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Improving Turning Machining Processes through Integration of Micro-Textured Tools: A Modelling Approach

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Abstract*—This study explores the enhancement of machining performance through incorporation of micro-textured cutting tools and machine learning based modelling techniques. Two different textured tool geometries in the form of micro-drilled holes and micro-channel textures were created on the rake surface of carbide cutting tools. The performance of these textured tools was compared experimentally with standard dry turning and lubricated turning conditions for AISI 1014 mild steel on a normal lathe for different cutting speeds (26 and 39m/min) and depths of cut (0.75 and 1mm). Experimental results indicated that textured tools substantially enhanced the machining quality as compared with standard turning conditions. The importance of machining variables was evaluated using Random Forest (RF) feature importance analysis. The study revealed that surface roughness was the most significant parameter followed by sawtooth distance, cutting force and power consumption. Additionally, machine learning regression and classification models were built using Support Vector Regression (SVR), Support Vector Classification (SVC) and RF techniques. When compared, the RF model resulted in higher performing model with higher R^2 and other statistical values. The RF classification model yielded better results with an accuracy of 0.954, F1-score of 0.936, precision of 0.943, and recall of 0.943. The results demonstrate that the integration of micro-textured tools and machine learning algorithms can significantly improve the machining efficiency, reduce the frictional and thermal effects, improve the surface quality and provide accurate predictions of the machining responses.

Keywords— Chip morphology, Machine learning, Micro Textured tools, Tool Wear

I. INTRODUCTION

During the machining process, precise patterns on the rake surface of the cutting tool improves the cutting operation. The patterns developed may be in the form of tiny ridges, micro holes, or channels for improving the cutting performance. In the turning process, the tool geometry decides the quality of the machined output, and the chip formation, surface characteristics, and tool wear vary with the tool morphology.

Earlier dry-turning machining that does not require lubricants has shown an improved contact area at the tool tip interface under high loads. This operation is considered clean because it minimizes the use of lubricants, as well as the associated maintenance and disposal costs [1, 2]. In the dry machining system, it is important to know the tools of morphology and materials technology. This process helps to achieve clean manufacturing and foster sustainability, making it a highly valuable process [3]. One of the major problems in dry turning is the formation of residual stresses and the surface changes during machining. This phenomenon has a substantial impact on fatigue life and durability of the finished part [4]. Additionally, larger contact area at the tool tip interface generates increased friction and heat, which raises the temperature and causes excessive wear on the tool rake and crater surface [5].

The application of lubrication over a tool tip helps reduce friction and improves chip flow over the rake surface [7]. This subsequently results in lowered temperature in the cutting zone [8]. The lesser contact length underneath the chip that reduces the cutting forces [9]. A minimum quality lubrication (MQL) method can further enhance the machining process. In this context, use of MQL [10] and MQCL [11] aids in cooling the tooltip junction, which reduces tool wear and improves machined surface roughness [12]. The dissipation of heat generated during the machining process is carried away by the lubrication that improves the machining efficiency in MQL [13] and MQCL [14] methods. In recent times the FEM model was employed to determine the machining attributes and then compared with the experimental values. In one research study, the deviation was 0.32% and 0.23% for cutting force and temperature, respectively, when FEM was compared with the actual values [6].

The rise in temperature breaks the tooltip chip, resulting in reduced tool life and performance during machining. Advanced machining techniques, such as tool surface texturing, can help mitigate the enhancement of tribological properties of the tool and reduce friction and heat transfer during the machining process [15].

Surface texturing has been shown to improve lubrication in various mechanical components. Lei [16] assessed textured and non-textured tools during the machining of mild steel and observed a 30% reduction in cutting force. Kawasaki [17] studied the machining performance improvement of aluminium alloys with the textured tools. Obikawa [18] investigated the effect of cemented carbide texture tools during the machining of aluminium alloy and found that the parallel-type texture was effective due to improved lubrication conditions. Other forms

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of textures, such as aerial [19], dimple [20], and channel textures [21], are also investigated.

Statistical models such as machine learning, Artificial neural networks and others have become popular tools for predicting output values based on several parameters. Das [22] worked with the ANFIS method to predict thrust force and surface roughness of composite materials. Nuawi [23] developed ANN models for machining process optimization. Shang [24] conducted a comprehensive review of various ANN models suitable for optimizing machining parameters. Patel [25] reviewed various ANN-based modelling techniques for machining parameter values.

