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PREDICTION OF RESPONSES IN A CNC MILLING OPERATION USING RANDOM FOREST REGRESSOR

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Abstract*. In the present-day manufacturing environment, the modeling of a machining process with the help of statistical and machine learning techniques in order to understand the material removal mechanism and study the influences of the input parameters on the responses has become essential for cost optimization and effective resource utilization. In this paper, using a past CNC face milling dataset with 27 experimental observations, a random forest (RF) regressor is employed to effectively predict the response values of the said process for given sets of input parameters. The considered milling dataset consists of four input parameters, i.e. cutting speed, feed rate, depth of cut and width of cut, and three responses, i.e. material removal rate, surface roughness and active energy consumption. The RF regressor is an ensemble learning method where multiple decision trees are combined together to provide better prediction results with minimum variance and overfitting of data. Its prediction performance is validated using five statistical metrics, i.e. mean absolute percentage error, root mean squared percentage error, root mean squared logarithmic error, correlation coefficient and root relative squared error. It is observed that the RF regressor can be deployed as an effective prediction tool with minimum feature selection for any of the machining processes.*

Key Words*: CNC Milling, Random Forest Regressor, Prediction, Decision Tree*

1. INTRODUCTION

In the manufacturing domain, machining is the process of removing unwanted material from a given workpiece to provide the desired shape geometry while fulfilling the requirements of better surface quality and close dimensional tolerance. In the milling process, the material is removed from the workpiece with the help of an advancing multiple-teeth cutter. As the milling cutter enters the workpiece, its cutting edges repeatedly cut into and exit from the materials, removing material from the workpiece

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with each pass due to shear deformation. The milling operation generally consists of four indispensable components, i.e. milling machine, workpiece, fixture and a suitable cutter. From small individual components to large heavy-duty products, the paradigm of milling covers a wide variety of operations. Based on the motion of the rotary cutter, milling operations can largely be divided into two categories, i.e. face milling and peripheral milling. In the face milling, the rotary cutter is placed perpendicular to the workpiece while generating a surface normal to the axis of rotation [1]. On the other hand, in the peripheral milling, the cutter is placed parallel to the workpiece so that its sides always come into contact with the top of the workpiece. A large variety of materials, like aluminum, brass, magnesium, nickel, steel, zinc etc. can be machined in conventional milling machines; but when high precision and close dimensional tolerance are required, computer numerical control (CNC) milling machines may be employed. As the dynamic nature of the face milling operation requires close control, investigation of the material removal mechanism, modeling of the interrelationship between the milling parameters and responses, prediction of the responses and optimization of the process have been found to be of utmost importance [2].

Like all other machining operations, the process outputs (responses) of a face milling operation, like material removal rate (MRR), average surface roughness (Ra), directional cutting force (Fc), active energy consumption (AEC) etc. are also observed to be influenced by its various input parameters, such as spindle speed (s), cutting speed (N), depth of cut (a_p), width of cut (a_e), feed rate (f), cutting power, etc. These process outputs usually determine the quality of the end products in order to satisfy the consumers' requirements. For this reason, it has become essential for the designer/process engineer to have a close control and better understanding of various milling parameters along with their interactions with the responses. Based on the available experimental dataset, these interrelationships between the milling parameters and responses can be effectively modeled with the help of various statistical and machine learning techniques [3]. The developed models would also act as the prediction tools to envisage the tentative values of the considered responses for the given sets of different milling parameters.

The main advantage of machine learning techniques lies with their ability to solve complex problems while reducing the complicacy of the dataset and making the models more interpretable [4]. With the help of these techniques, predictive monitoring of the process outputs has become easier, while integrating customers' demands and taking care of other external factors affecting the process under consideration [5]. They also provide a broader scope for continuous improvement while automating the related decision-making tasks by efficiently manipulating the huge volume of available dataset. There are mainly two types of machine learning techniques, i.e. supervised machine learning and unsupervised machine learning. In supervised learning technique, the learning algorithm is usually trained on the basis of labeled data, and when the training data are not labeled, it is called unsupervised learning technique. Classification and regression are the two popular examples of supervised learning technique, while unsupervised learning technique primarily encompasses clustering and association. In general terms, regression deals with quantitative anticipation of the responses, whereas, prediction of a qualitative response is termed as classification. In real time manufacturing environment, supervised learning algorithms are usually preferred due to availability of huge experimental datasets which would finally help in quantitative prediction of different responses based on the given sets of various machining parameters. In the domain of milling operation, the past researchers have already applied various statistical and machine learning techniques, mainly in the form of linear regression, *k*-nearest neighbors (KNN) regression, support vector regression (SVR), artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS) etc. for predictive modeling of the considered processes. Although all of those techniques have provided satisfactory results, they also have their own limitations which often hinder their widespread applications as effective prediction tools. The main disadvantages of different statistical and machine learning techniques are summarized in Table 1.

