Lecture Notes in Mechanical Engineering

Bijoy Bhattacharyya
Jose Mathew
N. Saravanakumar
G. Rajeshkumar *Editors*

Advances in Micro and Nano Manufacturing and Surface Engineering

Proceedings of AIMTDR 2021

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Lecture Notes in Mechanical Engineering

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Editors
Bijoy Bhattacharyya
Department of Production Engineering
Jadavpur University
Kolkatta, India

Jose Mathew
Department of Mechanical Engineering
National Institute of Technology
Calicut, Kerala, India

N. Saravanakumar
Department of Mechanical Engineering
PSG Institute of Technology and Applied Research
Coimbatore, Tamil Nadu, India

G. Rajeshkumar
Department of Mechanical Engineering
PSG Institute of Technology and Applied Research
Coimbatore, Tamil Nadu, India

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Foreword

8th International and 29th All India Manufacturing Technology, Design and Research Conference Proceedings (Volumes 1–5)

(Edited by Different Professors and Researchers)

First, I would like to congratulate the Editors of five different volumes of proceedings of 8th International and 29th All India Manufacturing Technology, Design and Research Conference (AIMTDR) proceedings being published by Springer. These volumes are very good collection of the research and review papers on the manufacturing processes like Modern Machining processes (Volume-1), Additive Manufacturing and Metal Joining (Volume-2), Simulation, Product Design and Development (Volume-3), Forming, Machining and Automation (Volume-4) and Micro and Nano Manufacturing and Surface Engineering (Volume-5). These five volumes are comprehensive collection of the research papers focusing on the most recent research and developments in the area of manufacturing processes. These subject areas continue to be dominant manufacturing technologies, say, the *technologies of future*, namely, 3-D printing (Additive Manufacturing) which generally lacks speed, surface finish and dimensional accuracy. To compensate these weaknesses of 3-D printing in the real life production, I could also see good papers on Micro-/nano-manufacturing and nano-finishing. Theoretical analysis, optimization and simulation of manufacturing processes would definitely provide the necessary insights into the physics and mechanisms of these processes, as well as their basic understanding. These five volumes would be invaluable to the researchers working in research laboratories and engineers in industrial organizations working on shop floors for learning, consulting and applying some of the findings deliberated in the conference by the authors of different research papers.

Such conferences encourage the interaction between the research scholars, faculty members and user industries' representatives from different parts of the world. Unfortunately, this could not happen in this hybrid conference to the desired extent due to the pandemic effects across the globe. Apart from these contributed papers, there were many on-line and off-line keynote lectures delivered by the researchers from different countries including India. I am sure that these papers should be of great help to the readers of these proceedings. These proceedings/collection of the papers should be of great help to the academia and industries as well as reference books in different sub-fields of manufacturing processes.

I would like to congratulate the authors for their contributions to all these five volumes of the proceedings and the Editorial Committee Members for their untiring efforts made in bringing out these research papers' collections in five volumes. I will also like to thank the technical committee members in general and ex-vice-president of NAC, Prof. U. S. Dixit for inviting me to write this foreword.

Kanpur, India

Dr. V. K. Jain
Professor (Retired) I.I.T. Kanpur
Member, National Advisory
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About the Editors

Dr. Bijoy Bhattacharyya is Professor of Production Engineering Department in Jadavpur University, Kolkata, India. He had completed his B.E. in the year 1983 from REC, Calicut, Kerala and his M.E. in the year 1985 and Ph.D. in 1991 from Jadavpur University. He is specialized in Advanced manufacturing technology, non-traditional machining, micromachining and production management. He has published 166 research papers in reputed journals and more than 350 research papers in conferences. Several Ph.Ds. have been completed under his guidance. He has completed several research projects and he is a recipient of various awards. Dr. Bhattacharyya served as a reviewer and editorial board member for various reputed national and international journals.

