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CNC Cutting Tools` Life Prediction Using Data Mining Approach

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Abstract: The failure of CNC machine tools has always been a negative impact on the manufacturing environment. The consequences of the failure will influence the production control, which further increases the duration of unplanned maintenance. To avoid such situations, it is required to predict the tools' behaviours based on the raw data collected from machines. Hence, the objective of this paper is to obtain the machine tool life using the machining parameters including cutting speed, feed rate, and depth of cut which may affect the tool life in the prediction. All the data is collected by using different types of machine tools material against different types of workpieces. In this paper, classification is chosen to be the data mining approach with two algorithms to build the model for prediction, which are linear regression and multilayer perceptron. The data collected was being split into training and testing data. There are 40% of the data used for training data to build the predictive models while 60% of the data collected is used as testing data. The result of predicted tool life is then validated with the Taylor's Extended Tool Life equation according to the ISO standard 3685 and ISO 8688-2. The results show that our proposed method is on par with the tool life predicted by Taylor's method.

Keywords: CNC' Tool life; Linear regression; Multilayer perceptron; Taylor's equation

Introduction

Computer Numerical Control (CNC) machine is an automated control machine develop to perform different operations such as drilling, milling, and 3D printing in manufacturing fields. This system is able to reduce interaction between humans and machines by automation system and resulted in cost reduction and produce high quality of products with less machining time (Borkar et al., 2014). One of the CNC machines used in the manufacturing plant including a three-axis drilling or milling machine, which is control by an automatically programmed tools processor. The CNC machine is designed to ensure user safety, and rapid manufacturing by utilizing some of the programming sets of commands in computerized controls.

During the machining process, the effectiveness of the machine is always depending on the tools used. By using well-condition machine tools, it is able to increase the quality and accuracy of the machining operation while reducing the time taken to complete the work. The tools' behaviour and lifetime are always the determination by researchers by using a monitoring system. According to Lee (1986), (Roget, 1988) Roget (1988), and Dan & Mathew (1990) had monitored the review and monitoring of tools' condition based on the cutting force applied, acoustic emission, and vibration of tools during operating of the machining process. Hence, the determination of the lifetime of the CNC machine tool is important to ensure the machining process is ongoing continuously by replacing the worn tool at its tool life. In the past, there are numerous methods have been proposed to estimate the machine's tool life including tool wear index (Kwon & Fischer, 2003), Artificial Neural Network (ANN) (Palanisamy et al., 2008), and Physics guided neural network (Wang et al., 2020). However, the prediction accuracy generated by these methods is not convincing and further analysis is required to obtain a more precise result.

In this paper, the data extracted from the CNC machine is pre-processed and transformed into numerical data in order to predict the tool's life. There are two models proposed in predicting the tool's life including linear regression and multilayer perceptron. The predicted model is then validated by comparing it with the existing method, which is Taylor's extended tool life equation.

Methodology

The flowchart of the research is illustrated in Figure 1.

