ANALYSIS OF TOOL WEAR IN MILLING USING MACHINE LEARNING TECHNIQUE

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Abstract - *Predicting tool wear while machining is a difficult aspect. Traditional methods to use process characteristics that affect tool wear are available, however, some parameters are particular to the machining process, and existing prediction models fail. The current work discusses a process supervision system that uses machine learning (logistic regression) to anticipate tool wear. An application for the prediction of tool wear while milling is chosen as a case study to demonstrate the methodology. The next dataset will be created by running the milling operation with the end mill cutter under three different conditions, namely 1. New Tool, 2. Medium Wear Tool, and 3. Blunt Tool, and recording the vibration reading as acceleration and frequency using an FFT analyzer. There are many vibration analysis techniques, but choosing the best one requires evaluating the parameters and surroundings of the milling operation. The frequency domain is used for vibration analysis. Utilizing the Logistic Regression Method, train the acquired dataset and predict accuracy, as well as the tool condition using this prediction. The accuracy of the trained model is 99.1%. Now with the obtained accuracy, it is possible to implement this algorithm in industrial working conditions to accurately predict the conditioning of the tool.*

***Key Words*: tool wear prediction, logistic regression, milling machine, vibration Analysis, FFT Analyzer.**

1.INTRODUCTION

To be competitive, manufacturing sectors prioritize improving both quality and production costs. The 'Quality at Source' idea mandates that quality be inspected at every stage. Poorly completed items are the result of using worn-out tools for milling. Due to subpar output, a bad finish results in quality loss and rejection. Costs will go up if a tool is used to prevent a drop in quality.[1] Track the machining quality by foreseeing tool wear, monitoring the Tool Life Cycle has gained popularity in the research community. It is challenging and complex to mathematically describe the machining process. There are attempts to propose Artificial Neural Network (ANN) based approaches to predict that a tool is worn. The above approaches lack a robust method to select features to predict tool wear. Techniques with specific sophisticated optical sensors, such as laser displacement sensors, have been used to monitor tool conditions and identify the status of tool wear in real-time. However, these methods are still challenging to utilize in the sector because to their high cost and challenging assembly. Data-driven solutions are becoming more and more successful at predicting downtime and keeping track of the health of machine tools because to substantial advancements in computing and data science. Large volumes of data are being gathered during machining due to the availability of better sensor technologies, necessitating the need of a robust feature selection approach. The milling machine that was tested. In this paper the approach used for tool monitoring is based on vibration analysis and applying those vibration data (Acceleration Vs Frequency) on machine learning techniques to predict tool wear. FFT used for data acquisition. There are several methods to analyze vibration. Frequency domain works with higher frequency. It is observed that abnormal peaks are obtained at higher frequency.[2] So, acceleration taking as a parameter to vibration analysis. It is observed when machining with different tool conditions the acceleration peak also varies with respect to tool condition. Observations are then collected with higher frequency. New tool, medium worn tool and blunt tool is used for dataset preparation. In this project a logistic regression approach is used to describe the tool wear based on features that is determined by the multinomial logistic regression algorithm. The proposed method sets up a process for supervision and a predictive model on a milling machining process dataset.

2. LITERATURE REVIEW

Pooja V. Kamat, et.al.[1] The key findings are that machine learning techniques help in making machines more accurate. This paper discussed a comparative approach to tool wear monitoring using the clustering machine learning technique of K-Nearest Neighbour (k-NN) and deep learning technique of Convolutional Neural Network (CNN). The CNN and AE-LSTM techniques out-perform k-NN by achieving a higher degree of separability of around 93% and 87%, respectively. The techniques provide improved outcomes in terms of precision, recall, and f1-score, indicating that the models are more accurate at detecting false positives.

Vedant Parwala, et.al.[2] Paper suggests about the dataset on milling machine. Tool wear prediction during machining is a challenging problem. Traditional approaches are available to use the process parameters which influence tool wear but there are certain parameters which are very specific to the machining process and available prediction models fail. Present work discusses a Machine Learning based process supervisory system to predict the tool wear.

M. A. Elbestawi, et.al. [3] gives information about machine learning techniques. This paper presents an in-process tool wear prediction system, which uses a force sensor to monitor the progression of the tool flank wear and machine learning (ML), more specifically, a Convolutional Neural Network (CNN) as a method to predict tool wear. The proposed methodology is experimentally illustrated using milling as a test process.

