

Retraction

Retracted: Modelling of Metal Removal Rate in Copper Alloy Milling Using MATLAB

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] M. M. Abdul Zahra, E. Yanmaz, and T. Bothichandar, "Modelling of Metal Removal Rate in Copper Alloy Milling Using MATLAB," *International Journal of Antennas and Propagation*, vol. 2022, Article ID 4550902, 6 pages, 2022.

Research Article

Modelling of Metal Removal Rate in Copper Alloy Milling Using MATLAB

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The copper found in Earth's soil ranks fourth in abundance among structural metals. Copper alloys are composed of copper and other elements. Most commonly, these alloys are used in aerospace, medical, and energy applications, but they are also used in many other areas. The amount of the stabilizing agents and the temperature determine which phase copper alloys exist in, including α , $\alpha + \beta$, and β . The temperature in the cutting zone is one of the most important factors to control when machining copper alloys. Copper alloys have low thermal conductivity and high heat capacity, meaning that they have low heat conduction from the cutting zone, which leads to the built-up heat in the cutting edge. As the workpiece and cutting tool moves at different speeds, the temperature is strongly affected by the cutting speed. The physical and chemical properties of tool wear progression have been used in several studies and research projects to model tool life and metal removal as a result of this fact. The focus of this article is on establishing a model connecting cutting parameters and measured responses in terms of tool life, using the design of experiments and metamodelling to establish a model that can be used to predict tool life from milling experiments. In order to secure reliable machining operations, these models were designed for customer recommendation and cutting data optimization. The study focused on copper alloys 6Al-4V, the most common being $\alpha + \beta$ alloy. In conclusion, the two models developed in this study are able to predict the tool life based on the cutting speed and radial width of cuts. As long as certain parameters are met, the models will ensure the highest possible metal removal rate.

1. Introduction

As one of the fourth most abundant metals on Earth [1], copper is used for a variety of different industrial sectors and applications, including medical, energy, automotive, sports, and more, but is primarily used in the aerospace industry. New technologies and materials are developed to reduce fuel costs within the aerospace sector. Besides the increased air traffic, another driving force behind the increase in emissions is the new more stringent standards that have been set for the environment. In order for the goals to be achieved, the aircraft's total weight should be less and the engines should be more efficient. In addition, these new designs require a more complex use of materials, such as improving

the energy efficiency of engines and developing new stronger and lighter materials, such as different copper alloys. Copper alloys are some of the most versatile engineering materials available. The combination of physical properties such as strength, conductivity, corrosion resistance, machinability, and ductility make copper suitable for a wide range of applications. There are many important properties that copper alloys can meet, such as requiring minimal maintenance, sustaining high temperatures, possessing low thermal conductivity, being tough, and possessing good corrosion resistance [2]. In order for high-value components to be successfully machined, a structured process may be required [3]. A copper-alloy can be classified into four different categories or more accurately into four different

phase conditions: alpha (α), near alpha, alpha + beta ($\alpha + \beta$), and β -titanium. Machinability of milling is primarily determined by the phase condition of the alloy, with β -Ti having higher machinability demands than α -Ti. The cutting speed, v_c , is a crucial parameter for machining, and especially milling, in Ti. The cutting speed can be described as the relative speed between the cutting edge of the tool and the workpiece material [4]. A critical factor of the v_c is that Ti-alloys has a low thermal conductivity and high heat capacity, which contributes to high temperatures in the cutting zone. In addition to changing the value for v_c , other parameters such as axial depth of cut, a_p , radial width of cut, a_e , and feed rate per tooth, f_z , can equally affect heat generation. Ti-6AL-4V (or Ti 6-4) is also known as titanium-6 aluminum 4 vanadium (or titanium 6-4) due to its chemical composition of almost 90% titanium, 6% aluminum, 4% vanadium, 0.25% iron (maximum), and 0.2% oxygen (maximum). The material is resistant to corrosion, strong, has low modulus of elasticity, is good to weld, and is heat treatable. In this research, the aim is to increase the milling efficiency of copper alloys by maximizing material removal rates and tool life. We will also evaluate the impact of the combination of cutter radial engagement and cutting speed on tool wear as well as how to predict tool wear.

