ABSTRACT

The paper presents a model for predicting tool life when end milling IS2062 steel using P30 uncoated carbide tipped tool under various cutting conditions. Based on Taguchi's method, three factors (spindle speed, feed and depth of cut) - three level orthogonal experiments are employed. A tool life model is developed from regression model obtained by using results of the experiments conducted. A second model is developed based on artificial neural network (ANN) for predicting tool life. The results obtained from ANN are compared with regression model. And the results of the ANN model are found to be closer to experimental values.

Keywords: Tool life, Wear, Milling machine, Taguchi’s method, Regression model, Artificial neural network

1. INTRODUCTION

In a machining process, the prediction of tool life is of crucial importance, and the factors that affect tool life can be divided in three categories: the machine tool, the machining parameters and the workpiece material [1-4]. The parameters with a higher effect on tool life contain the cutting speed, the feed rate, the depth of cut and the cutting fluid. Tool life prediction is has a great influence on productivity in industrial activities. High material removal rate is intended to reduce the manufacturing cost and operation time, while the productivity in terms of machining cost and operation time for an expected workpiece quality strongly depends on tool wear, and consequently is determined by tool life [5]. The maximum utilisation of cutting tool is one of the ways for an industry to reduce its manufacturing cost[6]. In order to maximise gains from a machining process an accurate process model must be constructed for an end milling process with speed, feed and depth of cut as input variables and tool life as the output variable.

Taguchi technique is a scientific approach of conducting experiments to generate, analyse and interpret data so that valid conclusions can be drawn efficiently. Here, experiments are conducted to measure tool life based on Taguchi approach for three level three factors. The experimental values are used in statistical package Minitab 15 to form the regression model to predict the tool life. The accuracy of the model is tested using the analysis of variance technique (ANOVA). The regression model values are compared with ANN model values.

2. LITERATURE SURVEY

In the literature, tool wear and tool life modelling has been extensively studied. Oraby and Hayhurst [7] developed models for wear and tool life using non linear regression analysis techniques in terms of the variation of a ratio of force components acting at the tool tip. Richetti et al. [8] investigated the effect of the number of tools used in face milling operations and related it to the establishment of tool life under specified cutting conditions. Choudhury et al. [9] predicted response variables like flank wear, surface finish and cutting zone temperature in turning operations using design of experiments and the neural network technique, and the values obtained from both methods were compared with the experimental values to determine the accuracy of the prediction.

Yongjin et al. [10] developed a tool wear index (TWI) and tool life model for analysing wear surface areas and material loss from the tool using micro-optics and image processing/analysis algorithms. Huang et al. [11] applied a multiple regression model in detecting the tool breakage based on the resultant cutting forces in end milling operations. Srinivas and et al. [12] developed a neural network model to predict tool wear and cutting force in turning operations from cutting parameters like cutting speed, feed and depth of cut.

Chattopadhyay et al. [13] used feed forward back propagation artificial neural network for evaluation of wear in turning operations using carbide inserts with speed, feed and depth of cut as input parameters. Thomas et al. [14] investigated the effect of cutting parameters on tool stiffness and damping, and obtained an empirical model for predicting the tool stiffness variation.

Prediction of tool life is of a great importance in metal cutting in order to maximize the utilization of the tool and minimize the machining cost. The main goal of this work is to study the influence of cutting conditions such as cutting speed, feed and depth of cut on tool life in the end milling process for a certain process configuration. In this work, it is carried out experiments on mild steel using uncoated tungsten carbide insert, and the experimental work is performed according to Taguchi’s approach. A regression model and an artificial neural network (ANN) model are developed to predict tool life, and predicted values are compared with experimental values to determine the prediction accuracy.

3. TOOL LIFE DETERMINATION

Tool life can be defined as the total value of cutting time that a tool can be used until its excessive wear or catastrophic failure. The cutting tool should have as long life as possible. Conditions giving a very short tool life will be uneconomical because tool grinding and tool replacement cost will be excessively high. There are different ways of expressing tool life such as (i) volume of metal removed (ii) number of work pieces machined and (iii) time units [18]. ISO standard 3685 [19] dictates that the end of useful life is determined when a tool ceases to produce the desired part size and surface quality. In this work, allowable limit of flank wear is taken as the criteria for estimating tool life.

3.1 Tool Life Model

In this paper, Taguchi’s approach and regression method are applied to develop a mathematical model to predict the tool life for end milling of IS2062 steel. The relationship between the independent variables of process parameters (spindle speed $v$, feed $f$ and depth of cut $d$) and tool life $TL$ can be represented by the following mathematical model:

$$TL = C v^l f^m d^n$$

where $C$ is a model constant and $l$, $m$ and $n$ are exponents for process parameters [16], with spindle speed expressed in rpm, feed in mm/min, depth of cut in mm and tool life in min.

