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Cutting Tool Condition Monitoring and Validation Using ANN- A Comprehensive Research

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ABSTRACT: Tool life determines the rate of production in machine shop. The acceptance of part depends on how close the specifications of the work part are met. The specification of a part normally comprises of dimensional accuracy in terms of tolerance and surface finish. The performance of tool is also measured in terms of metal removal rate. It is thus becomes imperative to measure the Tool Life. The aim of the present paper is to develop a methodology for collection of real time data and diagnosis of the conditions of tool failure. The method shall include a setup for collection of data under defined cutting conditions and developing appropriate computer software for acquisition and analysis of the relevant data. This Expert system shall contribute towards determination of Tool life in the Real World Usage. The worn out tool affects the accuracy of the work part and also produces machine chatter which further aggravates the problem. The problems due to these are cumulative and difficult to trace in time. The proposed work aims at developing a system to measure the accuracy and surface finish of the work part along with the vibrations generated due to variations in cutting parameters which affects the Tool Life using the intelligent systems. The system shall determine the condition of the tool at any given point. [13][16].The intelligent system thus develop shall exhibit the tool performance and predict its failure and determine the Tool Life. Tool life and tool quality are decisive criteria for the successful application of bulk metal forming in industrial production. They directly affect production costs and therefore competitiveness of the process and may as well have a considerable impact on tool supply, stability of production and last but not least delivery performance. Since tool failure is unavoidable, tool life must be properly taken into account for the calculation of tooling cost and planning of tool supply for production. [15]

KEYWORDS: Tool Life, Expert System, Tooling cost, Real world Usage.

I. INTRODUCTION

Every cutting process is designed and operated upon considering the working life of the tool. The tool life can be calculated using the Taylor's formula. The difficulty is that once the cutting starts, the cutting parameters no longer remains constant as pre-decided but varies frequently. This leads to the early failure of the tool than the calculated span of tool life. Another problem arises is due to these variations in cutting parameters in the midway of machining there is no procedure to calculate the remaining life of the tool. It is proposed to develop an artificial intelligent based system which shall not only determine the tool life for any cutting parameters but during the course of machining it shall calculate the remaining life of the tool. For this purpose the vibration signals may be collected and trained against the machining process for the entire tool life and the neural network is trained to meet the objective.[12]

The method shall include a setup for collection of data under defined cutting conditions and developing appropriate computer software for acquisition and analysis of the relevant data. The comparison will be made between data for experimental study and software study comparing the data for variation of tool wear rate, material removal rate and surface hardness using MATLAB R2009a software. The objective of this study is to predict the effects of cutting parameters on the variations of cutting forces during end milling operation on vertical milling machine. As a mandatory and important step a review of past researches is performed. [11]

The tool wear cutting condition is a crucial factor in all metal cutting processes. It's noteworthy that, direct monitoring systems are not easily implemented because their need of ingenious measuring methods. For this reason, indirect measurements are required for the estimation of cutting tool wear. Different machine tools sensors signals are used for monitoring and diagnosing the cutting tool wear condition. [12][19]

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II. MATERIALS AND METHODS

For the Operation we have conducted on Lathe Machine the SPCT (Single point cutting tool) used is High carbon tool steels with appropriate hardening and tempering. Usually these May contain combinations of tungsten, chromium, vanadium, molybdenum, cobalt and can take heavy cuts, withstand shock and maintain sharp cutting edge under red heat. In our current case the tool contain 25% to 35% chromium, 4% to 25% tungsten and 1% to 3% carbon, Remainder cobalt and it Operates 2 ½ times speed of high-speed steel.
To lay out a brief about the methods undertaken is, we have conducted a simple turning operation on the lathe machine and for every new set of parameters (as can be understood in the lines below) we have used a new work piece.