2. Materials and Methods

2.1. Maximum Chip Thickness. When a milling cutter is used for side milling, referred to as shoulder milling, the a_e for the tool is directly affecting the h_{ex} . For shoulder milling tools, with an approach angle, κ , of 90° , and the radial engagement angle, α , in the interval 90° to 180° , h_{ex} and f_z relates simply as $h_{ex} = f_z$. However, for $\alpha < 90^\circ$, the relation between h_{ex} and f_z , can be calculated as

$$f_z = \frac{h_{ex}}{\sin(\alpha)} \left[\frac{\text{mm}}{\text{tooth}} \right]. \quad (1)$$

It clearly shows that h_{ex} is getting thinner when a_e is decreasing. The engagement angle can then be expressed as a relation between the diameter of the cutting tool, d_c , and a_e , by the following equation:

$$\cos(\alpha) = \frac{(0.5d_c - a_e)}{0.5d_c}, \quad (2)$$

and combining (1) and (2) holds

$$f_z = \frac{h_{ex}}{\sin[\arccos(d_c - 2a_e/d_c)]} \left(\frac{\text{mm}}{\text{tooth}} \right). \quad (3)$$

With (3), it can be noted that $h_{ex} \neq f_z$ when a_e is less than 50% of d_c [5].

2.2. Metal Removal Rate, Q . The metal removal rate for milling operations can be calculated by the equation for Q [6]

$$Q = \frac{a_p a_e v_f}{1000} \left(\frac{\text{cm}^3}{\text{min}} \right), \quad (4)$$

where a_e and a_p is in millimeter and the table feed

$$v = n f_z z = \frac{1000 v_c f_z z}{\pi d_c} \left(\frac{\text{mm}}{\text{min}} \right). \quad (5)$$

The z -term is the number of active cutting edges for the milling cutter.

2.3. Metamodeling. A metamodel is a data model for metadata, which describes the core metadata objects, along with their relationships and associated business rules. It is usually hard to describe the physical properties of a system using metamodels also known as surrogate models [5]. A metamodel consists of three steps, including selecting a sampling method and gathering the data. The next step is to select a model or models that will represent the data. A response value is predicted by the model. The tool life for different settings of v_c and a_e was used for this study as the response value. The data were then fitted to the model by fitting the models to the inputs. The least-squares method was used here. A metamodel in general functions as follows: input data are transferred through a transfer function that contains properties that predict the output well (Figure 1).

2.4. Multiple Linear Regression. The first metamodel is established using multiple linear regression. In simple linear regression one independent variable (IV), X , together with a constant β and an error term, ϵ , gives the response value, in terms of a dependent variable (DV), T [4],

$$T = X\beta + \epsilon. \quad (6)$$

This method employs a regression line, the best fit to a table of sample data. The least-squares criterion is used for calculating a regression line based on one variable. In this step, the distance between each sample of test data and the predicted line is squared. The line is in its optimal alignment when the sum of the squared distances is as small as possible.

Least square analysis is not restricted to being used for the one-variable situation, and it can be used with several variables and is referred to as multiple linear regression (MLR) [7]. Multiple linear regression (MLR), also known simply as multiple regression, is a statistical technique that uses several explanatory variables to predict the outcome of a response variable. Multiple regression is an extension of linear (OLS) regression that uses just one explanatory variable. In MLR, two or more IVs are used to predict a DV. The IVs need to be selected in a way so that problems with multicollinearity can be avoided. Therefore, it is important that the IVs do not correlate with each other. The MLR equation is