In this work, the channel type and multiple micro hole channels are textured over the rake surface to study its performance in the machining process. Furthermore, different machine learning models are developed to compare robust model for different cutting tools. Overall, this study aims to conduct experiments on machining processes with various tool morphologies in order to evaluate their machining performance.

II. EXPERIMENTAL DETAILS

The tests were done on a lathe machine with AISI 1014 mild steel as workpiece. The detailed specifications of the machine and configuration of tool employed in the present work are similar to those reported in previous works by Shailesh [26]. The processes are carried out with both smooth and textured cutting tools and for dry and wet cutting conditions. A machine tool dynamometer was used to quantity the cutting force. The textures of having micro-drills with a diameter of 0.5mm/1mm with depth of 1mm are developed on the rake surface, Fig 2a, and channel textures with a set width of 0.5mm and a depth of 1mm are created, Fig 2b.

TABLE I. Different Turning Methods and Defined Process Name

Method	Process Name
Dry turning Process	A1
Turning process with lubrication	A2
Micro-drilled textured tools used for machining	A3
Micro-channel-textured tool used for machining	A4

The different process parameters and their defined process name are mentioned in Table I. Two different cutting speeds (26 and 39m/min) and depths of cut (0.75 and 1mm) are employed for the machining process. During the tests, petroleum-based lubricants were used, keeping the flow rate constantly at 40cc/hr. A lathe tool dynamometer from CONTECH accurate to 0.1N is used to determine the cutting power. Table 2 represents the various machining parameters employed for the present work.

To find out surface roughness, the Talysurf tool from Mitutoyo is used. A standard three-axis accelerometer is used to measure the vibrations. The tooltip temperatures were calculated analytically through an empirical thermal model than direct sensor measurements, Equation 1. The equation considers the friction power at tool tip (P_u in N), rate of metal removal (M_c in kg/s), and workpiece specific heat coefficient (C_s in Nm/kg °C).

$$\Delta Tc = Pu / (Mc \times Cs) \quad —— \quad (1)$$

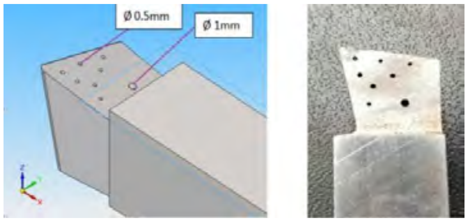

Fig. 2a. Micro-holes on the rake surface

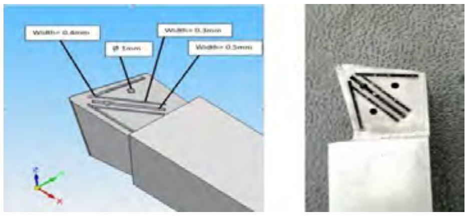

Fig. 2b. Micro-channels on the rake surface

TABLE II. Consolidated Data of Different Process Parameters

Cutting Speed (m/min)	Depth of cut (in mm)	Tooltip Temperature (in °C)	Cutting Force (in N)	Power (in HP)	Surface Roughness (in µm)	Amplitude (in mm)	Sawtooth Distance (in mm)	Method
26	1	103	67	0.476	9	0.2	62	A1
26	1	79	59	0.45	8.8	0.18	52	A2
26	1	102	60	0.45	7.1	0.175	55	A3
26	1	88	55	0.432	6.8	0.17	43	A4
26	0.75	88	56	0.274	5.5	0.12	44	A1
26	0.75	86	51	0.254	5.3	0.11	33	A2
26	0.75	64	49	0.225	5	0.1	34	A3
26	0.75	61	46	0.21	4	0.09	22	A4
39	1	138	85	0.673	8.2	0.3	74	A1
39	1	120	78	0.523	7.9	0.24	66	A2
39	1	119	77	0.512	5.8	0.27	68	A3
39	1	114	68	0.569	4.95	0.21	59	A4
39	0.75	101	67	0.4	4	0.2	56	A1
39	0.75	103	60	0.322	3.5	0.14	49	A2
39	0.75	80	61	0.255	2.85	0.17	49	A3
39	0.75	72	58	0.24	2.4	0.12	42	A4

A previous publication has reported the initial research on the machining performance of micro-textured tools during turning operations [26]. The current investigation is an extension through comprehensive evaluation of the machining responses under different textured tool conditions and machine learning-based regression and classification modelling with Random Forest and Support Vector approaches.

