STUDY AND PREDICTION OF TOOL WEAR USING MACHINE LEARNING

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Abstract: **Industry 4.0 demands high degree of automation and accuracy, high efficiency, high productivity, less rejection, less manpower, and shorter lead time in production. NC, CNC and automated machine shops are playing vital role for higher productivity. Similarly, Quality inspection of the product should have higher productivity and shorter lead time. In Machining processes, tool wear significantly affects product quality, production efficiency, and cost. The ability to predict tool wear and remaining tool life is important for optimizing machining operations. This project focuses on study and predictive model using machine learning techniques to estimate tool wear and remaining tool life. These models will utilize various input parameters such as cutting speed, feed rate, material properties, tool geometry and many more to forecast tool wear progression. By analyzing historical data on tool wear and performance, the machine learning model will learn tool behavior and various significant parameters, enabling accurate predictions. The outcome of this project aims to enhance machining efficiency by reducing unplanned downtime and optimizing tool replacement schedules, ultimately leading to cost savings and improved productivity.**

Keywords: Machining process, Machine Learning, Tool Life, Tool Wear, Prediction.

INTRODUCTION

The use of technology has become essential to modern living. Different technologies are used by humans in their daily lives. Automation is essentially assigning human labor to automated machinery in order to boost output, improve quality, satisfy consumer demands and expectations, cut costs, and improve worker safety. Reducing physical and emotional stress and improving human life quality are the primary goals of technology implementation. In this project, an automated approach to dealing with mechanical applications has been used to meet the growing demand for automation in Industry 4.0 to reduce human efforts, increase productivity, efficiency, and accuracy, and to make the process simpler and more automated. This approach makes use of mechanical data, machine learning techniques, and computer science algorithms.

Advanced manufacturing technologies and automated production lines enable industries to make things more efficiently and at a reduced cost. This may encourage greater market competitiveness and aid in the growth of the clientele for the various sectors. As a result of recent developments in technology, the industrial sector is moving toward Industry 4.0, where sensor fusion is crucial to raising machine quality. Using sensory networks, the machine's behavior may be monitored during the manufacturing process and adjusted to increase efficiency. By combining data from multiple sensors, businesses can gain insights that would not be possible by any of the methods, leading to improved efficiency, quality, and safety in manufacturing and other industries. Prediction of tool life is much more important in high production industry which directly links to more productivity and quality control in production for industry. In these project we are basically using data based prediction model.

1.1 Background

Hobbing is a machining process used to produce gears. A very precise and effective method for creating a wide variety of gears, including worm, helical, and spur gears, is hobbing. During the hobbing gear production process, industries are primarily concerned with three things: stability, safety, and efficacy. The stability and extended life of a machine are attributed to high-level gears, which are essential components of every mechanical system. These gears are affected by specific factors that can damage or shorten the gear's lifespan while it is being produced. This results from temperature variations brought on by tension and strain while cutting. The impact of specific variables (such as temperature, current, vibration, etc.) may result in the workpiece developing fractures, uneven surfaces, and sharp edges, which could jeopardize the quality of the gear and result in significant losses for the industry.

The prediction of a tool's life is a critical during these production process and is necessary to change it before any sudden failure occurs. This is a part of predictive maintenance, and by predicting the remaining useful life (RUL) of the cutting tool during the hobbing process. Manufacturers can schedule tool replacements at the optimal time, minimizing downtime and reducing costs by using these techniques. This can be achieved using a variety of techniques, including sensor-based monitoring, machine learning algorithms, and predictive analytics. Manufacturers are able to learn about the wear of the cutting tool and its remaining useful tool life by tracking it continuously and evaluating the data that they collect.

1.2 Basic hobbing process

Hobbing is a machining process that uses a hobbing machine, a specialized milling machine, for splines, cutting gears,etc. Hobbing is utilized for a wide range of parts and quantities and is comparatively quick and affordable when compared to most other gear-forming techniques. Hobbing is very prevalent for helical and spur gear machining. Internal gears are cut with a rotary cutter, and their skiving can be done in a manner similar to that of hobbing external gears.

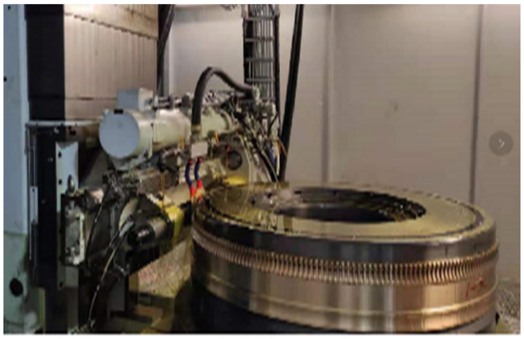


Fig 1.1. Hobbing machine

Key Components:

- Hob: The hob is a cutting tool with helical teeth that correspond to the gear teeth profile
- Hobbing Machine: This machine is designed specifically for hobbing operations. It holds the workpiece and the hob and synchronizes their movements.
- Workpiece (Gear Blank): The part that eventually becomes the gear after the hobbing process.