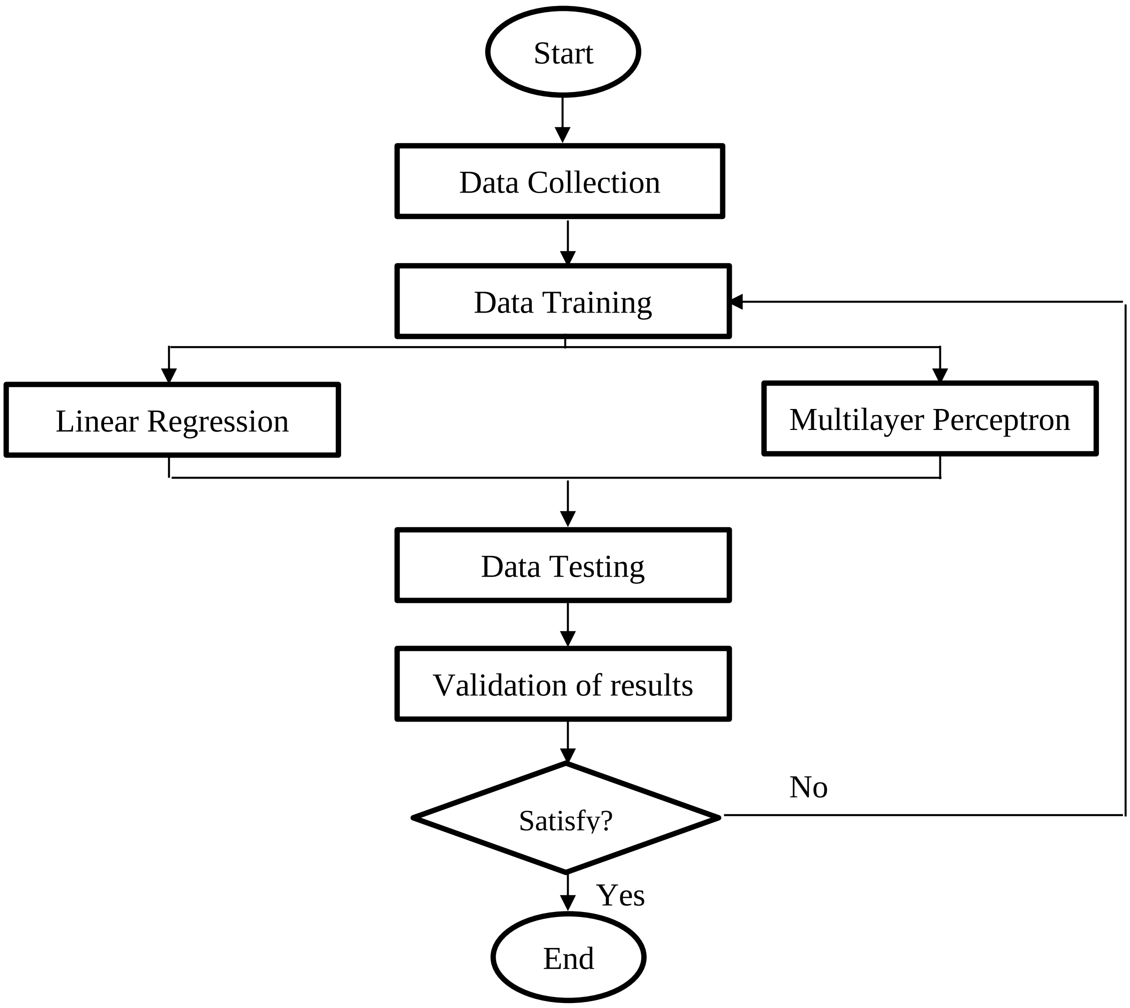

Figure 1. Research flowchart

The first stage to initiate the research is by collecting the raw data from the online database (Kumbhar & Waghmare, 2013; Lajis et al., 2008; Rao et al., 2014; Shah & Gawande, 2020; Srinivas et al., 2015; Yang & Tarng, 1998). Table 1 shows the sample of the CNC turning data obtained from Rao et al. (2014). This raw data are often contained lots of missing values due to manual data entry mistakes, equipment errors, and incorrect measurements (Luengo et al., 2012). To build the prediction model, the data is then split into 67% of training and 33% of testing categories. The data is trained using the classification approach in WEKA software, where two functional algorithms namely linear regression and multilayer perceptron are used. Once the model is built from the training data, the prediction is conducted on the testing data.