Dr. Jose Mathew is Professor and Ex-Dean (Research and Consultancy) of the National Institute of Technology Calicut, Kerala. He received his M.Tech. and Ph.D. from IIT Kanpur (1990) and IIT Bombay (1999), respectively. His research interests are micro and nano-machining process, precision and ultra-precision machining, modelling and analysis of machining of 'difficult to machine' materials, etc. He has published about 65 research papers in international journals and more than 100 research papers in international conferences. Several M. Tech and Ph.D. thesis have been completed under his guidance. He has also worked on a number of industry sponsored research and development projects and consultancy projects. He is a recipient of various awards from DST, ISTE and NITC.

Dr. N. Saravanakumar is Professor and Head in the Department of Mechanical Engineering, PSG Institute of Technology and Applied Research, Coimbatore. He obtained his B.E. (Mechanical Engineering) and M.E. (Engineering Design) from Bharathiar University, Coimbatore, and Ph.D. from Anna University, Chennai. His major areas of research include Tribology, Development of nano-particulate lubricants, Composites and Metal forming. He has published 15 papers in peer reviewed international journals and more than 25 conference publications. Dr. Saravanakumar received project fundings from various agencies like DST, DRDL, NPOL, etc., to carry out research.

Dr. G. Rajeshkumar obtained his B.E. (Mechanical Engineering) from Sri Ramakrishna Institute of Technology, Coimbatore in 2010 and his M.E (Engineering Design) at Kongu Engineering College in 2012 with a Gold Medal. He received his Ph.D. in Mechanical Engineering from Anna University, Chennai in 2017. He is serving in PSG iTECH since 2017 and is presently an Associate Professor in the Department of Mechanical Engineering. He is presently carrying out research in Natural fibers, Polymer matrix composites, Mechanism of needle Insertion in Soft Tissues, Tribology and Vibration. He has published about 50 peer reviewed international journal papers, 15 book chapters, 40 international and national conference proceedings and a text book. He has also edited a book titled *Bast Fibers and their Composites,* as well as a proceedings titled *Materials, Design and Manufacturing for Sustainable Environment,* both of which were published by Springer Nature, Singapore.

Prediction of Machining Quality and Tool Wear in Micro-Turning Machine Using Machine Learning Models

T. Rajesh Babu and G. L. Samuel

1 Introduction

All the processes, including manufacturing, in today's world are being revolutionized due to the introduction of Industry 4.0. Industry 4.0 is being widely adapted as it exhibits outstanding results. Any machined product should meet stringent quality standards and have a better surface finish for precise outcomes. The vast range of applications for micro-components, such as aerospace, medical, electronics and logistics communications. [1] is driving up the demand. The tolerance for the micro-components is quite negligible. Hence, efficient in-process monitoring and control methods are necessary to manufacture a high-quality product without any rejection. The importance of micro-manufacturing technologies has become increasingly significant. As a matter of fact, miniaturized titanium alloys are vigorously used in many biomedical and aeronautical industries. As a result, it is critical to specialize in micro-manufacturing processes for titanium alloys [2]. Micro-turning is a manufacturing process wherein miniaturized components can be manufactured with high precision at the micrometer level. Titanium alloys possess superior strength to weight ratio, excellent wear and corrosion resistance. Due to the low elastic modulus, low thermal conductivity and high chemical reactivity with the cutting tool material, titanium alloys are machined using coated carbide cutting tools [3].

Titanium alloys are extremely hard to machine due to their remarkable chemical and mechanical characteristics. Hence, tool wears out rapidly during the machining of these materials resulting in chatter and poor surface finish [4]. The forecast of tool wear and surface roughness of the machined component is important to ensure the performance of the machine tool. PCD tools perform better for machining Ti alloys

T. R. Babu · G. L. Samuel (✉)
Manufacturing Engineering Section, Department of Mechanical Engineering, IIT Madras, Chennai 600036, India
e-mail: samuelgl@iitm.ac.in

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as compared to NbC, TiC, VC, WC, ZrC, TiN, ZrO and TiB2 as they do not form TiC layer which avoids diffusion of constituents from work materials [5].

