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Comparative Machining Performance Analysis between Taguchi's Method and Random Forest Model

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Abstract

Objectives: To optimize the process parameters in dry turning of hardened 20MnCr5 using a PVD coated insert to minimize surface roughness and power consumption and maximize material removal rate using the Taguchi technique and machine learning model. **Methods:** For carrying out the experiments, an L27 orthogonal array was employed and Taguchi's means of mean method was used to find the optimal condition. ANOVA was utilized for determining the significance of factors. The Random Forest model uses an ensemble learning method where multiple decision trees are developed and then predictions are made. To boost the prediction efficiency, averages are made from these multiple decision trees and the voting method to finalize the model that needs to be used for the prediction. Finally, experimental and predicted values are compared using statistical metrics to determine the model's effectiveness. **Findings:** From experimental data at 80 m/min, 0.2 mm/rev, 0.5 mm and 120 m/min, 0.05 mm/rev, 0.25 mm and 100 m/min, 0.2 mm/rev, 0.1 mm are the optimal conditions found for material removal rate, surface roughness and power consumption respectively. Feed was the most influential factor, with a percentage contribution of 90.98%, 46.86% and 87.053% for surface roughness, material removal rate and power consumption respectively. The developed random forest models had an accuracy of 91.057%, 96.546% and 96.0122% for surface roughness, power consumption and material removal rate respectively, and they had less mean absolute errors. **Novelty:** Alloy steels are used to manufacture components that need to resist wear and plastic deformation, so it's important to know how hardened material behaves under dry turning operations as the world is focusing on green manufacturing. Moreover, the experimental approach is time-consuming and costly, so a machine learning model was developed based on the available experimental data to predict the output responses for additional inputs.

Keywords: Dry turning; MQL machining; Taguchi technique; ANOVA; Random Forest model

1 Introduction

Dry machining is an application that has just arisen and grown rapidly. It is a method of machining that avoids the utilization of lubricants and cutting fluid. It additionally must assure acceptable tool durability, product quality and efficiency. As the cutting fluid utilization ceases in the cutting process, it should be able to produce components with the desired characteristics. It asks for the adoption of dry machining tools with outstanding durability[1]. In recent times, every manufacturing plant has been focusing on increasing its yield by balancing cost and quality. Environmental pollution is not possible with dry machining, as it is a green manufacturing process. Dry machining was made possible with the evolution of surface coating technology and high-temperature-resistant tool material by the dawn of high-speed machining. Dry machining can be made possible with a little effort. As cutting fluid usage is eliminated, the prime predicament is the tool life and the amount of heat generated. Overheating of the workpiece during the machining process results in the workpiece hardening. Tools should be excessively worn and heat resistant for dry machining to be viable. Swift heat dissipation during machining is crucial. Dry machining became realistic with the emergence of high-hard materials. Shock resistance, thermal resistance and wear resistance are some of the properties of the tool required for dry machining. For dry machining diamonds are some of the ultra-hardened tool materials currently in use. The absence of recycling of chip material and cutting fluid handling eliminates the extra costs. MQL machining is another method that is also called near dry machining. Cutting fluid is employed in the mode of mist during the execution of the turning process; this has fewer negative effects compared to the flood lubrication method and with respect to dry machining, heat generated in this method is successfully minimized[2].

Manoj Kumar Sinha et al.[3] reviewed literature on superalloy machining and investigated superalloy characteristics. Machining under various environmental circumstances was investigated, and it was established that tools with high hardness and strength are necessary for superalloy machining. Flood lubrication was best suited since the heat generated in the machining of super alloys was quite high, but it had some severe adverse effects. Moving to a dry environment for sustainable machining was investigated, however tool wear was quite high. It was determined that the MQL and cryogenic conditions were best suited for superalloy machining since tool wear and heat produced were significantly reduced. Djordje Vukelic et al.[4] attempted dry machining on AISI 1040 using Chemical Vapour Deposition (CVD) coated tools with varying corner radii. Experiments were carried out at various "V_c", "DoC" and "f". This experiment examined the tool's life as well as the "R_a" of the workpiece. The Response Surface Modelling (RSM) technique and Analysis of Variance (ANOVA) were used to identify changes in output owing to the influence of input. Based on the developed regression model, a genetic algorithm was utilized to multi-optimize the output parameter. It was attempted to produce more than one optimal parameter combination. Gürbüz Hüseyin et al.[5] conducted experiments on AISI 4140 under dry and MQL conditions. MQL gave better results than dry machining for cutting force, tool wear and "R_a". Abidin Şahinoğlu et al.[6] studied vibrations, sound intensity, surface roughness, and machine current when rotating on AISI 4140. RMS and ANOVA were used to investigate the relationship between input parameters and output responses. A mathematical prediction model was created using the multi-linear regression approach. To validate the expected and experimental results, confirmation tests were performed. It was discovered that the output responses were all connected to one another, and that changes in one caused changes in the others. Paturi Uma Maheshwera Reddy et al.[7] conducted dry turning experiments on AISI 52100. The process parameters were optimized using MOO to minimize surface roughness and tool wear. For evaluating and measuring the correlation between the input and output parameters, a response surface method, a complete factorial design, and a desired functional approach were used. Feed rate, cutting speed, and depth of cut all had a significant impact on surface roughness. Cutting speed had the greatest impact on tool wear, followed by feed rate and depth of cut. Ugonna Loveday Adizue et al.[8] used a CBN insert for ultra-precision hard-turning finishing operation for AISI D2 steel (62 HRc). Support vector machine, artificial neural network, gaussian process relation and neuro-fuzzy interface system models were developed for the prediction of surface roughness. Adaptive neuro fuzzy interface systems and artificial neural networks were highly accurate. Feed was the most influential factor for surface roughness. Shanmugasundar et al.[9] considered each case study of electro-discharge machining and wire electro-discharge machining from the literature and applied linear regression, random forest regression and AdaBoost regression as the experimental methods were costly and time-consuming. Random forest and Adaboost models gave better results compared to linear regression. Kamal Kishore et al.[10] performed Inconel 625 grinding under dry, wet, and MQL conditions. The output checks in this investigation were tangential forces and surface roughness. The association between inputs and outputs was discovered using RSM and four distinct ML models. Overall, it was determined that MQL gave better outcomes, with wheel speed and depth of cut being important variables in both outputs.

