International Journal of Scientific & Engineering Research Volume 11, Issue 7, July-2020
ISSN 2229-5518

Tool Condition Monitoring using Machine Learning Approach

A. D. Patange, A.A. Tadamalle*, S. S. Mulik

RMD Sinhgad School of Engineering, Warje, Pune 411058-, Maharastra, India
akshata360@gmail.com,

Abstract—The continuous monitoring of the machine tool is required to obtain consistent performance of the machine tool. The machine tool wear/ breakage lead to deterioration of machining accuracy, poor quality and variation in product dimension. Developing and implementing real time monitoring on–board diagnostic system is essential. To take online decision about machine tool condition monitoring, the implementation of on board/Real time health monitoring system is need of the hour. The aim of this project is to implement real time health monitoring system for multipoint cutting tool of Vertical Machine Center using Machine Learning Approach. The significantly affecting parameters on tool condition monitoring, sensing technique and sensors are selected from the literature. The experiments are conducted to obtain the data from defect free and defective samples through DAQ system using sensor and FFT analyzer. The features are extracted from acquired signals using signal processing techniques such as time and frequency domain analysis methods. whereas features are selected using Pearson correlation or Taguchi orthogonal array method. The tool condition monitoring provides a better health condition, promises higher productivity reduced maintenance cost saving idle time, enhancing tool and machine life.

Index Terms — Machine Tool Condition Monitoring, Signal Processing, Sensors, Decision making, VMC, Neural Network

1 INTRODUCTION

The monitoring of machining processes can represent economy and practicality by identifying tool wear, surface roughness, and anomalies during metal cutting operation. Traditional assessment of tool life using Taylor's tool life equation does not provide sufficient information about the complete life cycle of the tool. In some situations, it may lead to an overestimation of tool life and in some situations to underestimation of tool life and this will lead to excessive replacements of the tool. As a consequence, precious time and scarce resources are wasted. Excessive wear and tool breakage are the main reasons for the downtime. The damaged cutting tool can increase its strain level and result in poor surface finish of the product. Production rate increases significantly by reducing the machine tool downtime. Tool condition monitoring (TCM) is extremely viable in reduction of cutting tool downtime. Failure of a milling cutting tool has occurred when it is no longer capable of producing parts within required specifications. Every tool, when put to use is subjected to wear after certain machining time. This is called gradual or progressive wear of the tool. During gradual wear, the tool will reach its limit of life by either flank wear or crater wear.

The lack of a tool condition monitoring system (TCMS) can lead to excessive power take-off, inaccurate tolerances and uneven work piece surface finish, sometimes damage to the machine tool and also injury to the operator. Research is going on for the past several years for the development of a reliable TCMS. The nature and characteristics of the utilized sensor signals in general, tend to be stochastic and non-stationary and therefore difficult to model [2]. It poses a practical problem, because of the complex nature of a typical metal cutting process, limiting the precision and control of the cutting process. There is a need for the TCMS to be capable of diagnosing and identifying the fault and to possibly isolate or respond with remedial action within a prescribed response time

The increase in training time with the increase in input dimension and size of the training data set makes ML algorithms are less efficient for practical applications. The optimal input process parameters are very much essential for condition monitoring. In present study focuses on creation of efficient learning algorithms for tool condition monitoring in milling operations is advocated. Supervised Machine Learning used for tool condition monitoring. Supervised Learning uses previous data i.e. Input and Target data and gives output.Feature extraction, feature selection and feature classification have been used under Statistical features like mean, mode, median etc.

2. LITERATURE REVIEW

Korand et al proposes method to enable robust and power full diagnosis machine tool for milling cutting tool using radio of signal increment for feature extraction and neural network and fuzzy logic for feature selection and classification [1]. Paul W. Prickett Provides effective low-cost tool condition monitoring systems for milling using Statistical Overlap Factor and Engineering Judgement Rule [2]. In end milling using real time, Time domain and threshold limit Paul W. Prickett et al Provides powerful intelligent tool condition monitoring systems [3]. A tool wear threshold strategy has been introduced and successfully implemented in milling for vibration using Fast Fourier Transform(FFT) analyzer,Acoustic Emission (AE)and Artificial Neural Network [4]. Mashhood Asad butt et al used FFT and group signal value to increase damping ratio by 12-18% in milling. [5]. Yiqian Dai et al presented research work on effectiveness tomea-

