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Determination of Machining Parameters of Corn Byproduct Filled Plastics

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Abstract

In a collaborative project between the USDA and Northern Illinois University, the use of ethanol corn processing by-products as bio-filler materials in the compression molding of phenolic plastics has been studied. This paper reports on the results of a machinability study in the milling of various grades of this material. Three types of samples were studied: 100%, 75% and 50% phenolic samples. The milling operation was carried out with a fixed depth of cut of 2.0 mm using a 12.5 mm diameter two-fluted end-mill. The cutting speed was varied between 120 and 160 m/min at feeds between 200 and 300 mm/min. Surface roughness measurements were taken after each combination of feed and speed. Mathematical models for surface roughness have been developed in terms of speed and feed at constant depth of cut by response surface methodology (RSM); the significance of the speed and feed on the surface roughness has been established with Analysis of Variance (ANOVA) for the three types of samples. The optimum cutting conditions were obtained by constructing contours of constant surface roughness using MINITAB statistical software.

Introduction

Plastics are manufactured from petroleum resources that are not renewable and not biodegradable. To minimize the environmental impact of plastic products and enhance biodegradability, many plastic products utilize low-cost, bio-based materials as fillers. Corn processing coproducts (DDGS), once dried, represents a potential biofiller [1]. This filler can be added in a concentration by weight so as to maintain the mechanical and physical properties of the resin. It appears that filler concentrations between 25% and 50% represent reasonable inclusion values and sufficient mechanical strength. The main aim of this work is to study the machinability of corn processing coproduct filled plastics.

For the selection of optimum machining conditions Computer Aided Manufacturing (CAM) has been widely implemented. In the present work, experimental studies have been conducted to see the effect of cutting conditions on the machining performance of resin and corn coproduct filled resin. This paper presents an approach to develop mathematical models for surface roughness by response surface methodology (RSM) in order to optimize the surface finish of the machined surface [2, 3]. RSM is a combination of mathematical and statistical techniques used in an empirical study of relationships and optimization, where several independent variables influence the process. The first and second order mathematical models, in terms of machining parameters, were developed for surface roughness prediction using RSM on the basis of experimental results.

The influence of the speed and feed on the surface roughness has been established with the Analysis of variance for 100% phenolic,75% phenolic (25% DDGS), 50% phenolic (50% DDGS) samples. The response or dependent variable is viewed as a surface to which a mathematical model is fitted in RSM. The optimum cutting condition was obtained by constructing contours of constant surface roughness by MINITAB and used for determining the optimum cutting conditions for a required surface roughness.

Methodology

a) General Approach

Response surface methodology (RSM) is an optimization technique in the field of numerical analysis. For optimization, it uses a function called a response surface. A response surface is a function that approximates a problem with design variables and state quantities, using several analysis or experimental results. In general, design of experiments is used for analysis or experiment point parameter setting, and the least square method is used for function approximation. Response surface methodology is a combination of mathematical and statistical techniques useful for modeling and analyzing the problems in which several independent variables influence a dependent variable or response.

The RSM technique attains convergence by repeating numerical and sensitivity analysis until the optimal solution as obtained. For problems with high non-linearity, and for multimodal problems, there may be cases in which no solution can be found because of problems such as inability to obtain sensitivities or a lapse into a local solution. To solve such problems with conventional optimization, the RSM has been adopted. With RSM, optimization conditions are first set, and then a response surface is created between design variables and objective functions or constraint conditions [4]. Since the expected experimental and theoretical relations in machining are expected to be non-linear, in this work response surface models are used for optimization.

The mathematical model generally used is represented by:

$$Y = f(v, f, \alpha, r) + \text{€} \quad (1)$$

where Y is the machining surface response, v, f, α, r are milling variables, and € is the error which is normally distributed about the observed response Y with zero mean.

Considering only the parameters v and f, a relation can be formulated between these independent variables and the dependent variable, surface roughness R_a, as follows[5]:

$$R_a = Cv^a f^b \tag{2}$$

where C is a constant, v is cutting speed (m/min), f is the feed rate (mm/min), and a and b are the empirically-estimated exponents.

