AJAPAS

African Journal of Advanced Pure and Applied Sciences (AJAPAS)

Online ISSN: 2957-644X

Volume 3, Issue 1, January-March 2024, Page No: 99-110

Website: *https://aaasjournals.com/index.php/ajapas/index*

معامل التأثير العربي 2023: (1.55) SJIFactor 2023: 5.689 ISI 2022-2023: 0.557

Proposed Machine Learning Model Using Levenberg-Marquardt Algorithm to Predict the Remaining Useful Life of cutting tools by monitoring sound or temperature measurements

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Received: December 03, 2023	Accepted: February 10, 2024	Published: February 17, 2024

Abstract:

The story of industrial optimization centers around advances in reducing waste generation and lowering costs. Any industrial institution needs to constantly optimize their production processes in order to gain competitive advantage over its competitors in the industry. One of the challenges manufacturing is to monitor and minimize the gradual failure of cutting tools. The remaining useful life (RUL) of a cutting tool must be used carefully to ensure precision of surface finish, since tool wear can cause damage to cutting tool and scraping machined.

This paper presents a research project to monitor and optimize the life of the cutting tool during turning process. Machine tool data was collected from sets of experiments to estimate parameters of the modified Taylor's equation using the Levenberg-Marquardt (LM) non-linear least squares algorithm. The LM nonlinear results are used as data structure for a proposed machine learning model to alarm the factory to replace tool before reaching the end of life. In this study, the LM nonlinear estimation results were compared to linear least squares solutions of the linearized form of the extended Taylor equation. The LM nonlinear least squares model showed better fitting results. In this study, the cutting tool temperature is also recommended as other techniques to teach machine to monitor the RUL cutting tools.

Keywords: Optimal tool life, Levenberg-Marquardt algorithm, Nonlinear optimization, Machine learning, Cutting tool temperature.

Cite this article as: A. I. Alkhwaji, M. M. BenIsa, M. O. Hakoumah, "Proposed Machine Learning Model Using Levenberg-Marquardt Algorithm to Predict the Remaining Useful Life," *African Journal of Advanced Pure and Applied Sciences (AJAPAS)*, vol. 3, no. 1, pp. 99–110, January-March 2024.

نموذج مقترح لتعليم الآلة باستخدام خوارزمية ليفنبرج-ماركوارت للتنبؤ بالعمر المفيد المتبقي لأدوات القطع (RUL) من خلال مراقبة قياسات الصوت أو درجة الحرارة

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الملخص

يتمحورتاريخ التحسين الصناعي حول المحاولات المضطردة لتقليل تولد النفايات المصاحبة للعملية الانتاجية وخفض تكاليف الانتاج. تحتاج أي مؤسسة صناعية لضمان الأستمرار في تحسين عملياتها الإنتاجية من أجل الحصول على ميزة تنافسية

على منافسيها في الصناعة. أحد أهم التحديات في مجال التصنيع هو مراقبة وتقليل الفشل التدريجي لأدوات القطع. يجب استخدام العمرالإنتاجي المتبقي (RUL) لأداة القطع بعناية لضمان الدقة المطلوبة لتشطيب السطح، وكذلك فإن تآكل أداة القطع سيتسبب فشل أداة القطع.
تقدم هذه الورقة مشروعًا بحثيًا لمراقبة وتحسين عمر أداة القطع أثناء عملية الخراطة. تم جمع بيانات أداة الآلة من مجموعات من التجارب لتقدير معاملات معادلة تايلورالموسعة باستخدام خوارزمية المربعات الصغرى غير الخطية (Levenberg Marquardt).
يتم أستخدام نتائج معاملات معادلة تايلر الموسعة غيرالخطية كقاعدة بيانات (Library) لنموذج التعليم المقترح لألة الخراطة لتنبيه المصنع لتغييرأداة القطع قبل الوصول لنهاية عمرأداة القطع. في هذه الدراسة، تمت مقارنة نتائج التقديراللاخطي (LM) مع حلول المربعات الصغرى الخطية للشكل الخطي لمعادلة تايلور الموسعة. وتبين ان نموذج المربعات الصغرى غير الخطية (LM) يعطي نتائج أكثر دقة. وكذلك فإننا في هذه الدراسة، نوصى أيضًا بإستخدام مجسات قياس درجة حرارة أداة القطع كتقنيات أخرى لتعليم الآلة كيفية مراقبة العمر المفيد المتبقي لأدوات القطع.

الكلمات المفتاحية: العمرالأمثل للأداة، خوارزمية ليفنبر ماركواد، التحسين غير الخطي، تعلم الآلة، درجة حرارة أداة القطع.

