Available online at www.ijiit.net

International Journal of Integrative sciences, Innovation and Technology (IJIIT)

(A Peer Review E-3 Journal of Science Innovation Technology)

Journal homepage: http://www.ijiit.net/

eISSN 2278-1145

Research Unlimited

Vol. IV Iss 6

Original Research Article

Application of Data Mining to Evaluate Process parameters while turning Hybrid composites

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ARTICLE INFO

Article history:
Received 27 November 15
Received in revised form 00 January 00
Accepted 00 February 00

Keywords:
Data Mining
Data Analysis
Hybrid Composites
Response Surface Methodology

ABSTRACT

Data Mining (DM) has emerged as one of the key features of many applications in information system. While Data Analysis (DA) represents a significant advance in the type of analytical tools currently available there are limitations to its capability. Data Mining is identified to address the limitations of data analysis. The objective of this paper is of two fold. First, Al/SiC/RHA hybrid composite is prepared with varying reinforcements using stir casting technique. The process parameters considered are speed, feed, and depth of cut and % of reinforcement. Secondly, usage of Response Surface Methodology (RSM) technique integrated with DM which can efficiently find significant factors and the optimal settings by reducing large data.

How to cite this article: Ch Sampath Kumar, Ch Shoba and V Lakshmi (2015). Application of Data Mining to Evaluate Process parameters while turning Hybrid composites, International Journal of integrative Sciences, Innovation and Technology (IJIIT), 4 (6), xx – xx.

1. Introduction

Continuous improvement and application of information system technology has become widely recognized by industry as critical in maintaining a competitive advantage. It is also identified that the improvement and application activities are the most efficient and cost effective when implemented during an early process design stage. Data Mining (DM) plays a vital role in many applications of computer science. DM involves the usage of data analysis tools to discover unknown patterns and relationships from large data base. Machining includes large data while cutting the composites with varying reinforcements at different parameters. A tool that no longer performs the desired function is said to have failed or reached the end of its useful life. The variables that can affect the tool life are the cutting conditions, tool geometry, work material and the cutting fluid. A material is said to have good machinability if the tool wear is low. Metal matrix composites (MMC's) emerged as the superior class of materials with improved properties than alloys in various applications like automotive, aircraft, defense, ship industry, etc. Out of various combinations, aluminium reinforced with ceramics play a vital role. Ceramics are harder particles which improve the mechanical properties of the composites compared to base alloy [1]. The tool wear plays a dominant role while machining such composites because of the hard reinforced ceramic particles. This feature is more significant in machining hybrid composites with more than one reinforcement. The tool wear may be due to adhesion, abrasion and diffusion as suggested in metal cutting. The

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tool wear may occur along the flank face or along the rake face. Wear along the flank face is due to rubbing phenomenon of the flank face against the surface of the composite. Wear along the rake face is due to the hardened chip that flows over it while turning. The wear along the rake face is termed as crater wear. Studies were carried out on the tool flank wear by Jinfeng Leng et al [2]. In the work they presented that the tool wear rate decreases with increasing volume fraction of graphite particles in SiC/Gr/Al composites. They concluded that SiC/Gr/Al composites possess good machinability when the volume fraction of graphite is 5-7%. In machining Al-SiC metal matrix composite Lin et al [3] observed that the flank is the primary mode of tool failure. In their experimentation with PCD insert tool wear was found to increase with the increase of cutting speed and feed. Quan Yamin et al [4] studied the machinability of Al/SiC- MMC. The tool wear mechanism was discussed. It was found that volume fraction and the size of SiC particulates play an important role in tool life. Edge and corner breakage of carbide and hard film coated tools were also reported. Rajesh Kumar Bhushan et al [5] made an attempt to investigate the influence of the machining parameters during machining of 7075 Al alloys and 10 wt. % SiC particulate MMC's. They have investigated that for minimum flank wear machining should be carried at cutting speed less than 200m/min, feed rate of 0.1 mm/rev and depth of cut 0.5 mm. Kilickap et al [6] developed a relationship between tool wear and the cutting parameters for machining SiCp reinforced aluminium metal matrix composites. Machining of Al/SiCp/RHA hybrid composites is hardly seen in the literature. Rice husk ash (RHA) is found to be the most inexpensive and low density reinforcement available in large quantities as a waste byproduct [7]. RHA contains above 90% of silica, which makes the possible use of it as a reinforcement of widespread applications in automotive and small engine applications. As RHA is an agricultural waste byproduct the utilization of RHA has an additional benefit for decreasing the pollution. Prasad et al [8] studied the mechanical behavior and tribological characteristics of Al//RHA composites and the results show improved mechanical and tribological properties compared with the base alloy. Various investigations have been carried out for minimum tool wear while machining the composites but the problem of selecting cutting parameters is not fully solved due to its inherent complexity. Various approaches involving Artificial neural networks, Fuzzy logic, Grey Taguchi etc have been used till now. In this paper an attempt has been made to analyze the cutting data to discover the optimal parameters by applying data mining.