Literature studies shows that researchers have evaluated turning performance on alloy steel considering input parameters "V_c", "f" and "DoC" and evaluated output characteristics like "R_a", "T_w", "MRR" and "P_c" under various environmental conditions (dry, wet, and MQL). The MQL technique provided the best results of all. In some studies, turning was conducted using uncoated, PVD and CVD coated tools and the output responses were compared with each other. Coated tools produced better results compared to uncoated tools; in uncoated tools, tool wear was high, which in turn affected the surface roughness and material removal rate.

In most studies, the turning of alloy steel was carried out at a hardness below 45 HRc. Therefore, heat treatment was not carried out to increase the hardness of the workpiece in a major number of studies. As the application of alloy steel is in the manufacturing of gears, crankshafts, axles, cutting tools, etc., alloy steel needs to have high wear and abrasion resistance as these components are always in contact with other parts adjacent to them and have relative motion with each other. Friction is eminent, due to friction, wear of the component is unavoidable, which affects the life of the component, so these components should be of high hardness to increase the life of the component. It is necessary to investigate the behaviour of hardened alloy steel under turning operation, as hardened materials are hard to turn and need highly hardened tool materials for turning. As most of the studies were not conducted on hardened material, there was not much data on the dry turning of hardened 20MnCr5 using a PVD coated tool. It is a costly and time-consuming process to perform machining operations and find the output characteristics each time the input parameters differ, so a machine learning model can be created where the model will be trained based on the available input data as well as output data and can be used for the further prediction of output responses. The prediction accuracy will be based on the training data provided to the model for training.

Using the Taguchi optimization technique and the Random Forest model of machine learning model, optimal conditions for "R_a", "MRR" and "P_c" for turning hardened 20MnCr5, which was hardened through the case hardening process, using a PVD coated insert are found in this study. As in most of the previous studies, optimal conditions for outputs are found at the primary available hardness of specimens, which is around 20–25 HRC generally. From the literature review, it was found that PVD coated (TiAlN) is best suited dry turning process, therefore a PVD coated tool of Ti-Al-Si-N nanolaminate coating, which is similar to the suggested tool is utilized in this study. Moreover, the random forest model needs less data to train compared to other machine learning models and can develop a model that can predict the data with high accuracy. The turning process opts to be carried out under dry conditions as every manufacturing industry is moving towards green manufacturing, as the usage of cutting fluid is eliminated in dry machining conditions, hence it is regarded as green manufacturing. In wet and MQL machining, cutting fluids are used, which can cause environmental problems, affect the operator and corrode the machine tool. Under the right conditions, tool life can be increased in dry conditions. Moreover, dry machining costs less as compared to MQL and wet machining. Hence, this study was conducted focusing on dry machining.

2 Methodology

The primary aim of this work is to model and predict output responses, such as "R_a", "MRR" and "P_c" when considering input parameters like "DoC", "f" and "V_c" during the dry turning of hardened 20MnCr5 using the random forest machine learning technique. Analysing the behaviour of hardened materials during machining is crucial. Experimentally determined optimal conditions were identified for each output response. The influence of input parameters is measured using the statistical approach of ANOVA. The performance of the random forest model in predicting output responses is compared with experimental results using statistical metrics such as the R^2 score (which ranges from 0 to 1 and should be as high as possible) and the mean absolute error (which should be as low as possible). The following are details about the experimentation that has been carried out.

2.1 Input Variables

A preliminary study was conducted to finalize the input variables. The input variables considered for the experimentation were the "DoC", "V_c" and "f." Their levels were determined based on the literature survey carried out. From the handbook, various standard ranges of cutting conditions for turning (cutting speed, feed and depth of cut) based on the workpiece and tool materials were opted [11]. As the workpiece material used for this study is case hardened up to 51–52 HRc, case hardening is a coating process, the hardness of the workpiece increases only up to a certain thickness. Based on the thickness of the hardness layer of the workpiece, the depth of cut for the experiment has been determined. Based on the hardness of the workpiece and the tool selected from the experiment, cutting speed levels were selected from the cutting speed ranges. The feed was selected from the feed rate range. The input parameters for the experimentation are presented in Table 1.

Table 1. Input factors for turning operation

Process Parameters	Levels		
	1	2	3
Cutting Speed (m/min)	80	100	120
Feed (mm/rev)	0.05	0.1	0.2
Depth of cut (mm)	0.1	0.25	0.5

2.2 Design of Experiments

The Taguchi technique was utilized for the Design of Experiments (DOE) for optimization purposes. Taguchi proposed a specific kind of matrix called orthogonal arrays (OA) that assists in conducting a smaller number of tests with varied combinations of process parameters; it is an effective strategy for experiment design. Minitab 17 software has been utilized for DOE. The experiments were conducted using the L_{27} orthogonal array after completion of DOE. Three parameters each with three levels were considered input parameters for the experimentation. The input parameters mapped in the L_{27} orthogonal array are presented in Table 2.