This mathematical model is linearized by performing a logarithmic transformation as follows:

$$\ln R_a = \ln C + a \ln v + b \ln f \tag{3}$$

The constants and exponents C, a, and b can be determined by the method of least squares. The first order linear model, developed from the above functional relationship using the least square method, can be represented as follows:

$$Y_1 = Y - \in = b_0 x_0 + b_1 x_1 + b_2 x_2 \tag{4}$$

where Y_1 is the estimated response.

Based on the first-order equation, Y is the measured surface roughness on a logarithmic scale, $x_0(=1)$ is a dummy variable; x_1 and x_2 are logarithmic transformations of cutting speed and feed. b_0, b_1 and b_2 are coefficients found from least squares method.

The second order model can be extended from the first order model's equation as

$$Y - \in = b_0 x_0 + b_1 x_1 + b_2 x_2 + b_{11} x_1^2 + b_{22} x_2^2 + b_{12} x_1 x_2 \tag{5}$$

And the same method is used to determine coefficients b_0, b_1, b_2, b_{11}, b_{22} and b_{12}.

b) Experimental Details

Based upon the research conducted by Alauddin et al. [5], which identified feed rate and cutting speed as key variables, in our study a milling operation was performed on each test specimen using different feeds and speeds. A CNC milling machine was used to machine a slot with a 12.5 mm diameter carbide two-flute end mill. Six slots were machined on each sample (three on each side). A new end mill was used after every specimen to reduce effects of tool wear on the measured parameters. The depth of cut was kept constant at 2mm. The table 1 below shows the selected cutting conditions.

The design of experiments was based on the Taguchi approach [6]. Since the range of values of each factor was set at three different levels and the factors considered were 2, the design of experiments was based on a full factorial. Therefore the number of tests conducted was 9 (3^2). Table 2 shows the full experimental schedule.

Table 1: The Two Process Variables in the Experiment were Each at Three Levels

Parameter	Level-1	Level-2	Level-3
Speed, v (m/min)	120	140	160
Feed, f (mm/min)	203	254	305

Table 2: The Experiments were Conducted Following a 3^2 Factorial Design

Experimental Treatment	Speed, v (m/min)	Feed, f (mm/min)
1	120	203
2	120	254
3	120	305
4	140	203
5	140	254
6	140	305
7	160	203
8	160	254
9	160	305

c) Coding of Independent Variables

The variables were coded taking into account the capacity and limiting cutting conditions of the milling machine so as to avoid vibration of the work-tool system. The coded values of the variables shown in Table 2 for use in equations (4) and (5) were obtained from the following transformation equations [7]:

$$x_1 = \frac{\ln v - \ln 140}{\ln 140 - \ln 120} \qquad (6)$$

$$x_2 = \frac{\ln f - \ln 254}{\ln 254 - \ln 203} \qquad (7)$$

where x_1 is the coded value of the cutting speed corresponding to its natural value v, x_2 the coded value of the feed corresponding to its natural value f. The axial depth of cut, d, was kept constant at 2 mm.

d) Statistical Analysis

Analysis of the variance (ANOVA) and the F-ratio test have been performed to justify the accuracy of the fit for the response surface model. The ANOVA method is based on a least squares approach. This analysis was carried out for a level of significance of 5% (a level of confidence of 95%) [8]. The regression parameters of the postulated model were estimated by the method of least squares using the following basic formula [9]:

$$b = (X^T X)^{-1} X^T Y \qquad (8)$$

where b is the matrix of parameter estimates, X is the matrix of independent variables or design matrix, X^T is the transpose of the matrix X, and Y is the matrix of logarithms of the measured surface roughnesses (i.e., responses).

Results and Discussion

The variation of machining response with respect to the variables was shown graphically in figures 1 through 3. The graphs are shown for 100% phenolic, 75% phenolic and 50% phenolic samples. 100% phenolic samples show minimum surface roughness values at high speeds and low feeds (figure 1). 75% phenolic samples show minimum surface roughness values at medium speeds and low feeds (figure 2), while the 50% phenolic samples show minimum surface roughness values at low speeds and high feeds as in (figure3).