Table 1 Disadvantageous features of some popular statistical and machine learning techniques

Method	Disadvantages
Linear regression	It assumes normal distribution of the input variables, and presence of a linear relationship between the dependent and independent variables. In reality, these assumptions are often not valid. It is also quite sensitive to the presence of outliers.
KNN regression	It is highly sensitive to the scale of the data. It also does not perform well for large datasets and widely varying dimensional data.
Ridge regression	It includes bias in the model output. Selection of hyper-parameters may also affect its accuracy.
Lasso regression	Its prediction performance largely depends on the variability of the data under consideration. The selected features may result in higher bias.
SVR	In this technique, selection of the appropriate kernel influences its prediction performance. It is also not at all suitable for large datasets and suffers from poor interpretability.
ANN	Its performance greatly depends on the system configuration and volume of the training data. Being a black box type approach, it has poor interpretability. Selection of the right activation function along with the number of hidden layers and number of nodes per layer affects its prediction accuracy.
ANFIS	It is highly sensitive to the number and type of the membership functions selected. Cross-validation error would largely differ from the actual error for a smaller dataset.
Decision tree regressor	Being a highly unstable technique, a small change in the dataset may cause a significant change in the developed tree structure. It cannot be employed for continuous numerical variables.

From Table 1, it can be clearly noticed that all the considered statistical and machine learning techniques have some deficiencies, especially with respect to either flexibility or interpretability. Thus, a trade-off has become essential between prediction accuracy and model interpretability. Many of the machine learning algorithms are unstable, showing high variance resulting in poor prediction for the test datasets. Using ensemble learning, these unstable and weak learners can be combined together to bring stability in the prediction process. The random forest (RF) regressor is based on ensemble learning, and can effectively bridge the gap between prediction accuracy and model interpretability. It is an aggregation of decision trees having more stability and capability to deal with continuous numerical variables. The RF is an example of the bagging method, which is an amalgamation of tree predictors that operates by constituting a profusion of decision trees, making it less prone to bias. Despite having a wide range of flexibility, it has not been specifically applied to predict responses for any of the machining processes. This paper lays down a framework to model a CNC face milling process using the RF regressor. Unlike linear regression, it does not assume the presence of any existent relationship between the dependent and independent variables, and also does not need the dataset to be normally distributed. Its prediction accuracy would suppose to increase with large datasets, unlike SVR or KNN regressor. Its application does not require any super-sophisticated hardware configuration (like ANN); neither is there any need to choose any membership function (like ANFIS). There is also no requirement to scale the training and testing data before its application. All these advantageous features of the RF regressor make it a suitable machine learning technique having good prediction accuracy without a convoluted feature selection process. In this paper, an endeavor is thus put forward to explore the application potentiality of the RF regressor to predict values of MRR, Ra and AEC based on 27 experimental observations with N, f, a_p and a_e as the input CNC face milling parameters.

This paper is organized as follows: Section 2 presents a brief literature survey on the applications of different statistical and machine learning techniques in face milling operation. In Section 3, the experimental details are presented, while in Section 4, the theoretical and application framework for the RF regressor is laid down. Section 5 introduces different statistical metrics along with the prediction results. Conclusions are drawn in Section 6.

2. LITERATURE SURVEY

It has already been mentioned that different statistical and machine learning techniques have been deployed by the past researchers as effective prediction tools for milling operation. Table 2 provides a comprehensive review of the past literature mainly focusing on different milling parameters, responses and prediction tools considered for milling operations. It has become quite clear that although several forms of regression analysis, ANN, ANFIS, SVR, etc. have been adopted by the past researchers, the literature seriously lacks the application of the RF regressor as an effective prediction tool in the machining domain. To the best of the authors' knowledge, there is no application of the RF technique as a predictive and regressor model in CNC milling operation. In order to validate the performance of the previously adopted prediction tools, a limited number of statistical metrics has been considered by the past researchers. In this paper, five statistical metrics in the form of mean absolute percentage error (MAPE), root mean squared percentage error (RMSPE), root mean squared log error (RMSLE), correlation coefficient (R) and root relative squared error (RRSE) are taken into account to evaluate the performance of the RF regressor as an effective prediction tool during CNC face milling operation.