Challenges and Optimization in machining process:

- Achieving precise gear tooth profiles.
- Controlling vibrations and chatter during the cutting process.
- Optimizing cutting parameters for better efficiency and tool life.

1.3 Basic procedure for prediction technique

Prediction using machine learning is computerized algorithmic technique is application used with the applications in various industries majorly in manufacturing sector. Predictions can be done using various approaches in machine learning. These are used in various fields such are assembly,as maintenance, manufacturing, product development, etc. Model is selected based on the application on which it is to be implemented. It uses various datas and models for prediction. Models include numeric datas, linear datas, categorialdatas, image based data and many more. These have been seen useful in many other industries.

Various techniques that are used are:

- Image based
- Data based
- Numeric Based,ets

These techniques has made great progresses in the past few decades in various industries and applications. A lot of industrial activities have benefited from the application of prediction system. These activities include delicate manufacturing, production, printing, and many others. In the past, due to lack of datas, technology and many other factors these technique was not used before or developed before. Through continuous improvement, the technology is maturing daily. In recent years, as PCs have become more powerful and capable, prediction systems have become much more easier to apply on various applications. In these technique data is one of the most important input for the prediction model. Various datas are required for the training and implementation of models. Advantages of prediction system include:

- Higher Production rate with controlled quality.
- Decreased Downtime.
- Unnecessary tool wear will be avoided.
- Sudden failure and accident is prevented.

Basic procedure which is used is shown in the figure below.

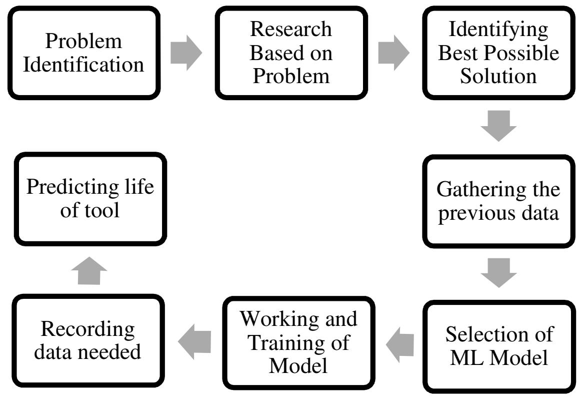


Fig. 1.2. Basic procedure for prediction

1.4 Problem Statement

The project focuses on development of a prediction model for tool wear in manufacturing industry which will help in reduction of downtime, controlling the quality of final product obtained. From these particular current system, industry will obtain a fully automated system which will help in higher, faster and quality production of goods. These project basically is based on data which is required for prediction. All machine parameters as well and tool and workpiece parameters are required for these project. These project algorithm is basically doneonmatlab and data is gathered in excel format. The aim is to "Predict the remaining useful tool life for particular production" and majorly will be used in manufacturing industry.

1.5 Objectives

Develop a Predictive Model: Create a machine learning model that predicts hob tool life based on input parameters such as cutting speed, feed rate, depth of cut, workpiece material, and tool material. Identify Key Predictive Factors: Determining key factors for prediction. Optimize Cutting Parameters: Use the predictive model to optimize cutting parameters (speed, feed, depth of cut) to maximize hob tool life while maintaining production efficiency and gear quality. Validate Model Accuracy: Validate the accuracy and reliability of the predictive model using experimental data collected from actual hobbing operations. Implement Real-time Monitoring System: Integrate the predictive model into a real-time monitoring system that continuously evaluates cutting conditions and provides feedback to operators to optimize tool usage. Reduce Manufacturing Costs and time: Predictive model can reduce tooling costs and minimize downtime by scheduling tool changes proactively based on predicted tool wear. Compare Different Machine Learning Approaches: Evaluate and compare the performance of different machine learning algorithms (e.g., regression models, decision trees, neural networks) for hob tool life prediction. Enhance Gear Manufacturing Efficiency: Show how accurate tool life prediction leads to improved overall efficiency in gear manufacturing processes, reducing scrap rates and improving production. Factor in Tool Wear Patterns: Develop insights into the wear patterns of hobs under different operating conditions and use this information to enhance the predictive model

2. LITERATURE REVIEW

This chapter sets the background for up-coming sections. It is an overview of the project with the wide and complex field of prediction model with machine learning technique. In addition, this chapter separately reviews what did in the past in the area of application. Also there are comparisons made pratically and measured with different techniques.

Martin B.G. Junb and John W. Sutherlanda [1] in these research paper worked on prediction of tool wear using cnc data.For the PdM of the cutting tool and the spindle, the flank wear and the bearing's RUL are used, respectively, as a metric to represent the component's conditions (normal, warning, and failure) in the systems. To classify the condition of the tools, the SVM and ANNs (RNN and CNN) methods are applied with the different feature extraction techniques.