III. LITERATURE REVIEW AND BACKGROUND

A vibration study, as performed by Metso[17], covers the mechanical condition and the dynamic behaviour of the entire machine line from stock preparation to finishing, or of specific machine sections in troubleshooting. Both current production speeds and targeted speeds are studied. The cost of the study can be quickly recovered through subsequent savings on parts purchases, problem solving, line speed up, and machine rebuilds. A vibration study may also be included as part of a larger scope Machine Analysis. Vibration and noise in metal cutting are ubiquitous problems in the workshop. Today the industry aims at smaller tolerances in surface finish. Harder regulations in terms of the noise levels in the operator environment are also central. One step towards a solution to the noise and vibration problems is to investigate what kind of vibrations that is present in an operation. The vibrations in a specific machining operation performed on the lathe machine have been put under scrutiny in the first part of this proposed research. Analytical models have been compared with experimental results and the vibration pattern has been determined. [16][14][17]

When it comes to calculating the tool life we must recall nearly last one decade that has been capitalized by calculation and statistical analysis of tool wear and tool life. We have often believed that tool wears' basic mechanisms and various kinds of wear produced at the tip of the tool can be well determined depending on the experimental measurements of different tool wears and application of suitable statistical techniques and because of this it was possible to predict the tool life and hence the intervals of changing the tool after it is worn out. This period was marked my exclusive and intensive work on popular concept of "data bases on machining parameters" but parallel forecast was directing towards poor future prospects for the cutting process following the high energy coming into play because of HSM- high speed machining and economic constraints clubbed with each other. On the contrary the point to be noted is that various recent developments in machine tools, automation, computerized controls and in addition the improvement in the cutting tool material, various protective coatings and special geometrical shapes make such intense forecasts completely wrong and undermines the argument of flaw. The degree of use of the machining operations has increased notably which is a good sign. The new improvements in cutting materials increase the tool efficiency costs of performing machining operations and also tremendously increase the cutting reliability and quality of products. [15][20]

Various Tool Monitoring Techniques by Researchers:
D.E. Dimla Sr.(2004) has done an experimental investigation aimed at identifying and isolating effects of cutting conditions on cutting forces and vibrations from those arising as a result of cutting tool wear. Machining test cuts were conducted using sharp and worn inserts and the effects of cutting conditions (depth of cut, cutting speed and feed rate) studied. Signals were recorded with significant variation of the cutting conditions when the tool was relatively fresh/sharp and/or old/worn such that only the effects of cutting conditions alteration were pronounced on the signals. Time and frequency domain was used to pinpoint the exact nature of changes on the signals due to alteration of the cutting conditions. The depth of cut and feed rate was deemed to affect the signal characteristics significantly and a specific frequency band most sensitive to the changes identified. **M. Rogante(2009)** have done tool condition monitoring (TCM) of dry turning processes on automatic lathes, and describe the information generated by different measuring systems applied to the single point turning situation. The outputs measured were correlated with the state and wear rate of the cutting tools. Semi-finishing and rough-shaping tests have been carried out at different cutting speeds. The behaviours of the utilized power, the tool-holder shank vibrations and the surface roughness vs. pass number were studied. Taylor's equation was determined for the three types of inserts used. The parameters investigated show that the results are directly influenced by degree of the tool wear and also give indications when the tool insert has reached the end of its life. [8][18]

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Classifications of tool wear by Researchers:
All the above mentioned changes reduce the challenge of calculating the tool life in a conventional method. ValeryMarinov's Publication on tool wear and tool life says that the life of a cutting tool can be terminated by a number of means, although they fall broadly into two main categories:

