Novel machine learning based models for estimating minimum surface roughness value in the end milling process

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Abstract: Average surface roughness value (R_a) is an important measure of the quality of a machined work piece. Lower the R_a value, the higher is the work piece quality and vice versa. It is therefore desirable to develop mathematical models that can predict the minimal R_a value and the associated machining conditions that can lead to this value. In this paper, real experimental data from an end milling process is used to develop models for predicating minimum R_a value. Two machine learning techniques, Model Tree and Sequential Minimal Optimization based Support Vector Machine, which have not been used before to model surface roughness, were applied to the training data to build prediction models. The developed models were then applied to the test data to determine minimum R_a value. Results indicate that both techniques reduced the minimum R_a value of experimental data by 4.2% and 2.1% respectively compared to the previously reported values. Model trees are found to be better than other approaches in predicting minimum R_a value.
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1. Introduction

Machining is the process of removing material from a work piece to transform it to a desired shape. Different machining processes include conventional processes such as grinding, milling, drilling etc. and non-conventional processes such as electrodischarge machining, electrochemical machining, waterjet cutting etc. The milling process uses a rotating cutter for material removal. Two main types of milling are: peripheral milling and face milling. In peripheral milling the machined surface is obtained parallel to the spindle rotation whereas in face milling the machined surface is produced normal to the spindle rotation. Further the milling process is classified as conventional milling and climb milling. In conventional milling the direction of feed of workpiece is against the cutter rotation whereas in climb milling, both the cutter rotation and the workpiece feed are in the same direction. End milling involves a mix of peripheral and face milling and employs bottom and edges of the milling cutter. Figure 1 shows the geometry of milling process. The important parameters are cutting speed, feed rate, depth of cut and rake angle. Cutting speed is the speed at which the tool tooth cuts through the workpiece. It is expressed in meters per minute or surface feet per minute (SFPM). Feed rate is the speed at which the workpiece is fed into the cutting tool and is expressed in inches per minute or millimetre per minute. Depth of cut specifies the penetration of the milling cutter into the workpiece and indicates the amount of material removed in each pass. The rake angle specifies the direction of chip flow as the workpiece is machined.

One of the commonly used measures of the performance of any machining process, such as milling is the surface roughness of the machined work piece. Surface roughness is defined as the vertical deviations of the surface from its ideal form. Different surface roughness parameters are in use such as root mean square roughness (R_q), roughness average (R_a) and maximum peak-to-valley roughness (R_y or R_{max}) etc.(Yang and Chen, 2001). However, roughness average (R_a) is the most widely used parameter. It is defined as the integral of the absolute value of roughness profile height over the evaluation length i.e.

$$R_a = \frac{1}{l}\int_0^l |y(x)|d(x)$$

where l is the sampling length and y is the ordinate of the profile curve as shown in Figure 2.

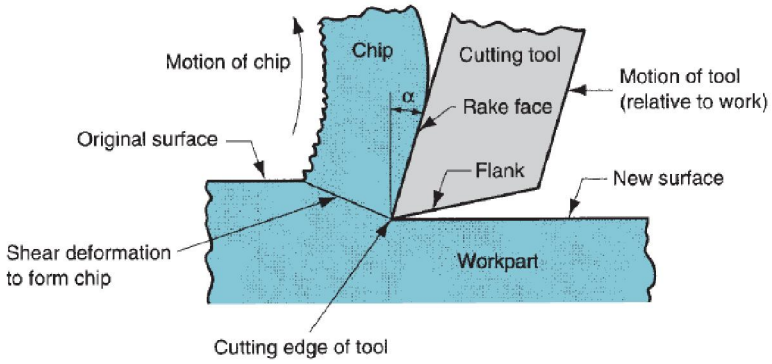

Figure 1. Geometry of milling process showing the workpiece, cutting tool, newly formed surface, chip and different angles (adapted from (Groover, 2010)). α is the rake angle which specifies the direction of chip flow. The angle β between flank and the new surface is called the clearance angle.