Before a particular surface quality threshold is surpassed, necessary action should be taken to reduce the damage. Hence, it is vital to predict the cutting tool condition at any instant of time to avoid any damage to the workpiece and the tool. Recent research has shown that many Artificial Intelligence (AI) algorithms have been developed for the predictive analysis of the machine tool. Atluru et al. [6] introduced a smart machine supervisory system framework that incorporates individual process monitoring and control modules to achieve a globally optimal machining solution. A LabVIEW application that incorporates process planning, health monitoring and tool condition monitoring was used to demonstrate the system's decision-making mechanism. Cheng et al. [7] addressed four types of smart cutting tools for ultra-precision and micro-manufacturing applications, including a force-based smart cutting tool, a temperature-based internally cooled cutting tool, a fast tool servo (FTS) and smart collets. Ploughing rather than cutting occurs in high-speed micro-turning when the depth of cut and feed are less than the tool nose radius and edge radius [8].

Wu et al. [9] investigated and discussed the wear properties of the diamond tool and the micro-topography of the ultra-precision turned surface. Kumar [10] studied the measurement of cutting conditions, surface roughness and material removal rate of micro-turning process, and a Genetic Algorithm was developed to optimize the process parameters. Aslantas et al. [11] explored the multi-objective optimization of cutting parameters of micro-turning of Ti-6Al-4 V by response surface method (RSM). Agrawal et al. [12] developed multiple regression, random forest and quantile regression to estimate the surface roughness of machined components in hard turning of AISI 4340 steel based on the cutting parameters.

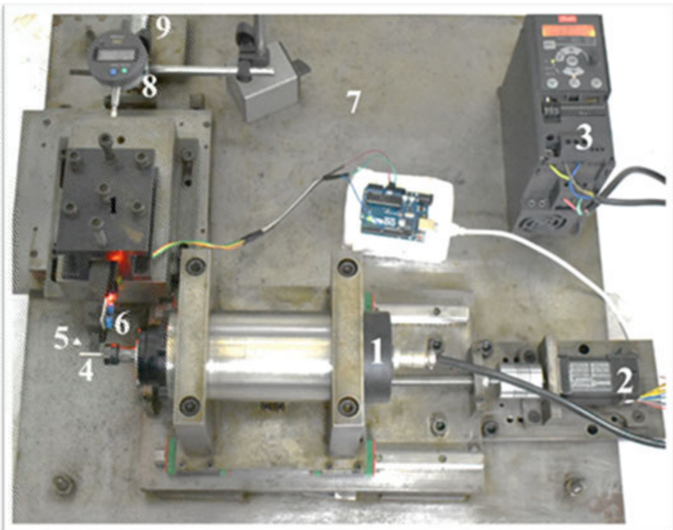
Liu et al. [13] proposed systematic steps to construct the Cyber Physical Machine Tool (CPMT) and an MTConnect-based CPMT prototype also has been developed. Aghazadeh et al. [14] proposed a condition monitoring smart machine tool based on the current signal of spindle motor as the fault indicator signal. Spectral Subtraction Algorithm and Artificial Intelligence methods like Gaussian Process Regression (GPR), Bayesian Ridge Regression, Nearest Neighbours Regression (KNN), Support and Decision Trees Regression are used to build the smart machine tool. Ridwan et al. [15] implemented a STEP-NC-enabled Machine Condition Monitoring system by real-time cutting power, vibration and feed-rate. Data from several sensors was broadcast in MTConnect format, and fuzzy logic was used to achieve self-contained in-process feed-rate optimization. Morgan et al. [16] described the design of an Industry 4.0-compliant framework implemented as an Internet-based client–server approach for monitoring and teleoperation of CNC machine tools.

This work presents AI-based models to predict the surface roughness of the machined component and the flank wear of the cutting tool based on multiple input parameters. This predictive analysis is based on the experimental data obtained from the micro-turning machine. A series of machine learning models, Random Forest (RF), Standard Multilayer Perception (MLP), Regression Trees and Radial-based functions are developed, and the comparisons have made among them for accuracy in prediction and tuning time.