Martin Zekveld, et.al. [4] Vibrations occur in all moving machinery while in operation. Every material has a characteristic pattern of vibration under specific conditions. Measuring, recording, and studying the changes in these vibration characteristics can be used to understand the changes in the test material itself. This paper presents the use of vibration analysis of the cutting process in milling to indicate the presence and progression of damage incurred by an end mill. The metal cutting experiments were performed on a mild steel workpiece without using any coolant to accelerate damage to the cutter, and classical processing schemes in time and frequency domains were applied to the resulting vibrations of the cutting process to obtain diagnostic information.

3.IDENTIFICATION OF GAPS/SCOPES OF WORK

- The manual tool wear analysis is time consuming and not precise.
- Most of the existing modern methods are complicated and costly.
- As a good alternative, there is a requirement of simple, fast, precise, cost effective and appropriate machine learning based methodology for analysis of tool wear and thus to improvise tool performance.

4. PROBLEM STATEMENT

To analyse tool wear in milling using machine learning technique and its incorporation on milling machines to investigate end mill cutter performance.

5. OBJECTIVES

- To study and understand the fundamentals of tool performance and logistic regression technique.
- To develop logistic regression-based method algorithms to investigate tool condition for the end mill cutter on a milling machine.
- To incorporate vibration correlation developed an algorithm to analyse tool condition for end mill cutters.

6. METHODOLOGY DETAILS

The project is carried out on an experimental basis. Tool failure happens randomly while machining. Workpiece damage and quality of work decreases because of tool failure.

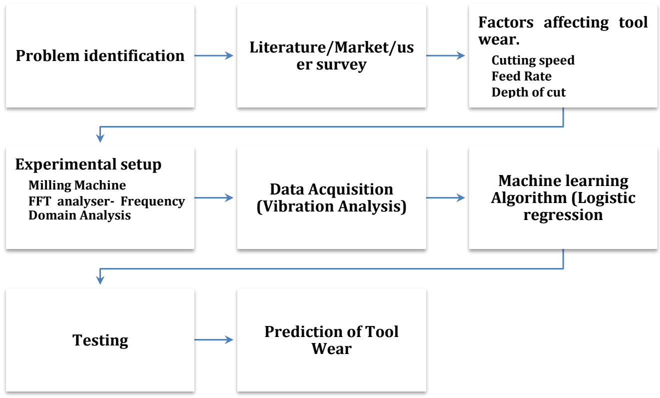

Fig -1 Process Flowchart

To reduce risk of failure of tools the machine learning techniques used. According to the literature survey tool failure seems to be a major issue while machining. Factors affecting tool life i.e., Cutting speed, Feed rate, Depth of cut. Vibrations produced because of worn tools. So, consider vibration as a parameter for prediction of tool wear. Milling machine used for experiment. Setup of experiment carried on a mailing machine. For detection of vibration FFT analyser used. FFT analyser provide vibration of different tool conditions i.e., new tool, medium wear tool, blunt tool while machining. Data is collected in the excel format. Machine learning technique used to predict tool wear. Logistic regression method used for classification and the logistic regression model train with dataset. with the maximum accuracy model available publicly for testing of milling tools.

7. VIBRATION ANALYSIS

Vibration analysis is a process that involves the measurement, analysis, and interpretation of vibration signals to understand the behavior and condition of a system or structure.

7.1 VIBRATION VARIABLES

The amplitude is measured and recorded in terms of three physical parameters.[5] They are:

- Displacement

Represents the distance between the component's at-rest position and the location from which it deviates the most. It counts the amount of movement of the component. Millimeters (mm), micrometers (m), or other suitable displacement units are used as the units of measurement.

- Velocity

represents the distance travelled per instant. It represents the rate of vibration of the component. Micrometers per second (m/s) or millimeters per second (mm/s) are the units.

- Acceleration

represents the velocity change rate. When the component is moving in the opposite direction, it is highest. Micrometers per second squared (m/s^2) or millimeters per second squared (mm/s^2) are used to measure it.

7.2 Time Domain Analysis

In time domain analysis, the tool vibration signal is examined directly in the time series. This approach provides insights into the tool's dynamic behavior over time. Key parameters commonly analyzed in the time domain include:

- Amplitude:

The magnitude of the vibration signal at a given time point.

- Time waveform:

The graphical representation of the vibration signal as a function of time. It allows for visual inspection of the signal's characteristics, such as the presence of spikes, irregularities, or trends.

- Statistical metrics:

Quantitative measures such as mean, standard deviation, and variance can provide information about the central tendency and variability of the vibration signal. Figure 4.3 represents an example of time domain analysis.