III. RESULTS AND DISCUSSIONS

A. Percentage Reduction Comparison for Operating Parameters

Comparing several machining conditions, tooltip temperature rises with a higher cutting speed and depth of cut (Fig. 3a). The dry turning process achieved a higher temperature due to higher friction and heat generation at the tool-chip interface. For the A1 process condition, the maximum tooltip temperature was 138°C at cutting speed of 39m/min and depth of cut 1mm. The petroleum-based lubrication used in the A2 process has reduced the tooltip temperature. In addition, the textured tools (A3 and A4) experienced lower temperatures than the conventional tool conditions by 8 to 15%.

For the A4 cutting process and depth of cut 0.75mm, the temperature decreased from 138°C to 101°C (a reduction of approximately 26.8%) when compared with the A1 process. Fig. 3b,c depicts the variation in cutting force and power consumption. The peak cutting force values emerged in the dry turning process. Under the conditions of the A1 process, the cutting force was a maximum of 85N when the cutting speed was 39 m/min and the cut depth was 1mm. The A4 condition reduced the cutting force from 85N to 68N at 39 m/min and 1 mm depth of cut, which is a reduction of almost 20% compared to dry turning conditions.

The textured tools (A3 and A4) presented further reductions in cutting force due to the increased retention of lubrication and improved tribological conditions at the rake face. The reduced resistance and higher stability of material removal is observed with reduction of cutting force at lower depth of cut.

The power consumption possessed similar trend as the cutting force. This is due to additional energy necessary to eliminate the material at higher cutting speeds. The maximum power consumption under the A1 condition was 0.673HP at 39m/min and 1mm of depth of cut. The A4 process resulted in a reduction of power consumption from 0.673HP to 0.569HP. The reduction was more apparent at lower depth of cut, from 0.400HP to 0.240HP, which is nearly a 40% reduction as compared to dry turning conditions [27].

Fig. 3d displays the difference in surface roughness for various machining process. The conventional dry turning process shows a variation in surface roughness with higher cutting speed and depth of cut. Among all machining environments, the surface roughness values of the A4 textured tool seemed the lowest. With a cutting speed of 39 m/min and a cut depth of 1mm, the A4 condition reduced the surface roughness from 8.2 to 4.95µm, an improvement of about 39.6% compared to the dry turning conditions [28, 29].

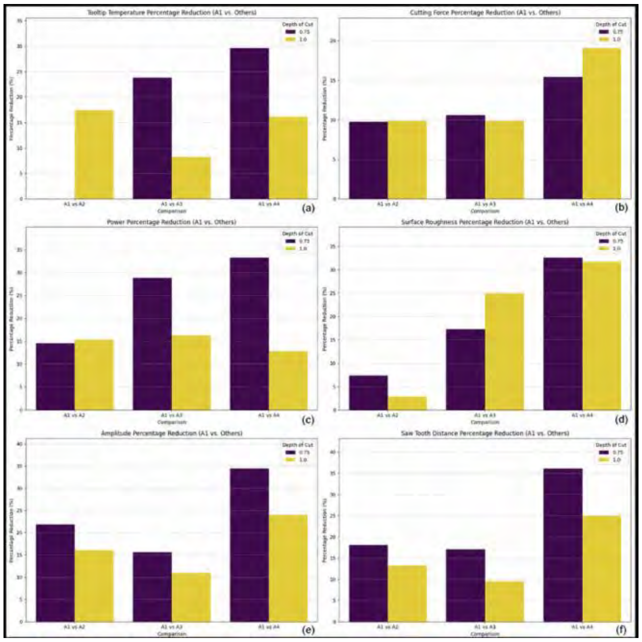

Fig. 3. Percentage reduction comparison of operating parameters for A1 with respect to A2, A3 and A4 at different depths of cut: (a) tooltip temperature, (b) cutting force, (c) power consumption, (d) surface roughness, (e) amplitude, and (f) sawtooth distance.

