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APPLICATION OF FULL FACTORIAL DESIGN FOR OPTIMIZATION OF PRODUCTION PROCESS BY SOME MATERIALS

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Abstract
Production process of turning machine was investigated. Three level Full Factorial Design has been employed to study the effect of different experimental variables on the production of some materials. Three variables of spindle of speed (200, 220, and 270 rpm), flow rate (0.25, 0.36, and 0.45 mm/rev), and depth of cut (0.3,0.5, and 0.7 mm.) were used to identify the significant effects and interactions in the batch studies. A polynomial regression model has been developed using the experimental data. The results show that production process of turning machine was strongly affected by the variations in spindle of speed, flow rate, and depth of cut. The minimum material removal rate activity was achieved when the production was carried out at 270 rpm of spindle of speed, 0.36 mm/v of flow rate and 0.3 mm. of depth of cut with edge condition of MRR. The predicted value produced 0.0473 grams of MRR is in close agreement with turning machine activity produce from experiment, which is 0.034 grams of MRR.

Keywords: Application, full factorial design, optimization, analysis of variance, material removal rate, turning machine.

INTRODUCTION

Design of Experiments (DOE) was developed in the early 1920s by Sir Ronald Fisher at the Rothamsted agricultural field research station in London, England. His initial experiments were concerned with determining the effect of various fertilizers on different plots of land. The final condition of the crop was not only dependent on the fertilizer but also on a number of other factors (such as underlying soil condition, moisture content of the soil, etc.) of each of the respective plots. Fisher used DOE which could differentiate the effect of fertilizer and the effect of other factors. Since then DOE has been widely accepted and applied in biological and agricultural fields. A number of successful applications of DOE have been reported by many US and European manufacturers over the last fifteen years or so. Design of Experiments refers to the process of planning, designing and analyzing the experiment so that valid and objective conclusions can be drawn effectively and efficiently. In order to draw statistically sound conclusions from the experiment, it is necessary to integrate simple and powerful statistical methods into the experimental design methodology (Jiju Antony., 2003). In this research that an experimenter wishes to study the influence of three variables or factors on the process of turning the machine of faculty of engineering, Rajamangala University of Technology Lanna. Figure 1 shown the research of a turning machine process with possible inputs and outputs

The research has focused a study between the full and fractional factorial design of experiments (DOE) method when they applied on the outputs of a material removal rate process i.e., turning of steel. Note that numerous authors have published studies aimed at evaluating the effects of the cutting parameter variations on the resulted cutting forces. In planning the experimentation, some authors have used full factorial designs; others used fractional ones (Youssef, Y.A., Beauchamp, Y., Thomas, M., 1994), (Tanco, M., Viles, E., Pozueta, L., 2009),(Prvan, T., Street, D.J., 2002).The performance of the turning process depends on many factors such as speed, feed rate, depth of cut, cutting tool, material to be tested. Cutting lubricant and lathe Including the working environment. Under the conditions set to use statistical data analysis tools offer an efficient optimization method of process parameters, one of the first steps in designing. The experiment was a screening design. Use screening design before conducting the optimization and durability tests. Design of experiment is multipurpose tool that can be used in various situations for identification of important input factors (input variable) and how they are related to the outputs (response variable). Therefore, DOE mainly uses "hard tools" as it was reported in (Durakovic, H. Bašić and H. Muhič., 2014).