2. Experimental Procedure

Aluminium alloy reinforced with 2, 4, 6 & 8% SiC and RHA particles (in equal proportions by weight) are fabricated using stir casting method. Experiments are carried out on Aluminium alloys as they have wide applications in aerospace and marine. The chemical composition of Al alloy and RHA is shown in Table 1 and 2 respectively. The detailed procedure of fabrication is presented in the earlier works [9]. The composite slurry thus obtained were poured into a mold of dimensions Ø35X350 mm for mach inability studies. All the experiments were carried on HMT lathe machine with cemented carbide as the cutting tool whose specifications are presented in Table 3. Tool wear measurements were carried out using optical metallurgical microscope (Model: OLYMPUS GX 51) to determine the degree of flank and crater wear on the worn cutting tool after each test. The machining was carried for 60 seconds. Data mining approach was used to study the effect of input parameters on the output namely flank wear and crater wear. The range values for the input parameters have been carefully chosen based on the experimental evaluation of one factor at a time method.

Table 1: Chemical composition of A356.2 Al Alloy matrix

Si	Fe	Cu	Mn	Mg	Zn	Ni	Ti
6.5-7.5	0.15	0.03	0.10	0.4	0.07	0.05	0.1

Table 2: Chemical composition of RHA

Constituent	Silica	Graphite	Calcium Oxide	Magnesium Oxide	Potassium Oxide	Ferric Oxide
%	90.2	4.77	1.58	0.53	0.39	0.21

Table 3: Cutting conditions

Cutting tool	Cemented carbide
Specification	SNMG 120408
Tool holder	CTANR 2525-M16
Tool geometry	0-10-6-6-8-75-1mm (ORS)
Spindle speed (rpm)	560,900,1250,1500
Feed (mm/rev)	0.2,0.25,0.3,0.35
Depth of cut (mm)	1.0,1.5,2.0,2.5
Reinforcement (%)	2,4,6,8
Cutting condition	Dry

3.1 Data Mining

Data mining process has the following four steps to follow

Data Pre Processing: Data collection, Data cleaning and Data Transformation are the three steps used to gather data, clean the data and to transform the collected data for further processing.

Pattern Search: To find and compare the patterns in data which is the most crucial part is done here. Statistical Methods can be used for this purpose.

Analysis: In this step the output of the pattern search is analyzed and investigated to decide to stop or perform a revised search.

Interpretation: Investigation findings are finally interpreted in this step.

3.2 Best First Search Method

Best First Search Method (BFSM) method is based an advanced search strategy that allows back tracking along a search space path. If the path being explored begins to look less promising, the best first search can back tract to a more promising previous subset and continue searching from there.

The procedure using the proposed BFS algorithm is given by the following steps.

Step 1: Begin with the OPEN list containing the start state, the CLOSE list empty, and BEST ⟵

Start state (put start state to BEST)

Step 2: Let a subset, θ = arg max EVg (Subset) gets the state from OPEN with the highest evaluation EVg)

Step 3: Remove S from OPEN and add to CLOSED

Step 4: If EVg (θ) > EVg (BEST), then BEST ⟵ θ (put θ to BEST)

Step 5: For each next subset θ of θ that is not in the OPEN or CLOSED list, evaluate and add to OPEN