Fig. 3e shows the variation of the vibration amplitude. Vibration amplitude rises with higher cutting speed and depth of cut for all machining conditions. The A4 amplitude decreased from 0.30 to 0.21mm at a cutting speed of 39m/min and a depth of 1mm, corresponding to a reduction of nearly 30% [30, 31].

Fig. 3f shows the change in the sawtooth distance. The dry turning process showed the highest saw-tooth distance values. The minimum values of the saw-tooth distance were obtained by the A4 textured tool for all machining conditions. The sawtooth distance decreased from 74mm for A1 to 59mm for A4, approximately a 20.3% reduction at 39m/min and 1mm depth of cut [29].

Fig. 4 presents the normalized performance comparison of various machining methods. The dry turning condition resulted in maximum normalized values, indicating severe frictional interaction, unstable chip formation and poor machining stability. The A4 condition showed the best overall machining performance with minimum normalized responses for cutting temperature, surface roughness, amplitude, and saw-tooth distance.

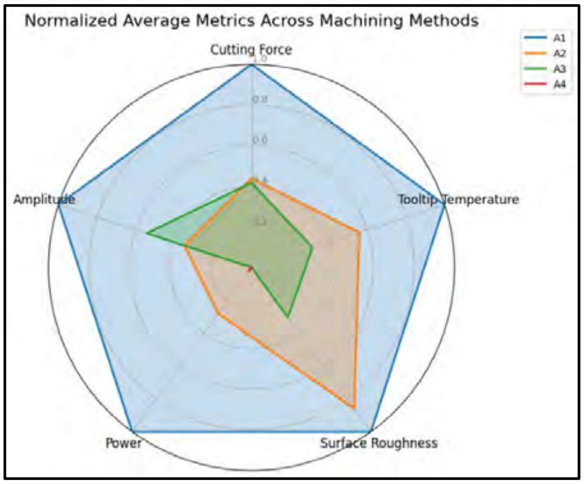

Fig. 4. Normalized performance comparison of different machining methods and cutting conditions.

B. Feature Importance Analysis – Random Forest Method

Fig. 5 represents the feature importance method using the RF method. The model was trained on experimental data obtained from the turning operations. The results indicate that surface roughness possessed the higher variance value of 0.310, contributing roughly 31% towards the prediction performance of the RF model [23, 24].

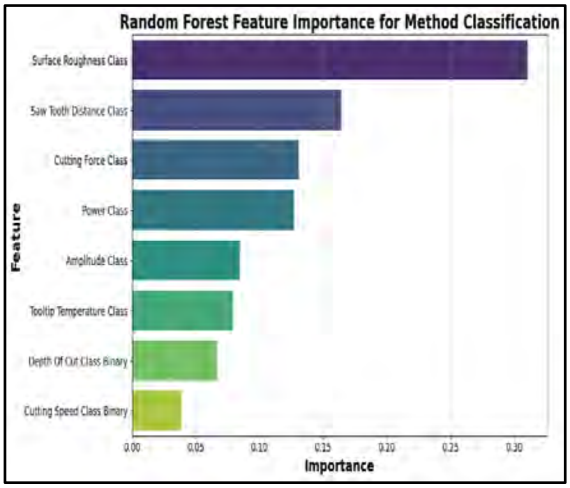

Fig. 5. Feature Importance Method (Random Forest Regression).

The sawtooth distance had the second variance value of 0.164, contributing about 16.4% to the prediction process. Moreover, the variance values of cutting force and power were 0.131 and 0.127 respectively. The cumulative importance analysis indicated that the selected parameters cumulatively contributed more than 80% to the prediction capability of the RF model [32, 33].

C. Comparison of Various Machine Learning Models

1) Regression Models

Table III shows the comparative evaluation of created ML regression models with Support Vector Regression (SVR) with kernels K=1 and K=2 and RF regression are employed. The SVR model with K=1 exhibited a moderate prediction ability with an R^2 of 0.742. The second-order SVR model (K=2) showed better prediction ability with an R^2 of 0.821. The RF algorithm was the best among all the models, showing the maximum prediction accuracy with an R^2 of 0.890 and lower RMSE (0.812), MAE (0.653), and MAPE (4.85%).