A low surface roughness value (R_a) indicates high machining performance and a better quality work piece and vice versa. A high quality work piece with lower surface roughness will be more corrosion resistant and have high creep life and fatigue strength. Therefore, considerable research effort has been put into the development of models that could predict machining parameters resulting in minimum R_a value. These models establish relationship between cutting conditions (usually expressed in terms of cutting speed, feed rate, depth of cut and rake angle) and the resulting R_a value. Artificial Neural Networks (ANN) have been used in the prediction of surface roughness in drilling (Sanjay and Jyothi, 2006), abrasive waterjet machining (Çaydaş and Hasçalık, 2008), CNC lathe (Karayel, 2009) and end milling (Topal, 2009; Zain et al., 2012). Least Square Support Vector Regression (LS-SVR) is employed in (Dong et al., 2006; Xiaoh, 2009) to predict surface roughness in the end milling process. In (Zain et al., 2012) regression and ANN models for predicting minimum R_a value in the end milling process were developed. As compared to experimental data, they achieved a reduction in minimum value of R_a by 1.57% and 1.07% by regression and ANN models respectively. References (Lu, 2008) (Benardos and Vosniakos, 2003) provide a detail review of techniques for predicting surface roughness in different machining processes. In this paper we use Sequential Minimal Optimization (SMO) based Support Vector Machine (SVM) (Smola and Schölkopf, 1998) (Shevade et al., 2000) and Model trees (Quinlan, 1992; Wang and Witten, 1996) to determine minimum R_a value in the end milling process.

This paper is organized as follows: Section one introduces the significance of finding minimum value of surface roughness and describe some existing techniques, Section two discusses the techniques of Model Tree and SMO based SVM, Section three describes the data set used in this paper and elaborates the results of employing Model trees and SMO-SVM for estimating minimum R_a value, Section four evaluates the results using *t* tests and making comparison with (Zain et al., 2012), finally Section 5 concludes the paper.

2. Models for predicting surface roughness

Developing mathematical models for predicting R_a value is a challenging task because surface roughness value is the result of complex interdependence between various process parameters. In this section we describe the techniques of model trees and SMO based SVM that can be employed to generate reliable regression based models for R_a value prediction. To the best of our knowledge, this is the first work that employs these two techniques for predicting minimum R_a value. These two techniques are selected as they belong to two different families of algorithms. The models produced by SVM are opaque like the models produced by ANN. Model trees, on the other hand, belong to decision tree family. As compared to ANNs, they produce more understandable models by providing greater visibility into the relationship between variables that build the model.

2.1 M5 Model Trees

M5 Model trees (Quinlan, 1992; Wang and Witten, 1996) have multivariate linear regression models at their leaf nodes, differing from regression trees (Breiman et al., 1984) that have numeric values or decision trees that have classes at the leaf nodes. They can thus be compared to piecewise linear functions. Decision tree induction algorithm is used to build model tree. However, in contrast to decision tree where maximization of information gain is the splitting criteria, in model tree the minimization of variation (standard deviation – sd) in the intra-subset class values is used as the splitting criteria.

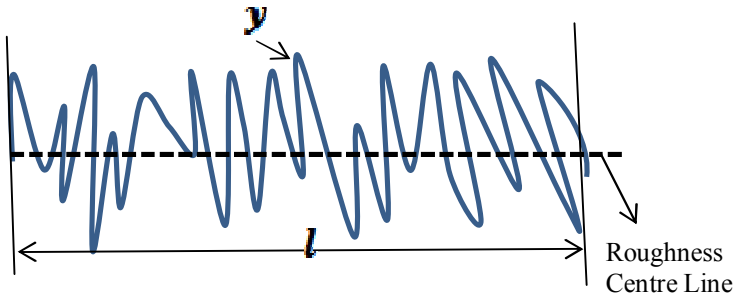

Figure 2. Definition of surface roughness. l is the sampling length and y is the ordinate of the roughness profile curve.