Step 6: If BEST changed in the last set of expansions, go to step 2

Step 7: Return BEST

3.3 Response Surface Methodology:

Using RSM based on both control and noise factors the data mining solution provides four significant factors such as speed, feed, depth of cut and % of reinforcement on the response variables. Speed is considered to be noise factor which is incorporated in the Robust Design (RD) principle in order to achieve robust process and the other factors as control factors. Using MINITAB software package the response function including both control factors and noise factors can be obtained for both flank wear and crater wear. Response Surface methodology is practical, economical and relatively easy to use. RSM is one of the important techniques for determining the relationship between various process parameters and the responses [10]. Response Surface methodology adopts both mathematical and statistical techniques which are useful for modeling and analysis of problems to optimize the response from several variables [11]. The objectives of quality improvement, including reduction of variability and improved process and product of performance can often be accomplished directly using RSM. In the RSM, the quantitative form of relationship between the desired response and independent input variables is represented as follows:

$$Y = F(A, B, C, D) \tag{1}$$

Where Y is the desired response, F is the response function, A, B, C and D represents spindle speed, feed, depth of cut and % of reinforcement.
In order to study the effect of the process parameters a second order polynomial response surface can be fitted into the following equation

$$Y = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_i X_i^2 + \sum \sum_{j} \beta_{ij} X_i Y_j + \xi \tag{2}$$

Where Y is the response and X_i is the value of its machining process parameter. The term β are regression coefficients. The second term under the summation sign of this response surface equation is attributable to linear effect, whereas the third term corresponds to higher order effects; the fourth term of the equation includes the interactive effects of the process parameter. ξ is the residual measure from the experimental error of the observations. This quadratic model works quite well over the entire factory space. The necessary data required for developing the response models have been collected by designing the experiments based on Central Composites Design (CCD). CCD is the most popular and second order design which was introduced by Box & Wilson. It is a factorial fractional factorial design with center points and star points. The test was designed based on a three factor three level central composite design with full replication. A CCD consisting of 21 experiments was used. The process variables used in the experimentation are shown in the Table 4. A CCD with actual variables and experimental values was shown in the Table 5. Using analysis of variance (ANOVA) the significance of input parameters is evaluated. Design expert 9.0 was used to establish the design matrix to analyze the experimental data and to fit the experimental data to a second-order polynomial. Sequential F-test, lack-of-fit test and other adequacy measures were used to check the model's performance.

Table 4: Process variables

Process variables	**Notation**	**Units**	**Limits**				
			-1.68179	-1	0	1	1.68179
Speed	A	Rpm	360	560	900	1250	1500
Feed	B	mm/rev	0.17	0.2	0.25	0.3	0.35
Depth of cut	C	Mm	0.5	1	1.5	2	2.5
Reinforcement	D	%	0	2	4	6	8

Table 5: CCD matrix with coded variables and experimental values

Exp.No	Run order	Input variables				Response	
		Speed (Rpm)	Feed (mm/rev)	Depth of cut (mm)	% of reinforcement	Flankwear (mm)	Crater wear (mm)
1	11	0	-1.68179	0	0	0.182	0.92
2	5	1	-1	-1	1	0.293	0.03
3	18	0	0	0	0	0.384	0.27
4	8	-1	-1	-1	-1	0.395	0.33
5	15	0	0	0	-1.6818	1.72	1.56
6	17	0	0	0	0	0.198	0.05
7	13	0	0	-1.68179	0	0.284	0.08
8	3	1	-1	1	1	0.568	0.14
9	16	0	0	0	1.68179	0.625	0.28
10	7	-1	1	1	1	0.446	0.45
11	4	-1	1	-1	1	0.482	0.98
12	14	0	0	1.68179	0	0.286	0.18
13	19	0	0	0	0	0.854	0.48
14	1	1	1	1	-1	0.468	0.37
15	10	1.68179	0	0	0	0.41	0.39
16	2	1	1	-1	-1	0.542	0.7
17	20	0	0	0	0	0.568	0.88
18	9	-1.68179	0	0	0	0.546	0.84
19	12	0	1.68179	0	0	0.539	0.7
20	21	0	0	0	0	0.5	0.52
21	6	-1	-1	1	-1	0.381	0.72