Introduction

Optimizing the material removal process is one of the most searched topics in manufacturing literatures [1-2]. In most manufacturing industry, efforts are given to look for optimizing cost and quality of products. Recent improvements in engineering design were achieved with machine learning by building computer systems that learn from data [3]. Using artificial intelligence to monitor tool life makes computer copy human intelligent to inspect and improve the production processes [4-6]. Where artificial intelligence can be defined as: "an area of study concerned with making computers copy intelligent human behavior" [7]. The goal of using artificial intelligence (AI) in machining is to train computer to extend tool life so that no need for human inspection of the end of the tool life. In most moderate automated machinery, optimizing material removal process are made by modelling machine learning algorithms for machines to completely rely on itself to monitor the optimal cutting parameters to insure long tool life. Sara et al. [8] proposed a machine learning method to find an algorithm to estimate the tool life in different turning conditions when machining small lots where parts and materials are changed constantly. They conclude that depending on the availability of historical data of similar production, the tool life can be estimated using Bayesian method. However, when only features, properties and condition data are available, the extended Taylor equation is used to estimate tool life. They also concluded that when no relevant data, it is not possible to estimate tool life. Each ML model requires the use of image processing, or sound sensor, or optical sensor, or vibration sensors, or radiation sensor, or ultrasonic sensors [9]. Liu et al. [9] predicted tool life of milling cutters by sound. They used Mel-Frequency Cepstral Coefficients (MFCC) to extract audio signals for the tool life model, then a Deep Neural Network (DNN) was used to build a relationship between the recorded audio and the tool life, and then define the audio signal corresponding to the end of tool life. Deep Neural Networks are useful in speech recognition [10 – 12] and are also commonly used in life cycle prediction models for machines and tools [9]. Al-Ahmari et al. [13] formulated an optimization model to predict three machining functions (tool life, cutting force and surface roughness), during turning process of austenitic AISI 302. They estimated machining functions using multiple linear regression analysis techniques (RA), response surface methodology (RSM), and computational neural networks (CNN). They have concluded that the CNN model was better than RA and RSM models in detecting machining functions. However, RSM model performed better in estimating tool life and cutting force compared to RA model. Bazaz et al. [14] used dimensional analysis to estimate the tool life in the metal cutting turning process for small-lot production by considering the effects of cutting speed, feed rate, depth of cut, workpiece hardness, tool hardness, cutting force, and cutting temperature. These parameters were extracted from a literature review of 101 published references from 2000 to 2022. They established a relationship matrix from the investigated literature review which demonstrates 29 parameters affecting 23 factors that directly or indirectly effected tool life. The relationship matrix demonstrates 29 parameters affecting 23 factors which directly or indirectly influence tool life, these factors affecting the tool life are illustrated by their weights on the graph. They also concluded that these relationships could be used to develop a production plan that use the optimized tool life in small-lot production to estimate tool life, including artificial intelligence development, big data analysis, and digital twins. Robin [15] proposed a machine learning model includes recording of the torque data and tool life measurements. The torque data is recorded for different time spans. The cutting tool is removed from the machine and a spare tool installed to prevent production interruption and to measure tool life for each time span. The procedure may be repeated until the end of tool life. Then a software code is written to implements the machine learning algorithm, transfers the data, trains the ML model and generates the tool life predictions. They predict tool life of a drilling tool to produce hydraulic valves where torque measured by a numerical control (NC). The torque values of the spindle were collected with a frequency of 1,000Hz for each tool until reaching the end of the tool life. After measuring the mechanical torque, it is required to measure the cutting-edge displacement of the used tool with a three-dimensional image capture and evaluate the image by an expert. These measurements can be stored in a matrix where row equals to measurements, and column equal to torque values of 1 millisecond or displacements).

It is possible to use human inspection (human learning models) to predict tool life to ensure accuracy of a cutting machine and the finished product precision. This method is used to identify problems early and predict the end of the tool life (ETL) of a machine to prevent machining downtime and to utilize the maximum life of the cutting tool. The human learning models are based on mathematical models and the experimental analysis of behaviour [16-17] to accurately predict the remaining useful life (RUL or ETL) of a cutting tool and parameters influencing the RUL or ETL. Some of these attempts to use human learning models are summarized here, Zhang et al [18] modelled tool life (ETL) for high-speed ultrasonic vibration cutting (HUVC) of Ti and Ni alloys based on the extended Taylor's equation. They concluded that both the separation condition and effective cooling influenced the tool life and that the cutting temperature reduced as result of cooling condition during separation process. They also specify limit of cooling pressure and duty cycle for Ti and Ni alloys, and suggested to consider the impact effect due to the tool-workpiece separation. Prince et al. [19] conducted wet-turning experiment to estimate the tool life of coated carbide insert in a CNC lathe machine to cut stainless steel SS316L. The tool life (ETL) was estimated using industrial and theoretical method (Taylor's tool life Equation). Theoretical method can be successfully implemented to estimate the tool life to save operator time and machining cost. They found that the Flank wear and brittle wear are the most common cause of tool failure. Kumar et al. [20] studied the tool life (ETL) and its failure mechanism. They concluded that the geometry of a cutting tool, cutting parameters, and the machining condition (dry or wet) influence tool life, meanwhile, the optimum values of rake and clearance angles are -50 to +100 and 50 to +80 respectively. They also concluded that tool failure increased under the influence of high thermal stresses, wear and mechanical forces.