Table 2 List of milling parameters, responses and prediction tools considered by the past researchers

Author(s)	Milling parameters	Response(s)	Prediction model(s)
Lo [6]	*s*, *f*, a_p	Ra	ANFIS
Radhakrihnan and Nandan [7]	*s*, *f*, a_p	Fc	Regression analysis, ANN
Ozcelik and Bayramoglu [8]	*s*, a_p, *f*, step over	Ra	Regression analysis
Lela et al. [9]	*N*, *f*, a_p	Ra	Regression analysis, SVR, Bayesian neural network
Rashid et al. [10]	*s*, *f*, a_p	Ra	Regression analysis
Dave and Raval [11]	*N*, *f*, a_p	Fx, Fy (cutting force along *x* and *y* directions)	Regression analysis, ANN
Sharkawy [12]	*s*, *f*, a_p	Ra	ANFIS, radial basis function network, genetically evolved fuzzy inference system
Durakbaşa et al. [13]	*N*, a_p, *f*	Ra	Regression analysis
Zhang et al. [14]	*s*, *f*, a_p	Ra	Gaussian process regression
Rubeo and Schmitz [15]	*s*, feed per tooth, radial immersion	Fc	Regression analysis
Bandapalli et al. [16]	*s*, *f*, a_p	Ra	ANFIS
Yeganefar et al. [17]	*s*, *f*, axial and radial depth of cut	Ra	SVR, ANN, regression analysis
Lin et al. [18]	*s*, *f*, a_p	Ra	Regression analysis, ANN
This paper	*N*, *f*, a_p, a_e	MRR, Ra, AEC	RF regressor

Table 3 Milling parameters and their operating levels [19]

Parameter	Symbol	Unit	Level 1	Level 2	Level 3
Cutting speed	*N*	rev/min	1200	1700	2200
Feed rate	*f*	mm/min	220	270	320
Depth of cut	a_p	mm	0.3	0.4	0.5
Width of cut	a_e	mm	5	10	15

3. Experimental Data

Using a CNC machine tool (Carver 400M_RT) with a spindle power of 5.6 kW and a maximum rotational speed of 6000 rpm, Khan et al. [19] performed face milling operations on AISI-1045 steel material. A three-fluted carbide cutting tool with 24 mm diameter was deployed for the milling operations. During the milling operation, four input parameters, i.e. N, f, a_p and a_e were considered and their settings were varied at three different operating levels. Those input milling parameters and their varying operating levels are shown in Table 3. Based on L_{27} orthogonal array, 27 experiments were conducted while treating MRR (mm^3/min), Ra (µm) and AEC (kJ) as the process outputs/responses. The experimental plan and values of the measured responses are exhibited in Table 4. During the application of the RF regressor as a prediction tool for this CNC face milling operation, among the 27 experimental runs, 21 trials are randomly selected for the training purpose and the remaining six trials are considered for testing of the developed model.

Table 4 Experimental dataset [19]

Sl. No.	N	F	a_p	a_e	MRR	Ra	AEC	Purpose
1	1200	220	0.3	5	330	3.30	535.802	Training
2	1200	220	0.4	10	880	2.95	184.929	Training
3	1200	220	0.5	15	1650	1.41	88.519	Training
4	1200	270	0.3	5	405	3.83	426.109	Training
5	1200	270	0.4	10	1080	3.87	146.050	Testing
6	1200	270	0.5	15	2025	1.68	69.823	Training
7	1200	320	0.3	5	480	3.97	361.832	Training
8	1200	320	0.4	10	1280	3.53	122.976	Testing
9	1200	320	0.5	15	2400	2.29	53.988	Training
10	1700	220	0.3	10	660	1.81	337.042	Training
11	1700	220	0.4	15	1320	1.13	142.727	Testing
12	1700	220	0.5	5	550	3.47	299.031	Training
13	1700	270	0.3	10	810	2.85	269.604	Training
14	1700	270	0.4	15	1620	1.41	113.648	Training
15	1700	270	0.5	5	675	3.91	238.476	Training
16	1700	320	0.3	10	960	2.55	213.559	Testing
17	1700	320	0.4	15	1920	1.39	92.551	Training
18	1700	320	0.5	5	800	4.12	193.109	Training
19	2200	220	0.3	15	990	1.76	244.303	Training
20	2200	220	0.4	5	440	3.33	425.797	Testing
21	2200	220	0.5	10	1100	2.36	165.620	Training
22	2200	270	0.3	15	1215	1.17	193.939	Training
23	2200	270	0.4	5	540	3.72	338.579	Training
24	2200	270	0.5	10	1350	2.58	131.343	Testing
25	2200	320	0.3	15	1440	1.41	160.886	Training
26	2200	320	0.4	5	640	3.86	286.850	Training
27	2200	320	0.5	10	1600	2.76	108.147	Training

4. APPLICATION OF RF AS A PREDICTION TOOL

During any machining operation, depending on the experimental plan employed, a large volume of useful dataset is usually generated. To better understand the machining operation and study the influences of the input parameters on the responses, a suitable model needs to be developed so as to extract valuable information from the experimental dataset. A subfield of artificial intelligence which mainly focuses on various ways of training the machines for having a better understanding of a problem/system, is called machine learning. As it can be interpreted, the goal of a machine learning algorithm is to better generalize an existing problem while providing the desired solutions. To achieve the desired outputs, a designer needs to train different learners. Often, due to presence of noise in the training data, the designed learners turn out to be occasionally weak. Ensemble learning is a machine learning archetype [20] where multiple learners are combined together to predict the response values. Two of the most commonly employed ensemble learning approaches are bagging and boosting [21]. Bagging or bootstrap aggregation is a parallel ensemble method, whereas boosting is considered as a sequential ensemble method. Ensemble learning models perform best for machine learning techniques that are generally unstable, like decision trees, ANNs etc. [22]. The main reason behind using unstable learners for ensemble learning is that they can produce different generalization patterns which help in minimizing variability to some extent [23].