Table 2. Standard L_{27} OA assigned with the input factors at three levels

S.no.	Cutting speed (m/min)	Feed (mm/rev)	Depth of cut (mm)
1	80	0.05	0.1
2	80	0.05	0.1
3	80	0.05	0.1
4	80	0.1	0.25
5	80	0.1	0.25
6	80	0.1	0.25
7	80	0.2	0.5
8	80	0.2	0.5
9	80	0.2	0.5
10	100	0.05	0.25
11	100	0.05	0.25
12	100	0.05	0.25
13	100	0.1	0.5
14	100	0.1	0.5
15	100	0.1	0.5
16	100	0.2	0.1
17	100	0.2	0.1
18	100	0.2	0.1
19	120	0.05	0.5
20	120	0.05	0.5
21	120	0.05	0.5
22	120	0.1	0.1
23	120	0.1	0.1
24	120	0.1	0.1
25	120	0.2	0.25
26	120	0.2	0.25
27	120	0.2	0.25

2.3 Workpiece dimensions and material

The material selected for the experimentation process is 20MnCr5, a low-alloyed engineering case-hardened steel. The major applications of 20MnCr5 include manufacturing spindles, camshafts, gears, piston bolts, and shafts. It has a percentage composition of C: 0.211, Si: 0.312, Mn: 1.287, P: 0.017, S: 0.0015, Cr: 1.057. The dimensions of the workpiece were a Ø32 mm diameter and a length of 150 mm. Turning was conducted for 100 mm in length from one end. The workpiece was case-hardened up to 51–52 HRc hardness using Gas Carburizing Furnace III, as the hardness of the workpiece was only 21 HRc initially. Figure 1 (a) illustrates the workpieces used for the experimentation.

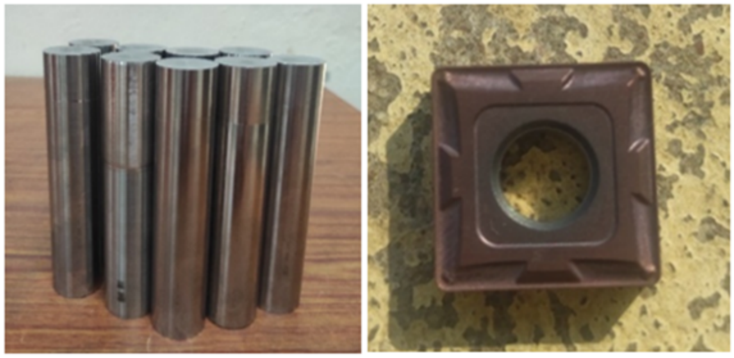

Fig 1. (a) Workpieces for the machining process (b) cutting insert used for the experimentation- SNMG 120408 MF2 TH1000

2.4 Tool material

In the present research work, an SECO-made PVD-coated carbide cutting insert was used. The insert has an ISO coding of SNMG 120408-MF2 TH1000 grade. The tool holder used for holding the tool is PSBNL 25 25 M12. Singh et al. [12] determined from their study that PVD coated (TiAlN) is best suited for dry machining. TH 1000 is a PVD coated tool with a Ti-Al-Si-N nanolaminate coating. SNMG 120408-MF2 TH1000 is a PVD-coated tool that is best suited for this study for various reasons like: it can be used for finish turning, even in superalloys and workpieces with hardness as high as 62 HRc, with speeds ranging from 75 m/min to 130 m/min, due to its remarkable edge toughness, high wear resistance, and deformation resistance. It serves as an attractive performance alternative to ceramics, and machining with this tool can achieve significant cost savings through increased tool life and maximum productivity [13]. Figure 1 (b) illustrates the cutting tool insert used for the experimentation.

2.5 Equipment and Instruments

The ACE DESIGNERS' SUPER JOBBER 500, a CNC lathe was used for the dry turning operation. The machine has a maximum turning length of 500mm, a maximum turning diameter of 290mm, a maximum spindle speed of 3500 RPM, and a spindle power rating of 9 kW. The Mitutoyo surface roughness tester SJ-310 was utilized to analyze the "R_a" of the workpieces. It has a measuring range on the x-axis of 17.5 mm, a detector measuring range of 360 μm (-200 μm ~ +160 μm), and a measuring speed of 0.75 mm/s, 0.5 mm/s, 0.25 mm/s in onward motion, and 1 mm/s in reverse motion.

2.6 Taguchi's optimization

In mono-objective optimization, each output response is optimized individually for the optimal parameter condition. Taguchi analysis, based on the means of means, is used to find the optimal condition, and the ANOVA general linear approach is employed to determine the significance of factors in mono optimization at a 95% confidence interval. That is, if the "p-value" is less than 0.05, then the factor is considered prominent; if the "p-value" is higher than 0.05, then the factor is deemed insignificant. Minitab 17 software has been utilized for performing Taguchi's optimization and ANOVA. Output responses obtained from the experimentation, as well as the predicted values from the random forest model are presented in Table 3.

Table 3. Results from the experimentation and machine learning model

S.no.	Experimental values			Predicted values		
	Surface roughness (μm)	**Material Removal Rate (mm^3 /min)**	**Powerconsumption (Wh)**	**Surface roughness (μm)**	**Material Removal Rate (mm^3 /min)**	**Powerconsumption (Wh)**
1	0.29125	249.273	0.023	0.4104	498.2727	0.010626
2	0.383	352.49	0.019	0.4104	498.05321	0.01063
3	0.432	359.754	0.024	0.4104	498.0532	0.010626
4	0.86275	1507.1136	0.005	0.826	1787.317735	0.00528
5	0.7155	1629.726	0.006	0.826	1787.3177	0.005276
6	0.94425	1831.018	0.005	0.82594	1787.3177	0.00528