2 Experimental Study

The experimental setup for micro-turning is shown in Fig. 1. It comprises of a cast iron machine base of size 600 × 600 × 20 mm, X-axis and Z-axis linear slides. The machine base is mounted over four levelling anti-vibration screw jacks which absorb the vibrations from the ground. Levelling screws are used to flatten the machine base with the help of spirit level while mounting on the machine table.

Linear slideways are mounted over the base for Z and X-axis movement. A backlash-free ball screw and nut mechanism is used to convert rotary motion to linear motion for the Z-axis and X-axis. The ball screws are supported by contact angular bearing, which can withstand both axial and radial loads. The ball screw has a dynamic load capacity of 340 kg and a static load capacity of 740 kg. A micro-drive (make: VLT) regulates the spindle speed. A stepper motor with an integrated drive controls the feed action, while a dial indicator assisted micrometre controls the depth of cut. A vibration sensor module is attached near the cutting tool tip to measure the vibration of the cutting tool during machining.



1-Spindle; 2-Stepper motor with integrated drive; 3-VLT micro drive; 4-Work piece; 5-Cutting insert; 6-Vibration sensor module; 7-Machine tool base; 8-Dial indicator; 9-Micrometer

Fig. 1 Micro-turning machine

2.1 Speed Control

2.1.1 Spindle

The spindle is connected to the VLT micro-drive FC 51 to control the speed, and RPM of the spindle is calibrated with a non-contact digital type tachometer. This machine's spindle spins at a maximum speed of 24,000 rpm. With the help of a VLT drive, the spindle speed can be manually regulated in increments of 60 rpm. To hold the work piece, a 5 to 5.5 mm ER 11 collet is fitted to the spindle. The runout of the spindle is measured as 10 μm.

2.1.2 Feed

A stepper motor with an integrated drive shaft is connected to the ball screw shaft through an aluminium based flexible coupling to regulate the feed. The microcontroller (Arduino UNO) is utilized to drive the stepper motor, which has a maximum speed of 500 rpm and a step angle of 1.8°. A non-contact type digital tachometer is used to calibrate the stepper motor speed. The ball screw integrated to the machine tool has a pitch of 2 mm. Hence, the feed motion resolution of 0.01 mm is achieved for the given step angle. The feed for revolution is the distance travelled by the spindle slide per one rotation of the spindle motor. The formula to calculate feed is shown in the Eq. (1)

$$\text{Feed (mm/rev)} = p \times \frac{N_m}{N_s} \tag{1}$$

where p = ball screw pitch, N_s = spindle speed and N_m = stepper motor speed.

2.1.3 Depth of Cut

The shaft of the ball screw mounted with tool post slideway is coupled with the anvil of screw gauge to regulate the depth of cut. A dial indicator is installed to track the cutting tool movement in the depth direction. With the use of a dial indicator and a micrometre, 1μm resolution is achieved in the depth direction.

2.2 Cutting Tool

The tool post is equipped with a tool holder. The tool holder is fastened to the coated carbide cutting inserts (CCMT060204LF KC5010). The cutting insert has a nose radius of 0.4 mm, approach angle of 90° and 70° clearance angle. Each sample has been machined with new cutting insert.

2.3 Vibration Measurement

A vibration sensor module (SW-420) is attached near the cutting insert for measuring the vibration of cutting tool during machining. The vibration sensor sw-420 and comparator LM393 are used in this sensor module to detect any vibrations that exceeded the threshold. The vibration data is collected by a microcontroller (Arduino UNO) attached to the sensor module. SW-420 is a closed-type vibration sensor that provides a comparator output, a clean signal, a good waveform and a high level of capability. The sensor chip is damaged when the signal is reversed.

2.4 Surface Roughness Measurement

The surface roughness of the machined component is determined using a Wyko NT110 surface roughness 3D profilometer. This enables high-resolution three-dimensional surface assessments spanning from nanometre-scale roughness to millimetre-scale steps. Readings for each sample were taken at three locations, and the mean value was recorded as the surface roughness (R_a). Sample data is shown in Fig. 2.