1. Gradual wearing of certain regions of the face and flank of the cutting tool, and
2. Abrupt tool failure.

Considering the more desirable (case 1) the life of a cutting tool is therefore determined by the amount of wear that has occurred on the tool profile and which reduces the efficiency of cutting to an unacceptable level, or eventually causes tool failure (case 2).[11]
Shaw classified tool wear types according to the system developed by:
1. Adhesive wears which occurs when the mating surfaces come close enough together to form strong bonds. If such bonds are stronger than the local strength of the material, a particle may transfer from one surface to the other. [9]
2. Abrasive wears which involves the loss of material by the formation of chips, as in abrasive machining. For such a type to be initiated it is necessary that one material be harder, or have harder constituents, than the other member of the sliding pair; or, that hard particles be formed by chemical reaction of the wear debris.[26]
3. Diffusion wear which results when surface temperatures become very high and surface velocities are very low, allowing the solid state to play a role in the wear process.[9]
Andri popa & co. carried out similar kind of work as our proposed research. In their research drilling tests were carried out on ø 80 mm forged bars, usually as raw material in turbine discs manufacturing. Same heat treatment is carried out on the bars as the discs (write outcome of the paper i.e. conclusion [10]
If we talk about the flank wear, it is necessary that we perform some experiment till the moment flank wear of the tool receive to criteria size but it takes large time and incur high costs. The wear time curve came into picture to prevent this. In case of almost all the cutting tools the wear time curve tentatively follows the pattern similar to what is shown in the figure [1] below, which has three distinct wear zones i.e. steady wear, initial wear and severe wear. It must well be taken care that the tool should be discarded before the moment it reaches the severe wear zone. When we carry out the machining process for several times, the wear after each cutting pass is noted down and by extrapolating the wear time curve the time for limiting flank wear is calculated. The same approach shall be implemented for our proposed research work too. The only difference shall be of the neural network and analysis platform we have adopted which is vibration.

IV. RESEARCH MOTIVATION

The reason for working on this activity is to anticipate the tool life while the machining is in process. The failure of cutting tool results in poor surface finish, increased vibrations in the machines, increased cutting forces & power consumptions, overheating of tools etc. It therefore becomes imperative to anticipate the tool failure and determine the tool life. Tool life as defined by the amount of material removed before it cease to work is in major depends upon the cutting parameters viz; cutting speed, depth of cut and feed rate. The tool life as calculated by using the above formula no longer remains useful when the tool is in operation and therefore the behaviour of cutting parameters and their effect on tool life becomes important. While working online it is rather difficult to determine the tool life as while machining the variation in cutting parameters and the specification of work leaves the operator in critical situation to predict the tool life.[15] The effort in the direction of developing a system with which the effect of various parameters and their characteristics affecting the tool life can be consolidated will bring about a significant contribution on the shop floor where the operator may get an opportunity to predict the tool failure, expected life of the cutting tool and determining its remaining life.[19]

V. DEVELOPMENT OF THE SETUP

The development an Expert system incorporating artificial intelligence with inbuilt intelligence based on the concept of neural network is the core of this research. [22][21]

The cutting process causes a kind of vibration peculiar for its cutting characteristics. It is planned to establish a relationship for the vibration observed for various cutting conditions. For every combination of *cutting speed, feed rate and depth of cut*, keeping other factors as constant a vibration shall be recorded which shall truly reflect the machine performance.Controlling vibration phenomena in production machines is one of the approaches for improving their efficiency. This also applies to cutting tool vibrations generated during machining, when the magnitude of the