In this paper, sound inspection is used to precisely detect the end of tool life (ETL). Then an algorithm is used based on nonlinear optimization (LM nonlinear least squares algorithm) to estimate parameters of the modified Taylor's equation. The modified Taylor's equation is a relationship relates the Tool life to cutting parameters (Cutting speed, Feed rate, and Depth of cut). This ML model will estimate end of tool life based on the learning process from sound inspection experiments of tool life. The learning process teach the computer to use the right parameters of the extended Taylor equations so that computer chose an optimal cutting parameters and alarms to stop the cutting machine to allow operators to replace the tool and prevent damage in time.

Predictive maintenance models & sensing methods

Predictive maintenance models (PM models) use analytics to estimate the RUL or ETL of a tool. The basic principle of PM models is to perform prediction and analyze the collected signals from sensors. Commonly used PM methods are statistical failure knowledge models, physics-based model (Mathematical models), and data-driven models (Data collected using sensors), figure 1 [21] shows the three predictive maintenance models.

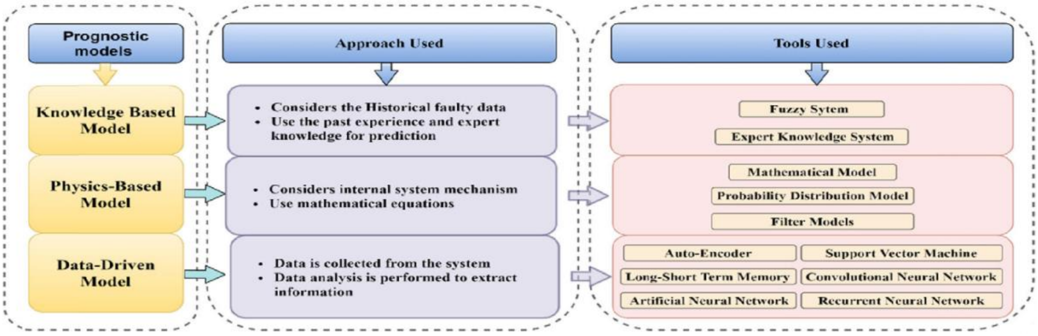


Figure 1: Predictive maintenance models [21]

The commonly used end of tool life monitoring techniques for data-driven predictive maintenance are direct monitoring and indirect monitoring. Where, direct sensing methods include microscope, lasers, cameras, Charge-Coupled Device cameras, laser, ultra-sonic sensors. While in-direct methods bring indirect information about the end of tool life from measurements of cutting forces (dynamometer), vibration (accelerometer), temperature, sound (microphone), current/power, acoustic emissions. Figure 2 [21] shows the direct and indirect methods.

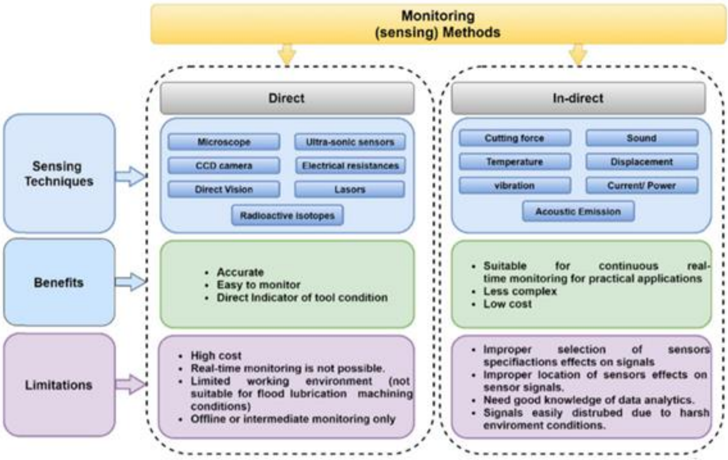


Figure 2: Sensing methods [21]

Case study: Carbide tip-KC5525 cutting tool

To demonstrate the process of machine learning and human learning models, a carbide tip-KC5525 cutting tool was used to collect the end of tool life during different designed cutting parameters. These data are going to be used to teach human being or a machine to prevent sudden production downtime. In this study, the material used for conducting experiments is C45 mild carbide steel. The experiment was carried out on lathe machine on the cylindrical workpiece mild steel (57 mm diameter and 500 mm length) with carbide tool and the end of tool life was measured by observing an abnormal change in the pitch of sound from the cutting tool. The experiments were conducted according to the Taguchi design of experiment as per Table-1. The results of 27 tests are shown in table-2. A 33 factorial design was used to study influence of the cutting parameters on the end of tool life Table 1, shows the three controlling parameters (cutting parameters).

Table 1 The procedure of the experiments.