4. Results and discussion

The microstructural characterization and the mechanical properties of the hybrid composites are presented in the earlier works [9, 12]. RSM technique was performed to predict the flank wear and crater wear in turning of Al/SiC/RHA hybrid composites. The analysis of variance of the experimental data was done to analyze the relative significance of the machining parameters such as spindle speed, feed, depth of cut and % of reinforcement on the response variables. From Table 6, model F value of 3.32 indicates that the model is significant. There is only 4.84% chance that this F-value could occur due to noise. The value of “Prob>F” for the model is less than 0.0500 which indicates that the model terms are significant. The ‘lack of fit F-value’ of 0.44 implies the lack of fit is not significant relative to the pure error. There is only 77.72% chance that a “lack of fit F- value” this large could occur due to noise. Non significant lack of fit is good for the model. The adequacy of the model is analyzed using R^2 value. The value of R^2 represents the regression confidence. R^2 (0.8329) value is high; close to 1 is obtained which is desirable. R^2 value represents high correlation between experimental and predicted values. A negative “Pred R-Squared” implies that the overall mean is a better predictor for the response. “Adeq Precision” measures the signal to noise ratio. A ratio greater than 4 is desirable. This model has a ratio of 9.514 which indicates an adequate signal. From Table 7, Model F-value of 3.43 implies the model is significant. There is only a 3.74% chance that an F-value this large could occur due to noise. Values of "Prob> F" less than 0.0500 indicates model terms are significant. The "Lack of Fit F-value" of 0.37 implies the Lack of Fit is not significant relative to the pure error. There is 84.72% chance that a "Lack of Fit F-value" this large could occur due to noise. Non-significant lack of fit is good for the model. A negative "Pred R-Squared" implies that the overall mean is a better predictor of your response than the current model."Adeq Precision" measures the signal to noise ratio. A ratio greater than 4 is desirable. This model has a ratio of 7.718 which indicates an adequate signal. The adequacy of the model R^2 (0.8074) value is high, close to 1 which is desirable is obtained. The final equation in terms of coded factors for the flank wear and crater wear with the variables like A, B, C and D are shown in Equation 3 and 4.

$$Flankwear = 0.50 - 0.040A + 0.11B + 0.011C - 0.33D - 0.33AB + 0.031AC + 0.069AD - 0.046BC$$
$$- 0.061BD - 0.082B^2 - 0.11C^2 + 0.21D^2 \quad (3)$$

$$Craterwear = 0.49 - 0.15A - 0.065B - 0.014C - 0.38D - 0.32AB - 1.000E - 002AC - 0.23AD$$
$$- 0.17BC + 0.079B^2 - 0.016C^2 + 0.12D^2 \quad (4)$$

Table 6: ANOVA table for the flank wear response variable

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob> F	
Model	1.68	12	0.14	3.32	0.0484	significant
A-speed	9.248E-003	1	9.248E-003	0.22	0.6522	
B-feed	0.064	1	0.064	1.51	0.2541	
C-doc	1.745E-003	1	1.745E-003	0.041	0.8440	
D-reinforcement	0.60	1	0.60	14.20	0.0055	
AB	0.35	1	0.35	8.34	0.0203	
AC	7.875E-003	1	7.875E-003	0.19	0.6772	
AD	0.016	1	0.016	0.37	0.5607	
BC	0.017	1	0.017	0.41	0.5411	
BD	0.012	1	0.012	0.30	0.6018	
B^2	0.10	1	0.10	2.39	0.1604	
C^2	0.18	1	0.18	4.20	0.0745	
D^2	0.63	1	0.63	14.95	0.0048	
Residual	0.34	8	0.042			
Lack of Fit	0.10	4	0.026	0.44	0.7772	not significant
Pure Error	0.23	4	0.059			
Cor Total	2.02	20				

ANOVA results of the flank wear using suggested quadratic model

Std. Dev.	0.21	R-Squared	0.8329
Mean	0.51	Adj R-Squared	0.5823
C.V. %	40.44	Pred R-Squared	-1.4338
PRESS	4.92	Adeq Precision	9.514

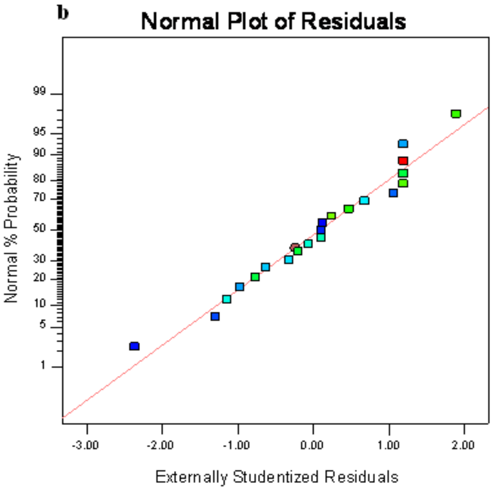
Table 7: ANOVA table for the Crater wear response variable