At each node, the standard deviation of the class values reaching that node is taken as a measure of error. At each node, the standard deviation of the class values reaching that node is taken as a measure of error. The expected reduction in error is then calculated for each attribute. The attribute which gives maximum reduction in error is chosen for performing splitting. The standard deviation reduction (SDR) is calculated by the following equation (Wang and Witten, 1996):

$$SDR = sd(K) - \sum_i \frac{|K_i|}{|K|} \times sd(K_i)$$

where K is the set of examples that reach the node and K_1, K_2,… are the sets resulting from splitting the node according to the selected attribute.

The splitting stops if the change in class values (standard deviation) of instances reaching a node becomes very small or when there are only few instances left. Pruning is performed from the leaf nodes and inner nodes are transformed into leaf nodes by replacing them with a linear regression function. To avoid discontinuities between the linear models of the adjacent leaf nodes in the pruned tree, a smoothing process is carried out. The trees formed by M5 algorithm are generally much smaller than the regression trees. M5 model trees have the ability to efficiently scale with very high dimensional data having hundreds of attributes.

2.2 Sequential Minimal Optimization based Support Vector Machine

Support Vector Machine (SVM) (Cortes and Vapnik, 1995) has found applications in numerous fields for solving both regression and classification problems. It solves a nonlinear low dimensional classification problem by projecting it into high dimensional space where an optimal separating hyperplane is constructed between the positive and negative classes with maximum margin. Support Vector Regression tries to find a continuous value function that fits the data. The input is mapped to a high dimension feature space and a linear model is constructed in that space. The aim is to minimize the functions of the following form (Flake and Lawrence, 2002):

$$L = \frac{1}{l}\sum_{i=1}^{l}|y_i - f(x_i,w,b)|_\varepsilon + \|w\|^2$$

In the above equation $|.|_\varepsilon$ is ε-sensitive error function defined as follows:

$$|x|_\varepsilon = \begin{cases} 0 & if\ |x| < \varepsilon \\ |x| - \varepsilon & otherwise \end{cases}$$

The output of SVM is then expressed as:

$$f(x,\alpha^+,\alpha^-,b) = \sum_{i=1}^{l}(\alpha^+ - \alpha^-)K(x_i,x) + b$$

Where α_i^+ and α_i^- are positive and negative Lagrange multipliers that obey $0 \le \alpha_i^+, \alpha_i^-, \forall_i$ and $\alpha_i^+\alpha_i^- = 0, \forall_i$.

Sequential Minimal Optimization is a learning algorithm for SVM originally proposed for classification problems(Platt, 1999). A variant of this algorithm for support vector regression was proposed in (Smola and Schölkopf, 1998) and subsequently improved by (Shevade et al., 2000). It continuously searches for two Lagrange multipliers that can be optimized with respect to each other and then computes the optimal step for the two Lagrange multipliers. For detailed explanation refer to (Flake and Lawrence, 2002).

3. Experimental dataset and Results

The experimental dataset reported by (Zain et al., 2012) was chosen to study the performance of M5 Model Trees and Support Vector Machine based regression models for predicting the minimum value of surface roughness. Their machining experiments involved 24 trials to measure R_a value in the end milling process based on eight data of two levels DOE 2^k full factorial, four center and twelve axial points. All R_a values were collected for three type of

cutting tools: uncoated, TiA1N coated and SNTR coated. The experimental results reported by them are shown in Table 1 and are used in this paper for developing M5 and Support Vector Machine based regression models.

Table 1. Experimental cutting conditions and R_a values for End Milling Process [1]. R_a values are taken for three tools: Uncoated, TiA1N coated and SNTR coated.