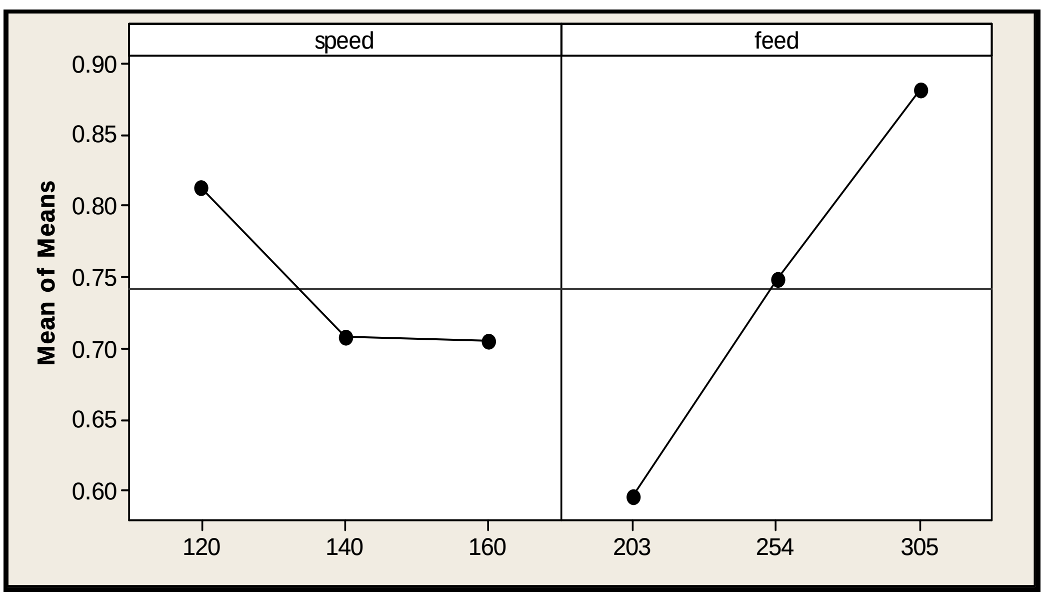

Figure 1: R_a Response Plot for 100% Phenolic Sample

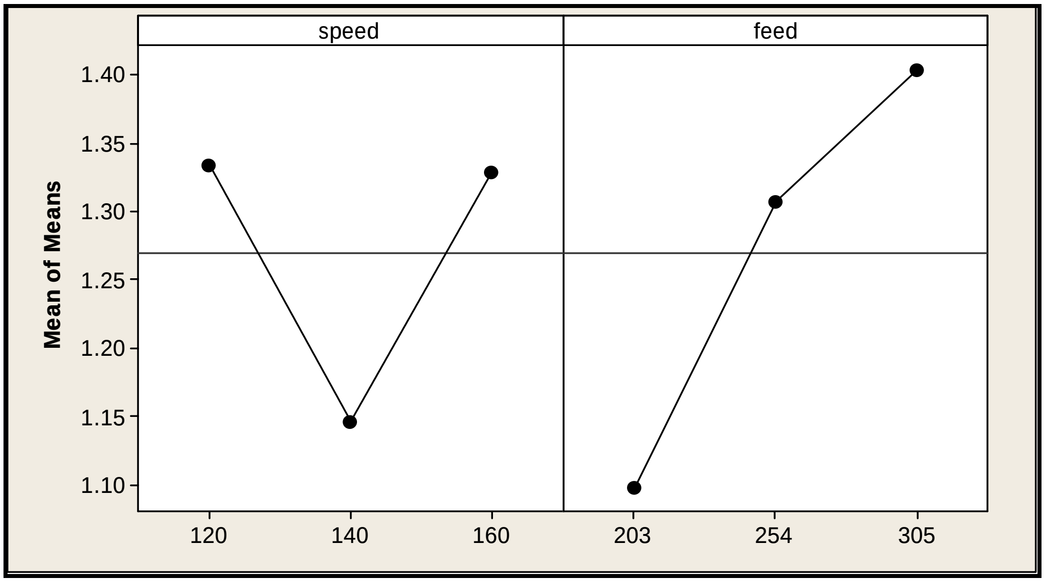

Figure 2: R_a Response Plot for 75% Phenolic Sample

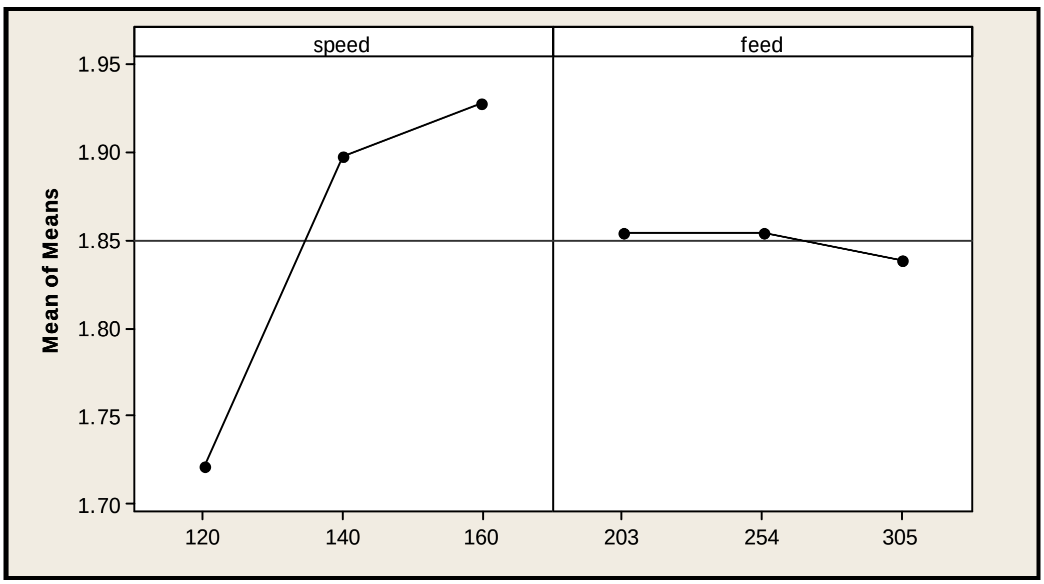

Figure 3: R_a Response Plot for 50% Phenolic Sample

a) The Roughness Model

Using experimental results, empirical equations have been obtained to estimate surface roughness with the significant parameters considered for the experimentation (i.e. speed and feed). The first order model obtained from the above functional relationship using RSM is as follows:

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i) 100% phenolic Sample:

The first order RSM model is given by:

$$Y_1 = Y - \in = 0.410923x_0 \ - 0.0027x_1 + 0.002791x_2 \quad (9)$$

The transformed equation of surface roughness prediction is as follows:

$$R_a = 1.207493v^{-0.017515}f^{0.01245} \quad (10)$$

Equation 10 is derived from 6 and 7 by substituting the coded values of x_1 and x_2 in terms of ln v and ln f. Results of ANOVA and F-ratio are shown in table 3 below. Since the calculated values of the F-ratio are less than the standard values of the F-ratio for surface roughness, the model is adequate at 95% confidence level to represent the relationship between the machining response and the machining parameters of the milling process. The multiple regression coefficient for the first order model was found to be 0.88613. This shows that the first order model can explain the variation in surface roughness to the extent of 88.613%.

Table 3: ANOVA Results for First Order Model - 100% Phenolic

	df	*SS*	*MS*	*F*	*Significance F*	R Square
Regression	2	0.139069	0.069534	23.35343	0.001475	0.886163
Residual	6	0.017865	0.002977			
Total	8	0.156933				

Since the first order model is not sufficiently predictable, second order model was developed for better results and is as follows:

$$Y_2 = Y - \in = 0.965073x_0 - 0.02622x_1 + 0.01118x_2 + 0.000126x_1^2 + 0.0000038x_2^2 + 0.000046x_1x_2 \quad (11)$$

The results for ANOVA and F-test are shown in Table 4 below. Since the calculated value of F is greater than $F_{0.01}$; there is a definite relationship between the response variable and independent variable at 95% confidence level. The multiple regression coefficient of the second order model was found to be 0.9759. On the basis of the multiple regression coefficient (R square), it can be concluded that the second order model was more adequate to represent this relationship.