Source	Sum of Squares	df	Mean Square	F Value	p-value Prob> F	
Model	2.35	11	0.21	3.43	0.0374	Significant
A-speed	0.29	1	0.29	4.69	0.0585	
B-feed	0.024	1	0.024	0.39	0.5483	
C-doc	2.694E-003	1	2.694E-003	0.043	0.8398	
D-reinforcement	0.82	1	0.82	13.17	0.0055	
AB	0.33	1	0.33	5.30	0.0468	
AC	8.000E-004	1	8.000E-004	0.013	0.9122	
AD	0.17	1	0.17	2.71	0.1344	
BC	0.23	1	0.23	3.72	0.0860	
B^2	0.094	1	0.094	1.51	0.2508	
C^2	0.39	1	0.39	6.28	0.0335	
D^2	0.21	1	0.21	3.35	0.1003	
Residual	0.56	9	0.062			
Lack of Fit	0.18	5	0.035	0.37	0.8472	not significant
Pure Error	0.38	4	0.096			
Cor Total	2.91	20				

ANOVA results of the crater wear using suggested quadratic model

Std. Dev.	0.25	R-Squared	0.8074
Mean	0.52	Adj R-Squared	0.5719
C.V. %	48.19	Pred R-Squared	-0.7554
PRESS	5.10	Adeq Precision	7.718

The normality of the data was done by means of the normal probability plot. The normal probability plot of the residuals for flank wear and crater wear are shown in Figure 1a and b respectively. Figure 1a is the normal probability plot for flank wear and Figure 1b is corresponding to the crater wear, which reveals that the residuals are falling on the straight line. This means that the errors are distributed normally. The residual plot for flank wear and crater wear are shown in Figure 2. Figure 2 (a) is the residual plot for flank wear and Figure 2 (b) is corresponding to the crater wear, which reveals that there was no predictable pattern observed because all the run residues lay on or between the levels of -3 to 3. The relationship between the predicted and the experimental values of the flank wear and crater wear are shown in Figure 3 (a & b). It is indicated from the figures that the developed models are adequate and the predicted values are in good agreement with the measured data. From the developed RSM based mathematical model the effect of machining parameters on flank wear and crater wear are examined. Figure 4 (a-d) shows the interaction effect of speed, feed, depth of cut and % of reinforcement It is evident from the 3-D surface plots that the flank wear is greatly influenced by the reinforcement compared to the other parameters. It is also understood that the flank wear decreases with the increase of reinforcement. This is evident from the optical micrograph shown in Figure 5a and b. From the optical micrograph it was observed that the flank wear while turning 2% reinforced is more than 8% reinforced composite.