Cutting parameters	Level-1	Level-2	Level-3
Speed of cut (V) m/min	92.68	122.83	155.63
Feed rate (F) mm/rev	0.09	0.18	0.36
Cutting Depth (D) mm	0.3	0.5	0.8

Experiments have been conducted at three different cutting speeds by varying the other two cutting parameters for each cutting speed. At each cutting speed, three feed rates were performed and at each of them three depths of cuts have been implemented. That makes 27 tests organized in table 1 and at each test, the end of tool life was measured by detecting the changes in the sound emitted from the operation.

Mathematical Model of the Tool life

Taylor has proposed a relationship between tool life, cutting velocity, (V), feed rate (F) and Cutting depth (D). The extended Taylor tool life [22] which defined as

$$V \mathrm{T}_L^n \mathrm{F}^{\mathrm{m}} \mathrm{D}^{\mathrm{k}} = C \tag{1}$$

Where, TL is the end of tool life in minutes, C is a constant effected by both the used cutting tool and the workpiece. The tool life exponents are n, m, and k influenced by the used tool, workpiece and the environment of the machine.

Tool Life Parameter Estimation by Non-Linear Least Squares

The Levenberg-Marquardt algorithm is used to solve nonlinear extended Taylor equation by fitting a parameterized extended Taylor equation (model function) to a set of tool life data points by minimizing an objective function as the sum of the squares of the residual between the model function and a set of tool life data points. The least squares problem requires an iterative solution algorithm, because of the nonlinearity in parameters of the fitted function. The Levenberg-Marquardt algorithm combines the gradient descent method and the Gauss-Newton method. Where the gradient descent method updates the parameters in the steepest-descent direction to reduce the sum of the squared residuals.

Whoever the Gauss-Newton method helps to reduce the sum of the squared residuals by the least squares function which is locally quadratic in the parameters, and to find the minimum of this quadratic function. The Levenberg-Marquardt method replaces a gradient-descent method when the parameters are far from the corresponding optimal value, and replaces the Gauss-Newton method when the parameters are close to the corresponding optimal value. The object function (Equation 5 & 6) is obtained by manipulating the Extended Taylor equation:

$$f = ETL - T_m = T_L(V,F,D) - T_m = \left[\frac{C}{V\ \mathrm{F^m}\ \mathrm{D^k}}\right]^{1/n} - \underbrace{T_m}_{y_{data}} \tag{2}$$

More general form:

$$f(z_1, z_2, z_3) = \left[\frac{C}{z_1\ z_2^m\ z_3^k}\right]^{1/n} - y_{data} \tag{3}$$

The unknown parameters are *C*, *n*, *m* and *k*, measurements are organized in the following form $([z_1\ z_2\ z_3]_1, y_{data_1}), ([z_1\ z_2\ z_3]_2, y_{data_2}), \dots, ([z_1\ z_2\ z_3]_n, y_{data_n})$. Then specifying an initial guess of the unknown parameters C_0, n_0, m_0 and k_0 and evaluate *f* at $([z_1\ z_2\ z_3]_1, [z_1\ z_2\ z_3]_2, \dots\dots, [z_1\ z_2\ z_3]_n)$ and the calculating residuals. From there we can update the unknown parameters *C*, *n*, m and *k* to make the mathematical model converges to the measured data. By repeating this cycle of evaluation,, then optimal parameters are obtained by minimizing the sum of squared errors between function *f* and the measured end of tool life.

$$f = \left[\frac{C}{z_1\ z_2^m\ z_3^k}\right]^{1/n} - y_{data} \tag{4}$$

The Levenberg-Marquardt is used to find the minimum of a function f(x) as a sum of squares of nonlinear functions.

$$F(z_1, z_2, z_3, z_4) = \frac{1}{2}\sum_{i=1}^{m}[f(x_i)]^2 = \frac{1}{2}(f_1(z_i)^2 + f_2(z_i)^2 + \dots + f_n(z_i)^2) \tag{5}$$

Initial guess of the unknown parameters:

$$[z_1^0, z_2^0, z_3^0, z_4^0] = [100, 0.1, 0.1, 0.1] \tag{6}$$

Subject to the constraints

$$\overbrace{[20, 0.1, 0.1, 0.1]}^{LB} \le [z_1, z_2, z_3, z_4] \le \overbrace{[150, 0.9, 0.9, 0.9]}^{UB} \tag{7}$$

The LM algorithm requires calculating the Jacobian of all the first derivatives the vector. The Jacobian of the vector f is given by the matrix

$$J = \begin{vmatrix} \frac{df_1}{dn} & \frac{df_1}{dm} & \frac{df_1}{dk} & \frac{df_1}{dC} \\ \frac{df_2}{dn} & \frac{df_2}{dm} & \frac{df_2}{dk} & \frac{df_2}{dC} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{df_N}{dn} & \frac{df_N}{dm} & \frac{df_N}{dk} & \frac{df_N}{dC} \end{vmatrix} \tag{8}$$