Table 1. Sample of CNC turning data (Rao et al., 2014)

No.	Cutting speed (rev/min)	Feed rate (mm/rev)	Depth of cut (mm)	Tool life (min)
1	1000	0.13	0.25	79.33
2	1000	0.13	0.3	72.85
3	1000	0.13	0.35	68
4	1000	0.13	0.4	66.2
5	1000	0.13	0.45	60.66
6	1000	0.13	0.5	57.96
7	1000	0.13	0.55	55.5
8	1000	0.13	0.6	53.67
9	1000	0.13	0.65	51.44
10	1000	0.13	0.7	49.62
11	1000	0.1	0.3	117.82
12	1000	0.11	0.3	99.57
13	1000	0.12	0.3	84.58
14	1000	0.13	0.3	73.21
15	1000	0.14	0.3	63.98
16	1000	0.15	0.3	56.24
17	1000	0.16	0.3	50.01
18	1000	0.17	0.3	45
19	1000	0.18	0.3	40.37
20	1000	0.19	0.3	36.59
21	700	0.13	0.3	214.55
22	800	0.13	0.3	143.83
23	900	0.13	0.3	100.64
24	1000	0.13	0.3	73.57
25	1100	0.13	0.3	54.64
26	1200	0.13	0.3	42.36
27	13000	0.13	0.3	32.94
28	1400	0.13	0.3	26.37
29	1500	0.13	0.3	22.08
30	1600	0.13	0.3	18.38

In this study, all the data consists of four attributes which are cutting speed, feed rate, depth of cut, and tool life. Since the data obtained are complete and no missing data due to incorrect measurement, hence, data imputation is not required in this stage. However, the unit of the data obtained from different sources are not identical and further conversion is required to standardize the unit. Equation (1) to (3) is used to convert the cutting speed from rpm to m/min, feed rate from m/min to m/rev and tool life from seconds to minutes.

$$V = \frac{\pi DN}{1000} \quad (1)$$

$$Fr = \frac{F}{N} \quad (2)$$

$$TL = \frac{Lifetime}{60} \quad (3)$$

The dataset was being trained by the linear regression and multilayer perceptron model. Linear regression is used to form linear trends which fit the unknown parameters. There are two types of linear regression which are simple and multiple linear regression. Simple linear regression is an algorithm to predict the relationship between a single predictor variable and a response variable. On the other hand, multiple linear regression is used to predict the relationship between the multiple predictor variables and the response variable (Prion & Haerling, 2020). Equation (4) is used to predict the response variable (tool life) in this study.

$$Y = b_0 + b_1X_1 + b_2X_2 + \ldots \ldots + b_nX_n \quad (4)$$

where Y = Outcome, Tool life

b_0 = Maximum tool life when all parameters are zero.

b_n = Slope of the regression line obtained from each parameter

X_n= Parameters to predict tool life

Meanwhile, multilayer perceptron or known as neural network is the algorithm that related with the networking system organized in layers. The model of neural network built from the multilayer perceptron algorithm is a non-linear neural network which used to obtain the hidden layer. In this study, the cutting speed, feed rate and depth of cut are the input layer while the tool life is the output node. The lines that connected the neurons is known as the perceptron or weight. Figure 2 shows the neural network model of this project.