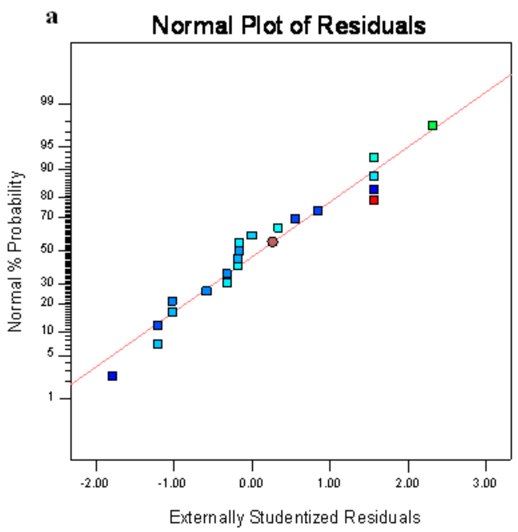


Fig. 1: Normal probability plot (a) Flank wear (b) Crater wear

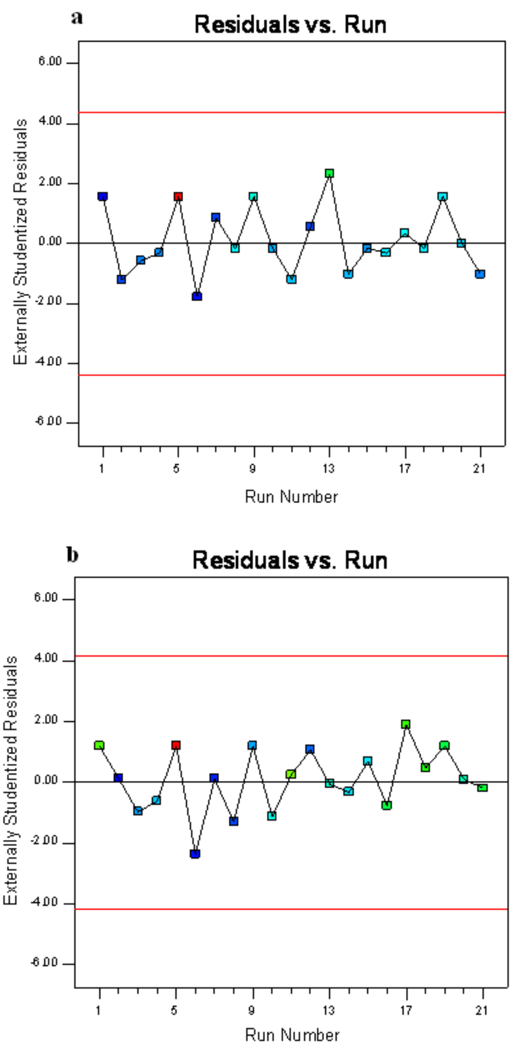


Fig. 2: Residual plot (a) Flank wear (b) Crater wear

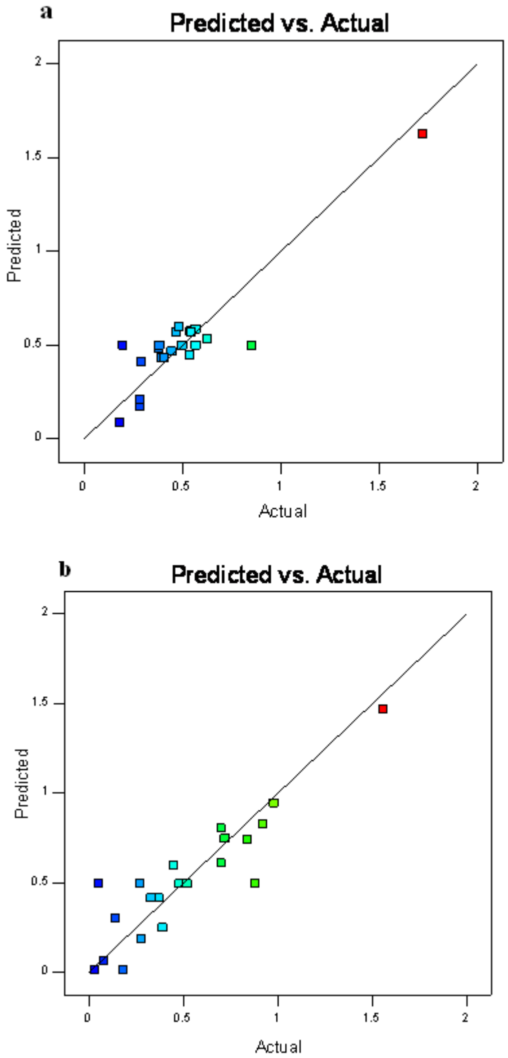
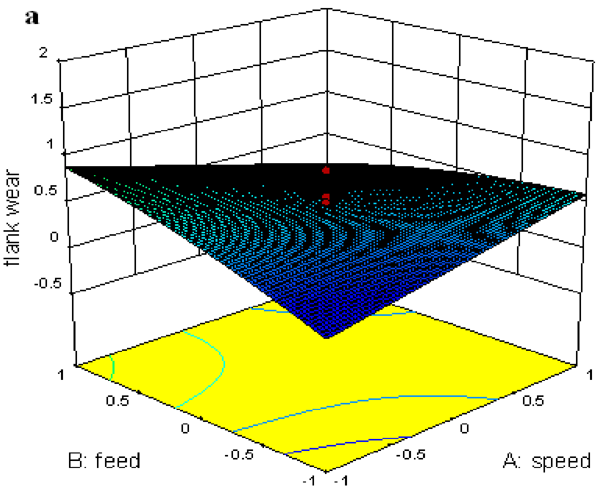


Fig. 3: Relationship between experimental and predicted values (a) Flank wear (b) Crater wear