The proposed machine learning procedures

The proposed ML model uses indirect sensing technique (sound) to build tool life mathematical model based on the extended nonlinear Taylor equation. The proposed model was tested for the case of Carbide tip-KC5525 cutting tool. The LM nonlinear detection model can be used to estimate the exponents of the extended Taylor equation tool life of different cutting tools used in the same Machine. The proposed ML model include library of all studied types of cutting tools. A user can select a type of tool so that library provides the right estimated exponents of the extended Taylor equation. Then the user can apply selected cutting parameters (V, F, and D) to predict the RUL or the ETL. By calculating the duration for which the tool was running (DTR), it is possible to get the RUL from equation 9.

$$\mathrm{RUL}\ (\mathrm{V}, \mathrm{F}, \mathrm{D}, \mathrm{ToolType}) = \mathrm{ETL}(\mathrm{n}_{\mathrm{ToolType}}, \mathrm{m}_{\mathrm{ToolType}}, \mathrm{k}_{\mathrm{ToolType}}, \mathrm{C}_{\mathrm{ToolType}}) - \mathrm{DTR} \tag{9}$$

An Arduino-based alarm system is used to display the RUL and if possible, to alarm users for the RUL. A sample of each experimented tool type can be arranged in a struct as in table 2, then saved into a library for use in the ML model.

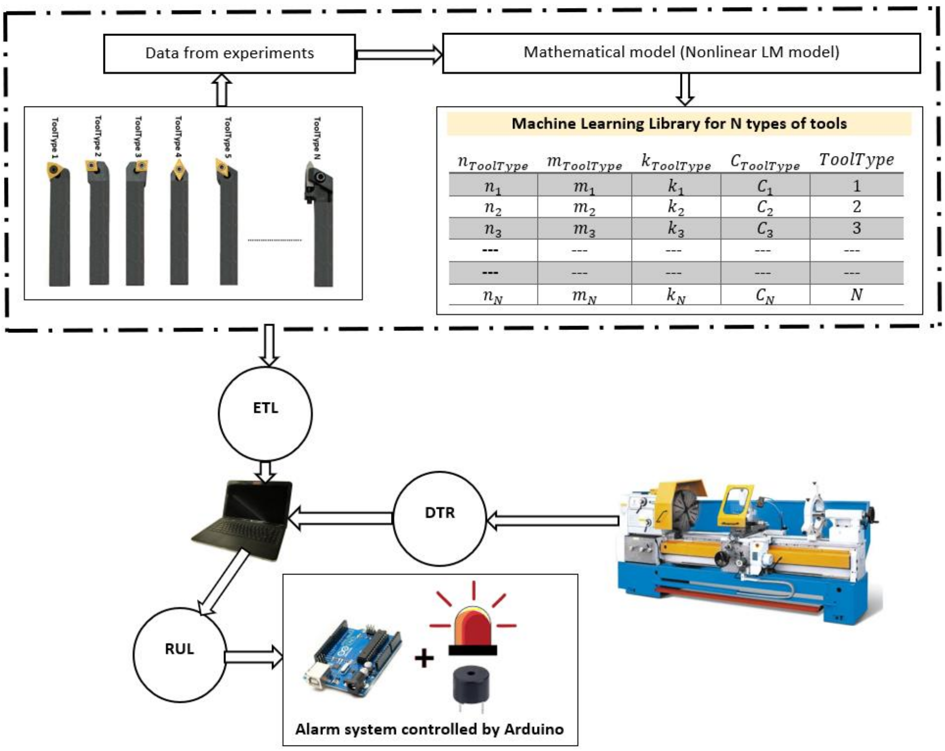


Figure 3: The proposed machine learning model.

Table 2 The ETL library for three cutting tools.

```
% MATLAB code shows how to add tool’s data to the ML structure (Library) %
Tools = struct ('const_C', [C1, C2, C3], ...
'exp_N', [n1, n2, n3], 'exp_M', [m1, m2, m3], ...
'expK', [k1, k2, k3],'names', char ('ToolType-1', 'ToolType-2', 'ToolType-3'));

Tools.names
%Tools.names(4)='Tool-4'; % To add new tools
Tools.names
% Saving Tools info in a file
save ('data.mat', '-struct', 'Tools');
% Creating a library for teaching the machine to monitor the RUT
ToolLibrary = load('data.mat');
ToolLibrary.names % names of tools from the created library
```

The schematic of the Levenberg-Marquardt algorithm to predict the end of tool life is summarized in table 3. The LM algorithm is a human leaning model which can be transferred to the ML model as well.