Paolo Mercorelli, etal [2] in these research paper worked on fault detection process. The findings of this study highlight the benefits of using supervised classification algorithms in manufacturing to identify subpar drilling operations. In this work, we compared the performance of nine machine learning classifiers—four of which were non-linear algorithms and five of which were ensemble approaches—that were implemented. SVM, KNN, Bayes, and Decision Trees are the non-linear classifiers that have been implemented; Gradient Boosting, Extreme Gradient Boosting, Bagging, Extra Trees, and Random Forests are the ensemble techniques that have been implemented. The results demonstrate that when we provide machine learning algorithms with the proper signal, these algorithms are highly accurate at spotting flawed processes. In this work, S4 and S7—which were discovered by trial and error and by using all of the signals—were the most suitable signals that yield the best performance of machine learning algorithms.

Sarmad Hameed, et al [3] studied and performed tool wear for hobbing with the help of sensors and other datas. This experimental work advances the concept of Industry 4.0 and suggests a revolutionary predictive maintenance technique. Three parameters have been selected for the experiment: temperature, current, and vibration. The vibration (X, Y, and Z), current (I1, I2, and I3), and tool temperature (T1) are the input parameters. Sensors are used to gather the values for various parameters, and the results are preprocessed. Subsequently, the data are utilised to train an ANN with single and multiple layers, a deep learning model that may be used to accurately predict the gear tool's remaining usable life (RUL). In order to determine how many gear tool components can be produced in eight working hours, experimentation involves tracking worker and machine downtime. The inefficiency of the workers and the subpar quality of the made tool components owing to tool wear are discovered to be the main causes of the four-hour downtime, which drives up the cost of tool manufacturing and wastes resources.

Dashuang Wang, et al [4] in this study, studied the wear hob's properties which were briefly discussed, and a method for predicting hob wear using real-time CNC data during worm gear machining is proposed. We obtain tool wear machine data straight from the OPC UA client. The sensorless data collecting system's dependability and stability are demonstrated by the hobbing test. It is better suited for industrial applications because to its low cost and great reliability. This work uses an innovative approach based on orthogonal experiments and deep learning theory to forecast hob wear. The impact of spindle speed, feed rate, and cutting depth during worm gear hobbing is examined using the Taguchi method. A growing DBN with transfer learning is proposed to automatically determine its optimal model structure, which can speed up the learning process and enhance training effectiveness and model performance. A DBN is used to generate a tool wear model using training data.

EmilianoTraini [5] in these research paper studied predictive maintenance for milling machine. The main aim of this work is to give a general framework that is applicable to cases of predictive maintenance of generic manufacturing tools. Particularly, this method is applicable, as a support to PM, to all tools which activity is managed by parameters provided by the operators and monitored through the application of analog sensors. Using sensors of this type and applying the algorithms and methodologies shown, it Is possible creating a prototype to improve the man-machine collaboration in production.

2.1 Practical based review

During research and collection of data, we visited and gone through various researches as well as various practical sources. During these we understood the need for these model and understood the problem arising in manufacturing industry in these competitive world. We also understood how these model will help in improvement of productivity as well as quality control in manufacturing industry. Not only manufacturing but these model will help in various industries for various purposes. Also we have made that from these model the final quality which was obtained was manually predicted and tool life was also been affected due to it. Some images showing tool wear are shown below.

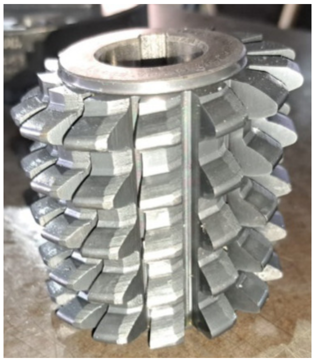


Fig 2.2. Tool Wear

3. METHODOLOGY

3.1 Methodology Overview

At Initial Stage ,modern trends in industrial technology were explored and different areas were identified. Industry 4.0 is booming and hot research topic. Machine Learning technology has a great potential in increasing the productivity of the production and quality control system. Different Research Papers were studied and research gaps were identified.

After successful completion of some part of research, objective and scope of project was defined clearly so to implement model to its end result with a flow. With the research and some practical analysis, it was decided to go for prediction model for current production in the manufacturing industry.

Tool wear and quality control application in machine production was found out too be some main parameters which can play an important role. Tool parameters, speed, feed, depth of cut were taken into consideration. Quality control with higher productivity is one of the most important part or requirement for industry 4.0. These model will finally solve the quality and downtime problem in an automated and modern way.