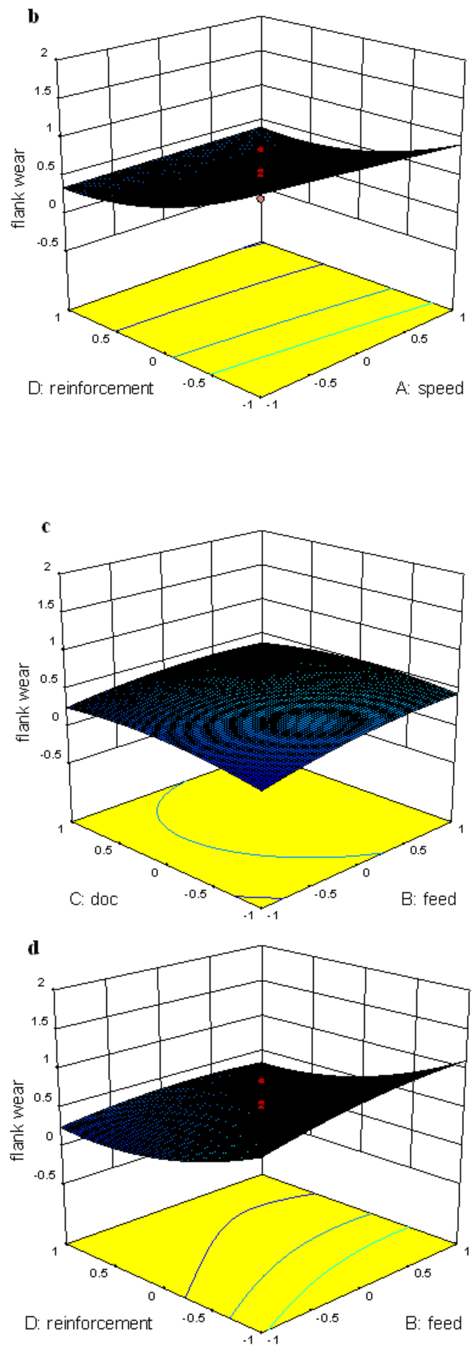
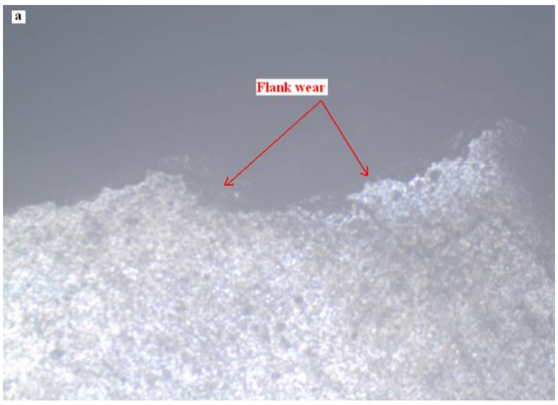


Figure 4: 3-D surface plots a) Interaction effect of feed and speed on the flank wear b) interaction effect of speed and reinforcement on the flank wear c) Interaction effect of depth of cut and feed on the flank wear and d) Interaction effect of reinforcement and feed on the flank wear.



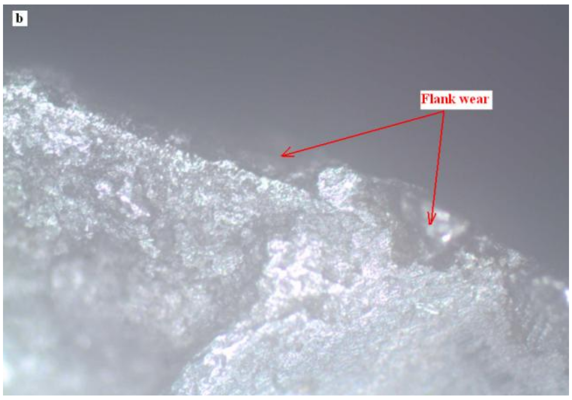
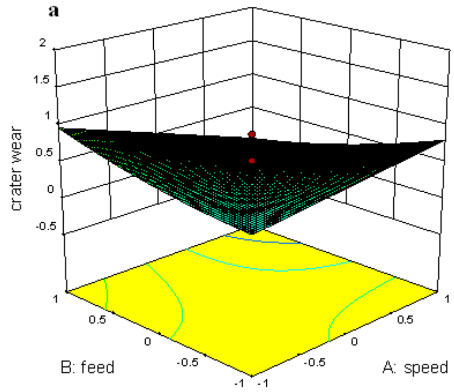
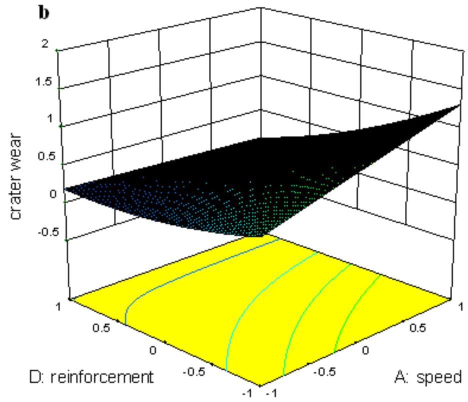
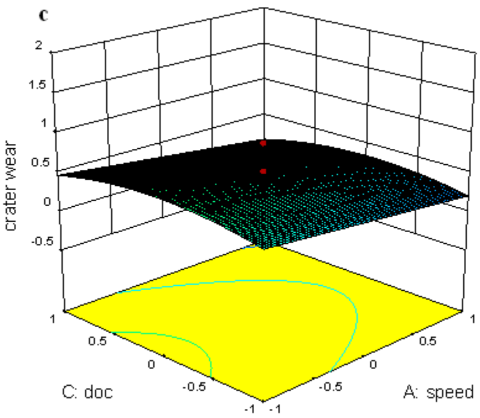