Continued on next page

Table 3 continued

7	2.79625	6963.218	0.003	2.56634	6757.5588	0.0031247
8	2.705	7312.466	0.003	2.56634	6757.5588	0.00269
9	2.08425	7755.577	0.004	2.56634	6757.558852	0.00399
10	0.504	960.738	0.007	0.4168	1166.2235	0.0087
11	0.38425	1085.138	0.009	0.4168	1166.2235	0.008295
12	0.33775	1282.907	0.01	0.4167	1166.2235	0.0087
13	0.8515	3442.604	0.004	0.771	3592.1928	0.0040525
14	0.672	3546.01	0.004	0.7701	3592.19281	0.0040525
15	0.79575	3844.8723	0.004	0.771	3592.1928	0.003722
16	3.90475	1769.78	0.005	3.1636	2016.41054	0.00269
17	2.84025	2006.798	0.005	3.1637	2016.4105	0.00269
18	2.86325	1549.307	0.006	3.1636	3592.193	0.003722
19	0.444	2085.767	0.008	0.3689	2081.04286	0.0082295
20	0.307	2082.943	0.009	0.3689	2081.0429	0.0087
21	0.3405	2076.3832	0.008	0.3689	2081.04286	0.0082295
22	0.67275	775.8253	0.008	0.7588	1332.5081	0.0040525
23	0.81225	766.0135	0.008	0.7588	1332.5082	0.00399
24	0.71025	1535.391	0.004	0.7588	1332.508141	0.00399
25	1.978	4174.552	0.003	2.596	3974.1661	0.003722
26	2.293675	4698.86	0.003	2.596	3974.16613	0.00312468
27	2.975	4994.1042	0.007	2.596	3974.1661	0.031247

2.7 Random Forest Modelling

Based on the experimental data, a machine learning model was developed using the random forest algorithm, which belongs to a supervised learning technique in machine learning. The random forest model was chosen for training and testing purposes. Ensemble learning is the principle on which random forest models are built. It is a practice where multiple classifiers are integrated to solve a complex problem and boost the execution of the model. The random forest model utilizes many decision trees on diverse subgroups of the experimental dataset and averages its findings to enhance the dataset's prediction efficiency. Instead of relying on a single decision tree, the random forest uses the predictions from all trees and predicts the results based on the voting on the results from the decision trees.

Google Colab was utilized for developing random forest models, in google colab the code for random forest models is written in Python language. Primarily several Python libraries are imported for data analysis, machine learning and visualization.; numpy, pandas, sklearn. ensemble, sklearn. preprocessing, matplotlib. pyplot, sklearn. metrics are the libraries that have been imported for developing the random forest model. Then the file with the inputs and outputs from the experimentation should be uploaded, the code reads the data available in the uploaded file and identifies the inputs and outputs in it. After reading the data, the code preprocesses the data and converts the data table into an array format. Then train-test-split feature is used to divide the total data into training data and testing data and random state is specified to ensure reproducibility. Then code creates a loop that iterates based on the iterations specified, for each iteration model is trained with a different random state. The score method is used to compute the accuracy for each iteration and stored for further reference. After completing the iteration of the loop, the random state with the highest accuracy is used as the optimal random state for developing the random forest model using the training data. Then the developed model is tested using the testing data. Finally, the model is evaluated when the code makes predictions for both training and testing data. Statistical metrics are used to assess the performance of the developed model. This model is saved for further usage. These predicted values are utilized to find the optimal conditions.

For the model, "V_c", "f" and "DoC" are the inputs, and "R_a", "MRR" and "P_c" are the outputs. A separate random forest model was developed for each output parameter, with inputs being constant. The total dataset presented in Table 3 was divided into training and testing data for each model, where 80% was used for training and 20% for testing. The model was executed from 1 to 10000 iterations, and the iteration with the highest accuracy was selected for model development. After the model is built, predictions are made, and the importance of input features on the output is determined (the sum of the feature importance of all features equals 1). Statistical calculations, such as mean absolute error, R^2 score, root mean squared error, and mean squared error were calculated between the actual and predicted values.

3 Results and Discussion

3.1 Taguchi's optimization

A means-based method was employed to determine the optimal parameter conditions for output responses using smaller-the-better or larger-the-better scenarios based on the desirable characteristics of the output responses. In this study, "R_a", "P_c," and "MRR" are the output responses. "R_a" and "P_c" should be as low as possible, so a lower-the-better scenario is used, while for "MRR," a larger-the-better scenario is applied.

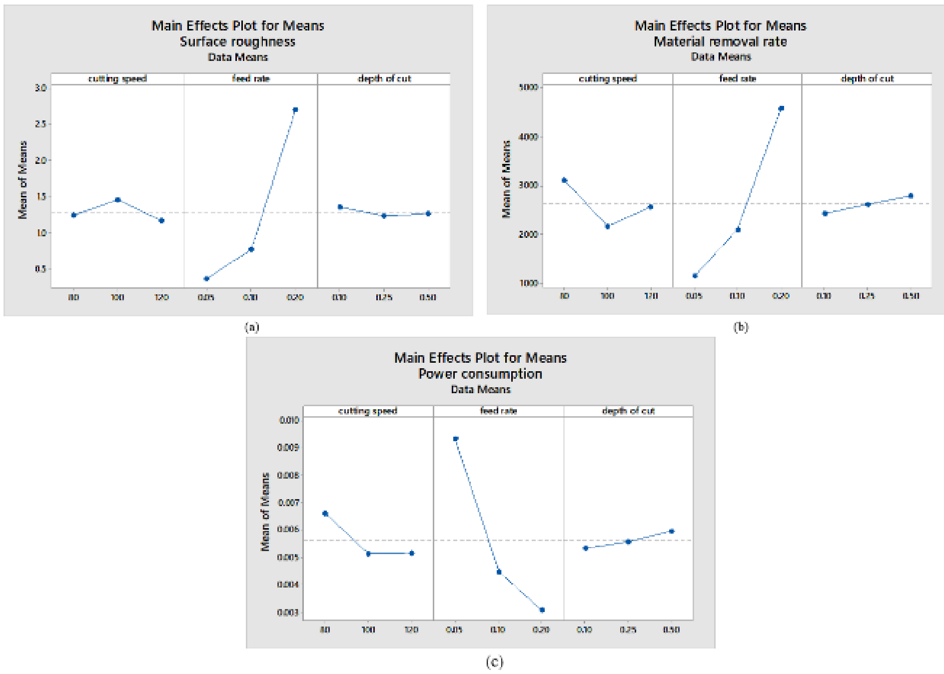

Fig 2. (a) Main effect plot for means of mean for surface roughness, (b) Main effect plot for means of material removal rate, (c) Main effect plot for means of power consumption