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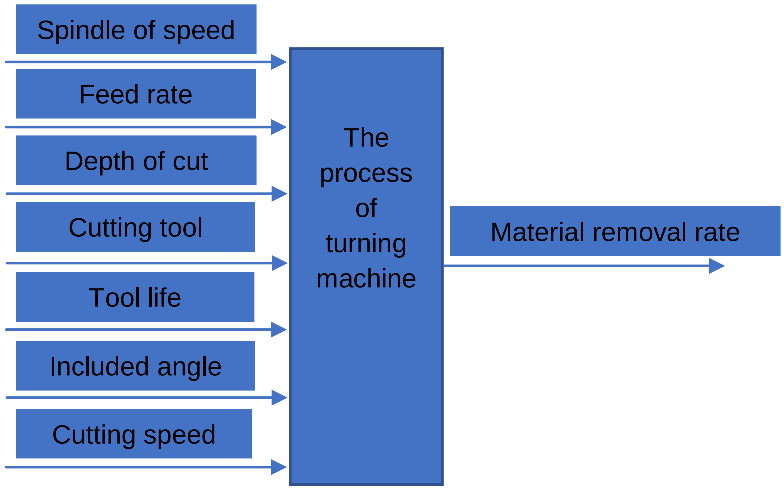

Figure 1 Illustration of a turning machine process

The research has focused a study between the full and fractional factorial design of experiments (DOE) method when they applied on the outputs of a material removal rate process i.e., turning of steel. Note that numerous authors have published studies aimed at evaluating the effects of the cutting parameter variations on the resulted cutting forces. In planning the experimentation, some authors have used full factorial designs; others used fractional ones Youssef (Tanco, M., Viles, E., Pozueta, L., 2009),(Prvan, T., Street, D.J.,2002),(Y.A., Beauchamp, Y., Thomas, M.,1994) the performance of the turning process depends on many factors such as speed, feed rate, depth of cut, cutting tool, material to be tested. Cutting lubricant and lathe Including the working environment. Under the conditions set to use statistical data analysis tools offer an efficient optimization method of process parameters, one of the first steps in designing. The experiment was a screening design. Use screening design before conducting the optimization and durability tests. Design of experiment is multipurpose tool that can be used in various situations for identification of important input factors (input variable) and how they are related to the outputs (response variable). Therefore, DOE mainly uses "hard tools" as it was reported in (Durakovic, H. Bašić and H. Muhič., 2014).

Full Factorial Design

A full factorial design is convenient for a low number of factors if the resources are available. Conceptual approach for DOE is explained for three 33 factors as well as general 3k factorial design, in which k represents number of factors while number 3 represents number of levels. Uppercase letters A, B, C… are usually used for factor designation while lowercase letters are used treatments. Each factor has three levels low (–), medium (0) and high (+). Number of combinations for 33 is twenty and so on. Each combination is called treatment which is represented with a lowercase letter. The number of test units for each treatment is called the number of replicates. This research is the number of replicates is three (Benjamin Durakovic., 2017).

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Full factorial DOE method is selected many times of the experimenters versus the fractional factorial design and vice versa (Chua, M.S., Rahman, M., Wong, Y.S., Loh, H.T.,1993),(Choudhury, I.A., El-Baradie, M.A., 1999),(Özel, T., Hsu, T.K., Zeren, E. ,2005),(Al-Ahmari, A.M.A., 2007),(Davim, J.P., Figueira, L.,2007).

The method of factorial design requires few runs per investigated parameter, allows identifying influential process parameters without time consuming and costly tests. Also regression model presents the nature of interconnection between process variables at high confidence level. The model can be upgraded to form composite designs. The results can be presented as 2- and 3-dimensional charts, thus factorial design has great practical value at early stages of a project (L. Eriksson, E. Johansson, N. Kettaned-Wold, C. Wikstrom, and S. Wold., 2008). Turning machines were modeled by applying full factorial design. As a response variable, cutting tool efficiency was obtained experimentally by a set of shop tests. Screening design is employed for the evaluation of interactions between a response variable and process variables. To determine the influence of turning machine process parameters on material removal rated by factor control from speed, feed rate and depth of cut the research method used is the full factorial method.