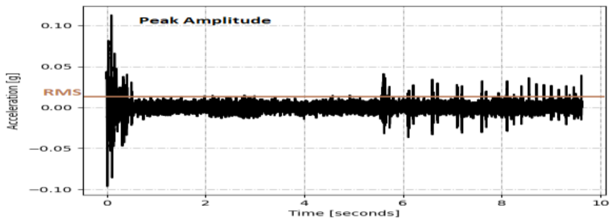

Fig -2 Time domain analysis

7.3 FREQUENCY DOMAIN ANALYSIS

In frequency domain analysis, the tool vibration signal is transformed from the time domain to the frequency domain using techniques such as the Fourier transform. This enables the examination of the signal's frequency components as represented as an example in Figure 3.

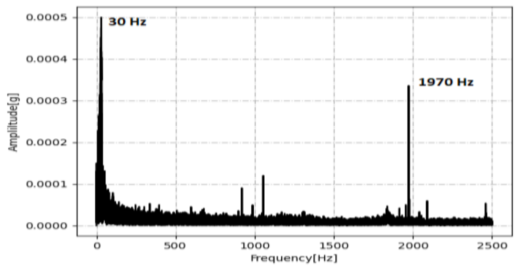

Fig -3 Frequency domain analysis

Combining Time and Frequency Domain Analysis: Both time and frequency domain analyses provide complementary information about tool vibrations. The time domain analysis allows for the observation of transient events and overall signal behavior. The time domain gives the best result at a lower speed below 100 RPM.[7] While the frequency domain works accurately at higher speeds i.e., above 100 RPM. Frequency domain analysis provides a detailed breakdown of the vibration's frequency components.

8 EXPERIMENTATIONS

In the Chapter experimental setup process is elaborated which includes milling machine setup and FFT Analyzer setup to acquire the vibration dataset and analysis part.

8.1MILLING MACHINE SPECIFICATION

Figure 4 shows the milling machine used for experimentation and below are the specifications of the machine. The conventional milling machine is used to perform end milling with the slotting operation.

Fig -4 Milling Machine

Table -1: Milling machine specification

Table	Working Pace - 1125mm - 250 mm. No. of T-Slots and size - 3 ✕ 18mm.
Range	Cross Feed by Hand - 250mm. Vertical Feed by Hand - 435mm. Longitudinal Feed by Hand/Auto - 600/525 mm.
Spindle	Spindle arbor - 25.4 mm. No. of spindle speed - 8 Range of spindle speed - 50 - 800 mm.
Feeds	No. of feeds - 4
Drive	Spindle motor 1440 RPM – 1.5kw / 2hp

8.2 FFT Analyzer Specification

Figure 5 shows the FFT (Fast Fourier Transform) Analyzer used in the Experimentation and the below table shows the specification of the FFT analyzer used in the Experiment.

Fig -5 FFT Analyzer

Table -2 Specification of FFT Analyzer

Number of channels	8
Inputs	Voltage, full bridge
ADC type	24-bit sigma-delta with anti-aliasing filter
Sampling rate	Simultaneous 200 KS/sec
Input type	Differential
Modes	Counting, waveform timing, encoder, tacho, gear tooth sensor

Figure 6 shows the experimental setup and procedure for the experimentation. To acquire vibration data of a milling tool using an FFT (Fast Fourier Transform) analyzer, procedure is mentioned below:

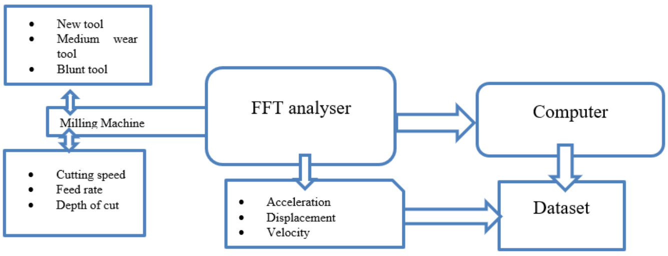

Fig -6 Experimental Setup

Initiate the data acquisition process on the FFT analyzer. Activate the milling machine to start the milling operation. With 0.5 mm of depth of cut and 380 RPM. Allow the machine to operate for the specified duration or number of revolutions. And perform slotting operation according to geometry.

Fig -7 Experiment

8.3 Analyse and Interpret Results:

Examine the frequency spectrum obtained from the FFT analysis. Identify significant peaks or frequency components that indicate vibration patterns or abnormalities. Analyze the amplitudes and frequencies to gain insights into the vibration characteristics of the milling tool.