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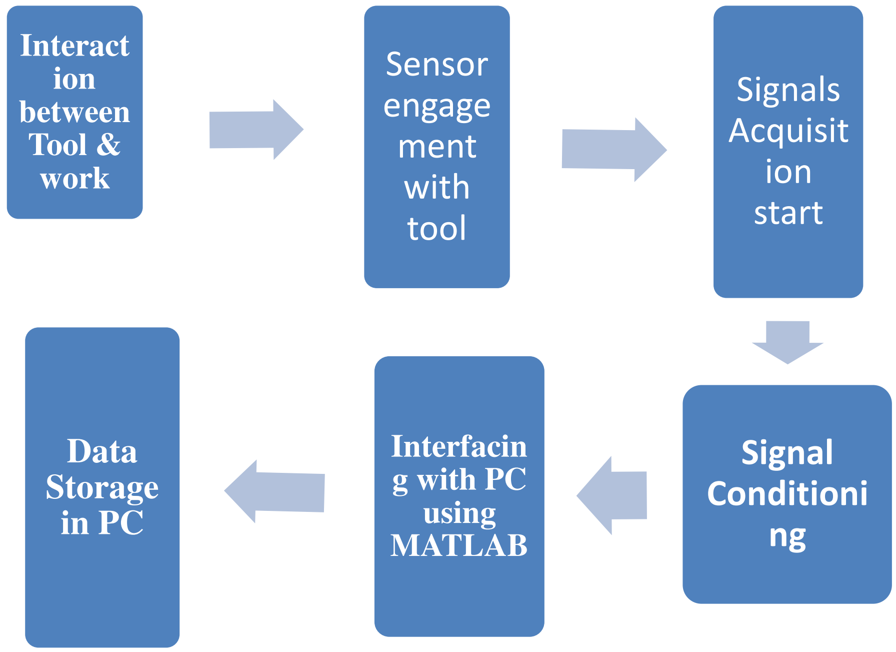
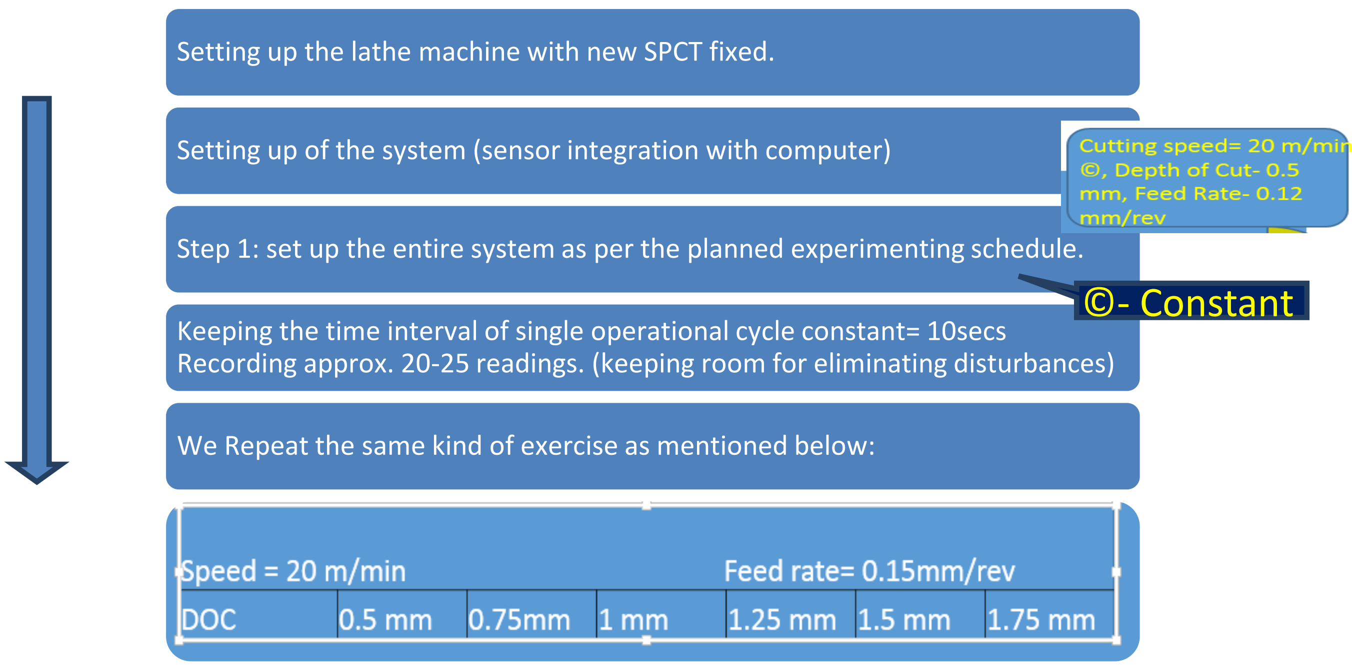
vibrations directly influences work piece surface quality. Continuous efforts to enhance cutting performance have revealed that machining quality may be improved if a tool is assisted with high-frequency vibrations.[23][11]
Vibration is widely used for condition monitoring of rotating machinery. However, vibration has not been used to the same extent in tool condition monitoring, probably because as a method it is rather sensitive to noise which is present in cutting processes.