Analysis of Variance (ANOVA)

In cases that there are more than two test samples ANOVA is used to determine whether there are statistically significant differences between the means the samples (treatments). In cases that experiment contains two samples only, then t-test is good enough to check whether there are statistically significant differences between the means of treatments. In this case it is tested hypothesis assuming that a least one mean treatment value (μ) differs from the others. Therefore, null and alternative hypotheses can be express as (D. C. Montgomery.,2009).

$$H_0: \mu_1 = \mu_1 = ... = \mu_k = 0$$
$$H_1: \mu_j \neq 0 \text{ for at least one j different than zero.} \quad (1)$$

EXPERIMENTAL DESIGN

The parameters study is performed in a three-level three-parameter design (3^3). In this study spindle of speed, feed rate and depth of cut by experimenting with cast iron was selected as control factors and their levels are shown in Table 1.

Table 1 Parameters designs.

Level	Spindle of speed (*rpm*)	Feed rate (*mm/rev*)	Depth of cut (*mm.*)
1	200	0.25	0.3
2	220	0.36	0.5
3	270	0.45	0.7

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Table 2 Presents all combinations of the parameter design 33: thus twenty experiments and replicates three.

Level	Spindle of speed (*rpm*)	Feed rate (*mm/rev*)	Depth of cut (*mm.*)	y_i
1	2	3	2	-
2	3	3	3	-
3	3	1	1	-
4	3	1	2	-
5	2	1	2	-
6	1	3	2	-
7	3	3	3	-
8	1	1	1	-
9	2	3	2	-
10	2	2	2	-
11	1	3	1	-
12	2	3	1	-
13	2	2	1	-
14	2	1	2	-
15	2	1	3	-
16	1	3	1	-
17	2	2	3	-
18	2	2	1	-
19	2	1	1	-
20	2	2	2	-
21	3	1	2	-
22	3	1	3	-
23	3	2	1	-
24	1	2	2	-
25	2	2	2	-
26	1	1	3	-
27	3	2	1	-
28	3	1	3	-
29	1	2	2	-
30	3	3	2	-
31	2	3	3	-
32	3	2	3	-
33	3	3	1	-
34	3	2	2	-
35	2	1	2	-
36	1	2	3	-
37	2	3	1	-

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38	3	2	1	-
39	1	2	1	-
40	1	2	1	-
41	1	1	3	-
42	2	3	2	-
43	2	2	3	-
44	2	3	3	-
45	1	1	2	-
46	1	2	3	-
47	3	1	3	-
48	2	1	1	-
49	3	1	2	-
50	2	3	1	-
51	1	2	2	-
52	1	3	2	-
53	1	3	3	-
54	3	3	2	-
55	1	2	1	-
56	3	2	3	-
57	3	3	1	-
58	3	1	1	-
59	2	2	1	-
60	1	2	3	-
61	3	2	3	-
62	2	3	3	-
63	3	3	3	-
64	3	2	2	-
65	2	1	1	-
66	3	1	1	-
67	2	1	3	-
68	1	3	3	-
69	3	2	2	-
70	3	3	1	-
71	2	1	3	-
72	1	1	3	-
73	1	3	1	-
74	1	1	1	-
75	3	3	2	-
76	1	1	2	-
77	1	3	2	-
78	2	2	3	-
79	1	1	2	-
80	1	1	1	-
81	1	3	3	-

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The experiment design is called an 81 full factorial design which required eight test runs, each with combinations of the three factors across three levels of each. According to the general statistical approach for experimental design four replicates were obtained to get a reliable and precise estimate of the effects. Therefore, eighty-one observations were taken in all to employ full factorial design as shown in Table 2. Throughout the experiment it was assumed that: the factor is fixed, the design was completely randomized and the usual normality assumptions of the data were satisfied.