Repeat the data acquisition process with different milling tool conditions to gather comparative data.

Fig -8 Experiment Outcome

8.4 Data Acquisition

The FFT analyzer records the vibration made by the milling tool, and it also records the readings for acceleration and frequency. The algorithm is then fed to the prepared dataset. There are natural vibrations, or the machine vibrates on its own while ignoring the universal natural vibrations present in every tool. The dataset format for Fast Fourier Transform (FFT) analysis typically follows a tabular structure, where each row represents a data point or sample, and each column corresponds to a specific attribute or feature. The dataset is manually created by choosing the frequency's highest acceleration peak. The dataset consists of 7360 rows. With 3 columns having Frequency, Acceleration and Tool as shown in Table 3.

Table -3 Dataset

	A	B	C
1	Frequency	Acceleration	Tool
2	15.63	0.387	New Tool
3	15.63	0.6	New Tool
4	15.63	0.547	New Tool
5	7.81	0.398	New Tool
6	7.81	0.162	New Tool
7	15.63	0.487	New Tool
8	15.63	0.11	New Tool
9	15.63	0.62	New Tool
10	7.81	0.396	New Tool
11	7.81	0.401	New Tool
12	7.81	0.195	New Tool
13	15.63	0.628	New Tool
14	15.63	0.344	New Tool
15	7.81	0.281	New Tool
16	7.81	0.23	New Tool
17	7.81	0.365	New Tool
18	7.81	0.354	New Tool
19	15.63	0.447	New Tool

9. Machine Learning Model

Logistic regression is supported by the Scikit-Learn library's Logistic Regression class. Set the "multi_class" argument to "multinomial" and the "solver" argument to a solver that supports multinomial logistic regression, such as "lbfgs" to configure the Logistic Regression class for multinomial logistic regression.[1] In this step the training and testing of the dataset is carried out. With respect to X and Y variable 70% of the data is used for the training and the remaining 30% is utilized for testing. Now this process of 70% training and 30% testing is randomized all over the dataset for better accuracy.

```
x_train,x_test,y_train,y_test=train_test_split(data[['Frequency','Acceleration']],data['Tool'],test_size=0.3)

from sklearn import linear_model

mymodel = linear_model.LogisticRegression()

mymodel.fit(x_train,y_train)
```

Now as per the required dataset model, the logistic regression model is imported in the algorithm.

```
LogisticRegression

LogisticRegression()
```

Now based on the above imported libraries and the dataset provided the accuracy of 98.87% is given by the algorithm.

```
mymodel.score(x_test,y_test)*100

98.87907608695652
```

10. Result and Discussion

10.1 Time Domain Result

Initially, the method was referred to as Time Domain analysis. When displacement, acceleration, and velocity were examined, it was discovered that these parameters were nearly the same for each tool. It is difficult to analyze because it is a new medium. And 58% accuracy is regarded as extremely poor.

- Accuracy of Machine learning model

58.92857142857143

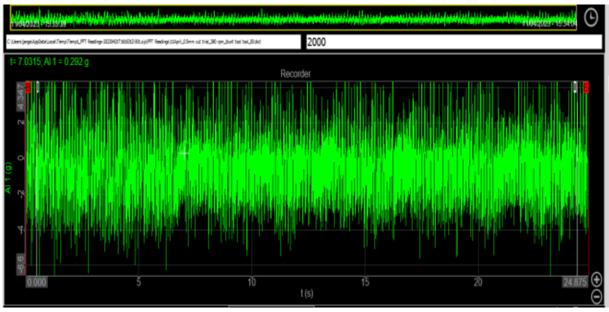

Fig -9 Time domain result

So, it is difficult to achieve the proposed goal with time domain analysis.

Milling Operation: Straight Slot

Table 4 indicates the acceleration range of tool in Time Domain with respect to time.

Table -4 Acceleration Range of the tool in Time Domain

Sr. No.	Tool Type	Tool Range (mm/sec^2)
1	New Tool	0.090-0.750
2	Medium Wear Tool	0.700-2.1
3	Blunt Tool	1.8-3.0

10.2 Frequency Domain Result

The frequency domain approach is used for the analysis of vibration. The data collected with manual observation is being analyzed. As per the considered parameter Frequency and acceleration, it is observed that there is variation in acceleration variation for three different tools. So, selecting Frequency domain analysis to achieve the proposed goal. The frequency at which the maximum peak of acceleration is observed. 7.81 Hz and 15.63 Hz. These two frequencies are of the two tips of the End Mill cutter.