The RF is an example of the bagging method [24], which is an amalgamation of tree predictors that operates by constituting a profusion of decision trees. It can be effectively employed for both classification and regression. The basic function of RF can be understood using the schematic diagram, as depicted in Fig. 1.

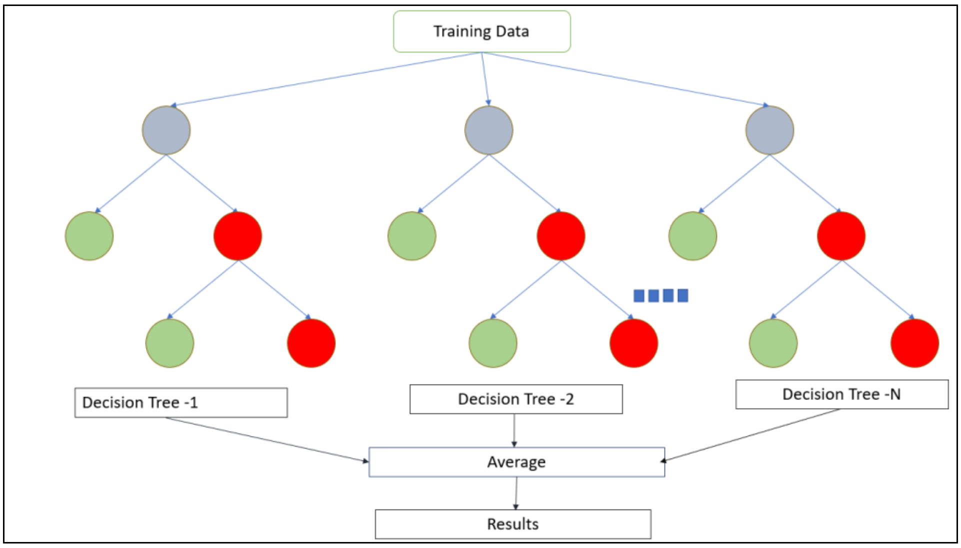

Fig. 1 Schematic Diagram of a Random Forest

From this diagram, it can be observed that, based on the training dataset, several decision trees are created which are assumed to be uncorrelated. Each of the decision trees is developed based on subsets of variables and samples from the training data. Again, each of the subsets of variables is considered with replacement. In the RF regressor, the final prediction is performed after averaging the outputs of all the developed decision trees. While employing the RF regressor as an effective prediction tool, there are few parameters to be tuned by the concerned designer, mainly based on intuition [25]. In Table 5, some important parameters of the RF regressor are provided, where p is the number of input variables.

Table 5 Parameters of a RF regressor

Parameter	Default value
Number of decision trees	500
Number of variables per split	$\sqrt{p}$
Maximum number of terminal nodes	Unrestricted
Resampling scheme	With replacement

While employing the RF regressor as a prediction tool for the CNC face milling operation, the number of decision trees generated plays a significant role. A smaller number of decision trees leads to underfitting of data, whereas a large number of decision trees are responsible for data overfitting. When each decision tree is framed, there is a scope of feature selection where the designer can choose all the input variables under consideration or set them accordingly. The maximum number of terminal nodes, as the name suggests, is the upper limit of number of nodes that each tree can have. Now, when a subset of training data is adopted to model the RF, the designer may wish to set features in such a way that if a subset is once used, it would not be used again. In this case, the resampling scheme needs to be considered without replacement. Among various parameters employed for modeling a RF regressor, number of decision trees and number of variables selected per split mostly affect the prediction accuracy. The default value for number of variables per split is the squared root of the number of input variables, but for datasets with a smaller number of input variables (preferably less than 13), number of variables per split is generally set equal to the number of input variables [25]. On the other hand, the optimal number of decision trees to be framed is identified after simulating the model for up to 500 decision trees and then selecting the number which would yield the lowest value of mean squared error (MSE). The variations of MSE value with changing number of decision trees for MRR, Ra and AEC are portrayed in Figs. 2-4, respectively. From these figures, the optimal number of decision trees for each RF is selected having the lowest MSE value for each of the responses under consideration. The optimal numbers of decision trees to be developed for MRR, Ra and AEC are provided in Table 6.