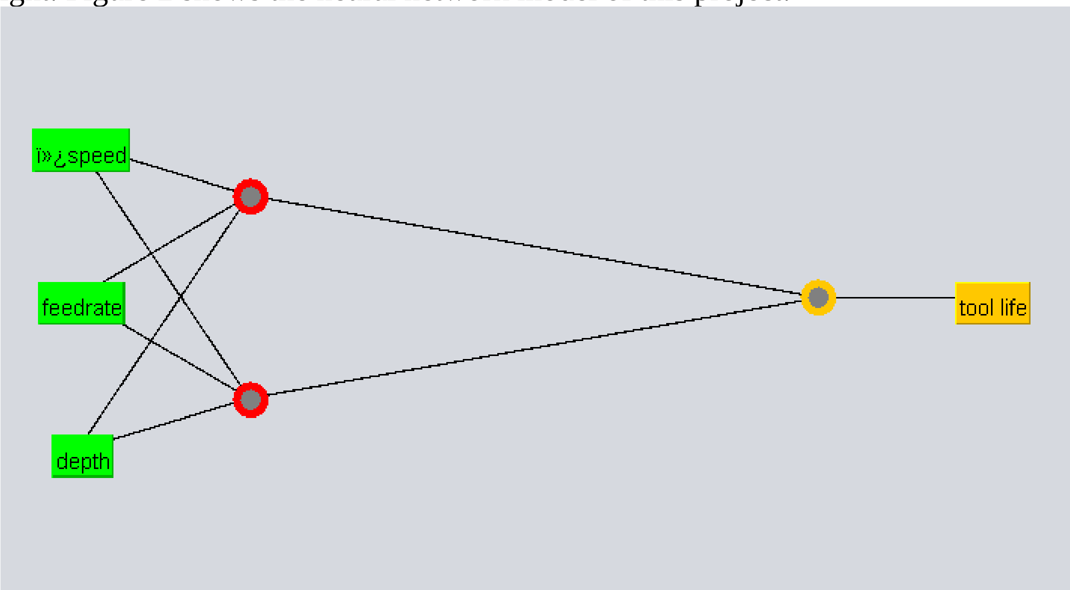

Figure 2. Neural network model using WEKA

Once the model is built, “supplied test set” option is chosen in the WEKA software to test the accuracy of the model. The outcome of the tested data is then validated using Taylor’s extended equation (equation (5)).

$$vT^n fr^a dp^b \quad (5)$$

where v = cutting speed in m/min,

T = tool life in min

fr = feed rate in mm/rev

dp = the depth of cut in mm

a, b = material constant

The material constant can be found in the reference (William & David, 2018). In this case, steel is using for all CNC machining process.

Result and Discussion

By using the multiple linear regression, a formula has been derived to express the relationship between the tool's life and the cutting speed, feed rate as well as the depth of cut. The formula of the multiple linear regression is shown in equation (6).

$$Tool\ life = -1.053speed - 46.667feedrate - 7.5depth + 69.105 \tag{6}$$

Equation (6) shows that the tool life is decreased once the speed, the federate, and the depth of cut is increasing. To test whether the model is accurate or not, the model is tested with the data mining software, WEKA, and the correlation coefficient evaluated is 0.9689, which shows a 96.89% of prediction accuracy (Figure 3).

```
Test mode:    evaluate on training data

=== Classifier model (full training set) ===


Linear Regression Model

tool life =

     -1.0529 * Im;speed +
    -46.6667 * feedrate +
     -7.5    * depth +
     69.1054

Time taken to build model: 0.41 seconds

=== Evaluation on training set ===

Time taken to test model on training data: 0 seconds

=== Summary ===

Correlation coefficient                  0.9689
Mean absolute error                      1.6757
Root mean squared error                  2.1065
Relative absolute error                 23.3607 %
Root relative squared error             24.7541 %
Total Number of Instances               11
```

Figure 3. Correlation coefficient of multiple linear regression model

On the other hand, the model developed by using multilayer perceptron is also been tested using WEKA. Figure 4 shows the correlation coefficient of the model built by the multilayer perceptron. Based on Figure 4, the prediction accuracy of the multilayer perceptron model is 99.91% and found to be higher compared to the multiple linear regression model.

```
=== Summary ===

Correlation coefficient                  0.9991
Mean absolute error                      0.2782
Root mean squared error                  0.3692
Relative absolute error                  3.8698 %
Root relative squared error              4.3388 %
Total Number of Instances               11
```

Figure 4. Correlation coefficient of multilayer perceptron model

Figure 5 shows the differences in tool life generated by multiple linear regression, multilayer perceptron (neural network), and Taylor's extended equation on the milling machine data.