Using the means of the mean method, "R_a" was evaluated for the optimal parameter conditions. It was found that at 0.05 mm/rev "f", 120 m/min "V_c" and 0.25 mm "DoC", the best surface finishing will be obtained, indicating a low "R_a". Figure 2 (a) illustrates the main effect plot of the means of the mean for "R_a". FromFigure 2 (a), it can be established that "R_a" is inversely proportional to "V_c" and directly proportional to "f", i.e., as "V_c" increases, "R_a" decreases, and with the increase in "f", "V_c" increases. At higher "f", the movement of the tool with respect to the workpiece is more, so the surface roughness is high. Variation in the "DoC" did not have much effect on "R_a". The general linear method in ANOVA was used to find the importance of the factors for "R_a", "f" and "V_c" which were significant factors for "R_a". Feed had the most significant factor with 90.986% significance, followed by "V_c" with 1.37% and "DoC" with 0.274% significance. Table 4 presents the ANOVA results for "R_a". Figure 3 (a), (b), (c) illustrates the interaction plots of inputs for "R_a". From Figure 3 (a) it can be concluded that at 0.05 mm/rev "f" for all "V_c" surface roughness was less and with the increase in "f" surface roughness increased irrespective of "V_c". From Figure 3 (b) it can be concluded that for each level of "f" change in "DoC" didn't have much effect on "R_a", "R_a" increased with an increase in "f" and "DoC". From Figure 3 (c) it can be concluded that at higher "V_c" even if "DoC" were high "R_a" was low.

Using the means of the mean method, "MRR" was evaluated for the optimal parameter conditions. It was found that at 0.2 mm/rev "f", 80 m/min "V_c" and 0.5 mm "DoC", maximum material will be removed during machining. Figure 2 (b) illustrates the main effect plot of the means of the material removal rate. From Figure 2 (b), it can be established that with an increase in the "DoC" and "f", "MRR" increases; with an increase in "f", the movement of the tool with respect to the specimen increases; and with an increase in "DoC", the material to be cut increases. The general linear method in ANOVA was used to find the importance of the factors for "MRR". All three input parameters, "V_c", "f" and "DoC" were discovered to be significant for "MRR". Feed was the most significant factor with 46.86%, followed by "V_c" with 3.39%, and "DoC" with 0.5074%. Table 5 presents the ANOVA results for "MRR". Figure 3 (d), (e), (f) illustrates the interaction plots of inputs for "MRR". From Figure 3

Table 4. ANOVA for surface roughness

Source	DF	Adj SS	Adj MS	F-Value	P-Value	P%
Cutting speed	2	0.8395	0.4197	7.39	0.002	1.3660824
Feed	2	55.9136	27.9568	492.39	0.000	90.985809
Depth of cut	2	0.1682	0.0841	1.48	0.241	0.2737047
Cutting speed * Feed	4	1.4227	0.3557	6.26	0.001	2.3150988
Cutting speed * Depth of cut	4	0.9605	0.2401	4.23	0.007	1.5629805
Feed * Depth of cut	4	0.1616	0.0404	0.71	0.590	0.2629648
Error	35	1.9872	0.0568			3.2336855
Total	53	61.4531				100

(d) it can be concluded that at lower “V_c” and “f”, “MRR” is low and at higher “V_c” and “f”, “MRR” is more. From Figure 3 (e) it can be concluded that for each level of “f” change in “DoC” didn’t have much effect on “MRR”, “MRR” increased with an increase in “f” and “DoC”. From Figure 3 (f) it can be concluded that “MRR” is high at 80 m/min for all “DoC” and decreased with the increase in “V_c”.

Table 5. ANOVA for material removal rate

Source	DF	Adj SS	Adj MS	F-Value	P-Value	P%
Cutting speed	2	8125432	4062716	174.19	0.000	3.3880491
Feed	2	112381715	56190858	2409.14	0.000	46.859634
Depth of cut	2	1216801	608401	26.08	0.000	0.5073677
Cutting speed * Feed	4	116592628	29148157	1249.71	0.000	48.615452
Cutting speed * Depth of cut	4	254955	63739	2.73	0.004	0.1063082
Feed * Depth of cut	4	438404	109601	4.70	0.004	0.1828007
Error	35	816341	23324			0.3403885
Total	53	239826277				100

Using the means of the mean method, ”P_c” was evaluated for the optimal parameter conditions. It was found that at 0.2 mm/rev ”f”, 80 m/min “V_c” and 0.1 mm ”DoC”, ”P_c” is low. Figure 2 (c) illustrates the main effect plot of means of mean for ”P_c.” From Figure 2 (c), it was observed that with the increase in ”DoC”, ”P_c” increased. At higher ”DoC”, the tool has more material to remove, requiring more power from tool movement to overcome opposing forces. The general linear method in ANOVA was employed to find the significance of the factors for ”P_c”. For ”P_c”, all the input variables, ”f”, ”DoC” and ”V_c” were prominent factors. However, ”f” was the most significant factor of all with 87.0536% significance, followed by ”V_c” with 5.8036% significance, and ”DoC” with 0.893% significance. Table 7 presents the ANOVA results for ”P_c”. Figure 3 (g), (h), (i) illustrates the interaction plots of inputs for “P_c”. From Figure 3 (g) it can be concluded that at all “V_c” with the increase in “f”, “P_c” decreased. From Figure 3 (h) it can be concluded that for each level of “f” change in “DoC” didn’t have much effect on “P_c”, “P_c” decreased with a decrease in “f” and “DoC”. From Figure 3 (i) it can be concluded that “P_c” was higher for 80 m/min for all “DoC” when compared to other “V_c”.