The Experimental design

The Experimental Design was based on Minitab Release 19.00 Full Factorial Design was used to obtain the combination of values that can optimize the response within the region of the two-dimensional observation spaces, which allows one to design a minimal number of experimental runs 81. The variables were spindle of speed, feed rate, and depth of cut were submitted for the analysis in the design. The variable of each constituent at levels –1, 0, and +1 is given in Table 3. The selection of low, middle, and high levels for all these variables was based on a prior screening done in our workshop. A 33 full factorial design at the center point, leading the total number of 20 experiments and three replicates. The behavior of the present system described by the following regression as in Equation (1), which includes all interaction terms regardless of their significance:

$$\hat{y}_k = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{21} x_2 x_1 + \beta_{22} x_2 x_2 + \beta_{23} x_2 x_3 \\ \beta_{31} x_3 x_1 + \beta_{32} x_3 x_2 + \beta_{33} x_3 x_3 + \beta_{123} x_1 x_2 x_3 \tag{1}$$

Here y is the response, the □ is the coefficients that have calculated using an appropriate method such as the least square method. The variables x1x2 and x3 are coded as 1,0 and -1, for the high, medium and low levels for their respective factors. The interaction between x1x2 and x3 is denoted as x2x1, x2x3, x3x1, x3x2 and x1x2x3 the other interaction effects are similarly defined.

Using a full factorial design with 81 runs for all three-factors and three- replicates, we can estimate 4 main effects, 25 two-factor interactions, 25 three-factor interactions, degrees of freedom in the 81 run (33) design, 61 are used for estimating three-factor or higher interactions. However, in many experiments, we often find that three-factor and higher order interactions are usually not important (Wu CFJ, Hamada M.,2009). This means that we are using over half of the degrees of freedom to estimate effects that are potentially not significant. Therefore, using a full factorial design to study three-factors and three- replicates in 81 runs is quite wasteful. A more practical and economical approach is to use a fractional factorial design that allows the estimation of lower-order effects.

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These factors were selected based on the information from scientific articles. The levels of independent variables; spindle of speed, feed rate, and depth of cut, were based on the results obtained in previous studies of OFAT (Azoddein, A.A.M., R.M. Yunus, N.M. Sulaiman, A.B. Bustary and K. Sabar., 2015). Each variable or factor was studied at three coded levels; -1 (low-level), level;0 (medium) and +1 (high-level). Tables 1 and 2 show designed factors and levels employed for the experiment and a total of eighty-one runs (33) were conducted in duplicate. The statistical software package of Minitab Release 19.00 was used to design and analyze the experimental data. The statistical significance was checked by the F-test (Onsekizoglu, P., K.S. Bahceci and J. Acar.,2009).

The objective of the experiment was to create a statistical model to predict the material output removal rate and the successful optimization using a 2k factorial design. The three factors and the three levels selected for the experiment were variables. Control, which plays an important role in the characterization of the process. These design factors have a period in which they organize, degree of freedom is an important figure for results analysis and in statistical analysis, Degree of freedom (DOF) is an indicator of the amount of information contained in a dataset. The number of degrees of freedom for any interaction is always equal to the product of the number of degrees of freedom of the main effect associated with the interaction. The resolution of the experimental data was set to 3 factors and there was a higher interaction between the variables. The cubic interactions between variables have been defined as the initial model for process factors. The accuracy of the model was verified by analyzing the values in the ANOVA table. Prediction limits were set to 95.0%. The Minitab Release 19.00 interactive statistical data analysis tool was used to create models for factoring designs.

IMPLEMENTATION AND RESULTS

A. DOE and full factorial design. The DOE simulation was accomplished with two parameters: spindle of speed (SS), flow rate (FR) and depth of cut (DC) respectively. It was performed according (see Table 3 and 4), and production process by turning machine in Fig 2. A model fitting was accomplished for the first 81-full factorial design in Table 3. The independent (SS, FR with DC) and the dependent variables were fitted to the second-order model equation and examined in terms of the goodness of fit. The analysis of variance (ANOVA) was used to evaluate the adequacy of the fitted model. The R-square value (determination coefficient) provided a measure of how much of the variability in the observed response values could be explained by the experiment factors and their interactions. DOE order defines the sequence that variables should be introduced in response surface analysis. See Table 3 shows the results according to simulated analysis performed in MINITAB Release 15.00 used for simultaneous optimization of the multiple responses. The desired goals for each variable and response were chosen. All the independent variables were kept within range while the responses were either maximized. The significant terms in different models were found by analysis of variance (ANOVA) for each response. Significance was judged by determining the probability level that the F-statistic calculated from the data is less than 5%. The model adequacies were checked by R2, adjusted-R2 (adj-R2). The coefficient