The above function can be represented in linear form as follows:

$$\ln TL = \ln C + l \ln v + m \ln f + n \ln d$$

and Equation (2) can be rewritten as:

$$TL = \beta_0 + \beta_1 v + \beta_2 f + \beta_3 d$$

where $TL$ is the model response, $v$, $f$ and $d$ are the process parameters and $\beta_0$, $\beta_1$, $\beta_2$ and $\beta_3$ represent the regression coefficients to be determined.

3.2 Development of regression model

In this study, a multiple regression model is developed to predict the tool life based on experimentally measured values. The coefficients for the regression model are determined using Minitab.

3.3 Taguchi’s Approach

Taguchi’s approach is applied as a systematic procedure for designing, conducting and analysing experiments which are of a great significance in quality planning. The steps to be followed according to this methodology are [20]:

1. Selection of factors for the study
2. Selection of the number of levels for the factors
3. Selection of the appropriate orthogonal array
4. Assignment of factors to columns
5. Conduct of the test
6. Analysis of the results

3.4 Selection of Factors

Desired tool life may be achieved by properly selecting the independent process variables or factors with special influence on the surface quality. Specifications of the vertical milling machine (Bharat Fritz Warner Ltd), the cutting tool and the work piece used for the experiment are given in Table 1. In this work, spindle speed, feed and depth of cut are selected as factors to carry out the experimental work and the subsequent development of a mathematical model.

| Table 1 |
| Specifications of Vertical Milling Machine, Cutting Tool and Work Piece |
| Parameter | Value |
| Power of spindle motor | 4 HP |
| Speed range of spindle motor | 45-2000 rpm |
| Power of feed motor | 0.75 HP |
| Feed range (X and Y axis) | 16- 800 mm/min |
| Cutting tool material | Uncoated tungsten carbide insert (P30 grade triangular shape) |
| Number of inserts | 5 |
| Diameter of insert holder | 80 mm |
| Work piece material | IS2062 steel |
| Hardness of work piece | 25 HRC |
| Size of work piece | 50 × 200 × 550 mm |
3.5 Selection of Levels for Process Variables
In order to develop the tool life prediction model, three factors and three levels for each of them are selected. The selected process parameters for the experiment with their limits, units and notations are given in Table 2.

<table>
<thead>
<tr>
<th>Process variable</th>
<th>Units</th>
<th>Notation</th>
<th>Limits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spindle speed</td>
<td>rpm</td>
<td>v</td>
<td>250 500 1000</td>
</tr>
<tr>
<td>Feed</td>
<td>mm/min</td>
<td>f</td>
<td>50 80 125</td>
</tr>
<tr>
<td>Depth of cut</td>
<td>mm</td>
<td>d</td>
<td>0.1 0.15 0.2</td>
</tr>
</tbody>
</table>

3.6 Selection of Orthogonal Array
The standard L18 orthogonal array [20] is shown in Table 3. From this standard table, the first three columns of factors are selected for obtaining all combinations of three process parameters. The selected columns in coded form and actual form are presented in a design matrix in Table 4. The experiments are conducted for all the possible combinations of the parameter levels. These combinations are written in the form of a design matrix where the rows correspond to different trials and the columns to the levels of the input parameters.
3.7 Experiments for the Measurement of Tool Life

Machining experiments are conducted in a vertical milling machine with IS2062 steel as work piece material using an uncoated tungsten carbide tipped tool (P30 grade). The work piece of $50 \times 200 \times 550$ mm is placed with its longitudinal axis aligned with the direction of feed. The tests are carried out along the edge of 550 mm. The spectro analysis report of work piece material used is given in Table 5. Five inserts mounted on the tool holder are used in machining of work piece in dry condition. Each experiment is started with a new cutting edge in the inserts. The maximum flank wear of the cutting tool for this use is about 0.7mm [12]. In this work, a flank wear of cutting tool upto 0.6 mm is considered as the limit. The cutting time is noted for different values of flank wear of 0.2, 0.4 and 0.6 mm. Flank wear is measured using an ARCS video measuring machine. Each experiment is continued until the flank wear limit (0.6mm) is reached. The tool life is obtained by summing up the cutting times for the three stages of flank wear. The tool life values (response) are presented in Table 6.