$$\bar{T} = X\bar{\beta} + \bar{\epsilon}. \quad (7)$$

In matrix form,

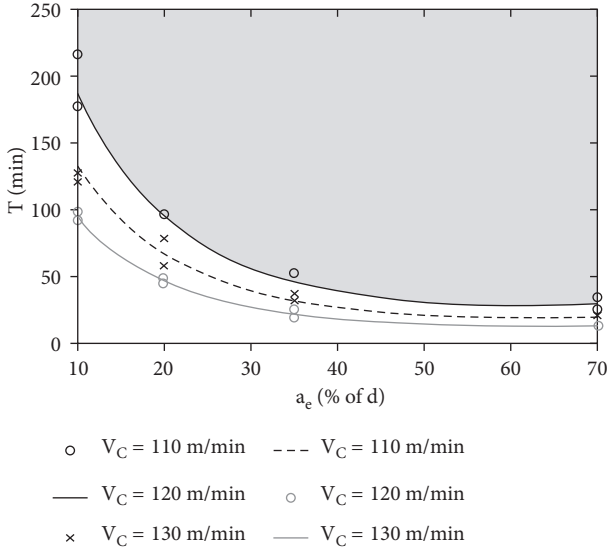


FIGURE 1: Predicted curves from the MLR model function.

$$\begin{bmatrix} T_1 \\ T_2 \\ \vdots \\ T_n \end{bmatrix} = \begin{bmatrix} 1 & x_1 & \cdots & x_{1,k} \\ 1 & x_2 & \ddots & \vdots \\ 1 & \vdots & \vdots & \vdots \\ 1 & x_{n,1} & x_{n,2} & x_{n,k} \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{bmatrix}. \quad (8)$$

The coefficients, β , estimates using the equation

$$\bar{\beta} = (X^T X)^{-1} X^T \bar{T}, \quad (9)$$

where X^T is the transpose of matrix X and $()^{-1}$ is the inverse of the expression. In some cases, when the input data have an exponential pattern, the β -coefficients assume a better fit when the input data are logarithmized. This changes the pattern of the input data from exponential to linear [8].

$$\bar{\beta} = (X^T X)^{-1} X^T \log(\bar{T}). \quad (10)$$

The error function can be established as the summarized squared error between measured data, subscript m , and predicted, subscript $pred$:

$$\varepsilon = \sum_{n=1}^N (T_m - T_{pred})^2. \quad (11)$$

The goodness of fit for a model is given by the coefficient of determination R^2 and is the distance between each measured data, subscript m , and predicted, subscript $pred$:

$$R^2 = 1 - \frac{\sum_{n=1}^N (T_m - T_{pred})^2}{\sum_{n=1}^N (T_m - \bar{T}_m)^2}. \quad (12)$$

Curve fitting approach:

$$\sum_{n=1}^N (T_i - T(\mu_1(\mu_2), \bar{a}))^2 \quad (13)$$

2.5. Modelling. A numerical calculations software called MATLAB was used to handle all data handling and analysis. This software has been designed especially for data analysis, data visualization, numerical computation, and the development of mathematical models and algorithms [9]. This programming platform was specifically designed for engineers and scientists to design, analyze, and build systems and products that will change our world for the better. The MATLAB language is at the heart of MATLAB. This matrix-based language allows the most natural expression of computational mathematics. The fact that MATLAB can transform, invert, and multiply vectors and matrices makes it a good tool for regression modelling. There are also several optimization algorithms and toolboxes available in MATLAB for curve-fitting. A search algorithm with *fm* optimization was used to minimize the error function. In the *fm* search algorithm, a constant is changed to determine the smallest error function value, by varying one or more constants, a . Logarithmizing the input data and calculating (10) were the steps required for calculating the values of for multiple linear regression. Using (11), the error function is used for both the multiple linear regression and curve fitting models, where N is given as 24 corresponding to the number of milling tests. (12) calculated the goodness of fit, R^2 , of the models based on their accuracy in predicting future events. The plots were combined with measure data in terms of tool life from the milling experiment. These plots were combined with milling experiment data that measured tool life [10].