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of determination, R2, is defined as the ratio of the explained variation to the total variation according to its magnitude. It is also the proportion of the variation in the response variable attributed to the model and was suggested that for a good fitting model, R2 should not be more than 100 %. A good model should have a large R2, adj-R2. Response surface plots were generated with MINITAB Release 19.00 according (S. Phanphet, N. Sukprasert, A. Wangmai, S. Bangphan, and P. Bangphan.,2018). Regression equation equations were obtained from design of experiments. Using all values (tests 1 to 81) to the system analysis, the following polynomial equations were generated according (S. Phanphet, N. Sukprasert, A. Wangmai, S. Bangphan, and P. Bangphan.,2018).

The estimated regression coefficients for percentage of MRR using data in uncoded units:

MRR = 0.512580 + 0.534086 SS_200 – 0.088432 SS_220 – 0.445654 SS_270 – 0.028284 FR_0.25

+ 0.018160 FR_0.36 + 0.010123 FR_0.45 – 0.074358 DC_0.3 – 0.025025 DC_0.5

+ 0.099383 DC_0.7 + 0.033728 SS*FR_200 0.25 – 0.045605 SS*FR_200 0.36

+ 0.011877 SS*FR_200 0.45 – 0.069864 SS*FR_220 0.25 + 0.074358 SS*FR_220 0.36

- 0.004494 SS*FR_220 0.45 + 0.036136 SS*FR_270 0.25 – 0.028753 SS*FR_270 0.36

- 0.007383 SS*FR_270 0.45 + 0.073247 SS*DC_200 0.3 + 0.044691 SS*DC_200 0.5

- 0.117938 SS*DC_200 0.7 – 0.128457 SS*DC_220 0.3 – 0.065679 SS*DC_220 0.5

+ 0.194136 SS*DC_220 0.7 + 0.055210 SS*DC_270 0.3 + 0.020988 SS*DC_270 0.5

- 0.076198 SS*DC_270 0.7 + 0.008062 FR*DC_0.25 0.3 – 0.004049 FR*DC_0.25 0.5

- 0.004012 FR*DC_0.25 0.7 + 0.028395 FR*DC_0.36 0.3 – 0.011494 FR*DC_0.36 0.5

- 0.016901 FR*DC_0.36 0.7 – 0.036457 FR*DC_0.45 0.3 + 0.015543 FR*DC_0.45 0.5

+ 0.020914 FR*DC_0.45 0.7 – 0.00506 SS*FR*DC_200 0.25 0.3 – 0.00073 SS*FR*DC_200 0.25

0.5 + 0.00579 SS*FR*DC_200 0.25 0.7 – 0.04084 SS*FR*DC_200 0.36 0.3

- 0.01040 SS*FR*DC_200 0.36 0.5 + 0.05123 SS*FR*DC_200 0.36 0.7 + 0.04590 SS*FR*DC_200

0.45 0.3 + 0.01112 SS*FR*DC_200 0.45 0.5 – 0.05702 SS*FR*DC_200 0.45 0.7

+ 0.00309 SS*FR*DC_220 0.25 0.3 – 0.00558 SS*FR*DC_220 0.25 0.5 + 0.00249 SS*FR*DC_220

0.25 0.7 + 0.07142 SS*FR*DC_220 0.36 0.3 + 0.00386 SS*FR*DC_220 0.36 0.5

- 0.07528 SS*FR*DC_220 0.36 0.7 – 0.07451 SS*FR*DC_220 0.45 0.3 + 0.00172 SS*FR*DC_220

0.45 0.5 + 0.07279 SS*FR*DC_220 0.45 0.7 + 0.00198 SS*FR*DC_270 0.25 0.3

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+ 0.00631 SS*FR*DC_270 0.25 0.5 – 0.00828 SS*FR*DC_270 0.25 0.7 – 0.03058 SS*FR*DC_270