Table 6 Optimal number of decision trees for each response

Response	Number of decision trees
MRR	367
Ra	25
AEC	195

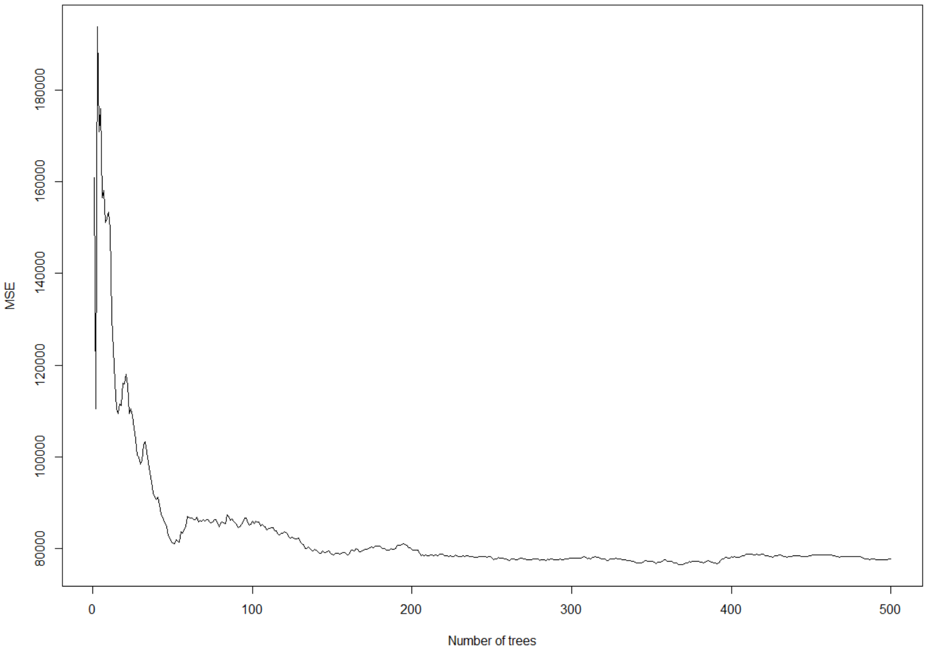

Fig. 2 Number of Decision Trees against MSE for MRR

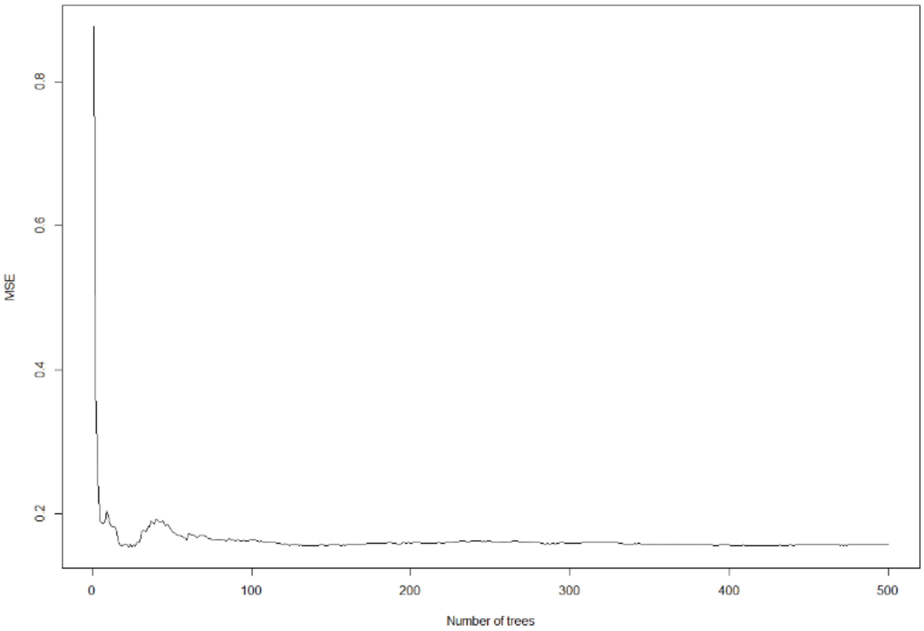

Fig. 3 Number of Decision Trees against MSE for Ra

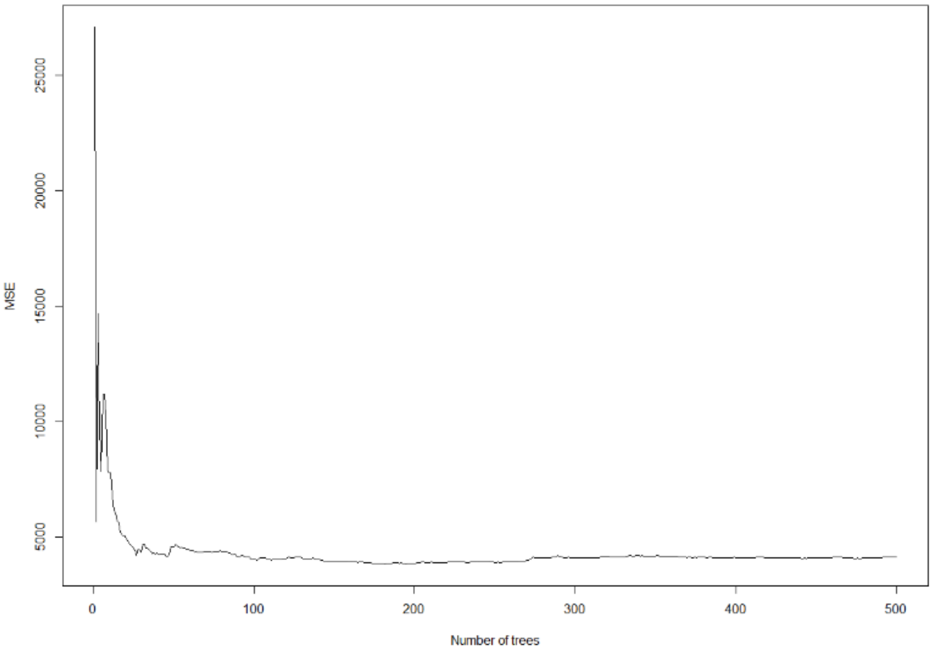

Fig. 4 Number of Decision Trees against MSE for AEC

In this paper, the entire modeling based on the past experimental data for the CNC face milling operation is performed with the help of Random Forest package available in the statistical programming software R [26], which is an open-sourced, robust and easy to apprehend language [19]. Based on the training dataset, the developed RF regressor generates a large number of decision trees (as mentioned in Table 6) for each of the responses under consideration which are finally aggregated to predict the corresponding response values. Some typical examples of the framed decision tress for MRR, Ra and AEC are respectively provided in Figs 5-7. In Fig. 5, for MRR, the RF regressor first treats width of cut (a_e) as the predictor variable in the root node. Now, depending on its value, two branches emerge from the root node. When its value is observed to be greater than 5 mm, feed rate (f) is considered as the next predictor variable. The RF regressor predicts the MRR value as 1628.8 mm^3/min for feed rate greater than 220 mm/min.

On the other hand, when the corresponding feed rate is less than or equal to 220 mm/min, it envisages the value of MRR as 1056 mm^3/min. In the experimental dataset, there are eight observations satisfying the condition of width of cut greater than 5 mm and feed rate greater than 220 mm/min. Similarly, five observations fulfill the condition of width of cut greater than 5 mm and feed rate less than or equal to 220 mm/min. In this decision tree, when the value of width of cut is less than or equal to 5 mm, spindle speed (N) is considered as the succeeding predictor variable.