Table 6. ANOVA for power consumption

Source	DF	Adj SS	Adj MS	F-Value	P-Value	P%
Cutting speed	2	0.000026	0.000013	44.11	0.000	5.8035714
Feed	2	0.000390	0.000195	663.06	0.000	87.053571
Depth of cut	2	0.000004	0.000002	6.38	0.004	0.8928571
Cutting speed * Feed	4	0.000012	0.000003	10.19	0.000	2.6785714
Cutting speed * Depth of cut	4	0.000003	0.000001	2.83	0.039	0.6696429
Feed * Depth of cut	4	0.000003	0.000001	2.34	0.074	0.6696429
Error	35	0.000010	0.000000			2.2321429
Total	53	0.000448				100

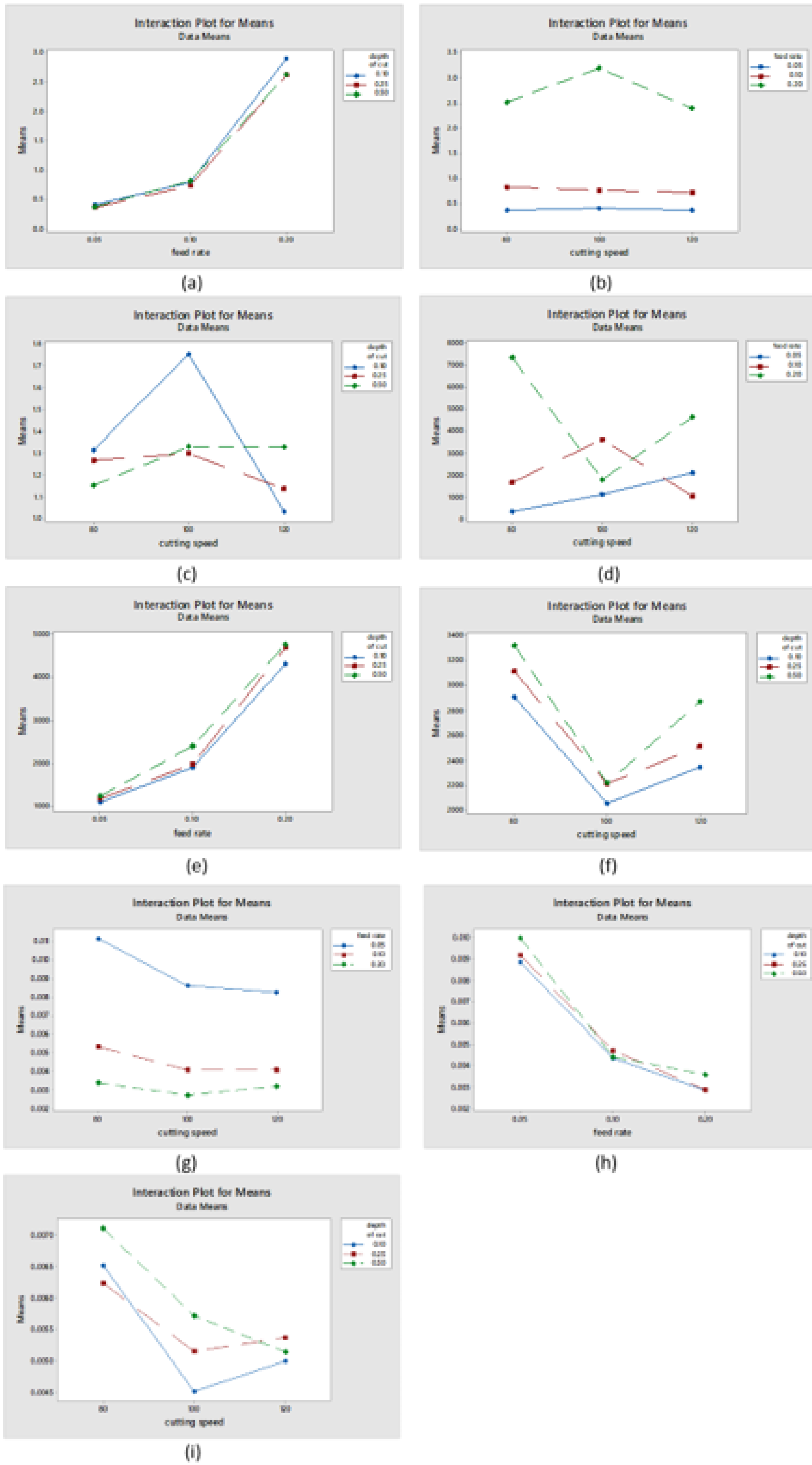

Fig 3. Interaction plots- for surface roughness: (a) between cutting speed and feed, (b) between feed and depth of cut, (c) between cutting speed and depth of cut, for material removal rate:(d) between cutting speed and feed, (e) between feed and depth of cut, (f) between cutting speed and depth of cut, for power consumption:(g) between cutting speed and feed, (h) between feed and depth of cut, (i) between cutting speed and depth of cut