<table>
<thead>
<tr>
<th>Material</th>
<th>Composition (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fe</td>
<td>97.94</td>
</tr>
<tr>
<td>C</td>
<td>0.128</td>
</tr>
<tr>
<td>Si</td>
<td>0.223</td>
</tr>
<tr>
<td>Mn</td>
<td>1.27</td>
</tr>
<tr>
<td>P</td>
<td>0.05</td>
</tr>
<tr>
<td>S</td>
<td>0.011</td>
</tr>
<tr>
<td>Cr</td>
<td>0.202</td>
</tr>
<tr>
<td>Mo</td>
<td>0.0272</td>
</tr>
<tr>
<td>Ni</td>
<td>0.0454</td>
</tr>
<tr>
<td>Al</td>
<td>0.0503</td>
</tr>
<tr>
<td>Cu</td>
<td>0.0467</td>
</tr>
<tr>
<td>Ti</td>
<td>0.0092</td>
</tr>
<tr>
<td>V</td>
<td>0.0001</td>
</tr>
<tr>
<td>W</td>
<td>0.0009</td>
</tr>
</tbody>
</table>

3.8 Coefficients of Regression Model

The process model describes the relationship among the independent variables of the process and the dependent variables that result. The relationships between these independent and dependent variables are to be determined by developing a regression based mathematical model. The regression model is obtained using the experimental data. A first order polynomial expression is used to form the mathematical model. The first order model for these selected factors is given in Equation (3). Minitab is employed to determine the regression coefficients for developing the mathematical model.
model. The value of the regression coefficients represent the quantitative influence of the different independent variables. The less significant coefficients can be eliminated along with the responses associated to them, without affecting the accuracy of the model. For this purpose, it is used the Student’s t-test. After finding the significant coefficients obtained using Minitab, the final model is deduced using only the significant coefficients. The regression model for tool life that results from the coefficients determined by the statistical package is given in Equation (4).

\[ \ln TL = 11.7 - 0.924 \ln v - 0.490 \ln f + 0.068 \ln d \]  
(4)

The above model can be finally reduced to:

\[ TL = 118824.2 v^{-0.924} f^{-0.490} d^{0.068} \]  
(5)

This model indicates that spindle speed would have a significant effect on tool life, followed by feed.

3.9 Accuracy of Regression Model

The accuracy of the model is tested using analysis of variance (ANOVA). According the principles of this technique, (i) the higher the value of \( R^2 \), the more successful is the simple linear regression model at the desired level of confidence (95%), (ii) adjusted \( R^2 < R^2 \), (iii) \( p \) values for the model must be lower to \( p \) values at the desired level of confidence (95%) and (iv) variance should be minimal [21]. Table 7 shows that the model is satisfactory in terms of the value of \( R^2 \). The results of the experimental values obtained by Minitab are depicted in Figure 1.

**Table 7**

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Coefficient</th>
<th>SE coefficient</th>
<th>t</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>11.6854</td>
<td>0.3466</td>
<td>33.72</td>
<td>0.000</td>
</tr>
<tr>
<td>Speed</td>
<td>-0.92367</td>
<td>0.03508</td>
<td>-26.33</td>
<td>0.000</td>
</tr>
<tr>
<td>Feed</td>
<td>-0.48979</td>
<td>0.05308</td>
<td>-9.23</td>
<td>0.000</td>
</tr>
<tr>
<td>Depth of cut</td>
<td>0.06795</td>
<td>0.06983</td>
<td>0.97</td>
<td>0.347</td>
</tr>
<tr>
<td>Variance</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

\( \text{Variance} \quad S = 0.0842432 \quad \text{R}^2 = 98.2\% \quad \text{Adjusted R}^2 = 97.9\% \)

**Analysis of variance (ANOVA)**

<table>
<thead>
<tr>
<th>source</th>
<th>DF</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regression</td>
<td>3</td>
<td>5.5299</td>
<td>1.8433</td>
<td>259.73</td>
<td>0.000</td>
</tr>
<tr>
<td>Residual error</td>
<td>14</td>
<td>0.0994</td>
<td>0.0071</td>
<td></td>
<td></td>
</tr>
<tr>
<td>total</td>
<td>17</td>
<td>5.6293</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 1: Results of ANOVA Technique
4. NEURAL NETWORK MODEL

The neural network technique is applied to obtain a model that simulates the behaviour of human brain neurons. It corresponds to a parallel processing structure, which can be divided into several processing procedures trained simultaneously. The neural network model is constructed from a set of data consisting of input and output variables. In the training process, the structure of the model is self-adjusted to the data, and the final model can be employed for prediction. Currently, neural network technique is being widely extended in industry, for applications such as machine condition monitoring, robotics, manufacturing processes and design [22]. The neural network can be categorized into unsupervised and supervised types. The supervised type is selected to build the model now, and it can precisely deduce the target values during the training process with accurate predictions.