0.36 0.3 + 0.00653 SS*FR*DC_270 0.36 0.5 + 0.02405 SS*FR*DC_270 0.36 0.7

+ 0.02860 SS*FR*DC_270 0.45 0.3 – 0.01284 SS*FR*DC_270 0.45 0.5 – 0.01577 SS*FR*DC_270

0.45 0.7

(2)

Table 3 Experiment design (uncoded units).

StdOrder	RunOrder	PtType	Blocks	SS	FR	DC	MRR
44	1	1	1	220	0.45	0.5	0.354
54	2	1	1	270	0.45	0.7	0.098
19	3	1	1	270	0.25	0.3	0.065
20	4	1	1	270	0.25	0.5	0.071
11	5	1	1	220	0.25	0.5	0.224
8	6	1	1	200	0.45	0.5	1.118
81	7	1	1	270	0.45	0.7	0.099
55	8	1	1	200	0.25	0.3	1.056
17	9	1	1	220	0.45	0.5	0.356
41	10	1	1	220	0.36	0.5	0.419
61	11	1	1	200	0.45	0.3	1.079
70	12	1	1	220	0.45	0.3	0.118
40	13	1	1	220	0.36	0.3	0.412
65	14	1	1	220	0.25	0.5	0.228
12	15	1	1	220	0.25	0.7	0.616
34	16	1	1	200	0.45	0.3	1.077
15	17	1	1	220	0.36	0.7	0.719
13	18	1	1	220	0.36	0.3	0.414
10	19	1	1	220	0.25	0.3	0.132
68	20	1	1	220	0.36	0.5	0.416
74	21	1	1	270	0.25	0.5	0.074
21	22	1	1	270	0.25	0.7	0.084
49	23	1	1	270	0.36	0.3	0.034
59	24	1	1	200	0.36	0.5	1.018
14	25	1	1	220	0.36	0.5	0.420
57	26	1	1	200	0.25	0.7	1.038
22	27	1	1	270	0.36	0.3	0.036
48	28	1	1	270	0.25	0.7	0.086
5	29	1	1	200	0.36	0.5	1.019

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Table 3 (Cont.) Experiment design (uncoded units).

StdOrder	RunOrder	PtType	Blocks	SS	FR	DC	MRR
80	30	1	1	270	0.45	0.5	0.068
72	31	1	1	220	0.45	0.7	0.813
78	32	1	1	270	0.36	0.7	0.085
79	33	1	1	270	0.45	0.3	0.042
50	34	1	1	270	0.36	0.5	0.048
38	35	1	1	220	0.25	0.5	0.225
33	36	1	1	200	0.36	0.7	1.038
43	37	1	1	220	0.45	0.3	0.115
76	38	1	1	270	0.36	0.3	0.035
31	39	1	1	200	0.36	0.3	1.008
4	40	1	1	200	0.36	0.3	1.007
30	41	1	1	200	0.25	0.7	1.035
71	42	1	1	220	0.45	0.5	0.359
42	43	1	1	220	0.36	0.7	0.717
18	44	1	1	220	0.45	0.7	0.818
29	45	1	1	200	0.25	0.5	1.066
60	46	1	1	200	0.36	0.7	1.034
75	47	1	1	270	0.25	0.7	0.087
64	48	1	1	220	0.25	0.3	0.133
47	49	1	1	270	0.25	0.5	0.074
16	50	1	1	220	0.45	0.3	0.115
32	51	1	1	200	0.36	0.5	1.014
62	52	1	1	200	0.45	0.5	1.112
9	53	1	1	200	0.45	0.7	1.011
26	54	1	1	270	0.45	0.5	0.054
58	55	1	1	200	0.36	0.3	1.002
24	56	1	1	270	0.36	0.7	0.088
25	57	1	1	270	0.45	0.3	0.043
46	58	1	1	270	0.25	0.3	0.066
67	59	1	1	220	0.36	0.3	0.415
6	60	1	1	200	0.36	0.7	1.033
51	61	1	1	270	0.36	0.7	0.087
45	62	1	1	220	0.45	0.7	0.820
27	63	1	1	270	0.45	0.7	0.097
23	64	1	1	270	0.36	0.5	0.049
37	65	1	1	220	0.25	0.3	0.138