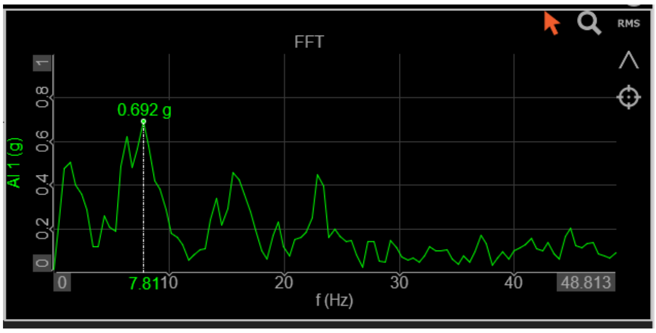

Fig -10 New tool analysis using frequency domain

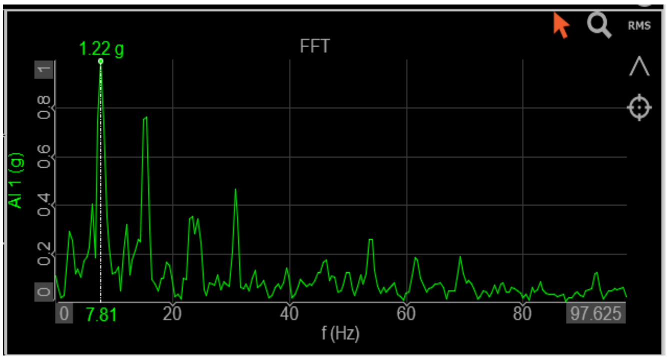

Fig -11 Medium wear tool analysis using frequency domain.

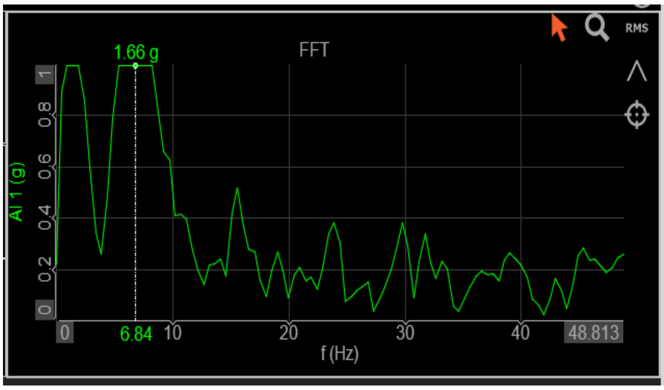

Fig -12 Blunt tool analysis using frequency domain.

Milling Operation: S-Slot

Table 5 shows the acceleration range of the tool with respect to frequency in the Frequency Domain. Acceleration varies with frequency.

Table -5 Acceleration Range of the tool in Frequency Domain

Sr.No.	Tool Type	Tool Range (mm/sec^2)
1	New Tool	0.090-0.650
2	Medium Wear Tool	0.650-1.8
3	Blunt Tool	1.8-2.9

The logistic regression model achieved an accuracy of 98% on the testing set, indicating its effectiveness in tool monitoring.

```
mymodel.score(x_test,y_test)*100
```

98.87907608695652

These metrics demonstrate the model's ability to identify faulty tools accurately. The model accuracy value of 0.98 indicates a good discriminatory power of the model. The confusion matrix shows the precision of the model as shown in Figure 13.

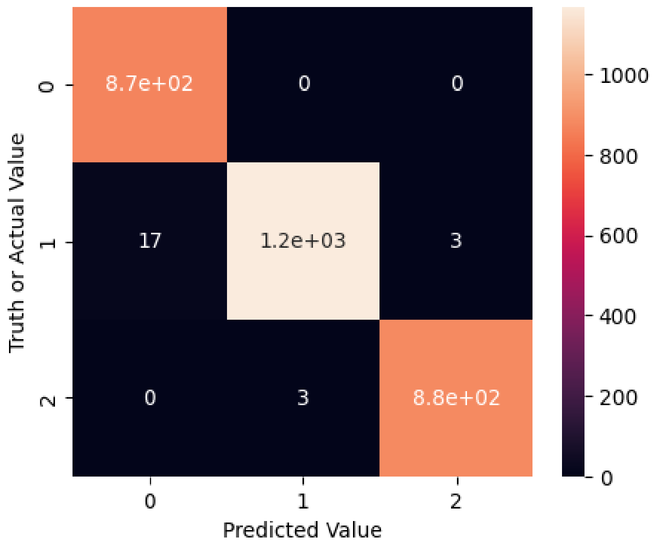

Fig -13 Confusion matrix

The result of the model is elaborated by a graph that shows the correlation of acceleration and frequency with different conditioned tools. The analysis of the result is shown in Figure 14.

