 | 0.0110* | Significant |
| Residual | 0.0046 | 4 | 0.0012 | | | |
| Lack of Fit | 0.0013 | 1 | 0.0013 | 1.2362 | 0.3473 | Not significant |
| Pure error | 0.0033 | 3 | 0.0011 | | | |
| Total | 3.5476 | 11 | | *Significant at 5% level | | |
| Std. Dev | 0.0034 | | R-Squared | | 0.9987 | |
| Mean | 0.5 | | Adjusted R-Squared | | 0.9967 | |
| C.V | 6.83 | | Predicted R-Squared | | 0.9742 | |

From the regression analysis, the predicted first-order tool life model based on the first 12 experiments in a coded form is given as;

$$\hat{y} = 0.460 - 0.511x_1 - 0.288x_2 - 0.293x_3 \tag{8}$$

with $x_1$, $x_2$ and $x_3$ representing the associated transformation equations for cutting speed, feed rate and depth of cut Respectively.

A mathematical relationship for tool life, T (min) as a function of the cutting speed, $V_c$, (m/min), feed per tooth, $f_t$, (μm tooth$^{-1}$) and depth of cut, $d$, (μm) can be further formulated by substituting Equations 4 - 6 into Equation 8. The model can therefore be expressed as;

$$Ln\ T = 6.241 - 1.145\ ln\ V_c - 0.807\ ln f_t - 0.458\ ln\ d \tag{9}$$

and by applying inverse logarithms,

$$T = 513.6 \, V_c^{-1.145} \, f_t^{-0.807} \, d^{-0.458} \tag{10}$$

It can be seen from Equation 10 that tool life is inversely proportional to cutting speed, feed per tooth and depth of cut. The equation is valid when micromilling hardened AISI D2 (62HRC) cold work tool steel under dry cutting conditions within the range of experimental conditions assessed; cutting speed ($20 \leq V_c \leq 50$ m/min), feed per tooth ($1.0 \leq f_t \leq 2.0$ µm/tooth), and depth of cut ($15 \leq d \leq 55$ µm).

A second-order relationship was considered to improve the correlation and hence accuracy of the predicted tool life with respect to the independent variables investigated. The model was developed utilising the CCD array ($L_{18}$) and the coefficients of the quadratic model were derived using the least squares method. Following the regression analysis, the second-order tool life equation in coded form can be expressed as;

$$\hat{y} = 0.5866 - 0.4660x_1 - 0.2737x_2 - 0.2571x_3 - 0.1062x_1^2 - 0.0875x_2^2 + 0.0708x_3^2 + 0.0874x_1x_2 + 0.0194x_1x_3 - 0.0913x_2x_3 \tag{11}$$

Here, the sign of the coefficients indicates the positive or negative influence of the respective input variables on tool life. However the identification of the specific effect/importance of individual input variables is complicated by their interaction ($x_1x_2, x_1x_3, x_2x_3$) and quadratic terms ($x_1^2, x_2^2, x_3^2$). Therefore, only significant terms (at the 5% level) were considered in developing the second order tool life model.

A graphical comparison of predicted tool lives using the various analytical models (linear, analytical and quadratic) versus the experimental results is shown in Figure 5. It was found that the predicted tool life values (calculated using Design Expert simulation) obtained with the first order linear model showed closed agreement to experimental data with percentage errors ranging between ±3%. Conversely, tool life predicted by the mathematical/analytical model detailed in Equation 10, highlighted relatively large deviations of between -21% and 20%. This was likely due to the fact that only the main variable parameters (cutting speed, feed rate & depth of cut) were considered, with interactions between factors neglected. Predictions using the second order quadratic model were shown to be similar to first order relationship with percentage errors within ±4% of the respective experimental values.
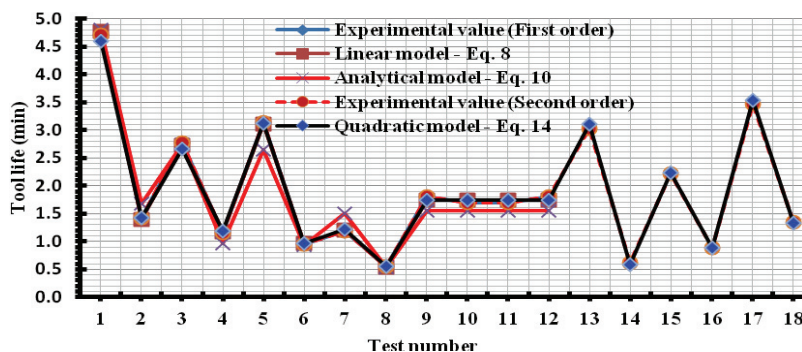