Singh et al.[12] concluded from their review that dry machining showed promising results and reduced the excess cost that comes with the usage of cutting fluid, employing coating technology is the best scope for dry machining and PVD coated (TiAlN) is best suited for dry machining. In agreement with the current study, Emrah Şahin et al.[14], Raman Kumar et al.[15], Sivaiah et al.[16], Rajarajan et al.[17] and Sarvam Patel et al.[18] have concluded from their studies that "R_a" decreases with the increase in cutting speed, and an increase in feed leads to an increase in "R_a". Feed is identified as the most prominent factor affecting surface roughness. Sarvam Patel et al.[18] also concluded from their study that for "MRR," "DoC" is the most significant factor, followed by feed, and with an increase in speed, feed, and depth of cut, "MRR" increases. Sarvam Patel et al.[18] concluded, like this study, that feed is the most prominent factor for energy consumption, followed by cutting speed. Emrah Şahin et al.[14] had similar results, indicating that as feed increases, energy consumption decreases. Aytaç Yıldız et al.[19] also experimented on AISI 52100 using three-level box Behnken experimental design and checked for "P_c" after the turning operation and it was established that the feed was the most prominent factor for power consumption. Jay Airao et al.[20] have compared results while performing traditional turning and ultrasonic assisted turning under dry, wet, MQL and LCO_2 conditions, it was concluded that the power consumption was least under dry conditions, but surface roughness was the highest under dry conditions as cutting fluids were not used.

3.2 Random Forest Modelling

The fundamental disadvantage of experimental research is that it only uncovers optimal circumstances within the given input parameters; if the inputs are altered, the testing must be repeated, which is a time-consuming and sometimes costly procedure. This problem can be addressed using machine learning, where a model is built from experimental data and used to predict values for additional inputs.

Surface roughness at iteration 1823 was found to have the highest accuracy, the model was built based on that; values were also predicted, with an accuracy of 91.057%. Based on the model built, it was found that "f" had the most importance of 0.957 on "R_a", followed by "DoC" with 0.030 importance and finally "V_c" with 0.0135 importance. Figure 4 (a) illustrates the feature importance of "R_a". The model had a mean absolute error of 0.256. From the predicted values, it was found that the optimal condition was achieved at 0.05 mm/rev "f", 120 m/min "V_c" and 0.1 mm "DoC". Figure 4 (b) illustrates the actual vs. prediction graph of "R_a".

Material removal rate at iteration 6270 was found to have the highest accuracy, the model was built based on that; values were also predicted, with an accuracy of 96.0122%. Based on the model built, it was found that "DoC" had the most importance of 0.4125 on "MRR", followed by "f" with 0.373 importance and finally "V_c" with 0.2145 importance. Figure 4 (c) illustrates the feature importance of "MRR". The model had a mean absolute error of 464.4. From the predicted values, it was found that the optimal condition was achieved at 0.2 mm/rev "f", 0.5 mm "DoC" and 80 m/min "V_c". Figure 4 (d) illustrates the actual vs. prediction graph of "MRR".

Power consumption at iteration 696 was found to have the highest accuracy, the model was built based on that; values were also predicted, with an accuracy of 96.546%. Based on the model built, it was found that feed had the most importance of 0.905 on "P_c", followed by "V_c" with 0.0553 importance and finally "DoC" with 0.04047 importance. Figure 4 (e) illustrates the feature importance of "P_c". The model had a mean absolute error of 0.00047. From the predicted values, it was found that the optimal condition was achieved at 0.2 mm/rev "f", 120 m/min "V_c" and 0.5 mm "DoC". Figure 4 (f) illustrates the actual vs. prediction graph of "P_c".

It was observed that all the models developed were highly accurate, i.e., above 90%, when predicted values were compared to the actual values. The optimal conditions achieved from actual values and predicted values were also mostly similar to each other for the output response. Therefore, the trained models can be utilized for further predictions without performing experiments in real time. Ugonna Loveday Adizue et al.[8], Shanmugasundar et al.[9] and Santhosh et al.[21] are some researchers who have used machine learning models for predicting various output parameters based on their experimental studies to eliminate the excess time and cost associated with the experimental procedure. The little difference observed is due to the smaller dataset used for training the model. Table 7 presents the comparison of optimal conditions from experimental and predicted data achieved and the statistical metrics mean absolute error.