No.	Data source	Setting values of experimental cutting conditions			Experimental R_a value (μm)		
		Cutting speed v (m/min)	*Feed rate f* (mm/tooth)	Radial rake angle ɣ (°)	$Ra_{\_uncoated}$	$Ra_{\_TiA1N}$	$Ra_{\_SNTR}$
1	DOE 2^k	130	0.03	7	0.365	0.32	0.284
2		160	0.03	7	0.256	0.266	0.196
3		130	0.07	7	0.498	0.606	0.668
4		160	0.07	7	0.464	0.476	0.624
5		130	0.03	13	0.428	0.260	0.280
6		160	0.03	13	0.252	0.232	0.190
7		130	0.07	13	0.561	0.412	0.612
8		160	0.07	13	0.512	0.392	0.576
9	Center	144.22	0.046	9.5	0.464	0.324	0.329
10		144.22	0.046	9.5	0.444	0.38	0.416
11		144.22	0.046	9.5	0.448	0.460	0.352
12		144.22	0.046	9.5	0.424	0.304	0.400
13	Axial	124.53	0.046	9.5	0.328	0.360	0.344
14		124.53	0.046	9.5	0.324	0.308	0.320
15		167.03	0.046	9.5	0.236	0.340	0.272
16		167.03	0.046	9.5	0.240	0.356	0.288
17		144.22	0.025	9.5	0.252	0.308	0.230
18		144.22	0.025	9.5	0.262	0.328	0.234
19		144.22	0.083	9.5	0.584	0.656	0.640
20		144.22	0.083	9.5	0.656	0.584	0.696
21		144.22	0.046	6.2	0.304	0.300	0.361
22		144.22	0.046	6.2	0.288	0.316	0.360
23		144.22	0.046	14.8	0.316	0.324	0.368
24		144.22	0.046	14.8	0.348	0.396	0.360
R_a (minimum)					**0.236**	**0.232**	**0.190**

It may be noted that for some instances in Table 1(such as 9 and 10 or 13 and 14 etc.), identical cutting conditions result in different R_a values. This discrepancy in Ra values may be attributed to uncontrollable factors that affect machining such as tool wear, chips formation, vibrations, non-homogeneity of tool and work piece material and machine motion errors etc. (Brezocnik et al., 2004). This implies that if further experiments are carried out, we may obtain further different R_a values corresponding to identical cutting conditions, some of which may be lower than the currently known values. *The aim of this research is to build mathematical models that can predict such potential cutting conditions that may lead to least R_a value.*

All the experimental data including cutting condition values as well as R_a values of Table 1 were first normalized using the following equation (Sanjay and Jyothi, 2006):

$$x_i = \frac{0.8}{d_{max} - d_{min}} (d_i - d_{min}) + 0.1$$

Normalized data is shown in Table 2. This data was then divided into two parts: training set and test set. DOE 2^k data (first eight rows of Table 2) were used as the training set. The remaining 16 tuples of data (the four tuples of center data and twelve tuples of axial data) were used as the test set. This is in contrast to (Zain et al., 2012) where the last 16 rows of Table 2 were taken as training data and the first 8 rows as the test data. Our rationale for this division is as follows: the first eight rows have distinct pairs of cutting conditions values; however, the last 16 rows have instances where identical cutting conditions have resulted in different R_a values. The data with distinct input and output values will give more opportunity to the training algorithm to better understand the characteristics of the data and build more accurate classifier than the data having identical

input values but different output values. Thus, the first 8 rows of Table 2 (with all distinct cutting conditions pairs) are selected as training data and the remaining 16 rows (with repeated identical cutting conditions pairs) as the testing data.

Table 2. Normalized experimental cutting conditions and R_a values for End Milling Process [1]. In contrast to (Zain et al., 2012) the first eight rows with all distinct cutting conditions pairs are taken as the Training set. The remaining 16 rows are used as the Test set.