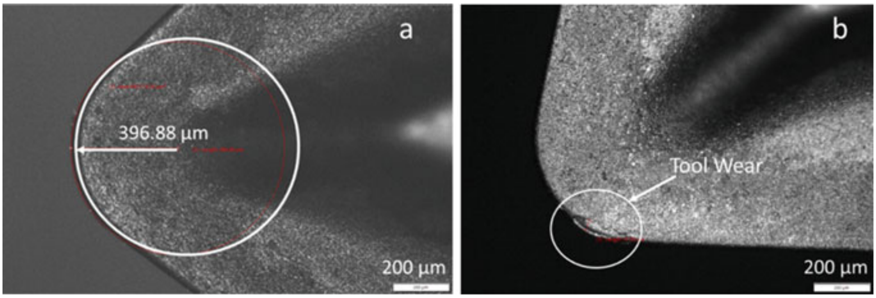


Fig.2 Cutting insert tool tip, **a** before machining, **b** after machining

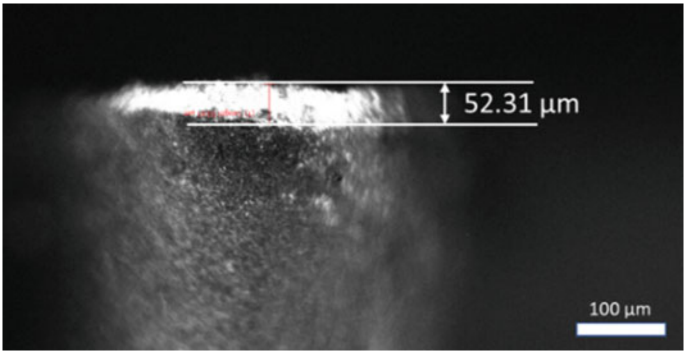


Fig. 3 Tool flank wear width after the Exp. no. 4

2.5 Tool Flank Wear Measurement

The width of the tool flank wear is measured by means of images collected with an Olympus inverted microscope. Figure 3 shows images taken by inverted microscope of the cutting tool tip before and after machining.

3 Machine Learning Models

Machine learning (ML) refers to the capability of computers to solve problems without being explicitly programmed to do so. Computational approaches that use the experience to improve performance or make accurate predictions are referred to as ML [17]. ML applications manufacturing industry includes cost reduction, less wastage, inventory control, operator safety enhancement, higher productivity, repair verification, overall profit and many more [18]. Multilayer perceptrons (MLPs), radial basis functions (RBFs), regression trees and random forest were used to assess ML regressors in this study (RF). In addition, linear regression was used as a baseline approach.

3.1 Multilayer Perceptron

The standard multilayer perceptron (MLP) is a torrent of single-layer perceptrons. This network contains a layer of input nodes, a layer of output nodes and one or more intermediate because the interior layers are not directly visible from the system's inputs and outputs, they are referred to as "hidden layers". An input layer of four nodes, an output layer of two nodes and three hidden layers of sixty nodes each were chosen and employed in this work on a trial-and-error basis.

3.2 Random Forest (RF)

A random forest is a collection of decision trees that have been trained using the "bagging" technique. The main idea of the bagging method is that combining many learning models enhances the total output [19]. In this study, the RF model is trained with 10 trees, mean squared error (MSE) as a criteria function to quantify the quality of a split and two sample splits with the rest of the parameters set to default.

3.3 Regression Trees

A regression tree is constructed using a technique known as binary recursive partitioning, which is an iterative operation that partitions data into partitions or branches and then divides each partition into smaller groups as the methodology continues up each branch. In this research, a decision tree algorithm with a cross entropy cost/loss function is devised, and tree pruning is used to reduce overfitting of the training data.

3.4 Radial-Based Functions (RBF)

RBF nets are extremely used many Gaussian curves to approximate the underlying functions. This network has only one hidden layer and fully connected with input layer and output of the hidden layer perform weighted some to get the output. This network only contains one hidden layer that is fully connected to the input layer, and the hidden layer's output does a weighted sum to produce the output. The output neurons and weights are matrix since the RBF was designed for multiple output in this work.