Different algorithms and refinement techniques were studied. Algorithm based on matlab that will train, test and implement data was developed. Algorithm Flowchart was prepared and important program loops were generated. Developed algorithm is transformed into reality using the MATLAB. At initial stage, MATLAB online was used to run, implement and test the algorithm. Data was gathered with some sources and through the production in the industry. Data was entered in excel format with all necessary parameters. Trial and error experiments were run until the algorithm was perfected.

Experimental trail was done according to the production capacity and production rate with different materials, jobs, tool material, etc. Algorithm will be trained and selected accordingly with the best suited according to data.

Experimental validation was done by comparative analysis of historical data, current data and analytical method.

Prototype model of the machine vision system which can be applied in the industry was proposed. Hardware and machinery has been recommended as per different applications. Layout and schematic sketch has been devised for the proposed prototype. Software and algorithm was proposed.

3.2 Brief methodology summary

1. Problem Identification: - Define the problem: Predict tool wear to prevent unexpected machine downtime and reduce maintenance costs. - Understand the impact: Tool wear affects production efficiency and quality.

2. Research Based on Problem: - Review existing literature on tool wear prediction methods and machine learning techniques. - Identify relevant features affecting tool wear (e.g., speed, feed rate, depth of cut, tool material).

3. Identifying Best Possible Solution: - Evaluate various machine learning algorithms suitable for regression tasks. - Consider feature selection techniques to identify the most relevant predictors.

4. Predicting Life of Tool: - Determine the target variable: Predict remaining useful life (RUL) or estimate tool wear progression. - Choose appropriate performance metrics (e.g., mean absolute error, root mean square error) to evaluate model accuracy.

5. Recording Data Needed: - Define the data required: Historical machining data including speed, feed, depth of cut, tool condition, and tool wear measurements. - Collect and record the data in a structured format.

6. Gathering the Previous Data: - Retrieve historical machining data from the production environment or simulation. - Ensure data quality and consistency.

7. Working and Training of Model: - Select a suitable machine learning model (e.g., linear regression, decision trees, random forests) based on the problem characteristics. - Split the dataset into training and testing sets. - Train the model using the training data, optimizing hyperparameters to minimize error. - Validate the model's performance using the testing dataset, fine-tuning as necessary.

8. Implementation: - Prepare the model for deployment in the production environment. - Remove unnecessary data and preprocess features (e.g., normalization, scaling). - Select appropriate thresholds for tool wear levels. - Monitor model performance and retrain periodically with new data to maintain accuracy.

9. Data Selection for Training and Testing: - Ensure representative data distribution across different operating conditions and tool types. - Use cross-validation techniques to assess model generalization.

10. Monitoring and Optimization: Continuously monitor the accuracy and reliability of the ML-based tool wear prediction system. Collect feedback from production operators and maintenance personnel to refine the model and improve its predictive performance over time. Explore advanced ML techniques like online learning or ensemble methods to enhance prediction accuracy and adaptability to dynamic machining environments.

11. Minimizing Error Rate: - Continuously refine the model by analyzing prediction errors and updating featured engineering strategies. - Consider ensemble methods or deep learning architecture for improved predictive performance.

4. Project Implementation

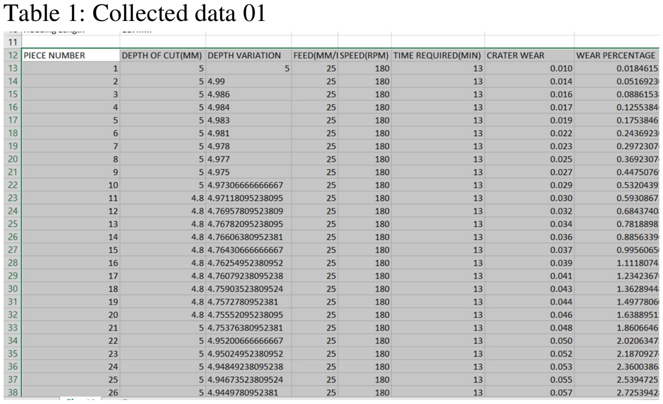
In order to satisfy the desired objectives the experimental layout has been set up and trials was be performed with the ongoing and upcoming production to test the algorithm. This chapter covers in-depth details of the experimental setup, procedure and results observed.

4.1 Collected Datasets

Data Collected was tool parameters, job parameters, coolant type, speed, feed, depth of cut,etc. The complete details of data is being listed in the figure shown below. Speed, feed depth of cut are some of the main parameters that will be helpful for tool wear prediction.

Constant parameters are: Coolant type, Tool material, Workpiece material.
Variables are: Speed, feed, depth of cut,etc.