2.6. Maximizing the Metal Removal Rate, Q . The tool life of a given tool could now be calculated and predicted by two models, depending on v_c and a_e . This method can also be used to satisfy the purpose of this thesis, to maximize the material removal rate by constraining the optimization to maximize Q , by taking into account the desired tool life as a constraint, to find an a_e and vc that maximize Q . MLR provides an excellent example of this. In order to accomplish this, one of the input parameters of the model, a_e or vc , was chosen, in this case a_e . The range of a_e could be calculated by selecting a tool life, T , and establishing a range of vc , ranging from the minimum to the maximum of the defined input model boundaries [11]. The manufacturer of the component must determine whether the tool life is acceptable in terms of, for example, production rate. To exemplify this step, T was chosen for 50 minutes and vc to a range of 100–120 m/min in step 1.

$$Q = \frac{a_p a_e v_c h_{ex} z}{\pi d_c \sin(\cos^{-1}(d_c - 2a_e/d_c))} \left(\frac{\text{cm}^3}{\text{min}} \right). \quad (14)$$

Inserting the fixed cutting tool and process parameters, used in the experiment, $d_c = 12$ mm, $a_p = 1.5$ mm, $h_{ex} = 0.05$ mm/tooth, and $z = 1$, the corresponding values of a_e and Q were calculated.

3. Results and Discussion

3.1. Curve Fitted Approach Model. The model function for tool life prediction ended up to

TABLE 1: Results for the curve fitted model function.

Test no.	v_c (m/min)	a_c (% of d)	T_m (min)	T_{pred} (min)	Error (min)
1	100	10	189.1	194.5	
2	100	10	174	169.3	
3	100	20	93.4	91.5	
4	100	20	68.5	63.5	
5	100	35	48.3	56.4	
6	100	70	38.7	42.3	
7	100	70	46.3	53.4	
8	100	10	84.5	79.5	
9	110	10	118	112.4	
10	110	20	106	119.3	
11	110	35	99.8	109.1	
12	110	35	100.2	112.3	
13	110	40	101.3	111.5	
14	110	40	81.3	74.6	
15	110	70	95.4	84.3	
16	110	70	76.4	84.6	
17	120	10	74.6	79.2	
18	120	20	19.5	23.2	
19	120	35	17.9	19.5	
20	120	70	13.2	17.3	
21	120	35	13.6	16.8	
22	120	40	13.8	18.2	
23	120	70	12.4	15.3	
24	120	35	12.9	14.23	