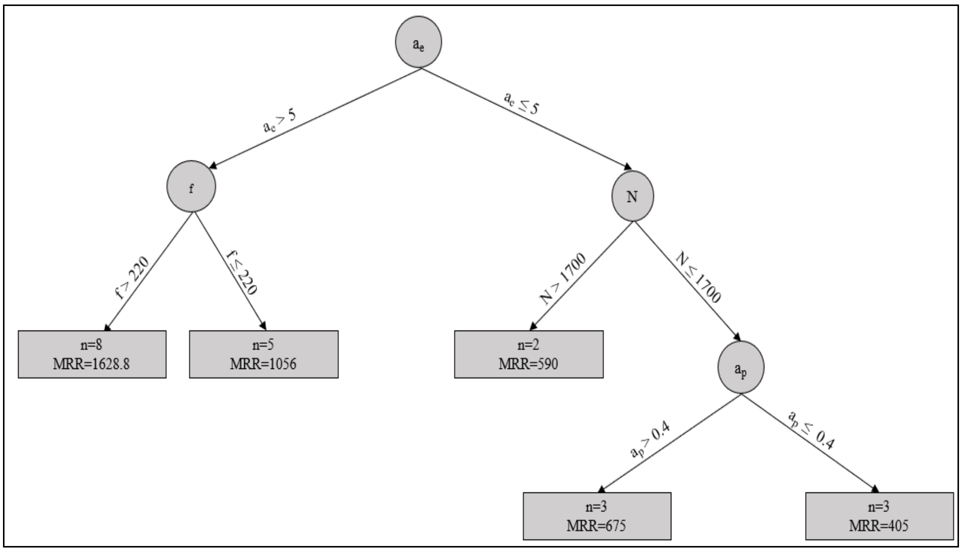

Fig. 5 A Sample Decision Tree for MRR

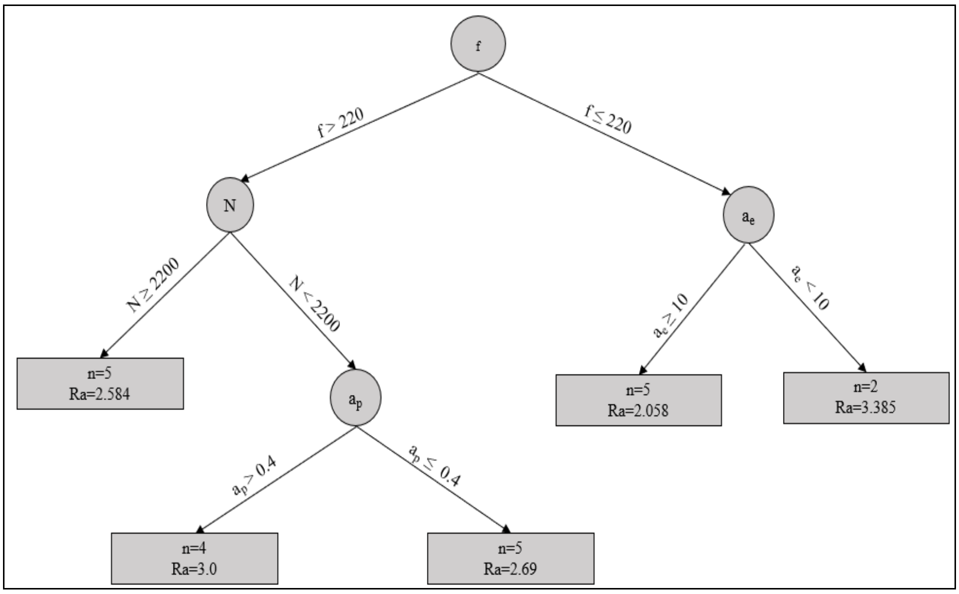

Fig. 6 A Sample Decision Tree for Ra

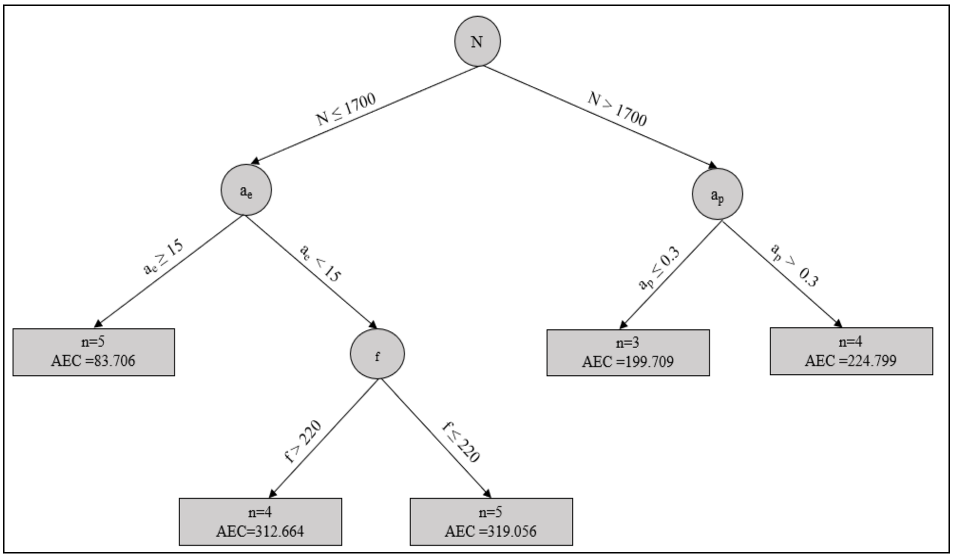

Fig. 7 A Sample Decision Tree for AEC

When the corresponding spindle speed is noticed to be greater than 1700 rev/min, it leads to a terminal node with the predicted MRR value as 590 mm^3/min. But, for spindle speed less than or equal to 1700 rev/min, depth of cut (a_p) is adopted to generate two more child nodes. The RF regressor predicts the MRR value as 675 mm^3/min when the depth of cut is found to be more than 0.4 mm, and for depth of cut less than or equal to 0.4 mm, the predicted value of MRR is 405 mm^3/min. The decision tress for Ra and AEC, in Figs. 6 and 7, can also be similarly explained.