Table 1: Collected data 01



	PIECE NUMBER	DEPTH OF CUT(MM)	DEPTH VARIATION	FEED(MM/I	SPEED(RPM)	TIME REQUIRED(MIN)	CRATER WEAR	WEAR PERCENTAGE
11								
13	1	5	5	25	180	13	0.010	0.0184615
14	2	5	4.99	25	180	13	0.014	0.0516923
15	3	5	4.986	25	180	13	0.016	0.0886153
16	4	5	4.984	25	180	13	0.017	0.1255384
17	5	5	4.983	25	180	13	0.019	0.1753846
18	6	5	4.981	25	180	13	0.022	0.2436923
19	7	5	4.978	25	180	13	0.023	0.2972307
20	8	5	4.977	25	180	13	0.025	0.3692307
21	9	5	4.975	25	180	13	0.027	0.4475076
22	10	5	4.97306666666667	25	180	13	0.029	0.5320439
23	11	4.8	4.97118095238095	25	180	13	0.030	0.5930867
24	12	4.8	4.76957809523809	25	180	13	0.032	0.6843740
25	13	4.8	4.76782095238095	25	180	13	0.034	0.7818898
26	14	4.8	4.76606380952381	25	180	13	0.036	0.8856339
27	15	4.8	4.76430666666667	25	180	13	0.037	0.9956065
28	16	4.8	4.76254952380952	25	180	13	0.039	1.1118074
29	17	4.8	4.76079238095238	25	180	13	0.041	1.2342367
30	18	4.8	4.75903523809524	25	180	13	0.043	1.3628944
31	19	4.8	4.7572780952381	25	180	13	0.044	1.4977806
32	20	4.8	4.75552095238095	25	180	13	0.046	1.6388951
33	21	5	4.75376380952381	25	180	13	0.048	1.8606646
34	22	5	4.95200666666667	25	180	13	0.050	2.0206347
35	23	5	4.95024952380952	25	180	13	0.052	2.1870927
36	24	5	4.94849238095238	25	180	13	0.053	2.3600386
37	25	5	4.94673523809524	25	180	13	0.055	2.5394725
38	26	5	4.9449780952381	25	180	13	0.057	2.7253942

4.2. Machine Specifications

Few data was collected according to machine and tool type. Specification of machine is listed below.

- CNC Gear Hobbing Machine
- Make- Laurenz
- Maximum Gear Daimeter: 400mm
- Maximum module: 4
- Maximum Length: 400mm
- Cut Length: 250mm
- Maximum Depth of Cut: 5mm
- Maximum RPM: 250rpm

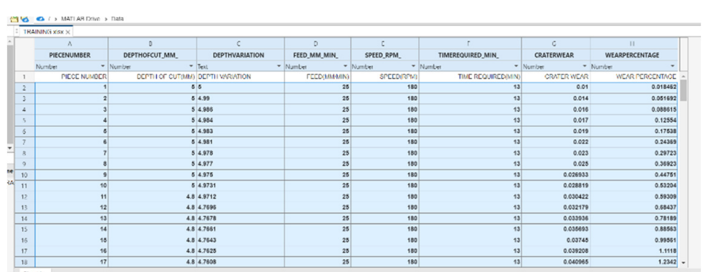
4.2.1 Tool Specifications

- Tool Material-M32
- Module: 3.5
- Lead angle : 4◦24′24″
- Rotation direction :Right
- Material: SAE4140
- No. of teeth: 16

Fig. 4.1. Tool Specification

Fig 4.2. Tool cutter

4.3 Training datasets



	PIECENUMBER	DEPTHOFCUT_MM_	DEPTHVARIATION	FEED_MM_MIN_	SPEED_RPM_	TIMEREQUIRED_MIN_	CRATERWEAR	WEARPERCENTAGE
	Number	Number	Text	Number	Number	Number	Number	Number
1	PIECE NUMBER	DEPTH OF CUT(MM)	DEPTH VARIATION	FEED(MM/MIN)	SPEED(RPM)	TIME REQUIRED(MIN)	CRATER WEAR	WEAR PERCENTAGE
2	1	5	5	25	180	13	0.01	0.018462
3	2	5	4.99	25	180	13	0.014	0.051692
4	3	5	4.986	25	180	13	0.016	0.088615
5	4	5	4.984	25	180	13	0.017	0.12554
6	5	5	4.983	25	180	13	0.019	0.17538
7	6	5	4.981	25	180	13	0.022	0.24369
8	7	5	4.978	25	180	13	0.023	0.29723
9	8	5	4.977	25	180	13	0.025	0.36923
10	9	5	4.975	25	180	13	0.026933	0.44751
11	10	5	4.9731	25	180	13	0.028819	0.53204
12	11	4.8	4.9712	25	180	13	0.030422	0.59309
13	12	4.8	4.7696	25	180	13	0.032179	0.68437
14	13	4.8	4.7678	25	180	13	0.033936	0.78189
15	14	4.8	4.7661	25	180	13	0.035693	0.88563
16	15	4.8	4.7643	25	180	13	0.03745	0.99561
17	16	4.8	4.7625	25	180	13	0.039208	1.1118
18	17	4.8	4.7608	25	180	13	0.040965	1.2342