No.	Data source	Setting values of experimental cutting conditions			Experimental R_a value (μm)		
		Cutting speed v (m/min)	*Feed rate f* (mm/tooth)	Radial rake angle ɣ (°)	$Ra_{\_uncoated}$	$Ra_{\_TiA1N}$	$Ra_{\_SNTR}$
1	DOE 2^k	0.203	0.169	0.174	0.346	0.266	0.249
2		0.768	0.169	0.174	0.138	0.164	0.109
3		0.203	0.721	0.174	0.599	0.806	0.856
4		0.768	0.721	0.174	0.534	0.560	0.786
5		0.203	0.169	0.733	0.466	0.153	0.242
6		0.768	0.169	0.733	0.130	0.100	0.100
7		0.203	0.721	0.733	0.719	0.440	0.767
8		0.768	0.721	0.733	0.626	0.402	0.710
9	Center	0.471	0.390	0.407	0.534	0.274	0.320
10		0.471	0.390	0.407	0.496	0.379	0.457
11		0.471	0.390	0.407	0.504	0.530	0.356
12		0.471	0.390	0.407	0.458	0.236	0.432
13	Axial	0.100	0.390	0.407	0.275	0.342	0.343
14		0.100	0.390	0.407	0.268	0.243	0.306
15		0.900	0.390	0.407	0.100	0.304	0.230
16		0.900	0.390	0.407	0.108	0.334	0.255
17		0.471	0.100	0.407	0.130	0.243	0.163
18		0.471	0.100	0.407	0.150	0.281	0.170
19		0.471	0.900	0.407	0.763	0.900	0.811
20		0.471	0.900	0.407	0.900	0.764	0.900
21		0.471	0.390	0.100	0.230	0.228	0.370
22		0.471	0.390	0.100	0.199	0.258	0.369
23		0.471	0.390	0.900	0.252	0.274	0.381
24		0.471	0.390	0.900	0.313	0.409	0.369
R_a (minimum)					**0.100**	**0.100**	**0.100**

3.1 Results of M5P Model Tree based regression models

Six model trees (3 cutting tools X 2 tree parameters: Pruning Enabled and Pruning Disabled) were built for the normalized data of Table 2 using M5P tree implementation of the Weka suite of machine learning algorithms (Hall et al., 2009). The results (predicted minimum R_a value) are shown in Table 3.

To select the best M5 Model tree, three factors: Root Mean Square Error (RMSE), correlation and minimum predicted value of R_a are considered. Table 4 states the correlation and RMSE values of the six model trees corresponding to the testing data as reported by Weka. First we select the top three best model trees having the lowest RMSE values. Table 4 shows that the models for SNTR cutting tool with pruning enabled, SNTR cutting tool with pruning disabled and Uncoated tool with pruning disabled have the lowest RMSE values of 0.0638, 0.0669 and 0.1404 respectively. Now, amongst these three selected models we consider the correlation value of each and select the best two having the highest correlation values. It is evident from Table 4 that the correlation values of the three models are 0.946, 0.9534 and 0.8209 respectively. Thus, we select the models for SNTR tool with pruning disabled and SNTR tool with pruning enabled as the best two models and proceed by considering the third factor, minimum predicted value of R_a. Table 3 shows that the predicted minimum values of R_a by SNTR tool with pruning disabled is 0.099 whereas for SNTR tool with pruning enabled it is 0.088. *Thus, we select SNTR tool with pruning enabled as the best prediction model.*

Table 3 Predicted R_a values of M5 Model Tress for the three tools. Two models are developed for each tool, one with pruning enabled and the other with pruning disabled.

No.	Data source	Pruning Disabled			Pruning Enabled		
		R_a_uncoated	R_a_TiA1N	R_a SNTR	R_a_uncoated	R_a_TiA1N	R_a SNTR
1	Center	0.333	0.280	0.326	0.358	0.301	0.361
2		0.333	0.280	0.326	0.358	0.301	0.361
3		0.333	0.280	0.326	0.358	0.301	0.361
4		0.333	0.280	0.326	0.358	0.301	0.361
5	Axial	0.333	0.280	0.326	0.358	0.301	0.361
6		0.333	0.280	0.326	0.358	0.301	0.361
7		0.333	0.280	0.326	0.358	0.301	0.361
8		0.333	0.280	0.326	0.358	0.301	0.361
9		0.165	0.120	0.099	0.157	0.109	0.088
10		0.165	0.120	0.099	0.157	0.109	0.088
11		0.682	0.618	0.803	0.713	0.640	0.841
12		0.682	0.618	0.803	0.713	0.640	0.841
13		0.333	0.403	0.326	0.358	0.448	0.361
14		0.333	0.403	0.326	0.358	0.448	0.361
15		0.333	0.084	0.326	0.358	0.066	0.361
16		0.333	0.084	0.326	0.358	0.066	0.361
R_a (minimum)		**0.165**	**0.084**	**0.099**	**0.157**	**0.066**	**0.088**

Table 4 Correlation and Root Mean Square Error values of Model Trees for the testing data.