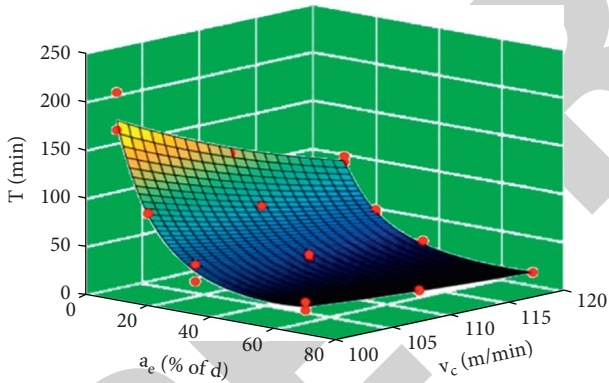


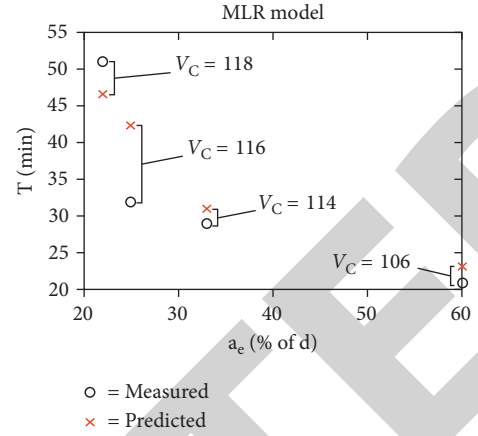
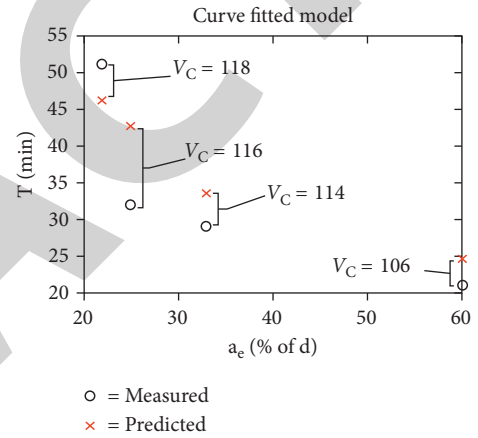
FIGURE 2: Surface plot corresponding to the MLR model function.

$$T_{pred} = a_1 \cdot \frac{v_{c,nom}}{v_c} \cdot a_e \left(\frac{v_{c,nom}}{v_c} - a_2 \right) [\text{min}], \quad (15)$$

where $v_{c,nom}$ has been selected to 110 m/min and the optimized constant terms a_1 and a_2 have been established as $a_1 = 1666$ and $a_2 = 1,9542$.

Summarized and squared error by (11).

$\varepsilon = 2450$ (min). R -squared, calculated by equation (12), is

FIGURE 3: Scatter plots of T_{pred} in the MLR model.FIGURE 4: Scatter plots of the T_{pred} curve fitted model.

$$R - \text{squared} = 0.978. \quad (16)$$

Table 1 presents the results, T_{pred} , for the curve fitted model function in combination with the measured data, T_m , from the milling experiment. To the right, the error value is shown. The results from Table 1 are further presented as a graph in Figure 2. Black circles for $v_c = 110$ m/min, black crosses for $v_c = 120$ m/min, and gray circles for $v_c = 130$ m/min and then curves for each level of v_c in the same color theme that present the predicted tool life, T_{pred} . The corresponding surface, Figure 3, that the curve fitted model function predicts, for a combination of v_c and a_e , within the range of the milling experiment. Red points correspond to the measured tool life for test nos. 1–24.

3.2. Maximizing the Metal Removal Rate, Q . Regression model, (17), solved for a_e , is

$$a_e = \left(\frac{-1}{2\beta_5} \right) \sqrt{4\beta_5 \log(T) - 4\beta_0\beta_5 - 4\beta_1\beta_5 v_c + (\beta_3^2 - 4\beta_4\beta_5) v_c^2 + \beta_2 + \beta_3 v_c}. \quad (17)$$

TABLE 2: Result for the value v_c and a_c .

v_c (m/min)	a_c (% of d)	Q (cm ³ /min)
100	32.18	0.84
101	31.19	0.83
102	31.12	0.82
102	30.56	0.81
104	29.51	0.80
105	28.64	0.79
106	28.71	0.78
107	27.12	0.78
108	26.36	0.77
109	25.25	0.77
110	25.46	0.76
111	25.22	0.75
112	24.32	0.75
113	23.91	0.74
114	22.34	0.74
115	22.61	0.73
116	21.81	0.72
117	20.42	0.70
118	20.56	0.69
119	19.23	0.69
120	19.04	0.68

TABLE 3: Comparison of the response error values in terms of tool life.

Test no.	v_c (m/min)	a_c (% of d)	MLR model error (min)	Curve fitted model error (min)
1	100	10	2.9	32.2
2	100	10	5.2	6.9
3	100	20	3.2	4.5
4	100	20	5.6	6.3
5	100	35	8.9	5.3
6	100	70	2.3	7.4
7	100	70	3.4	9.6
8	100	10	5.7	3.6
9	110	10	6.8	5.2
10	110	20	1.5	7.8
11	110	35	2.6	7.2
12	110	35	2.8	7.4
13	110	40	3.7	7.1
14	110	40	9.2	6.8
15	110	70	8.1	5.3
16	110	70	7.6	7.2
17	120	10	7.1	8.2
18	120	20	8.1	7.5
19	120	35	6.3	7.6
20	120	70	7.4	8.6
21	120	35	5.6	7.2
22	120	40	8.4	7.5
23	120	70	7.4	6.7
24	120	35	5.6	5.3