Figure 5: Optical micrograph showing flank wear a) 2 % reinforced b) 8 % reinforced (100X)







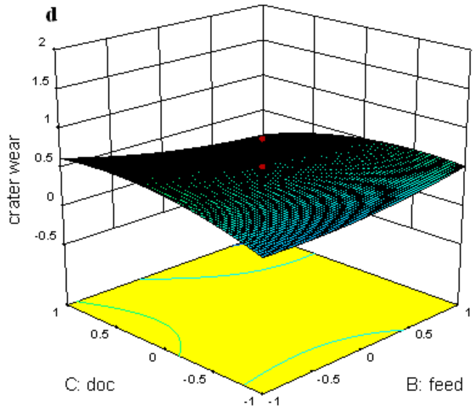


Figure 6: 3-D surface plots a) Interaction effect of feed and speed on the crater wear b) Interaction effect of speed and reinforcement on the crater wear c) Interaction effect of depth of cut and speed on the crater wear and d) Interaction effect of depth of cut and feed on the crater wear.

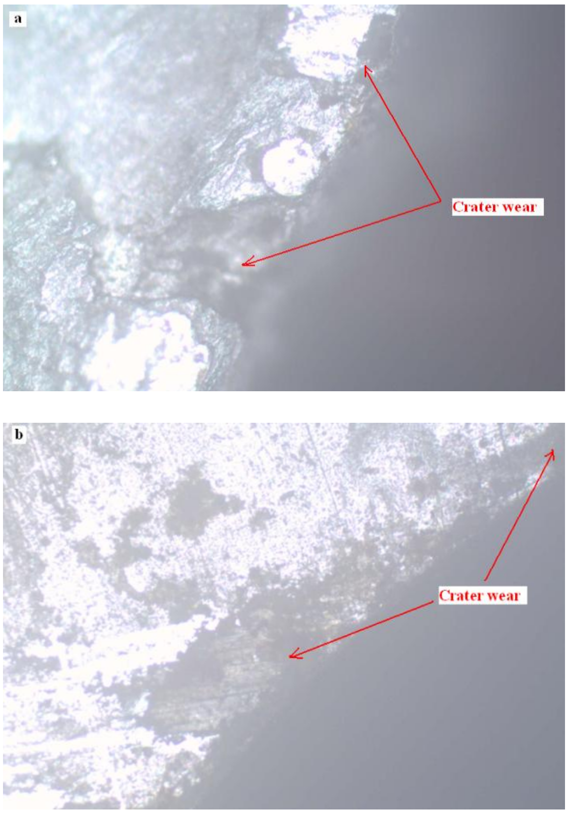


Figure 7: Optical micrograph showing crater wear a) 2 % reinforced b) 8 % reinforced (100X)

5. Conclusions

RSM can be successfully integrated to Data mining for finding significant factors. Based on the results of DM method it was found that the important factors from large set of data. The model is observed to be significant based on the results of f-test and p-values. The response model also has 80% R-Sq which implies that the model is adequate to be utilized as a response function. Best first search method is found to be promising to explore the optimal factors.

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