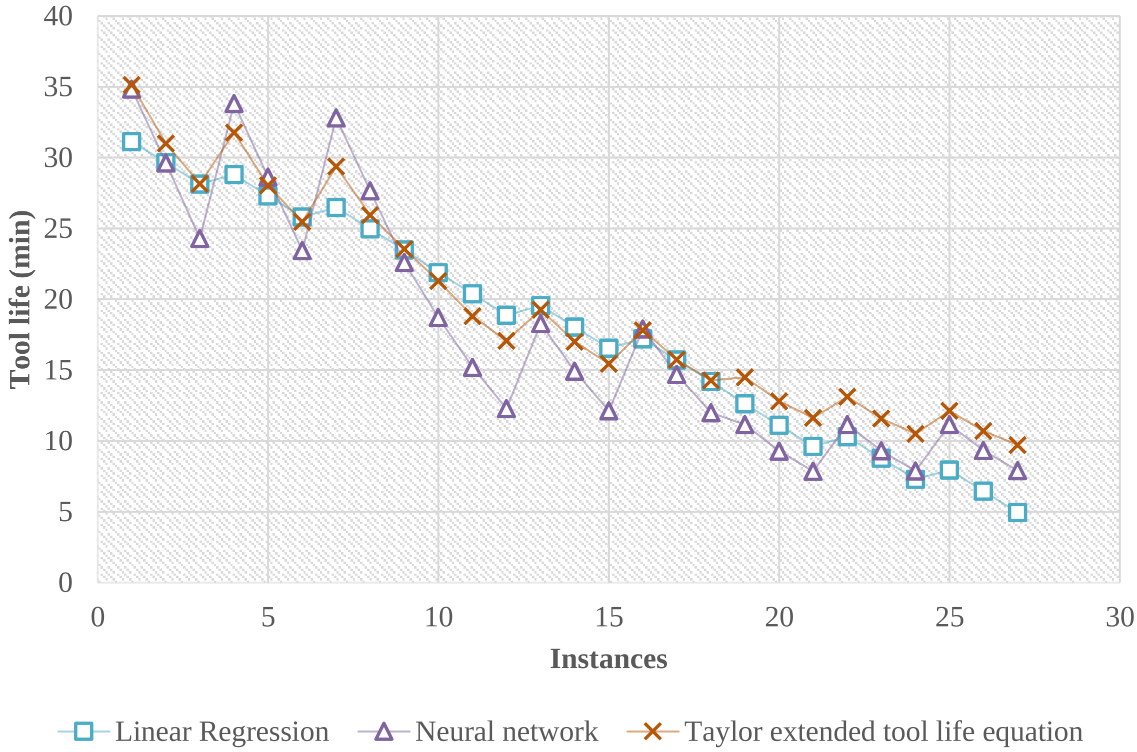

Figure 5. Comparison of tool life prediction using linear regression, neural network, and Taylor extended equation

As depicted in Figure 5, the predicted tool life using three methods are almost showing a similar trend. By comparing to Taylor's extended equation, it is shown that the neural network model is more fluctuating in terms of tool life prediction and the linear regression model is much more stable in every instance. A percentage error has also been calculated for linear regression and neural network model based on Taylor's extended equation, the average percentage error found for linear regression and neural network model is 12.09% and 13.38%, respectively.

Conclusions

Conclusively, the tool life is always decreased when the cutting speed, feed rate, and depth of cut are increasing while the tool flank wear is always 0.3mm according to ISO 8688-2 and ISO 3685 for the end milling tool. According to the prediction accuracy generated, the neural network is greater compared to the multiple regression model. However, by comparing the trend of the tool life predicted using multiple regression, neural network, and Taylor's extended equation, it was found that linear regression is somewhat more stable compared to the neural network model and it is closer to the model generated using Taylor's extended equation. In a nutshell, the multiple linear regression model is much more conservative compared to the neural network model as the tool life that predicted using linear regression model is always the lowest. To improve the reliability of the generated model, the proposed method can be implemented for a different set of data such as CNC turning machine data.

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