Fig. 5: Comparison between experiment and prediction model for tool life

### 3.1 Utilisation of the first order tool life model

A range of variables levels (cutting speed and feed per tooth) were substituted into Equation 8 with the axial depth of cut kept constant at 35µm to produce a contour plot for tool life, see Figure 6. The response surface shows the possible combinations of cutting speed and feed per tooth to achieve a specific tool life level. In a production environment, productivity is also a key concern, which generally entails higher operating parameters, but at the expense of tool life or part quality. Thus, further investigation on productivity was therefore carried out by considering the relationship between cutting parameters and material removal rates. The material removal rate, Q (mm³ min⁻¹) is given by Equation 12:

$$Q = f_t \times n \times N_s \times a_a \times a_r \tag{12}$$

where *ft* is the feed per tooth (mm/tooth), *n* is the number of cutter flutes, $N_s$ is the rotational speed of the microtool (rpm), $a_a$ is the axial depth of cut (mm) and $a_r$ is the diameter of the microtool (mm). By taking logarithms of each term, Equation 12 can be rewritten as;

$$ln\ Q = ln\ f_t + ln\ n + ln\ N_s + ln\ a_a + ln\ a_r \tag{13}$$

For the specified axial depth of cut of 35µm in a slot milling operation using a 4 flute, ⌀0.5mm end mill, and by employing the transformation functions in Equation 4 and Equation 5, thus, Equation 13 becomes;

$$ln\ Q = 0.5019 + 0.447x_1 + 0.357x_2 \tag{14}$$

For a given rate of material removal, Equation 13 can be represented by a straight lines which can then be superimposed onto the cutting speed – feed per tooth response surface plot shown in Figure 6. This can then be used to maximise tool life for a required/desired material metal removal rate (MRR). An example is detailed in Figure 6 where the operating parameters at both point A and B, produce equivalent MRR is 1.5 mm³/min, but with the latter giving a 22.2% higher tool life.
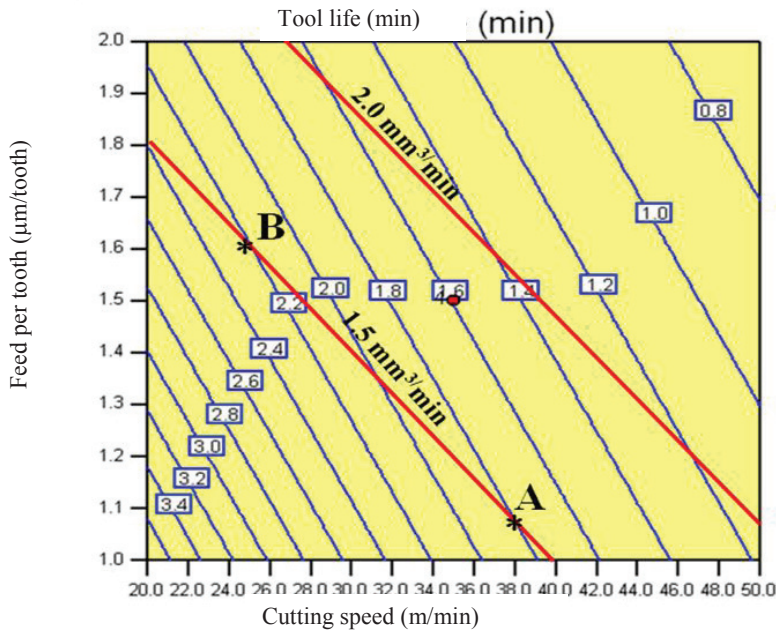