PROCESS FLOW

Functionality Block Diagram of the Network





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Step.4.Now changing the parameters and setting it as Speed- 90 FPM, Depth of Cut- 2 mm©, Feed Rate- Very Slow

Keeping the time interval of single operational cycle constant= 10secs Recording approx. 20-25 readings. (keeping room for eliminating disturbances)

We Repeat the same kind of exercise as mentioned below

Cutting speed = 20 m/min				Depth of cut= 0.5 mm		
Feed Rate mm/rev	0.12	0.15	0.18	0.21	0.24	0.27

Repeating Step 4 with settings as Speed- 90 FPM©, Depth of Cut- 2 mm©, Feed Rate- Medium

Step 7: Now changing the parameters and setting it as Speed- 90 FPM, Depth of Cut- 2 mm©, Feed Rate- Medium ©

Keeping the time interval of single operational cycle constant= 10secs Recording approx. 20-25 readings. (keeping room for eliminating disturbances)

We Repeat the same kind of exercise as mentioned below

Feed Rate= 0.15 mm/rev			Depth of cut= 0.5 mm			
Cutting Speed m/min	20	25	30	35	40	45

Take note of the Step by step Variation in different parameters for deriving Time- Domain Analysis.

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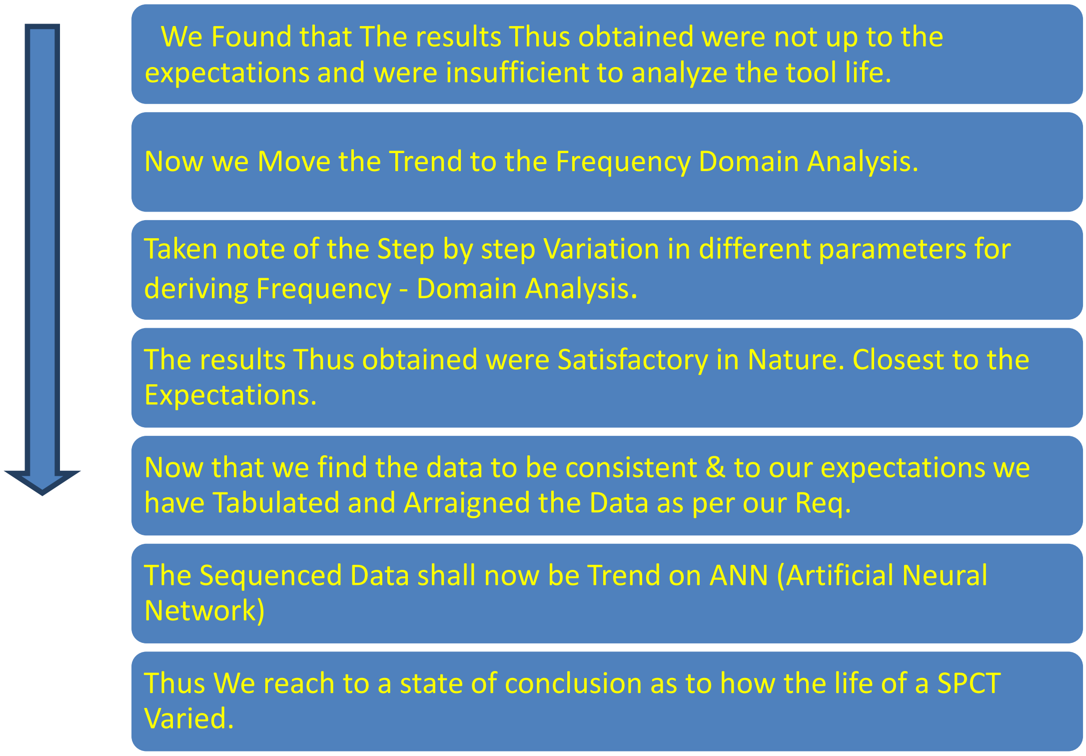

VI. DEVELOPMENT AND PROCEEDING OF THE TECHNOLOGY: (IMPORTANT)

As we know

- Time-domain response delivers data and plots, characteristics such as response time and overshoot, simulation
- When you perform time-domain analysis of a dynamic system model, you may want one or more of the following:
- A plot of the system response as a function of time.
- Numerical values of the system response in a data array.
- Numerical values of characteristics of the system response such as peak response or settling time.
- To obtain response plots we use:
- Plot system response data, visualize response characteristics on plots, and compare responses of multiple systems on a single plot.
- Linear analysis tool for plotting many types of system responses simultaneously, including both time-domain and frequency-domain responses
- We in this project have used time-domain and frequency domain responses.