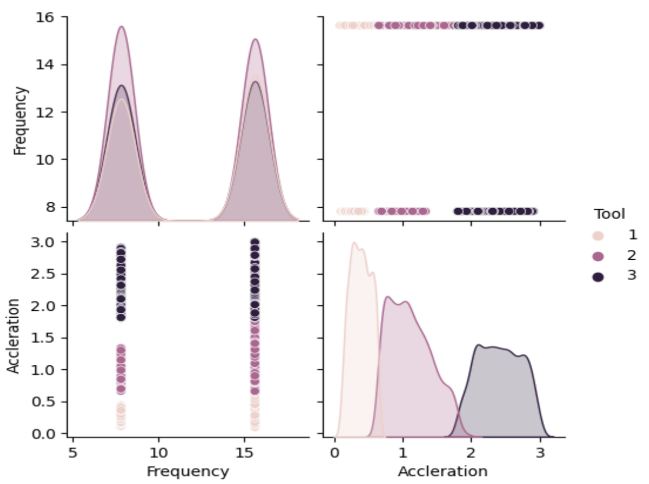

Fig -14 Result Analysis Graph.

3. CONCLUSIONS

In this project, logistic regression demonstrated promising results in tool monitoring, achieving high accuracy, precision, recall, and a good discriminatory power. The findings suggest that logistic regression can be a valuable tool for monitoring industrial processes, aiding in the timely detection of tool failures, and improving operational efficiency. The project suggests a strategy for creating a supervisory system for machining to track tool wear. The suggested solution demonstrates adaptability to operating circumstances and can be configured with any machining system that executes various operations or gathers various process data. This method can also be used to estimate the number of operations the cutting tool will survive given the probability of tool wear, which shortens the time required for a tool changeover. These monitoring systems can be utilized in medium-sized manufacturing facilities to efficiently halt operations and ensure continuous production. A strong tool management system will result from this, which will also lower the overall tool cost per unit of production. Using the logistic regression technique to train the data and collect the reading in the time domain one can achieve accuracy up to 58.92%. Using the logistic regression technique to train the data and collect the reading in the Frequency domain one can achieve an accuracy of up to 98.64%. Now with the obtained accuracy, it is possible to implement this algorithm in industrial working conditions to accurately predict the condition. Thus, by using the Logistic regression technique tool condition can be determined.

REFERENCES

[1] Pooja V. Kamat et. al., "Tool wear Prediction in milling: Comparative Analysis Based on Machine Learning" IJCDs journal Published 9 Jan 2022

[2] Vedant Parwala et.al,"Machine learning based approach for process supervision to predict tool wear during machining" Elsevier B. V. Procedia CIRP 98 (2021) 133–138.

[3] M. A. Elbestawi et.al., "In-process monitoring of tool wear in milling using cutting force signature" International Journal of Machine Tools and Manufacture, Volume 31, Issue 1, 1991.

[4] ShixuSun et.al., "Tool breakage Detection of milling cutting insert based on SVM" Elsevier Ltd. (International Federation of Automatic Control), Volume 52, Issue 13, 2019

[5] Sebastian Bombinski et.al., "Detection of accelerated tool wear in turning" by Elsevier Ltd. Mechanical Systems and Signal Processing.18 May 2021

[6] Caixu YUE et.al., "A review of chatter vibration research in milling" Chinese Journal of Aeronautics, 1 June 2018.

[7] Maciej Tabaszewski et.al., "Machine Learning Approaches for Monitoring of Tool Wear during Grey Cast-Iron Turning" MDPI Journal Conference Series: Materials Science and Engineering, Volume 624, Materials 2022, *15*(12), 4359.

[8] M Schwenzer1 et.al., "Machine Learning for Tool Wear Classification in Milling Based on Force and Current Sensors" IOP Publishing. DOI 10.1088/1757-899X/520/1/012009.

[9] Zhou Chang'an et.al., "Vibration singularity analysis for milling tool condition monitoring" by Elsevier Volume 166, 15 January 2020, 105254.

[10] Hamed Moradi et.al., "Forced vibration analysis of the milling process with structural nonlinearity, internal resonance, tool wear and process damping effects" International Journal of Nonlinear MechanicsVolume 54, September 2013, Pages 22-34.