4.1 Structure of Neural Network Model

In a standard structure, neurons are grouped into different layers including input, hidden and output layers. Feed forward three layered back propagation neural network is shown in Figure 2. The ANN configuration is represented as 3:5:1 (i.e., input layer = three inputs, hidden layer = five neurons and output layer = one output). The number of neurons in input layer consists of spindle speed, feed and depth of cut, which are used to assess the tool life in end milling process. There is no rigid rule for determining the number of neurons in the hidden layer [6]. Five hidden layers are chosen as an optimum number. A unique output node is taken in order to represent the tool life.

4.2 Training of Neural Network Model

MATLAB is employed for training the network model for tool life prediction. The network is trained with 70% of the measured data, 15% of the data is applied for testing and the other 15% for validation. Table 8 shows the parameter settings of the neural network model. The predicted values of ANN model are given in Table 9. The predicted values of tool life by both models (i.e. regression and ANN model) are compared with the experimental values for the validation of experiments. The comparison for validation in terms of % error is depicted in Figure 3. It is found that the predictive ANN model is capable to give a better prediction of tool life than the regression model.

Table 8
Parameter Settings for Neural Network

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Setting</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of input nodes</td>
<td>3</td>
</tr>
<tr>
<td>Number of hidden nodes</td>
<td>5</td>
</tr>
<tr>
<td>Number of output nodes</td>
<td>1</td>
</tr>
<tr>
<td>Type of learning method</td>
<td>Supervised learning</td>
</tr>
<tr>
<td>Algorithm</td>
<td>Back propagation</td>
</tr>
<tr>
<td>Learning rule</td>
<td>Gradient decent rule</td>
</tr>
<tr>
<td>Number of learning patterns</td>
<td>20</td>
</tr>
<tr>
<td>Learning parameter</td>
<td>0.5</td>
</tr>
<tr>
<td>Number of epochs</td>
<td>1000</td>
</tr>
</tbody>
</table>

Table 9
Predicted Values and % Error

<table>
<thead>
<tr>
<th>Trial no.</th>
<th>Speed (rpm)</th>
<th>Feed (mm/min)</th>
<th>Depth of cut (mm)</th>
<th>Response (measured value) (tool life) (min)</th>
<th>Predicted values (Using regression (min))</th>
<th>Predicted values (Using ANN (min))</th>
<th>% error (Using regression)</th>
<th>% error (Using ANN)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>250</td>
<td>50</td>
<td>0.1</td>
<td>80</td>
<td>93.9834</td>
<td>60.8653</td>
<td>-17.4792</td>
<td>23.9184</td>
</tr>
<tr>
<td>2</td>
<td>250</td>
<td>80</td>
<td>0.15</td>
<td>74</td>
<td>76.4918</td>
<td>74.1352</td>
<td>-3.3673</td>
<td>-0.1827</td>
</tr>
<tr>
<td>3</td>
<td>250</td>
<td>125</td>
<td>0.2</td>
<td>62</td>
<td>62.3853</td>
<td>61.1324</td>
<td>-0.6214</td>
<td>1.3993</td>
</tr>
<tr>
<td>4</td>
<td>500</td>
<td>50</td>
<td>0.1</td>
<td>51</td>
<td>47.1221</td>
<td>51.3880</td>
<td>7.6038</td>
<td>-0.7607</td>
</tr>
<tr>
<td>5</td>
<td>500</td>
<td>80</td>
<td>0.15</td>
<td>43</td>
<td>38.5120</td>
<td>43.0984</td>
<td>10.4374</td>
<td>-0.2288</td>
</tr>
<tr>
<td>6</td>
<td>500</td>
<td>125</td>
<td>0.2</td>
<td>33</td>
<td>31.4096</td>
<td>33.1056</td>
<td>4.8194</td>
<td>-0.3201</td>
</tr>
</tbody>
</table>
5. CONCLUSION

The paper highlights the use of Taguchi’s approach for conducting experiments. Two models (by regression and artificial neural network) for predicting tool life in end milling are presented. The experimental values are used to develop the regression model and feed forward back propagation artificial neural network model. The actual tool life values are compared with predicted values obtained from the regression model and artificial neural network model. The ANN model is proved to provide a good prediction of tool life. The results of the ANN model also evidences that it is much more accurate than regression model to predict the values of tool life.

REFERENCES