Fig. 6: First order tool life contours (35µm doc) and material removal rates

### 3.2 Utilisation of the second order tool life model

As with the first order relationship, Equation 14 comprising significant terms was plotted in the form of response surfaces for tool life at a depth of cut of 35µm as shown in Figure 7. By overlaying specific MRR values calculated using Equation 11 onto Figure 7, the best combination of operating parameters can be selected which optimises productivity without decreasing the tool life. As an example, the 3 points (A, B and C) highlighted in Figure 7 are all predicted to provide a tool life of 1 minute but with A giving a lower MRR of 1.5mm³/min. While the parameters at both points B and C gave equivalent MRR's (2.0mm³/min), the latter was preferred due to the superior surface finish obtained as a result of the lower feed rate.
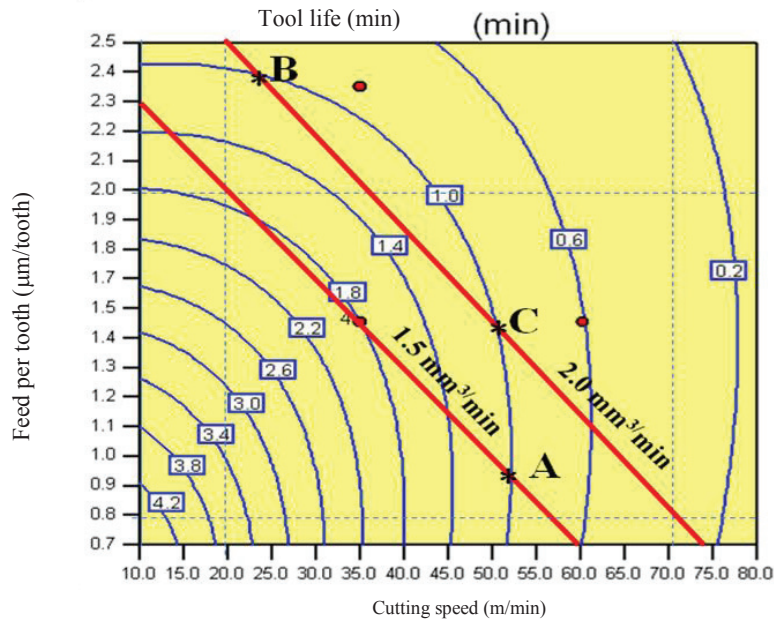
Fig. 7: Second order tool life contours and material removal rates

### 3.3 Checking the adequacy of the linear model

From the ANOVA results in Table 2, the regression analysis of the linear model was found to be significant, as both the predicted 'R-Squared' and adjusted 'R-Squared' values were comparable (0.9987 and 0.9967 respectively). This indicates that the model/prediction fits well with the experimental data, with only a 0.01% probability that the results observed were due to noise. Curvature however was highlighted as being significant and hence additional tests were required (6 axial points) to account for the non-linearity present in the model. These were subsequently performed with the results used to develop a second order predictive model for tool life.

### 3.4 Checking the adequacy of the quadratic model

Summary statistics of the various R-Squared measures (R-Squared, Adjusted R-Squared and Predicted R-Squared) from the different possible tool life models which can be generated from the $L_{18}$ design/array (performed using Design Expert), are shown in Table 3. This was used to identify the best model for use in future analysis/predictions. A cubic relationship was initially considered in the assessment however aliasing (confounding) between the factors/interactions was found to be significant and was thus disregarded. The results showed that the quadratic model was preferred based on the larger R-Squared value (0.9985) obtained, which suggests that 99.85% of the total variations are explained by the model. The Adjusted R-Squared is a modified R-Squared value which considers the size of the model as a result of the number of variables/terms considered (always smaller or equal to R-Squared). Correspondingly, the value of the Adjusted R-Squared (0.9968) indicates that 99.68% of the total variability is accounted for by the model after considering the significant factors. Similarly, the Predicted R-Squared value of 0.9916 (which is in close agreement with the Adjusted R-Squared term) implies that 99.16% of any variability when introducing new/future data would be covered in the model. Here, a value of 0.8 or higher is generally considered to be of an acceptable level.