Sample of one of the Time Domain Data:

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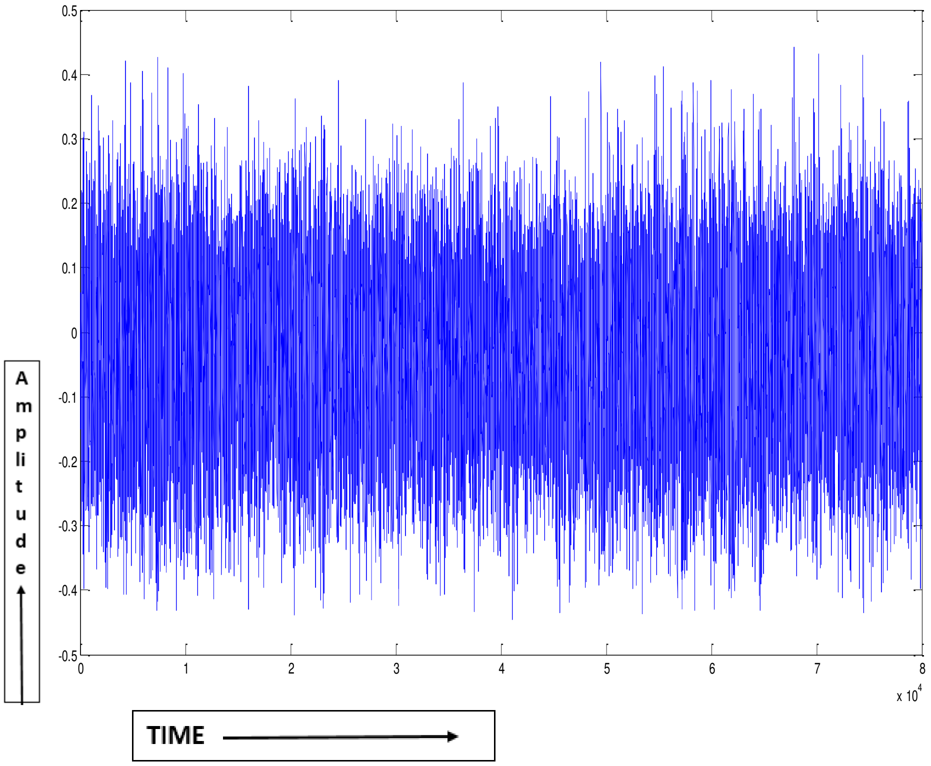
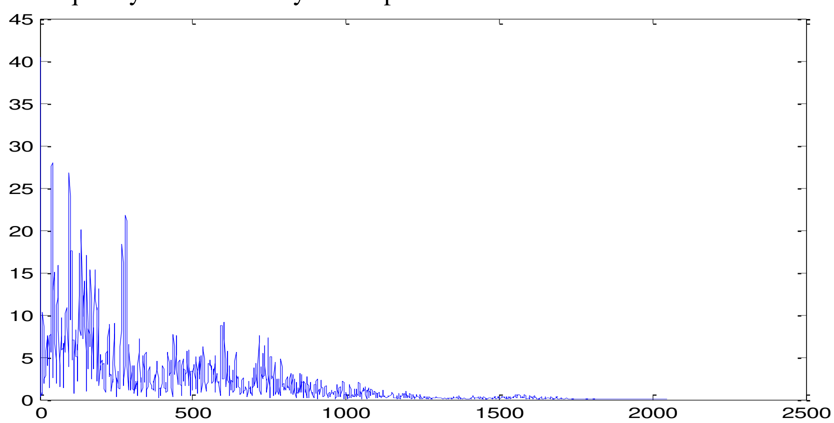


The conditions set were:

Speed = 20 m/min	Feed rate= 0.15 mm/rev
Depth of Cut- 1 mm	

For the same condition Frequency Domain Analysis sample:



Y- Frequency, X- Time

The classified acquired data is given as input for training the Network. The training of the Neural Network is carried out using MATLAB R2009a.