International Journal of Scientific & Engineering Research Volume 11, Issue 7, July-2020
ISSN 2229-5518

sure the progressive wear amount and tool life in milling using machine vision system, Image processing and neural network. [6]. Huang Zhigang et al Used signal feature values in milling to increase its accuracy up to 90% [7]. FranciČuš et al proposes that Neural network is able to classify the various cutting states in milling using ANFIS machine learning technic in real time neural networkdecision [8]. Muhammad Zahid et.al showed that FFT analysis is a reliable approach for tool conditioning monitoringusingSelf Organization Factor (SOF). [9]. BesmirCuka et al successfully implemented neural network Fuzzy Interference System in Milling [10]. Cutting tool life can be predicted by combining cutting force and AE to higher precision scale in Milling proposed by QunRen et al [11]. Hugo M.B. deCarvalho et al analysed vibration which is gathered by FFT and stated that vibration is responsible for minimizing energy consumption by 23% and vibration of cutting tool [12]

3.Experimentation

The machine can capable of machining a component of size 8,200 mm × 3,300 and operates at a cutting feed rate of 10,000 mm/min. FA series, the first 5-axis bridge type CNC milling machining center of Vision Wide, was released in 2014, and it provided excellent 5-axis simultaneous accuracy performance for 5-axis machining in mold cutting, highly precise contour finishing, milling, drilling, and tapping.

Fig.1: Experimental Setup

The plain low carbon steel is most commonlyused in various engineering applications. It contains approximately 0.05–0.25% carbon which makes the MS material malleable and ductile hence it has relatively low tensile strength.The different types of insets selected for the study are Non defective and defective inserts that is New insert, Flank Wearand Nose Wear. The specification of the insert having 4 cutting edges, Nexus 1-1/4" × 3 FLT High-Performance APKT 1604 Indexable Coolant End Mill Cutter Lamina Inserts.

The range of process parameters used for experimentation is selected by taking several trail experiments. During trail experiments, Feed, cutting Speed and Depth of Cut are varied independently from rough cutting to fine finishing obtaining desired surface roughness on work piece. The literature review reveals range of process parameters provides better surface characteristics and machined surface quality. The range of process parameters selected for the experimentation are given in Table 1

Fig. 2: Defective and New Inserts

Table1: Input parameters

Sr. No.	Input Parameters	Levels		
		1	**2**	**3**
1	Feed(mm/rev)	2400	2880	3120
2	Depth of Cut(mm)	0.5	0.35	0.2
3	Cutting Speed (mm/sec)	1000	1200	1400

Experimental Procedure:

The five set of experiments are conducted as per Taguchi orthogonal array design matrix L9 using following different combination of inserts. The inserts combination used for experimentation are:

1. All 4 new inserts
2. 3 New inserts&High Flank wear insert
3. 2 New inserts & 2 defective
4. All 4 defective

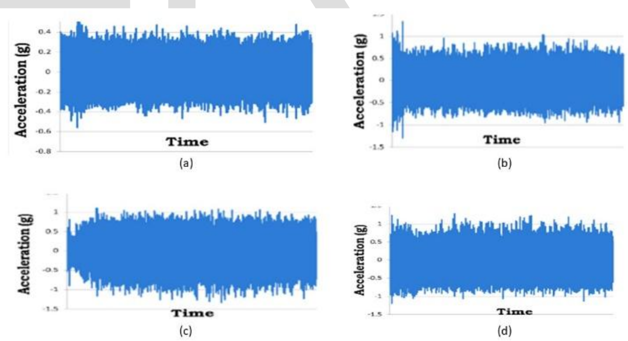


Fig. 3: Time domain signal acquisition for operation for all 4 four new inserts (a) All new, (b) High Flank Wear, (c) High Nose Wear, (d) High & Low flank and Nose wear

The process parameters and set of combinations selected process parameters for the experimentation is given in Table 2. The total of 36 operations were performed using above L9 array design matrix. The experiments are conducted for 4 set of different insert combinations are utilized to perform all 9 operations (9 operations × 4 tool conditions = 36 operations).

International Journal of Scientific & Engineering Research Volume 11, Issue 7, July-2020
ISSN 2229-5518

Table2: Taguchi orthogonal array design matrix

Operation No	Levels			Levels		
	1	2	3	Speed	Feed	DOC
1	1	1	1	1000	2400	0.5
2	1	2	2	1000	2880	0.35
3	1	3	3	1000	3120	0.2
4	2	1	2	1200	2400	0.35
5	2	2	3	1200	2880	0.2
6	2	3	1	1200	3120	0.5
7	3	1	3	1400	2400	0.2
8	3	2	1	1400	2880	0.5
9	3	3	2	1400	3120	0.35

4.RESULT AND DISCUSSION

The Feature are extracted from the time domain data acquired from FFT analyzer is a crude data which includes the effect of bearing, spindle, tool, inserts and its conditions. It means it consists of distinct characteristics observed directly from the acquired time domain plots.