No.	Modelling Technique	$R_{a\_uncoated}$		R_{a_TiA1N}		$R_{a\ SNTR}$	
		RMSE	Correlation	RMSE	Correlation	RMSE	Correlation
1	$M5_{Prunning\ Disabled}$	0.1404	0.8209	0.1614	0.6917	0.0669	0.9534
2	$M5_{Prunning\ Enabled}$	0.1412	0.8136	0.1669	0.6424	0.0638	0.946

The minimum normalized predicted R_a value by the selected best M5 model tree is 0.088 (row nine and ten of Table 3) and the corresponding normalized cutting conditions values are: v= 0.471, f= 0.100 and ɣ = 0.407 (seventeenth and eighteenth rows of Table 2). The actual cutting condition values are v=144.22 m/min, f= 0.025 mm/tooth and ɣ = 9.5° (seventeenth and eighteenth rows of Table 1). The denormalized minimum predicted R_a value is calculated using a modified Equation 1 as follows (Zain et al., 2012):

$$d_i = \frac{(y_{R_a} - 0.100)(d_{max} - d_{min})}{0.8} + d_{min} = \frac{(0.088 - 0.100)(0.596 - 0.190)}{0.8} + 0.190 \approx 0.182\ \mu m$$

3.2 Results of Sequential Minimal Optimization (SMO) based Support Vector Machine (SVM) models

Six SVM models (3 cutting tools X 2 SVM kernels) were developed using SMO-SVM implementation of Weka (SMOreg) with the normalized data of Table 2. Table 5 shows the result (prediction of minimum R_a value) of applying the SMO-SVM models to the test set. Two kernels: Normalized Polynomial Kernel and Radial Basis Function (RBF) kernel were used for each of the cutting tool data. Experiments were performed with different values of Exponent parameter for Normalized Polynomial Kernel and Gamma parameter for RBF Kernel and the values resulting in lowest RMSE were selected finally and reported in Table 5.

Table 5 Predicted R_a values of SMO-SVM models for the three tools. Two models are developed for each tool, one with normalized polynomial kernel and the other with RBF kernel. The values of exponent and gamma shown are the ones which resulted in least RMSE.

No.	Data source	Normalized Polynomial Kernel			RBF Kernel		
		R_a_uncoated	R_a_TiA1N	R_a SNTR	R_a_uncoated	R_a_TiA1N	R_a SNTR
		Exponent = 9	Exponent = 8	Exponent = 1.55	Gamma = 1	Gamma = 0.5	Gamma = 4.9
1	Center	0.360	0.324	0.423	0.372	0.318	0.393
2		0.360	0.324	0.423	0.372	0.318	0.393
3		0.360	0.324	0.423	0.372	0.318	0.393
4		0.360	0.324	0.423	0.372	0.318	0.393
5	Axial	0.494	0.426	0.630	0.469	0.361	0.481
6		0.494	0.426	0.630	0.469	0.361	0.481
7		0.158	0.160	0.244	0.273	0.272	0.335
8		0.158	0.160	0.244	0.273	0.272	0.335
9		0.113	0.088	0.094	0.171	0.136	0.117
10		0.113	0.088	0.094	0.171	0.136	0.117
11		0.635	0.740	0.735	0.712	0.630	0.821
12		0.635	0.740	0.735	0.712	0.630	0.821
13		0.486	0.498	0.520	0.370	0.392	0.426
14		0.486	0.498	0.520	0.370	0.392	0.426
15		0.344	0.271	0.328	0.388	0.208	0.392
16		0.344	0.271	0.328	0.388	0.208	0.392
Ra (minimum)		**0.113**	**0.088**	**0.094**	**0.171**	**0.136**	**0.117**

Table 6 Correlation and Root Mean Square Error values of SMO-SVM models for the testing data

No.	Modelling Technique	$R_{a\_uncoated}$		R_{a_TiA1N}		R_{a_SNTR}	
		RMSE	Correlation	RMSE	Correlation	RMSE	Correlation
1	SMO-SVM (Normalized Poly Kernel)	0.1639	0.6984	0.1551	0.6752	0.1364	0.769
2	SMO-SVM (RBF Kernel)	0.1403	0.8243	0.1346	0.7463	0.0780	0.9290