4 Results and Discussion

Experiments are performed in an indigenously developed micro-turning machine. The three-level full factorial technique is used to design the experiments by altering the process parameters. The vibration sensor module installed at the tooltip collects vibration signals during machining, the surface roughness of the workpiece is measured with a Wyko 3D profilometer, and tool flank wear is computed from the images obtained with an Olympus inverted microscope. All the measured values are listed in Table 1.

Figures 3, 4 and 5 show the measured tool flank wear width, surface roughness measurement details and vibration data for Exp. No. 4. The data from the experiments is cleansed before being used to train the model. The models are trained with 80%

Table 1 Experimental results of micro-turning machine

Exp. No.	Speed (m/min)	Feed (μm)	Depth of cut (μm)	Cutting tool vibration (Hz)	Flank wear width (μm)	Surface roughness (R_a) (μm)
1	126	5	30	128	22.24	0.448
2	126	5	50	177	31.15	0.658
3	126	5	70	213	37.59	0.763
4	126	10	30	182	52.31	0.407
5	126	10	50	230	59.99	0.538
6	126	10	70	308	70.11	0.835
7	126	15	30	190	52.99	0.541
8	126	15	50	1196	100.5	2.142
9	126	15	70	387	65.5	0.942
10	157	5	30	137	26.23	0.542
11	157	5	50	211	42.88	0.607
12	157	5	70	314	70.98	0.732
13	157	10	30	430	31.45	0.684
14	157	10	50	511	34.17	0.712
15	157	10	70	608	43.92	0.775
16	157	15	30	485	33.47	0.652
17	157	15	50	512	48.42	0.688
18	157	15	70	611	56.64	0.774
19	188	5	30	327	22.6	0.638
20	188	5	50	385	36.45	0.688
21	188	5	70	450	57.97	0.774
22	188	10	30	297	36.45	0.652
23	188	10	50	347	50.6	0.714
24	188	10	70	512	60.84	0.817
25	188	15	30	334	42.93	0.707
25	188	15	50	401	57.97	0.817
27	188	15	70	487	70.8	0.831

of the obtained data that is randomly selected, and the remaining data has been used to test them. Speed, feed, depth of cut and vibration data are used as input data, while surface roughness and tool flank wear width are output data for developing the model.

Four machine learning models based on RF, MLP, Regression tree and Radial-based function were built to predict the machine tool condition. The MLP model is trained with four hidden layers, a learning rate of 0.01 and a momentum of 0.3, whereas the RBF, regression tree and random forest (RF) models use a ridge of 0.1, a minimum of 8 instances and 200 iterations.

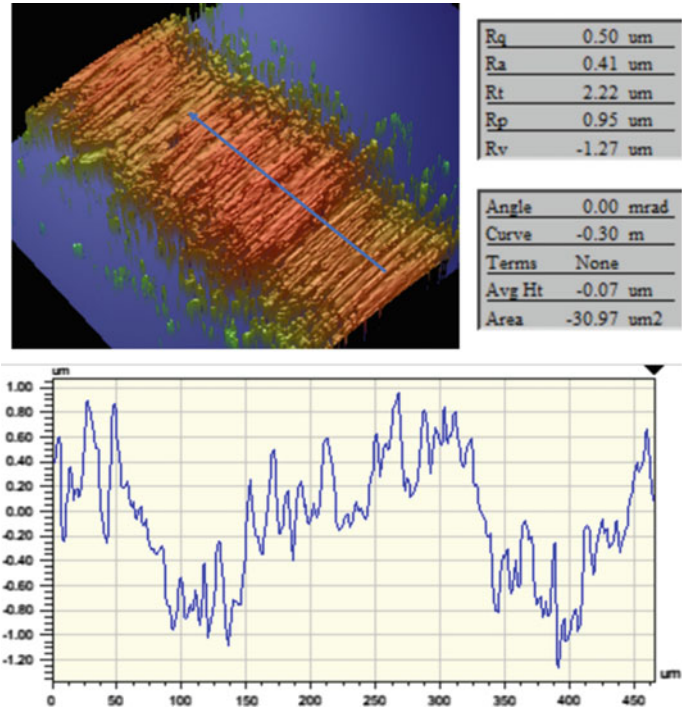


Fig. 4 Surface roughness measurement details of the machined component for the Exp. No. 4