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Table 3 (Cont.) Experiment design (uncoded units).

StdOrder	RunOrder	PtType	Blocks	SS	FR	DC	MRR
73	66	1	1	270	0.25	0.3	0.066
39	67	1	1	220	0.25	0.7	0.620
63	68	1	1	200	0.45	0.7	1.014
77	69	1	1	270	0.36	0.5	0.045
52	70	1	1	270	0.45	0.3	0.043
66	71	1	1	220	0.25	0.7	0.618
3	72	1	1	200	0.25	0.7	1.033
7	73	1	1	200	0.45	0.3	1.075
28	74	1	1	200	0.25	0.3	1.051
53	75	1	1	270	0.45	0.5	0.083
56	76	1	1	200	0.25	0.5	1.067
35	77	1	1	200	0.45	0.5	1.115
35	77	1	1	200	0.45	0.5	1.115
69	78	1	1	220	0.36	0.7	0.718
2	79	1	1	200	0.25	0.5	1.068
1	80	1	1	200	0.25	0.3	1.055
36	81	1	1	200	0.45	0.7	1.017

Regression Equation (2) is generate the graphic shown in Figure 3 shows optimal solutions considering optimization of production process by turning machine. Main solutions are positioned at spindle of speed, flow rate and depth of cut, and there is a range between 200,220 and 270 rpm, 0.25,0.36 and 0.45 mm/rev, and 0.3,0.5 and 0.7 mm. respectively. Where it is allowable to use other distances (see Table 1. parameters design). Result of the analysis of variance is given in Table 4 and estimated regressions of coefficient shown in Table 5.

Table 4 Analysis of variance.

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	26	14.8204	0.57001	46033.03	0.000
Linear	6	13.7414	2.29023	184954.08	0.000
SS	2	13.2753	6.63763	536039.93	0.000
FR	2	0.0333	0.01664	1343.46	0.000
DC	2	0.4329	0.21644	17478.86	0.000
2-Way Interactions	12	0.9754	0.08128	6564.12	0.000
SS*FR	4	0.1438	0.03595	2902.89	0.000
SS*DC	4	0.8016	0.20041	16184.48	0.000
FR*DC	4	0.0300	0.00749	605.00	0.000
3-Way Interactions	8	0.1036	0.01295	1045.59	0.000
SS*FR*DC	8	0.1036	0.01295	1045.59	0.000
Error	54	0.0007	0.00001		
Total	80	14.8210			

Table 5 Estimated regression of coefficients for MRR.

Term	Coef	SE Coef	T-Value	P-Value	VIF
Constant	0.512580	0.000391	1310.98	0.000	
SS					
200	0.534086	0.000553	965.90	0.000	1.33
220	-0.088432	0.000553	-159.93	0.000	1.33
FR					
0.25	-0.028284	0.000553	-51.15	0.000	1.33
0.36	0.018160	0.000553	32.84	0.000	1.33
DC					
0.3	-0.074358	0.000553	-134.48	0.000	1.33
0.5	-0.025025	0.000553	-45.26	0.000	1.33
SS*FR					
200 0.25	0.033728	0.000782	43.13	0.000	1.78
200 0.36	-0.045605	0.000782	-58.32	0.000	1.78
220 0.25	-0.069864	0.000782	-89.34	0.000	1.78
220 0.36	0.074358	0.000782	95.09	0.000	1.78
SS*DC					
200 0.3	0.073247	0.000782	93.67	0.000	1.78