To determine the best SMO-SVM prediction model, three factors: Root Mean Square Error (RMSE), correlation and minimum predicted value of R_a are considered. Table 6 states the correlation and RMSE values of the six SMO-SVM models corresponding to the testing data as reported by Weka. First we select the top three best SMO-SVM models having the lowest RMSE values. Table 6 shows that the models for SNTR cutting tool and TiA1N cutting tool with RBF kernel and SNTR tool with Normalized Polynomial kernel have the lowest RMSE values of 0.0780, 0.1346 and 0.1364 respectively. Now, amongst these three selected models we consider the correlation value of each and select the best two having the highest correlation values. It is evident from Table 6 that the correlation values of the three models are 0.9290, 0.7463 and 0.769 respectively. Thus, we select the models for SNTR tool with RBF kernel and Normalized Polynomial kernel as the best two models and proceed by considering the third factor, minimum predicted value of R_a. Table 5 shows that the predicted minimum values of R_a by SNTR tool with RBF kernel is 0.117 whereas for normalized Polynomial kernel it is 0.094. *Thus, we select SNTR tool with Normalized Polynomial kernel as the best prediction model.*

Table 7 Statistics and Correlations (experimental data vs. M5 Model Trees with pruning enabled)

	Mean	N	Std. Deviation	Std. Error Mean	Correlation
Experimental_SNTR	0.3895	16	0.20067	0.050168	0.946
$M5_{Pruning\ enabled}$_SNTR	0.3572	16	0.19017	0.047543	

Table 8 Paired-samples t test (Experimental SNTR vs SNTR M5 model tree with pruning enabled). Sig. (0.875) is the *p* value which is greater than 0.05 indicating that there is no significant difference between the means of the two data sets.

Pair	Paired Differences					t	df	Sig. (2-tailed)
				95% Confidence Interval of the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Experimental_SNTR and $M5_{Pruning\ enabled}$ SNTR	0.0026	0.065797	0.016449	-0.03244	0.03769	0.16	15	0.875

The minimum normalized predicted R_a value by the selected best SMO-SVM model is 0.094 (row nine and ten of Table 5) and the corresponding normalized cutting conditions values are: v= 0.471, f= 0.100 and ɣ = 0.407 (seventeenth and eighteenth rows of Table 2). The actual cutting condition values are v=144.22 m/min, f= 0.025 mm/tooth and ɣ = 9.5° (seventeenth and eighteenth rows of Table 1). The denormalized minimum predicted R_a value is calculated using a modified Equation 1 as follows (Zain et al., 2012):

$$d_i = \frac{(y_{k_2} - 0.100)(d_{max} - d_{min})}{0.8} + d_{min} = \frac{(0.094 - 0.100)(0.676 - 0.190)}{0.8} + 0.190 \approx 0.186\ \mu m$$

4. Evaluation of Results

The validation of model tree and SMO-SVM based models for predicting minimum value of R_a is carried out using paired-samples *t* tests. Tables 7 and 8 present the results of paired-samples *t* test of experimental data for SNTR tool paired with the predicated data by the best model tree (SNTR tool with Pruning enabled). Tables 7 and 8 prove that the mean R_a value is reduced by 0.0026 from experimental results for SNTR tool to the best model tree results, t (15) = 0.16 and p=0.875. The 95% confidence interval ranges from -0.03224 to 0.03769. Thus, the two means of experimental SNTR tool and the best model tree are not significantly different from each other.

Tables 9 and 10 show the results of paired-samples *t* test of experimental data for SNTR tool paired with the predicated data by the best SMO-SVM model (SNTR tool with Normalized Polynomial kernel). Tables 9 and 10 show that the mean R_a value is increased by 0.035 from experimental results for SNTR tool to the best SMO-SVM results, the 95% confidence interval ranges from -0.03224 to 0.03769, t (15) =-1.033 and p=0.318. Thus, the two means of experimental SNTR tool and the best SMO-SVM model are not significantly different from each other.