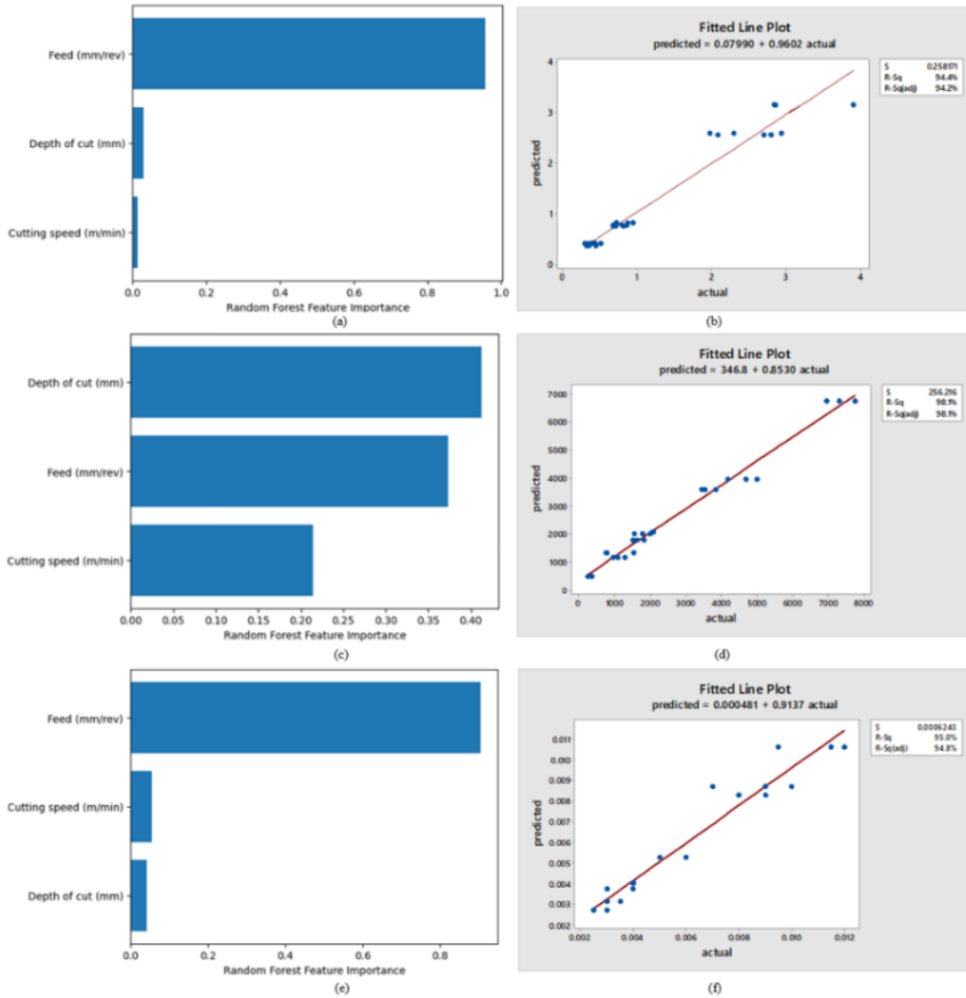

Fig 4. Graphs from Random Forest model (a) Feature importance of surface roughness, (b) Actual Vs Predicted graph of surface roughness, (c) Feature importance of material removal rate, (d) Actual Vs Predicted graph of material removal rate, (e) Feature importance of power consumption, (f) Actual Vs Predicted graph of power consumption

Table 7. Comparison of optimal conditions achieved from experimental values and machine learning predicted data

Output response	Optimal parameters		Statistical metric					
	Experimental values	Machine learning predicted values	R^2 score		Mean absolute error %		Root mean squared error	
			Training	Testing	Training	Testing	Training	Testing
Surface roughness (μm)	"V_c" = 120 m/min "f" = 0.05 mm/rev "DoC" = 0.25 mm	"V_c" = 120 m/min "f" = 0.05 mm/rev "DoC" = 0.1 mm	0.9461	0.9105	0.149	0.255	0.233	0.3143
Material Removal Rate (mm^3 /min)	"V_c" = 80 m/min "f" = 0.2 mm/rev "DoC" = 0.5 mm	"V_c" = 80 m/min "f" = 0.2 mm/rev "DoC" = 0.5 mm	0.9573	0.9601	230.65	464.39	342.17	548.092
Power consumption (Wh)	"V_c" = 100 m/min "f" = 0.2 mm/rev "DoC" = 0.1 mm	"V_c" = 120 m/min "f" = 0.2 mm/rev "DoC" = 0.5 mm	0.9407	0.9654	0.0004	0.0004	0.0006	0.0005

4 Conclusion

This research focuses on the dry turning of hardened 20MnCr5 (51HRc) using a PVD-coated TH1000 grade tool with Taguchi's technique. The input variables considered were "V_c", "f" and "DoC" while the output responses were "R_a", "MRR" and "P_c." Optimal conditions were determined for each output response to enhance turning performance. Random Forest models were developed for data prediction based on experimental data, and the results were compared with experimental results, revealing a considerable error. The following conclusions were drawn from the current experiment:

- The optimal condition for "R_a" from the Taguchi approach was obtained at 120 m/min "V_c", 0.05 mm/rev "f" and 0.25 mm "DoC". Feed was the most prominent factor affecting "R_a". The random forest model developed for predicting "R_a" had an R^2 score of 0.944.
- It is suggested that for better surface quality, machining should be performed at higher speeds, and as higher feed has a high effect on "R_a" it should be as minimal as possible.
- The optimal condition for "MRR" from the Taguchi approach was obtained at 80 m/min "V_c", 0.2 mm/rev "f" and 0.5 mm "DoC". Feed was the most influential factor on "MRR." The random forest model developed for predicting "MRR" had an R^2 score of 0.981.
- For a higher MRR, the depth of cut should be maximum. When the time factor is considered, it is suggested to employ a high feed rate when "R_a" is not an important criterion.
- The optimal condition for "P_c" from the Taguchi approach was obtained at 100 m/min "V_c", 0.2 mm/rev "f" and 0.1 mm "DoC". Feed was the most prominent factor on "P_c". The random forest model developed for predicting "P_c" had an R^2 score of 0.95.
- "P_c" increases with the increase in machining time, so it is suggested that at higher feed rates, "P_c" is low as machining time reduces.

In addition to the found outputs, tool wear can be checked, and multi-objective optimization (MOO) can be performed to find optimal conditions for all output responses at once. This work can be extended by machining with a CVD-coated tool and comparing its results with this study, as this study used a PVD-coated tool. The study only focuses on dry turning, so turning under wet and MQL conditions can be performed, and results can be compared to check which environmental condition produces better results. For prediction, other machine learning models like support vector machine models, regression models, artificial neural networks and genetic algorithms, etc., can be developed, and the model accuracy and mean absolute error can be compared to choose the best model for predicting all.

Nomenclature:

P_c- Power consumption; F- Feed rate (mm/rev); R_a- Surface roughness; DoC- Depth of cut (mm); MQL- Minimum quantity lubrication; MRR- Material removal rate; V_c- Cutting speed (m/min); MOO- Multi-objective optimization

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