Table 4 shows the ANOVA calculations for tool life based on the 'recommended' quadratic model, but which only takes into account statistically significant factors and interactions. It was found that all variable factors and interactions considered were found to be significant at the 5% level, except for the interaction between cutting speed and depth of cut (AC). This was therefore removed from the calculations which resulted in a marginally higher Predicted R-Squared value compared to that detailed in Table 4 (0.99266 vs. 0.99166)

Table 3: Summary statistics of the tool life models (based on $L_{18}$ array)

| Model | Std. Dev. | R-Squared | Adjusted R-Squared | Predicted R-Squared | Remarks |
|---|---|---|---|---|---|
| Linear | 0.17943 | 0.92481 | 0.9087 | 0.86279 | |
| Interaction | 0.1665 | 0.94913 | 0.92138 | 0.90133 | |
| Quadratic | 0.03317 | 0.99853 | 0.99688 | 0.99166 | Recommended |

Table 4: ANOVA results for tool life of quadratic model ($L_{18}$)

| Factor | Sum of Squares | DF | Mean of Squares | F Value | Prob > F | PCR |
|---|---|---|---|---|---|---|
| Cutting speed (A) | 3.32744 | 1 | 3.32744 | 2897.31 | < 0.0001* | 56% |
| Feed per tooth (B) | 1.055 | 1 | 1.055 | 918.618 | < 0.0001* | 18% |
| Depth of cut (C) | 1.16131 | 1 | 1.16131 | 1011.19 | < 0.0001* | 19% |
| $A^2$ | 0.10171 | 1 | 0.10171 | 88.5658 | < 0.0001* | 2% |
| $B^2$ | 0.07672 | 1 | 0.07672 | 66.804 | < 0.0001* | 1% |
| $C^2$ | 0.0716 | 1 | 0.0716 | 62.3464 | < 0.0001* | 1% |
| AB | 0.06913 | 1 | 0.06913 | 60.1945 | < 0.0001* | 1% |
| BC | 0.07509 | 1 | 0.07509 | 65.386 | < 0.0001* | 1% |
| Residual | 0.01034 | 9 | 0.00115 | | | |
| Lack of Fit | 0.00707 | 6 | 0.00118 | 1.08186 | 0.5159 | Not significant |
| Pure error | 0.00327 | 3 | 0.00109 | | | |
| Total | 5.99446 | 17 | | | | *Significant at 5% level |
| Std. Dev | 0.03389 | | R-Squared | | 0.99828 | |
| Mean | 0.48929 | | Adjusted R-Squared | | 0.99674 | |
| C.V | 6.92615 | | Predicted R-Squared | | 0.99266 | |

## 5. Conclusions

This paper presents the findings of an experimental investigation of the effect of cutting speed, feed per tooth and depth of cut on tool life and material removal in micromilling of AISI D2 steel using TiAlN coated tool. Adequacy of the models has been evaluated by ANOVA which indicates significant at 95%. The following conclusion can be drawn from this study:

1. Response surface methodology combined with the factorial design is useful techniques for tool life testing. Sequential approach in central composite design with ANOVA analysis is beneficial as it can determine whether the curvature exist for the second order design. It shows a small number of designed experiments are required to generate much useful information that is used to develop the predicting tool life equation.

2. Tool life equation shows that cutting speed is the main influencing factor on the tool life, followed by feed per tooth and depth of cut. The cutting speed, feed per tooth and depth of cut are significant in both the first and second order models. An increase in cutting speed, feed per tooth and depth of cut were decrease the tool life.

3. The response surface plot is good tool to estimate the region of maximum tool life.

4. By utilising the second order model, it is possible to extend the variable range based on the axial length of the design ($\alpha$). The predicting second order equation is valid within the speed range of $14.77 – 68.3$ m min$^{-1}$, the feed per tooth range of $0.78 – 2.5$ mm tooth$^{-1}$ and axial depth of cut range of $10.0 – 82.0$ μm.

5. Second order model gives more effectives prediction of the response with interaction of all factors.

6. Contours of the tool life outputs were constructed in planes containing cutting speed – feed per tooth as independent variables. These contours were further developed to select the proper combination of cutting speed and feed per tooth in order to determine maximum possible tool life at specific metal removal rates.

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