Considering the predicted R_a value, the model trees and SMO-SVM based models can be evaluated as follows:

(a) Experimental data vs. Model Trees

For the experimental data, the minimum value of R_a is 0.190 µm for SNTR tool (cf. Table 1). However, in case of model trees, the minimum predicted value of R_a is 0.182 µm (Equation X). Thus, the model tree has provided R_a value which is 0.008 µm less than the experimental data.

(b) Experimental data vs. SMO-SVM based model

The minimum predicted value of R_a by SMO-SVM is 0.186 µm (Equation X). Comparing with experimental data, it is evident that SMO-SVM based model has resulted in minimum R_a value which is 0.004 µm less than the experimental data.

(c) Model Tree vs. SMO SVM

As minimum predicted R_a value is 0.182 µm and 0.0186 µm for model tree and SMO-SVM based model respectively, it is evident that the model tree has given R_a value which is 0.004 µm less than SMO-SVM based model.

Table 9 Statistics and Correlations (experimental data vs. M5 Model Trees with Pruning enabled)

	Mean	N	Std. Deviation	Std. Error Mean	Correlation
Experimental_SNTR	0.3895	16	0.20067	0.050168	0.769
SMO-SVM-NormalizedPoly_SNTR	0.4246	16	0.199629	0.049907	

Table 10 Paired-samples *t* test (Experimental SNTR vs SNTR SMO-SVM with Normalized Polynomial kernel). Sig. (0.318) is the p value which is greater than 0.05 indicating that there is no significant difference between the means of the two data sets.

Pair	Paired Differences					t	df	Sig. (2-tailed)
				95% Confidence Interval of the Difference				
	Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Experimental_SNTR and SMO-SVM-NormalizedPoly_SNTR	-0.035	0.136036	0.034009	-0.10761	0.03736	-1.033	15	0.318

5. Conclusion

Two techniques, model trees and SMO-SVM were used for the first time in this research to build regression models for predicting the minimum value of surface roughness R_a in the end milling process. Table 11 summarizes the minimum value of R_a for the experimental data, model trees and SMO-SVM. Also the results reported in (Zain et al., 2012) using regression and ANN techniques are included for comparison.

Accordingly, Table 12 shows the percentage reduction in R_a value by all techniques. It is evident from Table 12 that both the techniques, model trees and SMO-SVM reported in this paper have performed better than regression and ANN techniques reported previously (Zain et al., 2012) as they have reduced the minimum R_a value of experimental data by 4.2 and 2.1 % respectively, with

Table 11 Minimum value of surface roughness. Model tree and SMO-SVM have been used for the first time in this research and use the empirical data with different training and test sets than ANN model of (Zain et al., 2012).

Technique	Minimum value of R_a (μm)
Experimental	0.190
Model Tree	0.182
SMO SVM	0.186
Regression (Zain et al., 2012)	0.187
ANN (Zain et al., 2012)	0.188

model trees generally giving better results in predicting the minimum R_a value than other models. These better results may be attributed partly to the careful selection of training data. In this paper the first eight rows of Table 2 are selected as training data that contain all unique attribute values. However, in (Zain et al., 2012) the last 16 rows of Table 2 were taken as training data. Many of these rows have different output values corresponding to identical input attribute values that can lead to poorer training and degraded performance of resulting regression models.

Statistical validation of the results indicate that both the techniques of Model Tree and SMO-SVM can be used as effective tools in modelling surface roughness. The application of these techniques may be extended to other tools and cutting conditions. The reliability of the results obtained through these machine learning based regression models can be enhanced further by increasing the amount of empirical data through additional experimentation.

Table 12 Percentage reduction in minimum surface roughness value. Model tree and SMO-SVM have been used for the first time for predicting R_a value in this research and use the empirical data with differently crafted training and test sets than ANN model of (Zain et al., 2012).

Technique	Percentage Reduction in R_a value
Experimental vs. Model Tree	4.2
Experimental vs. SMO- SVM	2.1
Experimental vs. Regression (Zain et al., 2012)	1.57
Experimental vs. ANN (Zain et al., 2012)	1.05

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