Fig 4.3. Training dataset

4.4 Testing datasets

PIECE NUMBER	DEPTH OF CUT(MM)	DEPTH VARIATION	FEED(MM/MIN)	SPEED(RPM)	TIME REQUIRED(MIN)	CRATER WEAR	WEAR PERCENT
1	4.9		25	180	13	0.012	0.02171
2	4.9		25	180	13	0.013	0.0
3	5.0		25	180	13	0.016	0.08861
4	4.8		25	180	13	0.018	0.12760
5	4.9		25	180	13	0.019	0.17187
6	5.0		25	180	13	0.021	0.23593
7	5.0		25	180	13	0.023	0.29981
8	5.0		25	180	13	0.025	0.36964
9	5.0		25	180	13	0.027	0.44861
10	5.0		25	180	13	0.029	0.53506
11	5.0		25	180	13	0.031	0.62905
12	5.0		25	180	13	0.033	0.73064
13	5.1		23	180	13	0.035	0.91292
14	5.1		23	180	13	0.037	1.0400
15	5.1		23	180	13	0.038	1.17566
16	5.1		23	180	13	0.040	1.31979
17	4.9		23	180	13.5	0.042	1.35855
18	4.7		23	180	13.5	0.044	1.44187
19	4.8		23	180	13.5	0.046	1.62133
20	4.8		23	180	13.5	0.048	1.7771
21	4.8		23	180	13.5	0.050	1.94003
22	5.0		23	180	13.5	0.052	2.19787
23	5.0		23	180	13.5	0.054	2.38222
24	4.9		23	180	13.5	0.056	2.52243
25	4.9		23	180	13.5	0.057	2.71594
26	4.9		23	180	13.5	0.059	2.91907
27	4.9		23	180	13.5	0.061	3.12953
28	4.9		23	180	13.5	0.063	3.34734

Fig 4.4. Testing dataset

5. Results and Discussions

Firstly, the feed, speed, depth of cut and other parameters related to tool wear are collected based on the requirement for the machine learning algorithm and predicted output need during the hobbing process. At the same time, tool wear is obtained by measuring the size of the cutting workpiece and tool wear measurement. Secondly, a DBN is used to generate a tool wear model with collected data, then, a growing DBN with transfer learning is proposed to automatically decide its best model structure. At last, the training model is designed to predict tool wear.

5.1. Parameters trained and tested

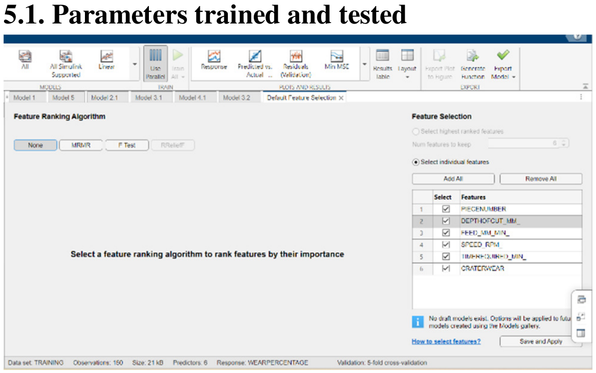


Fig.5.1. Parameters for prediction

5.2. Implemented datasets

PIECE NUMBER	DEPTH OF CUT(MM)	DEPTH VARIATION	FEED(MM/MIN)	SPEED(RPM)	TIME REQUIRED(MIN)	CRATER WEAR
1	4.9	4.888	25	180	13	0.012
2	4.9	4.887	25	180	13	0.013
3	5.0	4.984	25	180	13	0.016
4	4.8	4.782	25	180	13	0.018
5	4.9	4.881	25	180	13	0.019
6	5.0	4.9787	25	180	13	0.021
7	5.0	4.9768	25	180	13	0.023
8	5.0	4.96061428571429	25	180	13	0.025
9	5.0	4.973	25	180	13	0.027
10	5.0	4.98538571428571	25	180	13	0.029
11	5.0	4.99777142857143	25	180	13	0.031
12	5.0	5.01015714285714	25	180	13	0.033
13	5.1	5.02254285714286	23	180	13	0.035
14	5.1	5.03492857142857	23	180	13	0.037
15	5.1	5.04731428571429	23	180	13	0.038
16	5.1	5.0597	23	180	13	0.040
17	4.9	4.8578	23	180	13.5	0.042
18	4.7	4.6559	23	180	13.5	0.044
19	4.8	4.754	23	180	13.5	0.046
20	4.8	4.7521	23	180	13.5	0.048
21	4.8	4.7502	23	180	13.5	0.050
22	5.0	4.9483	23	180	13.5	0.052
23	5.0	4.9464	23	180	13.5	0.054
24	4.9	4.8445	23	180	13.5	0.056
25	4.9	4.83982222222222	23	180	13.5	0.057
26	4.9	4.83958888888889	23	180	13.5	0.059
27	4.9	4.83935555555556	23	180	13.5	0.061
28	4.9	4.83912222222222	23	180	13.5	0.063

Fig 5.2. Implementation datasets

The above shows the sorted implementation datasets which we used and an input for matlab model implementation.