The curve fitted model function is shown in Table 1. Given the fixed cutting tool and process parameters that have been used in this work, $d_c = 12$ mm, $a_p = 1.5$ mm, $h_{ex} = 0.05$ mm/tooth, and $z = 1$, the corresponding values of a_e and Q have been calculated and tabled in Table 1 for the predefined tool life of 50 minutes [12].

3.3. Validation of the Models. Both prediction models are built from statistical data carried out from the milling experiment, which means that they are only valid for these data and in combination with the used machine tool, the milling cutter, and the corresponding carbide inserts. During the experiment, only two runs were possible for each cut data combination due to the

available machine time. Based on those two runs, statistical prediction is poor. The input data consist of all 24 measured values and not the mean values for the two runs. The reason is that some values will amplify other values, and on the other hand, some values will reduce other values [13]. This increases the validity of the models. Figure 4 shows a comparison between both the prediction models and the measured data from the control tests. These control tests have only been tested in one run and may therefore be seen as a rough estimation. For both the prediction models, they seem to have a larger mismatch for the combination $a_e = 25\%$ of d_c , $vc = 115$ m/min. This is probably more connected to a poor tool life for that specific control test. To prove this, one more test run should have been carried out for that specific point, which has not been performed. The red crosses are predicted values, and the black circles are the measured data. To evaluate which model predicts the tool life most accurately, based on the measured data in this work, a comparison between the error values has been tabled in Table 2. When summarizing the prediction errors from each model to $\epsilon_{MLR} = 131.7$ min and $\epsilon_{curve_fit} = 166.4$ min, it clearly shows that the response values from the regression model are more accurate than the measured data. When looking at the error terms from the control tests, Table 3, we can obtain a larger error for test no. 26 that are described at the beginning of this section. In Table 2, the errors for $a_e = 20$ and 35 percent of d_c for the vc levels 110–120 m/min, show a generally lower error than 10.3–10.6 min, as for control test no. 26. This points that the measured tool life for control is a protruding value and is most likely a poor tool life for that specific test. It can be a consequence of variance intolerances for the cutting insert, the workpiece material inherent structure etcetera, but may be said to be in the varying window of tool life. The choice of running only one time for the control test may be a poor decision for the experimental planning process in the project.

4. Conclusion

The most important thing that this work brings forward is two mathematical models for cutting data prediction that can be seen as a platform for further development. These models hopefully help users, such as manufacturing technicians or salespeople from tooling companies, to maximize milling operations in the direction the manufacturing company wants. The direction could be in order to change the cycle time for a machining operation so that the cycle time better fits other components that shall pass the machine as well. For example, if a specific operation with a milling cutter is given 30 minutes to machine, the producing company wants to use the chosen milling cutter with its full potential so that the highest possible MRR can be kept. Material removal rate (MRR) is the amount of material removed per time unit (usually per minute) when performing machining operations such as using a lathe or milling machine. The more material removed per minute, the higher the material removal rate. A company can produce and sell more components, which will result in a higher profit. The tricky part in this equation is to select the cutting data to achieve the highest possible MRR to the desired tool life, as in this example which is set to 30 minutes. The models will, in this example, calculate the optimal vc and a_e for the milling cutter to fit the desired T or machining time. The

study has carried out two models, where one has been exemplified. The models have been developed and validated for a milling cutter, and the model can be optimized. The models take into account an increase of vc and/or a_e , shortening T , which was proved in the study. All the results carried out from the milling experiment in this study need to be considered as specific to the used setup in this work.

Data Availability

The data used to support the findings of this study are included in the article.

Disclosure

This work was performed as a part of the employment of institutions.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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