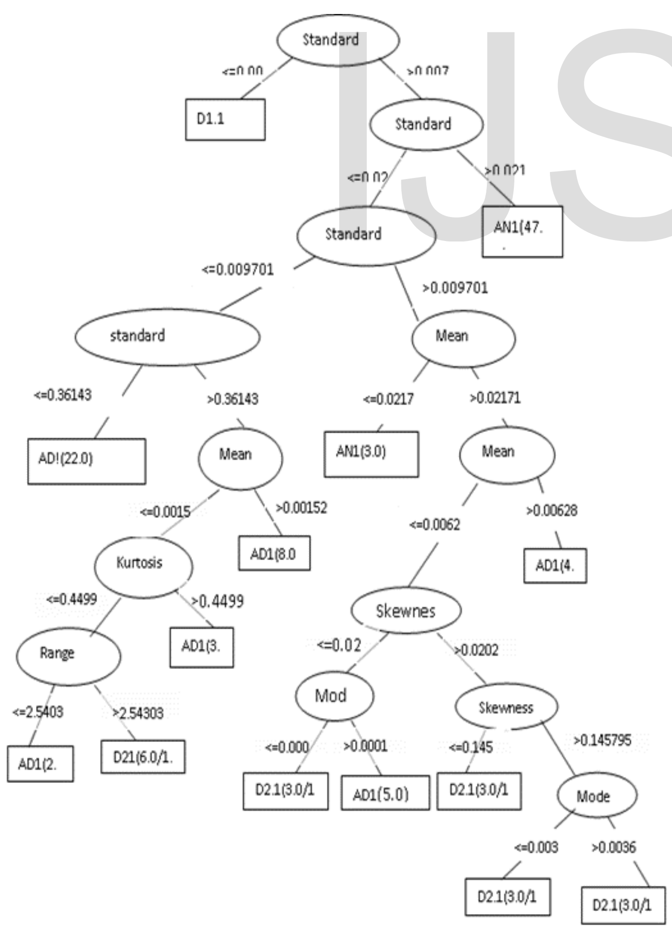
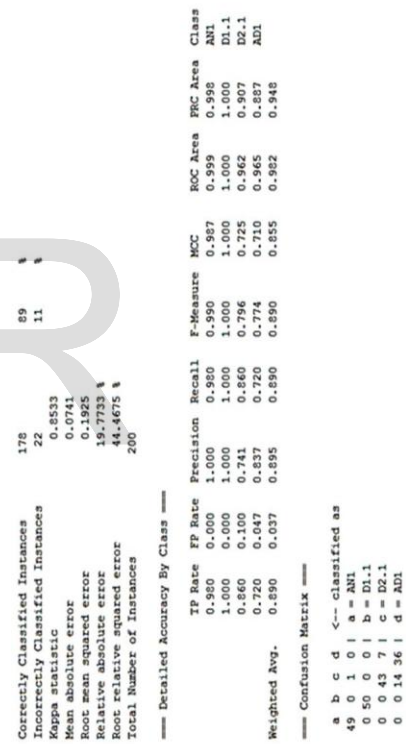


Fig. 4: Decision tree obtained from J48 algorithmfor operation-1 for 4 different tool conditions

The Visual Basic code described by [14] was used in Microsoft Excel to extract statistical features from all 4 different type of time domain plots of respective operations. A total 13 statistical features such as Mean, Standard Error, Median, Mode, Standard Deviation, Variance, Kurtosis, Skewness, Range, Minimum, Maximum, Summation, Count were computed to serve as features. In this work 200 samples are considered (50 samples for each condition * 4 conditions = 200 samples). The feature were selected using most significant steps of machine learning approach as it selects most significant features amongst all. It reduces dimensionality; speed up the classification algorithm; increases classification accuracy and makes the results more comprehensible [15]. The all 13 features are fed to J48 algorithm and generated decision tree structure is shown in figure 3. It is observed that only 7 feature such as Stand. Error + Stand. Deviation + Mean + Skewness + Mode + Range + Condition found to be selected by J48 algorithm will serve to be most significant. Hence these 7 features are only used for feature classification.



```
Correctly Classified Instances         178               89      %
Incorrectly Classified Instances        22               11      %
Kappa statistic                          0.8533
Mean absolute error                      0.0741
Root mean squared error                  0.1925
Relative absolute error                 19.7733 %
Root relative squared error             44.4675 %
Total Number of Instances              200

=== Detailed Accuracy By Class ===

                 TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                 0.980    0.000    1.000      0.980    0.990      0.987    0.999     0.998     AN1
                 1.000    0.000    1.000      1.000    1.000      1.000    1.000     1.000     D1.1
                 0.860    0.100    0.741      0.860    0.796      0.725    0.962     0.907     D2.1
                 0.720    0.047    0.837      0.720    0.774      0.710    0.965     0.887     AD1
Weighted Avg.    0.890    0.037    0.895      0.890    0.890      0.855    0.982     0.948

=== Confusion Matrix ===

  a  b  c  d   <-- classified as
 49  0  1  0 |  a = AN1
  0 50  0  0 |  b = D1.1
  0  0 43  7 |  c = D2.1
  0  0 14 36 |  d = AD1
```