Table 4: ANOVA Results for Second Order Model - 100% Phenolic

	df	*SS*	*MS*	*F*	*Significance F*	R Square
Regression	5	0.153164	0.030633	24.38117	0.012366	0.975982
Residual	3	0.003769	0.001256			
Total	8	0.156933				

ii) 75% phenolic sample:

The first order model obtained from the above functional relationship using RSM method is as follows:

$$Y_1 = Y - \in = 0.526967x_0 - 0.00011x_1 + 0.002983x_2 \tag{12}$$

The transformed equation of surface roughness prediction is as follows:

$$R_a = 0.45677v^{-0.00071}f^{0.013309} \tag{13}$$

ANOVA and the F-ratio results are shown in table 5 below. Similarly, since the calculated values of the F-ratio are less than the standard values of the F-ratio for surface roughness, the model is adequate at 95% confidence level. The multiple regression coefficient for the first order model was found to be 0.36342. As it is not sufficiently predictable, the second order model has been developed for better results.

Table 5: ANOVA Results for First Order Model - 75% Phenolic

	df	*SS*	*MS*	*F*	*Significance F*	R Square
Regression	2	0.138934	0.069467	1.705325	0.259176	0.362425
Residual	6	0.244411	0.040735			
Total	8	0.383345				

The second order surface roughness model thus developed is given below:

$$Y_2 = Y - \in = 7.921301x_0 - 0.12814x_1 + 0.014657x_2 + 0.000462x_1^2 - 0.000022x_2^2 - 0.0000051x_1x_2 \tag{14}$$

The data for ANOVA and F-test for the second order model is shown in table 6 below. Since the calculated value of F is greater than the standard values of the F-ratio, there is a definite relationship between the response variable and independent variable and independent variable at 95% confidence level.

Table 6: ANOVA Results for Second Order Model - 75% Phenolic

	df	*SS*	*MS*	*F*	*Significance F*	R Square
Regression	5	0.21362	0.042724	0.755174	0.63531	0.557253
Residual	3	0.169725	0.056575			
Total	8	0.383345				

iii) 50% phenolic sample:

The first order model is given by:

$$Y_1 = Y - \in = 1.168429x_0 + 0.005147x_1 - 0.00016x_2 \tag{15}$$

The transformed equation of surface roughness prediction is as follows:

$$R_a = 1.0073835v^{0.0333894}f^{-0.000713} \tag{16}$$

The ANOVA) and F-ratio test results are shown in table7 below. Again it has been found that the calculated values of F-ratio are less than the standard values of the F-ratio. Therefore the model is adequate at 95% confidence. The multiple regression coefficient for the first order model was found to be 0.478701, thus a second order model was considered.

Table 7: ANOVA Results for First Order Model - 50% Phenolic

	df	*SS*	*MS*	*F*	*Significance F*	R Square
Regression	2	0.063972	0.031986	2.754854	0.141664	0.478701
Residual	6	0.069665	0.011611			
Total	8	0.133637				

The second order model was found to be:

$$Y_2 = Y - \in = -1.52417x_0 + 0.048853x_1 - 0.00262x_2 - 0.00018x_1^2 - 0.0000032x_2^2 + 0.000293x_1x_2 \tag{17}$$

The data for ANOVA and F-test for the second order surface roughness is shown in table 8 below. The calculated value of the F-ration is greater than the standard value – thus, there is a definite relationship between the response variable and independent variable and independent variable at 95% confidence level.

Table 8: ANOVA Results for Second Order Model - 50% Phenolic

	df	*SS*	*MS*	*F*	*Significance F*	R Square
Regression	5	0.078351	0.01567	0.85031	0.593469	0.586295
Residual	3	0.055286	0.018429			
Total	8	0.133637				

b) Taguchi Analysis Results

The response tables show the average of each response characteristic for each level of each factor. The tables include ranks based on the delta statistics, which compare the relative magnitude of effects. The delta statistic is highest minus the lowest average of each factor. In MINITAB, ranks are assigned based on delta values: rank 1 to the highest delta value, rank 2 to the second highest, and so on. The ranks indicate the relative importance of each factor to another factor. The results for 100%, 75% and 50% phenolic are shown in tables 9 to 11 respectively. Based on these, contour plots of the surface roughness against speed and feed have been obtained and are shown in figures 4 to 6.