We have mentioned above that the MATLAB is the tool used for establishing a Neural Network.
As we have received various data and these data is segregated and classified in terms of:

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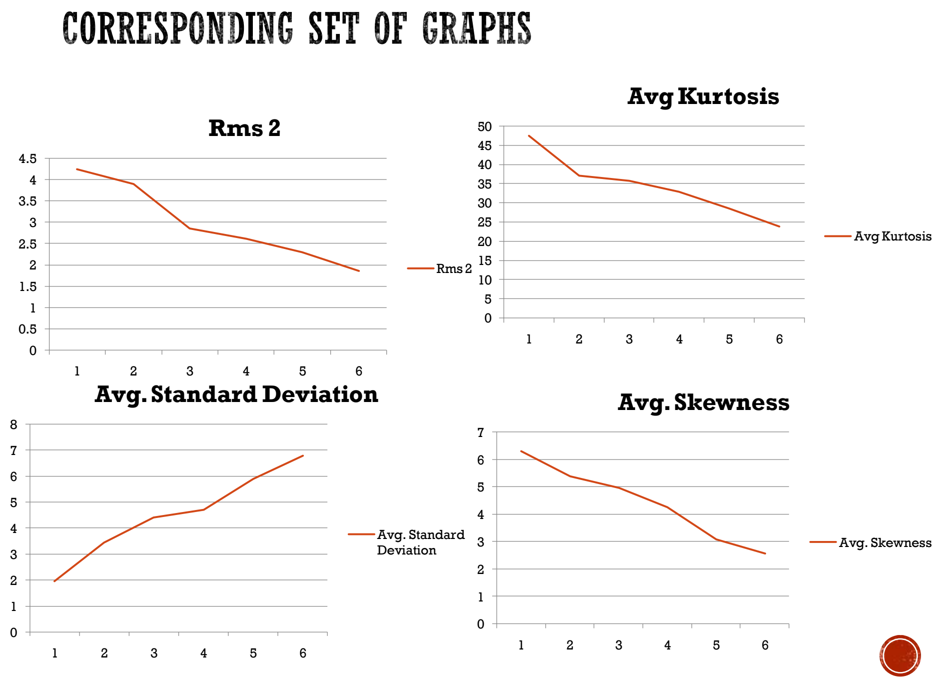
1) Parameters with Constant. Speed, with variation in DOC & Feed Rate.
2) Parameters with Constant Feed rate with variation in DOC & Cutting speed.
3) Parameters with Constant DOC with variation in Feed Rate and Cutting Speed.

Variation the values of Kurtosis, Standard Deviation, Variance and RMS are observed to be as below:



The data thus classified in terms of above statistical analysis is structured for the entire life of the cutting tool for different given conditions as above.
The statistical data is obtained for the given cutting conditions and identified as best tool condition & worst tool condition. Between the two extremes 18 different tool conditions are identified for all the tool conditions.
As a part of the in-depth and spot on research conclusion of the tool life calculation technique we intend to carry forward with FREQUENCY DOMAIN analysis followed by FFT(Fast Fourier transform) and then computing the Big Data through ANN(Artificial Neural Network).

It is based on the hypothesis that the real time data collected shall be analyzed and the intelligent system thus developed shall help to determine the tool life and its performance.

To validate that the analysis made by us was in line with the reality we did an activity and The cutting tool with unknown tool condition was used to get the data and then was tested with the ANN and its tool life was predicted which was found to be correct based on its characteristics matching with the ANN Trends.

We tool the ANN trends randomly to validate the trends we received and we found our Analysis to be correct.
As a part of the bottom line is it quite clear that when any of the 3 parameters were increased and was put to continuous operation the tool got wear rapidly increasing the vibration and the freq. of the vibrations which showed in the time domain analysis that the amplitudes mapped against the time were high. As a result of this further reinforcement shall be done using Frequency domain analysis and ANN Training.

The architecture selected and used for training of the network to meet the requirement is **FEED FORWARD NEURAL NETWORK.**

The Results of ANN Training is:
<u>Training of ANN based expert system</u>

Training Network

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No of training data	72
No of target epoch	1000
No of epoch achieved	945
Target error	0.01
Error achieved	0.0058

Testing of network

No of training data	6
Data with known conditions	4
Data with unknown condition	4

DATA KNOWN TO TRAINING

We train the Data we have acquired on the ANN and Tabulated the result.