TABLE III. Comparison of Error Metrics Using Different ML Regression Models

Model	**R^2 Value**	**RMSE**	**MAE**	**MAPE (%)**	**Performance**
SVR, K=1	0.742	2.184	1.865	11.42	Moderate
SVR, K=2	0.821	1.546	1.214	8.36	Improved
RF	0.890	0.812	0.653	4.85	Best

2) Classification Models

For robust model development, the experimental machining parameters were categorized into multiple performance classes using a quartile-based classification approach. The quartile classification procedure was performed by calculating Q1, Q2 and Q3 values for each machining response parameter. The classes for the data frame were labelled from Class 1 to Class 4.

The feature importance variance value of Surface Roughness class was found to be highest at 0.36. The second important feature was Sawtooth Distance class with approximately 0.23. Furthermore, the Cutting Force class variance was 0.21.

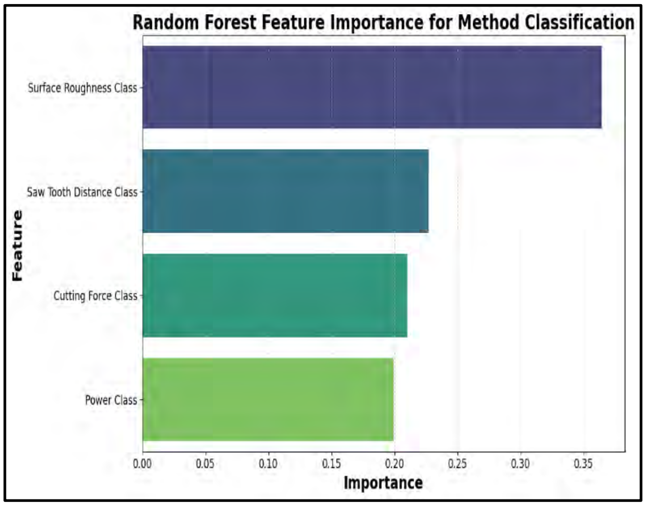

Fig. 6. Feature Importance Method (RF Classification).

TABLE IV. Comparison of Error Metrics Using Different ML Classification Models

Model	**Accuracy**	**F1-Score**	**Precision**	**Recall**
Random Forest (RF)	*0.954*	*0.936*	*0.943*	*0.943*
SVC, K=1	0.62	0.60	0.73	0.62
SVC, K=2	0.64	0.66	0.64	0.64

Table IV summarizes the performance of various ML models. Here the RF model resulted in superior model performance with higher accuracy and other statistical metrics. The SVC model with K=1 provided an accuracy of 0.62 that reflects the lower efficiency. The SVC model with K=2 showed a slight improvement with an accuracy of 0.64. The RF model performed more robustly in terms of classification accuracy, reliability, and prediction consistency.

IV. CONCLUSIONS

This study assessed the effect of micro-textured cutting tools on the performance of turning machining. A machine learning model was established to forecast machining responses during turning under varied cutting conditions. The following conclusions were drawn:

1) Machining responses were significantly influenced by cutting speed, depth of cut, lubrication, and tool geometry. Cutting speed and depth of cut increased tooltip temperature, cutting force, power consumption, vibration amplitude, surface roughness and sawtooth spacing in all machining conditions.
2) Textured tools outperformed normal tool settings. The micro-channel tool exhibited better lubricant retention, chip flow, and rake surface tribological interaction compared to conventional tools.
3) The micro-channel textured tool greatly reduced tooltip temperature, cutting force, power consumption, vibration amplitude, and sawtooth distance compared with dry turning conditions. Significant improvement (>40%) in

surface roughness was observed with textured tool configurations.

4) The RF feature importance method revealed that the surface roughness as the most essential machining parameter, followed by sawtooth distance, cutting force and power consumption.
5) The RF regression model delivered moderate R^2 values with low RMSE, MAE and MAPE values that performed significantly than the SVR models. However, the RF classifier approach has a 94% accuracy with improvement in F1-score, precision and recall value.

Author Contributions

Shailesh Rao A worked on Conceptualization, methodology, experimental investigation and original draft preparation. **Santhosh Kumar** looked for validation and methodology of various machining process. **Suresh** carried out the experimental work and tool texturing assistance. **Sathisha** carried out developing ML models completely. **Pavan Kumar** worked on the detailed technical support, manuscript review and editing

AI Tool Usage Acknowledgment

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