Fig. 5: Classification result using Random Forest classifier forest 1st operation performed for 4 different tool conditions

It is observed from confusion matrix shown in figure 5 that for 'AN1' condition (all inserts are new) of tool, 49 samples were correctly classified as 'All New', whereas 1 samples were misclassified as 'D2.1' (i.e. three inserts new and one with nose wear) conditionFor condition 'D1.1' (three inserts new and one with flank wear), 50 samples were correctly classified as condition of three inserts new and one with flank wear. For 'D2.1' condition (three inserts new and one with nose wear) of tool, 43 samples were correctly classified as 'three inserts new and one with nose wear', whereas 7 samples were misclassified as 'AD1' (i.e. all inserts are defective condition).

Table 3: Accuracy of Random Forest Classifier

Expt. Runs	Constrains used for classification (No. of Constrains selected by J48 tree)	Accuracy of RFC
1	Standared Error + Standared Deviation + Mean + Skewness + Mode + Range + Maximum+ Kurtosis + Median (9) [Average accuracy of random forest classifier]	86%

The Table 3 represents feature selection and classification accuracy of Random Forest classifier for all 9 features operationssuch as Standared Error,Standared Deviation, Mean, Skewness, Mode, Range, Maximum, Kurtosis and Medianare performed for 4 different tool conditions using Weka software. The average accuracy of random forest classifier is found to be 86%. It is also observed that, the approach adopted for predition of milling tool condition monitoring technique can predict upto the accuracy of greater than 14 percent.

5.Conclusion

The machine learning based condition monitoring of milling cutter of VMC was successfully demonstrated. The vibration signals were acquired from accelerometer mounted on milling cutter holder. The vibration data acquired with a combination of faulty and new inserts. The Excel based Visual Basic code and script was successfully implemented to extract statistical features.The Random Forest Algorithm provides fault detection accuracy upto14 % and found to be a best classifier. The approach adopted is most suitable for real time implementation of fault diagnosis in machine tools.

References

1. Konrad H., Isermann R., “Diagnosis of different faults in milling using drive signals and process models” 13th Trienaiul World Congress, San Francisco. USA, pp 601-606.

2. Paul W. Prickett, Raees A. Siddiqui & Roger I. Grosvenor, “A microcontroller-based end milling cutter monitoring and management system” Int J AdvManufTechnol, 2011, Issue 29 December 2010, pp 855-867
3. Paul W. Prickett&Raees A. Siddiqui & Roger I. Grosvenor, “The development of an end-milling process depth of cut monitoring system” Int J AdvManufTechnol, 2011,Issue 2 May 2010, pp 89-100.

4. H. Shao, H.L. Wang, X. M. Zhao, “A cutting power model for tool wear monitoring in milling” International journal of Machine of Tools and Manufacture, 2004, pp 1503-1509

5. MashhoodAsad Butt, Yiqing Yang, Xingzheng Pei, Qiang Liu, “Five-axis milling vibration attenuation of freeform thin-walled part by eddy current damping” Precision Engineering, 2018, Issue 9 November 2017, pp 682-690

6. YiquanDaia, KunpengZhua, “A machine vision system for micro-milling tool condition monitoring” Precision Engineering, 2017, Issue 5-12-2017, pp 12-19.

7. Huang Zhigang, “Research on Real-time Monitoring for Milling Cutter Wear Based on NeuralNetwork” 14th Youth Conference on Communication, 2009, pp 189-199.

8. FranciCus - UrosZuperl, “Real-Time Cutting Tool Condition Monitoring in Milling” Journal of Mechanical Engineering, 2010, Issue 2010, pp 142-150.

9. Muhammad Zahid, Hassan Mushtaq, “Development of a Prototype System for Milling ToolCondition Monitoring” MS, Thesis, 2011, pp 140-149.

10. BesmirCuka, Dong-Won Kim, “Fuzzy logic based tool condition monitoring for end-milling” Robotics and Computer-Integrated Manufacturing Manufacturing, 2016, Issue 26December 2016, pp 120-128.

11. QunRen, Marek Balazinski, Luc Baron, Krzysztof Jemielniak, RuxandraBotez, SofianeAchiche, “Fuzzy tool condition monitoring system based on acoustic in micromilling” Information Sciences, 2013, Issue 5 June 2013,pp 98-103.

12. Hugo M. B. de Carvalhoa,b*, Jefferson de Oliveira Gomesb, Marco Antonio Schmidta, Vitor L.C. Brandão, “Vibration analysis and energy efficiency in interrupted face milling processes” The 22nd CIRP Conference on Life Cycle Engineering, 2015, pp 245-250