Table 3 A schematic of the LM optimization algorithm for predicting end of tool life.

```
%% nonlinear least square using Levenberg-Marquardt algorithm
clear all; close all; clc;
%% generating vectors of the controlling parameter
V (1: N) = [V1 V2 …… VN]; % Applied Speed of cut vector
F (1: N) = [F1 F2 …… FN]; % Applied Feed rate vector
D (1: N) = [D1 D2 …… DN]; % Applied Depth of cut vector
T (1: N) = [T1 T2 …… TN]; % measured Tool life vector
%% initialization of variables
n_init = 0.1; m_init = 0.1; k_init = 0.1; c_init = 10.0;
%% Objective function
f_new = y_data - power (c_init./ (V.* power (F, m_init). * power(D,k_init)  ),1 ./n_init) ;
%% ……………………………….
%% loop for LM nonlinear optimization
for i = 2:max_iter % loop for LM nonlinear optimization
          .
          .
          .
         %% Here Levenberg-Marquardt algorithm
          .
          .
          .
End
```

Results and discussion

In Fig. 4, the predicted and the experimental end of tool life values are plotted on the y-axis, while the 27th experimental samples are plotted on the x-axis. The LM nonlinear model showed better accuracy in detecting experimental end of tool life (ETL) compared to the linear least squares [23]. Table 4 includes end of tool life equations for (a) non-linear least squares (LM model) (b) linear least squares (Solving system of linear equations) [23].

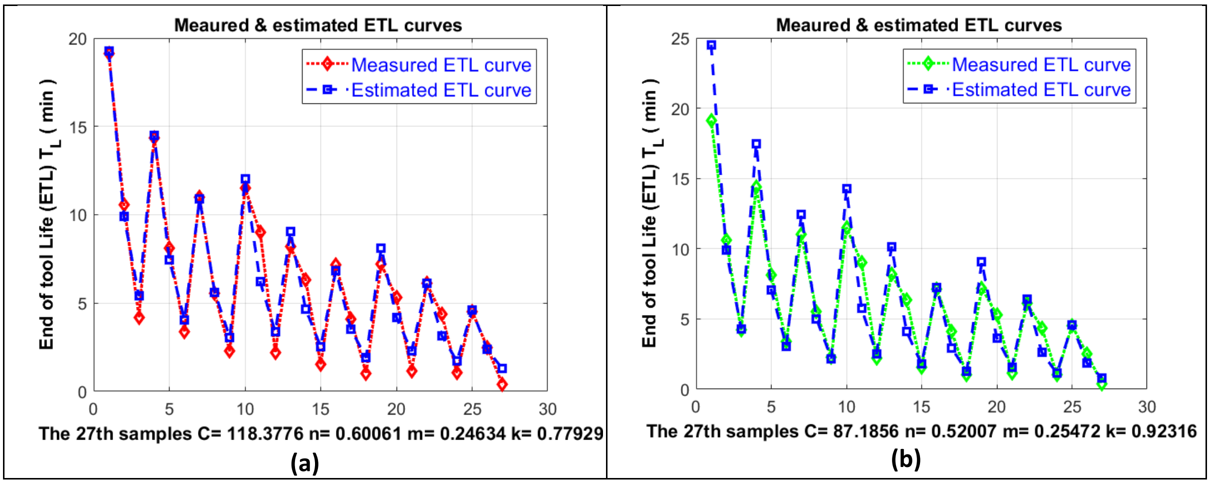


Figure 4: Estimated versus measured Tool Life.
(a) Optimizing of nonlinear objective function by the LM-nonlinear least squares
(b) Solving system of linear equations using Linear least squares

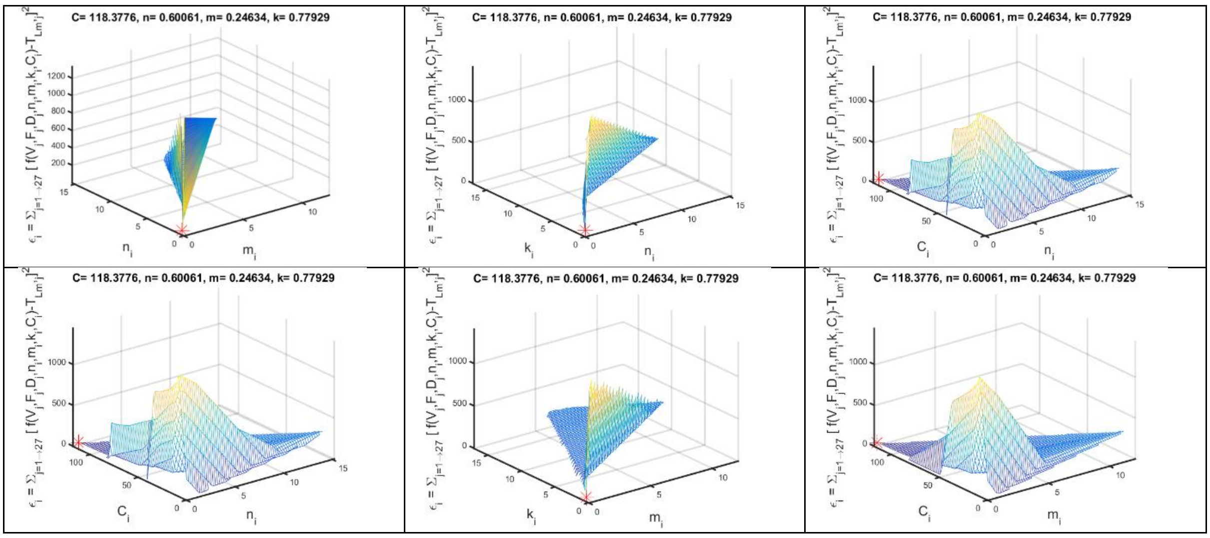
Table 4 Mathematical models of nonlinear & linear least squares.