5. Prediction Performance of The RF regressor

In this paper, the prediction performance of the proposed RF regressor is validated using five statistical metrics, i.e. MAPE, RMSPE, RMSLE, R and RRSE. The mathematical formulations of all these measures are presented as below:

MAPE:
$$\frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - P_i}{A_i}\right| \times 100 \tag{1}$$

RMSPE:
$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\frac{A_i - P_i}{A_i}\right)^2} \times 100 \tag{2}$$

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\log(P_i + 1) - \log(A_i + 1))^2} \tag{3}$$

R:
$$\frac{\sum_{i=1}^{n}(A_i-\overline{A})(P-\overline{P})}{\sqrt{\sum_{i=1}^{n}(A-\overline{A})^2(P-\overline{P})^2}} \quad (4)$$

RRSE:
$$\sqrt{\frac{\sum_{i=1}^{n}(P_i-A_i)^2}{\sum_{i=1}^{n}(A_i-\overline{A})^2}} \quad (5)$$

where A_i and P_i are the actual and predicted response values, $\overline{A}$ and $\overline{P}$ are the means of all the actual and predicted response values, and n is the number of observations in the test dataset. The MAPE measures the absolute percentage error between the actual and predicted response values. Its main problem is that it introduces a heavy penalty when the actual value is close to 0. On the contrary, RMSPE provides an estimation of the standard deviation of the residuals. But its value is significantly affected by the presence of outliers in the dataset. This problem can be avoided to some extent by the application of RMSLE along with RMSPE. The degree of association between the actual and predicted response values is computed using R value. Finally, RRSE calculates the total squared error and normalizes it while dividing by the total squared error of the simple predictor. While taking the square root of the relative squared error, the error is reduced to the same dimension as the response being predicted. Among all these measures, a higher value is always preferable for R, while for the remaining measures, lower values would indicate better prediction performance of the RF regressor [27]. In Table 7, the predicted values of all the responses for the considered testing dataset are provided. On the other hand, Table 8 shows the computed values of the five statistical metrics used to evaluate the prediction performance of the developed RF regressor.

Table 7 Predicted response values using the RF regressor

Sl. No.	Response					
	MRR		Ra		AEC	
	Actual	Predicted	Actual	Predicted	Actual	Predicted
1	1080	1026.07	3.87	2.66	146.050	182.17
2	1280	1173.09	3.53	2.67	122.976	174.08
3	1320	1546	1.13	1.53	142.727	132.51
4	960	1093.37	2.55	2.62	213.559	253.95
5	440	626.87	3.33	3.46	425.797	320.95
6	1350	1125.97	2.58	2.57	131.343	155.14

Table 8 Values of the statistical measures for the responses

Statistical measure	MRR	Ra	AEC
MAPE	17.23	16.34	22.51
RMSPE	21.00	21.78	24.77
RMSLE	0.19	0.16	0.23
R	0.85	0.78	0.92
RRSE	0.53	0.7	0.5

From Table 8, it can be noticed that although Ra has the lowest R value, its corresponding MAPE score is the best. For Ra, the model has overestimated and underestimated the true Ra value more frequently than the other responses. But, even after this, the relative deviation is the lowest. It can be noticed from both these tables that RF regressor performs satisfactorily while foreseeing the values of all the three responses of the CNC face milling operation under consideration. From the results of the test dataset, it can be noticed that the model has not overfitted the data. Otherwise, the outcome of the test dataset would have been far worse even after getting a good result from the training dataset.

Non-parametric machine learning techniques do not assume anything about the dataset, whereas, in parametric techniques, some assumptions are made with respect to the underlying distribution of the dataset as well as the relationship between the dependent and independent variables. Thus, modeling of a machining operation and prediction of the corresponding responses using a non-parametric machine learning technique with a small dataset is quite challenging, but the proposed RF regressor yields satisfactory results even with a small experimental dataset for CNC face milling operation. While predicting the corresponding response values, it also employs minimum number of milling parameters as the predictor variables in the decision trees.

6. CONCLUSIONS

Over the years, application of different machine learning techniques in the manufacturing domain has increased exponentially. It has now become a challenging task to choose an appropriate machine learning technique to depict the relationship between the dependent and independent variables of any machining process. In this paper, an attempt is put forward to employ the RF regressor as an effective prediction model based on a small experimental dataset of CNC face milling operation. It has several advantageous features as compared to other statistical and machine learning models. Its main advantage is that it does not consider the inherent distribution of the input data or existent relationship between the dependent and independent variables. Number of optimal decision trees and number of input variables per split are enough to develop this prediction tool. Its robustness makes it suitable for generalizing different machining-related applications. Machining conditions with binary or more than two categorical input variables can be accommodated in this tool without much effort. But, it has also some limitations. It fails in the cases when the data is outside the ‘scope’ of the model. Suppose that there is a training space where each input parameter has a particular range. If the test data has some values totally outside the range, the model would fail. This problem would not occur for linear regression. The RF regressor would also perform poorly in the case of sparse data where certain expected values do not exist at all. As a future scope, the prediction performance of the RF regressor can be explored using large datasets, although it may lead to overfitting of data. Its application potentiality can also be validated based on experimental datasets from other metal removal processes, like CNC turning, CNC end milling, and especially non-traditional machining processes.

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