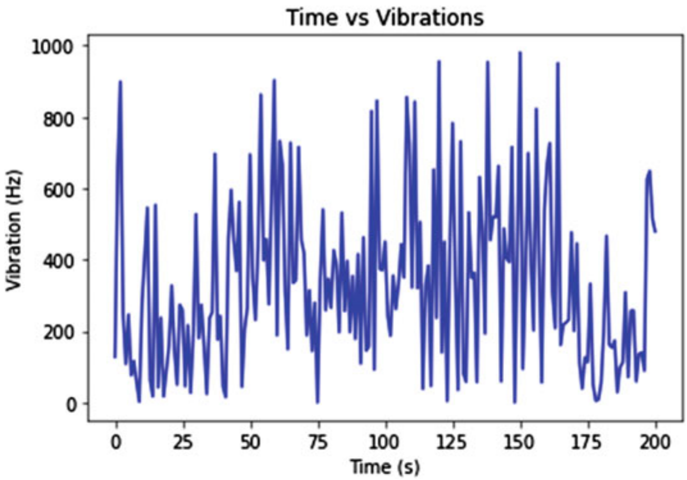


Fig. 5 Vibration of the cutting tool for the Exp. No.4

Table 2 Precision test results of machine learning models

ML model	Accuracy (%)	Tuning time (s)
Random forest	88	0.07
Regression tree	81	0.03
Multilayer perceptron	75	0.05
Radial-based Function	72	0.02

The prediction accuracies of all the models are low and the tuning time is quite short because the models are trained with little data. An Intel Core i5 2300 2.8 GHz processor was used to calculate the computation time. Table 2 shows the prediction accuracy and tuning time details for all of the produced models.

The prediction accuracy of RF models is 88%, which is higher than other models with a tuning time of 0.07 s, but the accuracy prediction of regression trees is 81% with a tuning time of 0.03 s, which is less than half the time of RF models. Because RF is composed of decision trees and trained with four trees, hence it has a longer tuning time with good prediction accuracy than a regression tree model. RBF model has lower prediction accuracy and takes less time to compute, as this model just contains one hidden layer. The performance of MLP depends significantly on the number of hidden layers and its associated neurons. The present study evaluates the MLP performance with varying hidden layers and nodes. It is found that three hidden layers with having six neurons each result in optimum performance. This MLP model has a prediction accuracy of 75, which is lower than both the RF and the Regression tree, and a tuning time of 0.05 s, which is slower than both the regression tree and the radial basis model. The computations take longer because the MLP was trained with three layers and 60 nodes in each layer. Figures 6 and 7 provide comparison graphs for predicting tool flank wear and surface roughness of the machined component using proposed ML models.

5 Conclusions

In this research, four common machine learning techniques, namely RF, MLP, Regression tree and Radial basis function, were used to predict tool wear of the cutting tool and surface roughness of machine components. The experiments are performed in a micro-turning machine. Vibrational data during machining, the surface roughness of the machined component and flank wear of the cutting tool were collected. The obtained data was used to train the model for predictive analysis of the machine tool. Vibrational data was recorded during the process, as well as the surface roughness of the machined component and flank wear of the cutting tool after each pass. The information gathered was utilized to develop a machine learning model that could predict machine tool performance.