Linear least squares (Linearizing & solving system of linear equations)	Nonlinear least squares (Levenberg-Marquardt)
$\boldsymbol{V\ T_L^{0.52007}\ F^{0.25472}\ \ D^{0.92316} = 87.1856}$	$V\ T_L^{0.60061}\ F^{0.24634}\ \ D^{0.77929} = 118.3776$

The RUL of the studied case (Carbide cutting tool inserts) can be calculated from the estimated ETL (TL) using equation 9.

$$\begin{aligned} \mathrm{RUL}\ (\mathrm{V, F, D, Carbide\ tip} - \mathrm{KC5525}\ ) &= \ \mathrm{ETL} - \ \mathrm{DTR} = T_L(V, F, D) - \mathrm{DTR} \\ &= \left[\frac{118.3776}{V\ \mathrm{F}^{0.24634}\ \mathrm{D}^{0.77929}}\right]^{1/0.60061} - \mathrm{DTR} \end{aligned} \tag{10}$$

Fig. 5, shows 3D-search for optimal tool life exponents (n, m, k and C) using the LM model. It is clear that errors have been reduced when optimal exponents were reached.



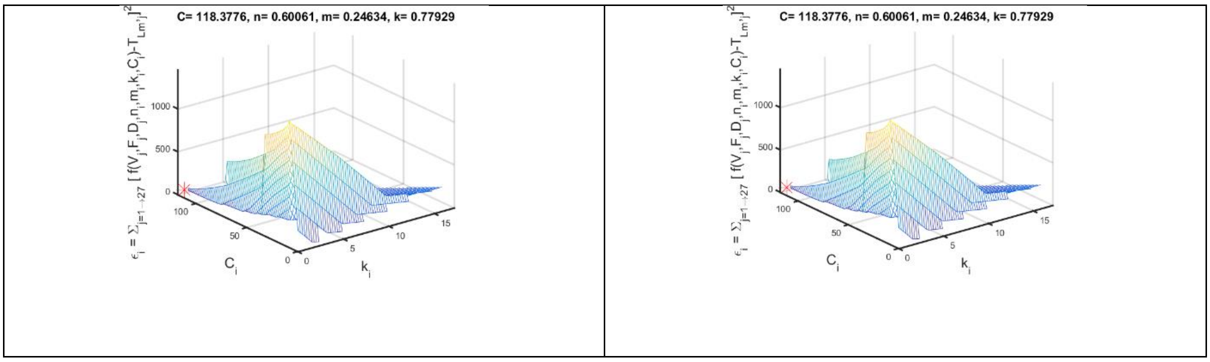


Figure 5: Illustration of minimizing errors during nonlinear least squares optimization between Mathematical model and experimental ETL measurements.

Figure (6) shows the end of tool Life results from experiments on Carbide insert tool during the selected controlled cutting parameters from table 1. The magenta circle-ball dotted curve performed at 92.68 m/min and three cutting depths of 0.3, 0.5 and 0.8 mm. The green triangles line curve for speed of cut of 122.83 m/min plotted for the three cutting depths, while the black square-dashed curve for speed of cut of 155.63 m/min are plotted for the same three cutting depths.

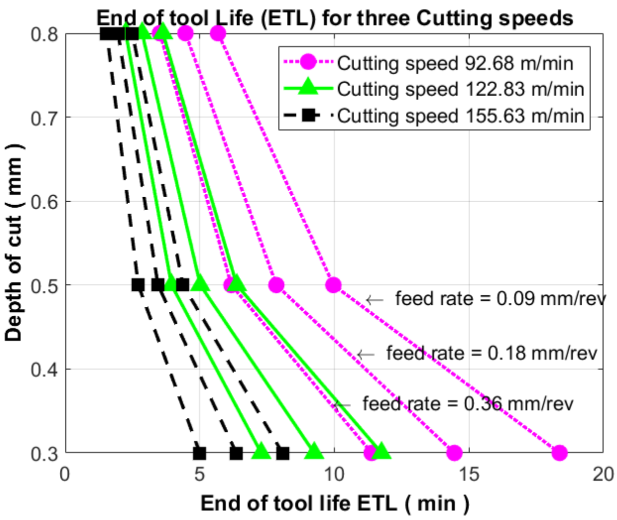


Figure 6: The effects of cutting parameters (V, F, and D) on the end of tool life ETL.