5.3. Output for training of datasets

Fig 5.3. Graph(Wear percentage vs Crater wear)

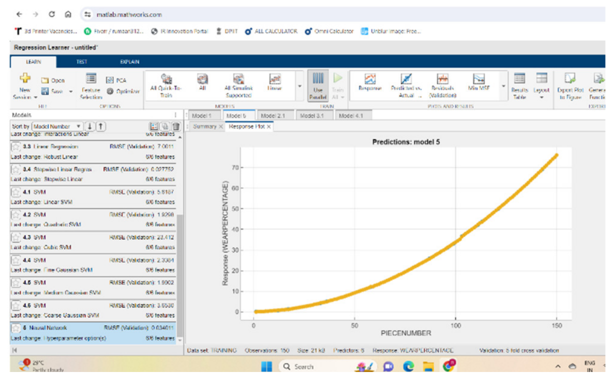


Fig 5.4. Graph(Wear percentage vs Piece number)

Above is the graphs obtained for two variable parameters i.e. Piece number and Crater wear which are the base for the prediction model against Wear percentage.

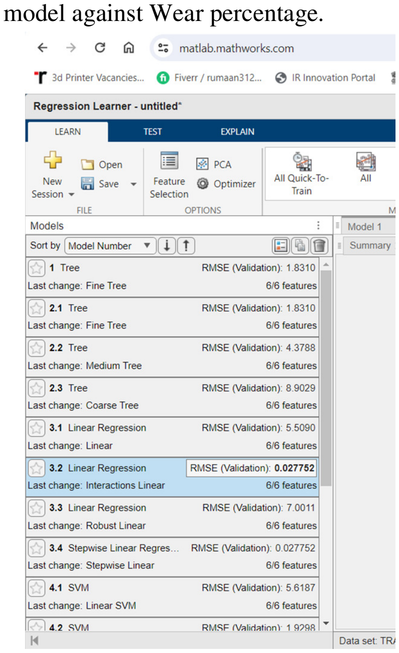


Fig 5.5. RMSE Values

Above three figures shows the output in graphical forms for training datasets. Matlab results are obtained during training and testing of data in graphical forms and also error rates are obtained. RMS values are too obtained while designing and inputting data.

5.4. Output for testing of datasets

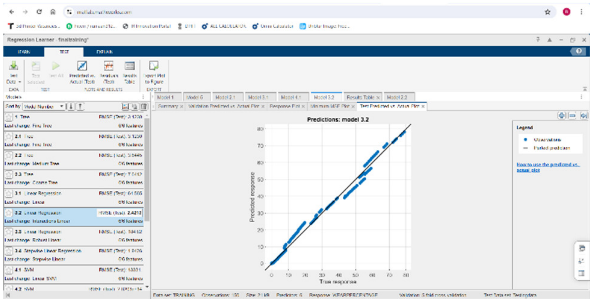


Fig 5.6. Graph(True response vs Predicted response)

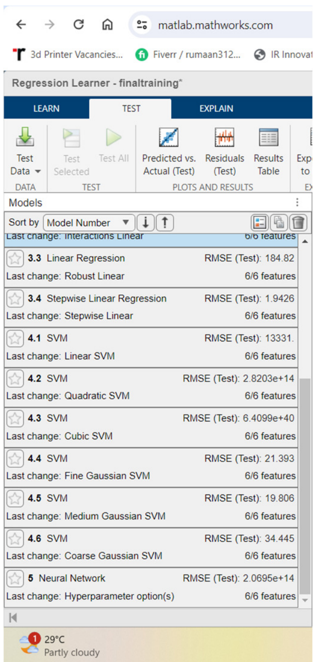


Fig 5.7. RMSE values after testing

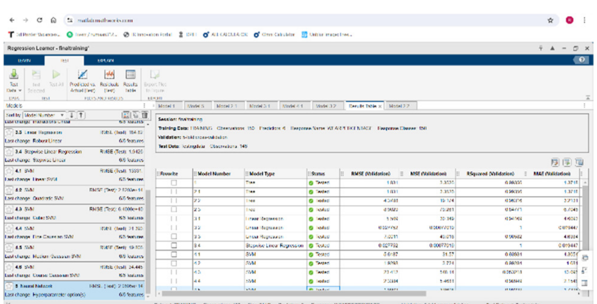


Fig 5.8. Tested models

Above figure shows the output results after testing of datasets. We have well defined datasets for testing. From the above fig. we got the triainig and testing model done with the help of matlab and final RMSE value obtained for different models are shown in figures above.