Table 9: Response Table for R_a Means - 100% Phenolic Sample

Level	Speed (m/min)	Feed (mm/min)
1	0.8128	0.5964
2	0.7085	0.7486
3	0.7048	0.8811
Delta	0.1080	0.2847
Rank	2	1

Table 10: Response Table for R_a Means - 75% Phenolic Sample

Level	Speed (m/min)	Feed (mm/min)
1	1.334	1.099
2	1.147	1.307
3	1.330	1.403
Delta	0.187	0.304
Rank	2	1

Table 11: Response Table for R_a Means - 50% Phenolic Sample

Level	Speed (m/min)	Feed (mm/min)
1	1.722	1.854
2	1.898	1.855
3	1.928	1.838
Delta	0.206	0.016
Rank	1	2

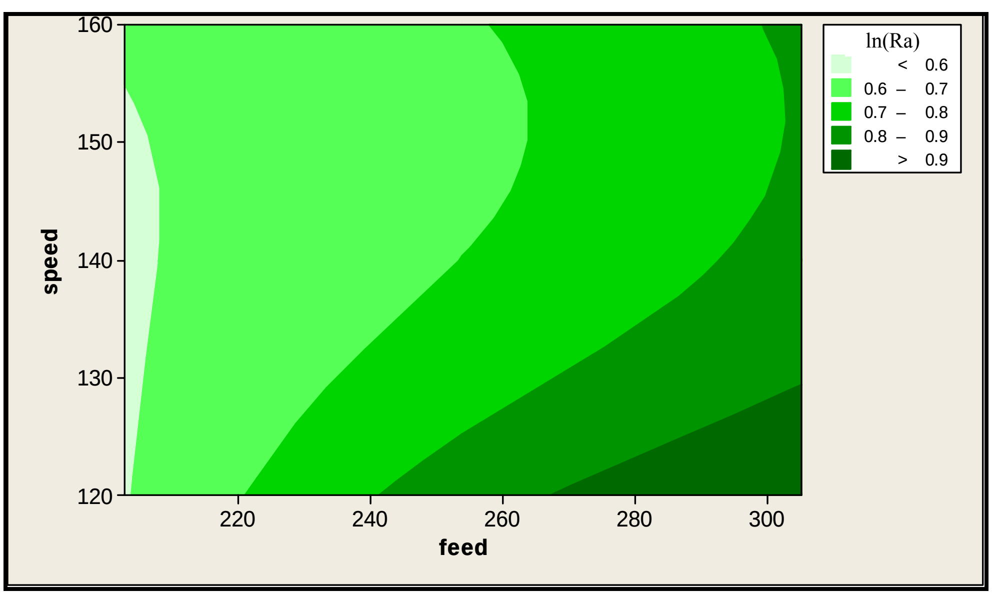

Figure 4: Contour Plot of ln(R_a) vs. Speed and Feed - 100% Phenolic Sample

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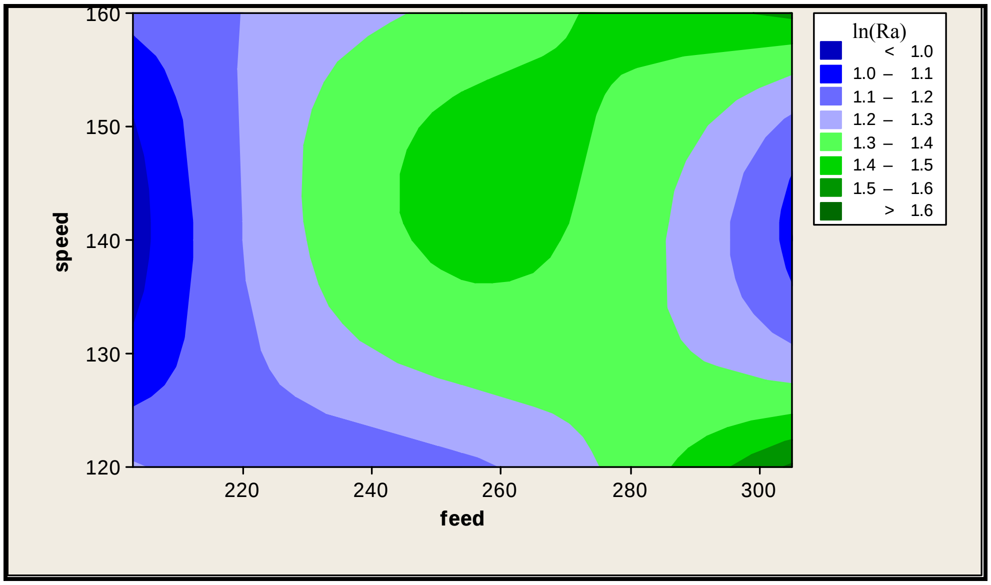