S. No	Feed (mm/rev)	Speed (m/min)	Depth of Cut (mm)	Remarks	Normal Data	
					Correct	False
1	0.12	20	0.5	---	✓	0
2	0.15	25	0.75	---	✓	0
3	0.18	30	1	---	✓	0
4	0.21	35	1.25	---	✓	0
5	0.24	40	1.5	---	✓	0
6	0.27	45	1.75	---	✓	0

[Table 5.39: ANN Training on Known Set of Data]

Known statistical parameters are used to test from among the intermediate steps of known cutting condition. The output obtained at the very initial i.e beginning indicates the 0% worn-out of the tool and remaining tool life in percentage. With the help of the plotted graphs below for condition 1 i.e Feed- 0.17 mm/rev, speed 30 m/min, DOC- 0.75 the tool is at 2nd part out of 20 parts thus we conclude that the tool is 20 % worn out and remaining life is 80%. The same is repeated for different known condition. NN is found to be well trained.

DATA KNOWN BUT RANDOMLY CHOOSEN

It's just to validate, we take different combinations in our same acquired data and process it on ANN. We find that our previous main reading is validated and the result is satisfactory.

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S. No	Feed (mm/rev)	Speed (m/min)	Depth of Cut (mm)	Remarks	Normal Data	
					Correct	False
1	0.17	30	0.75	---	✓	0
2	0.13	25	1.75	---	✓	0
3	0.19	35	1.5	---	✓	0
4	0.22	45	1.25	---	✓	0

[Table 5.40: ANN Training on Randomly chosen Data]

New unknown set of data acquired and input is given to NN. In the figures and diagrams below;
The output shows the result as tool worn out 25 %. That also indicates that the tool life left is 75 %. (refer the figures below) images.

Thus the Neural Network is well trained and able to give desired result. The NN Based on AI system is successfully analyzed and the performance is found to be satisfactory. The various input parameters are consolidated and the outcomes are as shown.

DATA UNKNOWN

TO Calibrate and verify the pattern in our data we have asked the operator to select any random value of his choice and we were on the pc storing the data in the digital form.

Sr. No	Feed (mm/rev)	Speed (m/min)	Depth of Cut (mm)	Remarks	Normal Data	
					Correct	False
1	0.26	20	0.25	---	✓	0
2	0.11	10	0.75	---	✓	0
3	0.14	25	0.5	---	✓	0
4	0.23	15	1.75	---	✓	0

[Table 5.41: ANN Training on Unknown set of Data]

VII. CONCLUSION AND FURTHER SCOPE

When the network was tested for the training data 6, data with known conditions was 4 and data with unknown conditions was also 4.

We Conclude that,

By doing Time domain analysis & frequency domain analysis and comparing the data with ANN, we find that the analysis is well matched by the ANN tool. With this entire work it can be concluded that on development of such an AI tool, a relation between the cutting conditions and tool life can be established. Further we can also predict the tool condition at different stages of cutting for the given cutting conditions by the use of Developed AI system. Thus the developed expert system is suitable for calculating t\elapsed and remaining tool life in terms of percentage. The developed system has been tested for several cutting conditions and found to be correct with nominal errors so that, an

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application in real time usage the operator working on the machine may be able to determine the present condition of the tool and can know the remaining life of the tool.

A very exhaustive and dedicated research has been carried out to develop an expert system to determine the tool like and condition at different stages of cutting based on the tool wear conditions at different stages of cutting. During this research work it was observed that the Taylor's equation is relevant and approximates the actual tool life but in the present research work the tool life has been established using the signals acquired for different tool wear conditions. Thus, the signals are acquired which shows the wear condition of the cutting tool at the extremes and the intermediate steps.The present system has a short coming that this cannot exactly calculate the tool life of a cutting tool. In order to achieve this it is recommended that identifying and establishing the various constraints of Taylor's equation for tool life and using these with the statistical parameters obtained in this research work may help in determining the tool life as well in terms of time value.

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