Figure 7 shows the approximated cutting temperatures based on Nathan Cook equation [14] for turning machine. Here we try to chick whether our machine learning model could benefit from connecting the end of tool life with the cutting tool temperature. Fig. 7 (a) and (b) conclude that when cutting speed was kept constant while depth of cut (D) changed from 0.3 mm to 0.8 mm, the tool temperature has been increased by 200 Co. However, tool temperature was increased by 100 C0 as cutting speed changed from 92.68 m/min to 122.83 m/min. Temperature behavior with respect to the end of tool life clarified by Fig. 8 where increasing cutting tool temperature causes finishing life of the cutting tool earlier. Therefore, it is recommended to try to use temperature sensor to teach the proposed machine learning model to detect the RUL of cutting tools. That will be our next project.

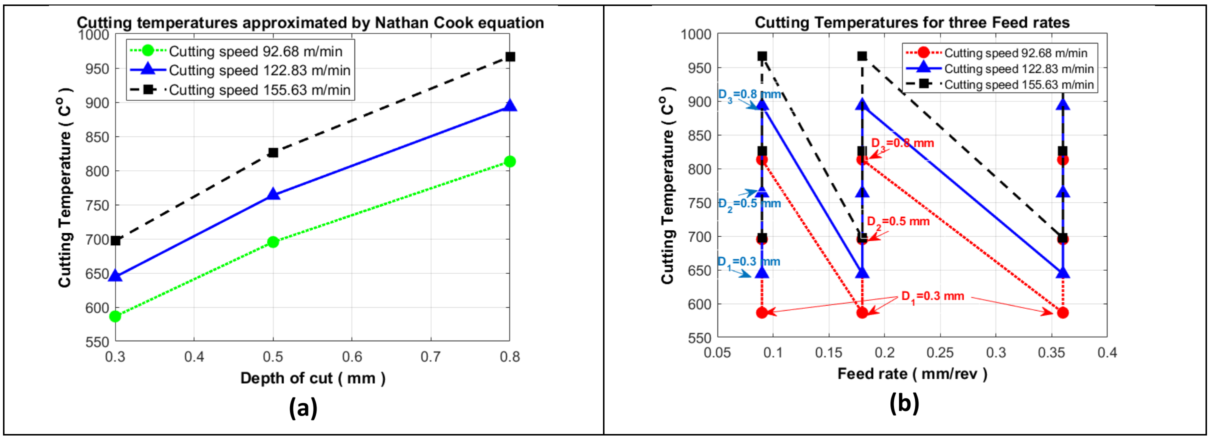


Figure 7: The approximated temperature rises of the cutting tool based on the Nathan Cook model versus cutting parameters.

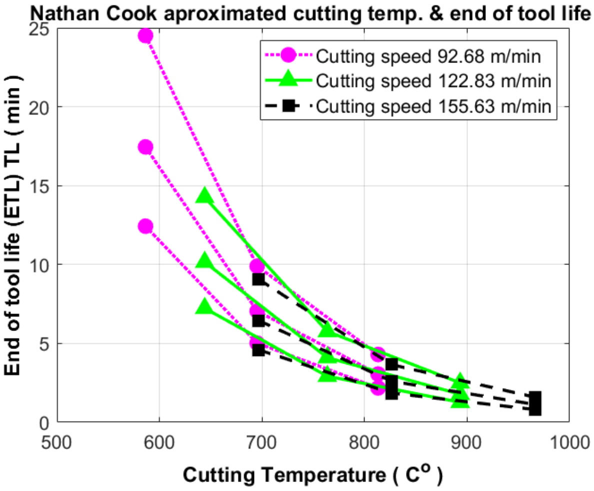


Figure 8: The approximated temperature rises of the cutting tool versus end of tool life.

Conclusion

The LM nonlinear algorithm was used as physics-based model (Mathematical models) to predict the RUL from sound signals of the ETL-measurements. The Mathematical model and the sensing technique are used inside the proposed machine learning model to alarm for the necessary tool replacement. An experimental-case study was conducted in the turning of C45 steel workpiece under dry condition using Carbide cutting tool inserts. This case study is used as an example of how to bult the machine learning library. The criteria of detecting the end of tool life (ETL) are based on a mathematical model which is obtained by solving the extended Taylor equation. There are two ways to solve the extended Taylor equation which are either by solving system of linear equations using linear least squares [23] or by solving the nonlinear optimization problem using LM nonlinear least squares. In this research study, the two solutions were compared using turning of C45 steel workpiece experiments. The nonlinear optimization solution {LM model) was better in fitting the experimental ETL data and in estimating the exponents of the Extended Taylor equation (n, m, k, C), compared to the solution of the system of linear equations (Linearized extended Taylor equation) [23]. Therefore, it is recommended to use the LM model to predict the end of tool life for the proposed machine learning model to get the RUL. This study recommends to use the cutting tool temperature for teaching turning machine by using signals from thermocouples to monitor the RUL cutting tools. That will be the next project.

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