From the analysis, it is seen that the RF model has more accuracy but takes a longer time to compute, whereas the Radial-based function has lower accuracy but takes

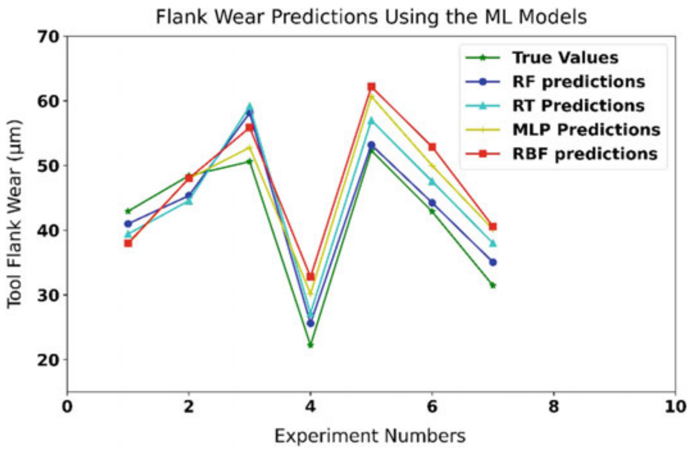


Fig. 6 Prediction of tool flank wear using ML models

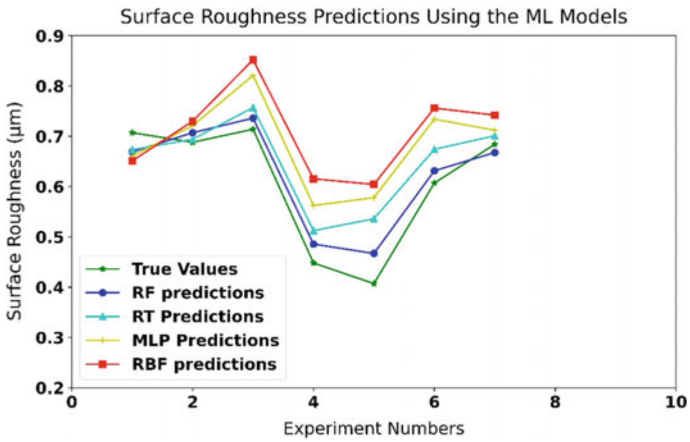


Fig. 7 Prediction of surface roughness using ML models

less time to compute. The accuracy of the Regression tree is 7% lower than the RF model, but it is two times faster. Considering the significance of computation time and accuracy associated with the various ML models, the Regression tree results in better performance to predict the machine tool condition. Tool wear and surface finish are primarily influenced by cutting parameters and cutting tool vibration. Lower feed rates and moderate depth of cut with high cutting speed result in less vibrations, minimum flank wear in cutting tool and good surface finish.

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Plasma Characterization in Ultrasonic Vibration-Assisted Micro-Electrical Discharge Machining (μ-EDM)

Leeba Varghese, Jerin George, and K. K. Manesh

1 Introduction

Micro-EDM is an advanced manufacturing process which has the capability to remove material in the sub-grain size range. It causes minimum damage to the material due to its non-contact nature and thus retains the properties of the material. This has made it a suitable choice for machining Nitinol shape memory alloy, widely used in biomedical and aerospace applications.

The material removal takes place due to a plasma generated in the gap between tool and workpiece, immersed in a dielectric. An electric potential is applied between the tool and workpiece electrodes by using a Resistance–Capacitance (RC) circuit. In the experimental set up, de-ionized water is used as dielectric. When breakdown potential of the dielectric is reached, it tends to break down into ions by releasing electrons. This breakdown process is initiated by primary electrons emitted by cathode, the tool electrode. Breakdown of the dielectric releases secondary electrons, through a series of chemical reactions and results in the formation of a plasma channel. The resulting avalanche of electrons is seen as the spark which will last only for a few microseconds. The bombardment of these ions and electrons on the surface of the tool and work piece, respectively, causes melting of corresponding electrodes and thereby material is removed from their surface. At the end of the discharge, the supply shutdown and plasma implode under the external pressure applied by the surrounding dielectric. The dielectric flushes the molten metal along with the debris and leaving a crater at the work piece surface [1].

L. Varghese (✉) · J. George · K. K. Manesh
Department of Mechanical Engineering, Government Engineering College, Thrissur, India
e-mail: leebavarghese1982@gmail.com

K. K. Manesh
e-mail: maneshkk@gectcr.ac.in

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