Figure 5: Contour Plot of ln(R_a) vs. Speed and Feed - 75% Phenolic Sample

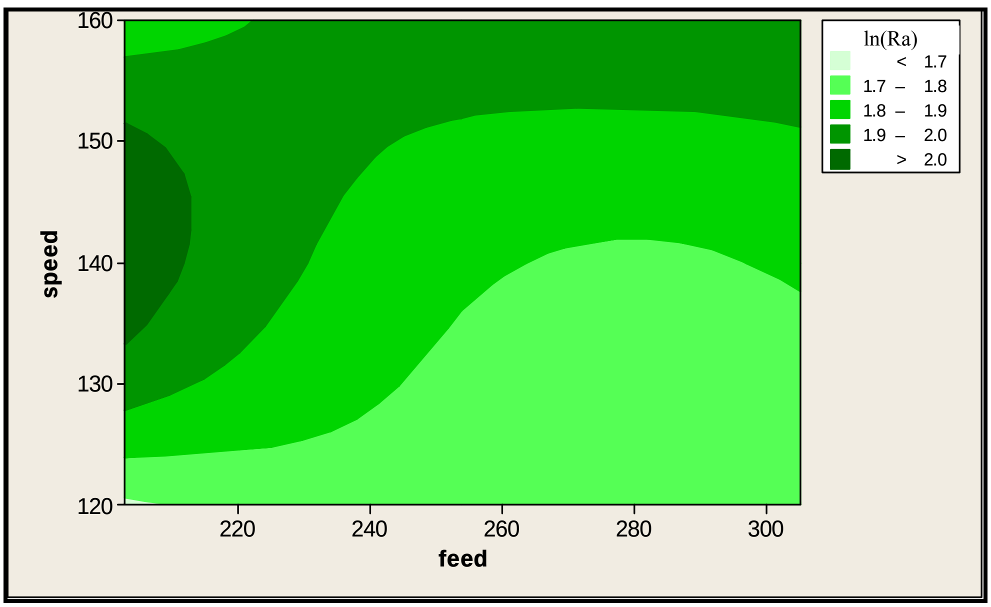

Figure 6: Contour Plot of ln(R_a) vs. Speed and Feed - 50% Phenolic Sample

Conclusions

From these results, the combinations of speed and feed from which the surface roughness value decreases can be observed. The combinations of optimum speed and feed that increases the surface finish for the samples mentioned above are given below:

- Contour and Surface plots of 100% phenolic samples show low surface roughness values at high speeds and low feeds. Therefore the better surface finish can be obtained at high speeds and low feeds. The Taguchi analysis shows that feed has relatively more impact on surface roughness compared to speed. The ANOVA shows that the first order fit is 88.6% accurate, and the second order, 97.5%. The second order model indicates the proportion of the variability in the response explained by the fitted model.

- Contour and surface plots of 75% phenolic samples do not follow any particular trend but in general lower surface roughness values are obtained at high speeds and low feeds. The Taguchi analysis results show that feed has relatively more impact on surface roughness compared to speed. The ANOVA shows that the first order fit is 36.24% accurate, and the second, 55.72%.
- Contour and Surface plots of 50% phenolic samples show low surface roughness values at low speeds and high feeds. The Taguchi analysis results show that speed has relatively more impact on surface roughness compared to feed. The ANOVA shows that the first order fit is 47.87% accurate, and the second order, 58.6%

Although a concerted effort has been made to study the machinability of plastic composites filled with corn ethanol processing coproducts, further research is needed to refine the relationship between surface roughness and cutting speed and feed rate. Additional experiments will be carried out to improve the sensitivity of the results. Additionally, other variables to be considered for future studies include cutting force measurement and the determination of overall machinability indexes.

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