The results obtained are in the graphical and numeric forms as shown.

5.5. Output after final implementation of datasets

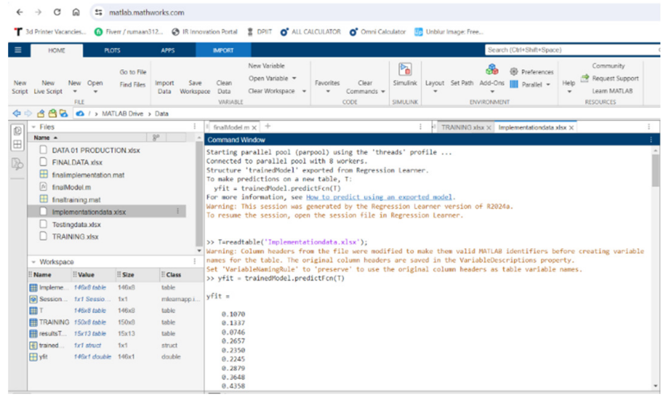


Fig 5.9. Predicted output 01

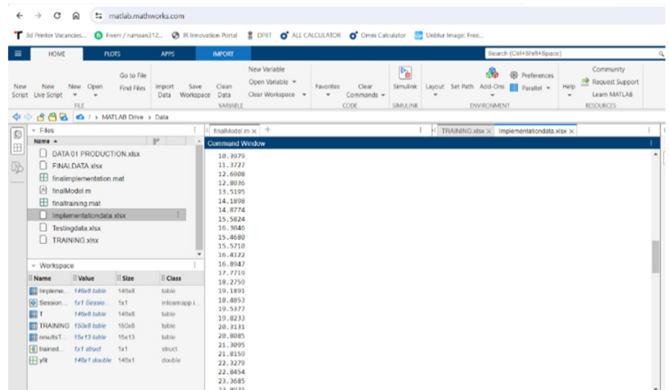


Fig 5.10. Predicted output 02

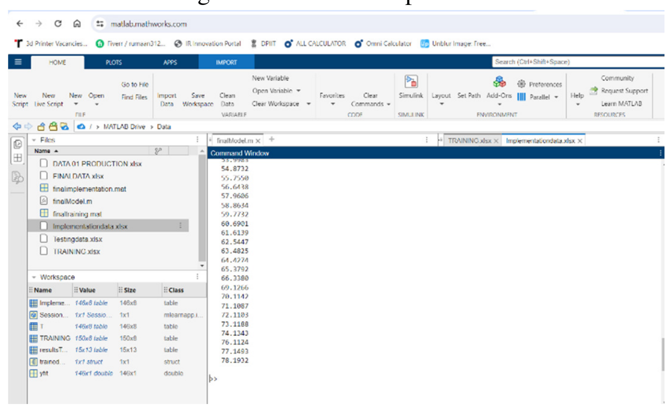


Fig 5.11. Predicted output 03

Above are some predicted outputs which we got after final implementation of datasets which were taken from industry for their production batch. The results obtained were having minimum errors and were in numerical form. The predicted output was wear percentage which when reached 70-80% needed to change or regrind the tool.

Also after comparison practically with physical and our machine learning model, we got results which are similar to practical way. The tool resharpning was done after the defined number of pieces and our model too predicted the same. Our main parameter for prediction was tool wear with sub parameters which helped for prediction i.e. speed, feed, depth of cut.

6. CONCLUSION AND FUTURE SCOPE

Model Development: We constructed a predictive model that estimates hob tool life based on input parameters such as cutting speed, feed rate, depth of cut, tool material, and workpiece material. The model was trained using historical data from gear hobbing operations and implemented using MATLAB's machine learning tools. Performance Evaluation: The performance of the predictive model was evaluated using validation datasets, and key metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) were calculated to assess prediction accuracy. The results demonstrated the effectiveness of the model in estimating tool life under varying operating conditions.

In conclusion, the development of a hob tool life prediction model represents a significant advancement in predictive maintenance strategies for gear manufacturing. By leveraging machine learning and MATLAB capabilities, this project contributes to optimizing machining processes, reducing tooling costs, and improving overall productivity in the manufacturing industry.

Following are some future scope for prediction of tool life.

Reducing Tooling Costs by accurately predicting hob tool life, manufacturers can optimize tool usage and reduce the frequency of tool replacements. This leads to lower tooling costs and more efficient utilization of resources. Application will also include other machining processes and industries beyond gear manufacturing. These techniques can be adapted to predict tool wear in milling, turning, and additive manufacturing processes. Integration with Industry 4.0 aligning the predictive model with Industry 4.0 initiatives by integrating it into smart manufacturing systems. Enabling seamless communication between the predictive maintenance system and other digital technologies (e.g., IoT devices, cloud computing) to achieve autonomous and data-driven manufacturing processes.

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