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200 0.5	0.044691	0.000782	57.15	0.000	1.78
220 0.3	-0.128457	0.000782	-164.27	0.000	1.78
220 0.5	-0.065679	0.000782	-83.99	0.000	1.78
FR*DC					
0.25 0.3	0.008062	0.000782	10.31	0.000	1.78
0.25 0.5	-0.004049	0.000782	-5.18	0.000	1.78
0.36 0.3	0.028395	0.000782	36.31	0.000	1.78
0.36 0.5	-0.011494	0.000782	-14.70	0.000	1.78
SS*FR*DC					
200 0.25 0.3-0.00506		0.00111	-4.58	0.000	2.37
200 0.25 0.5-0.00073		0.00111	-0.66	0.513	2.37
200 0.36 0.3-0.04084		0.00111	-36.93	0.000	2.37
200 0.36 0.5-0.01040		0.00111	-9.40	0.000	2.37
220 0.25 0.30.00309		0.00111	2.79	0.007	2.37
220 0.25 0.5-0.00558		0.00111	-5.05	0.000	2.37
220 0.36 0.30.07142		0.00111	64.58	0.000	2.37
220 0.36 0.50.00386		0.00111	3.49	0.001	2.37
Model Summary					
S	R-sq	R-sq(adj)	R-sq(pred)		
0.0035189	100.00%	99.99%	99.99%		

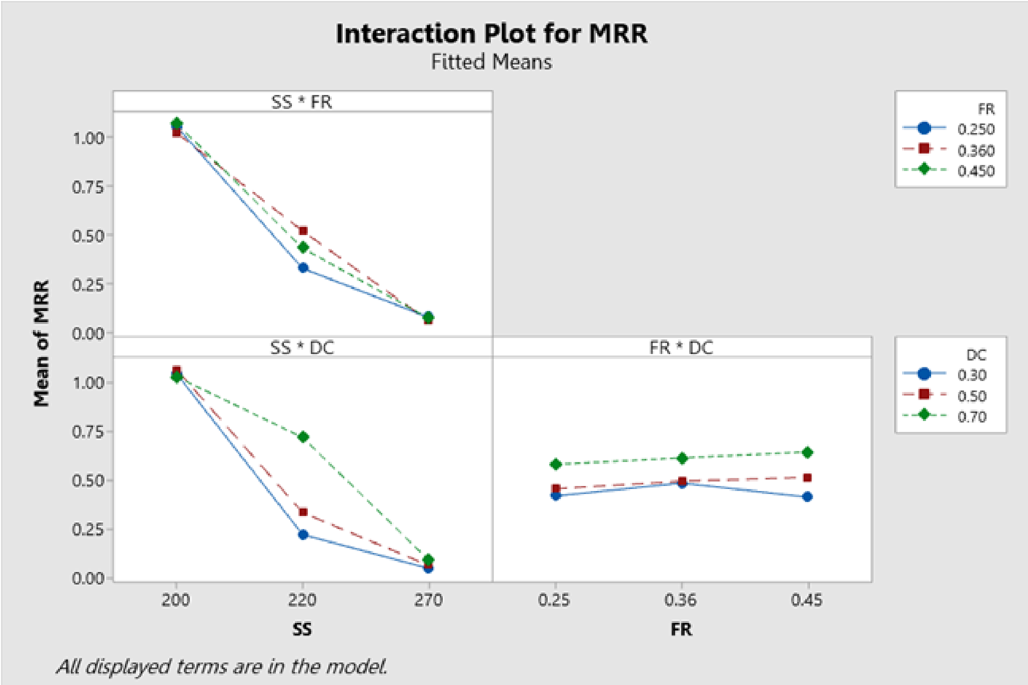

Figure 2 Interaction plot for MRR

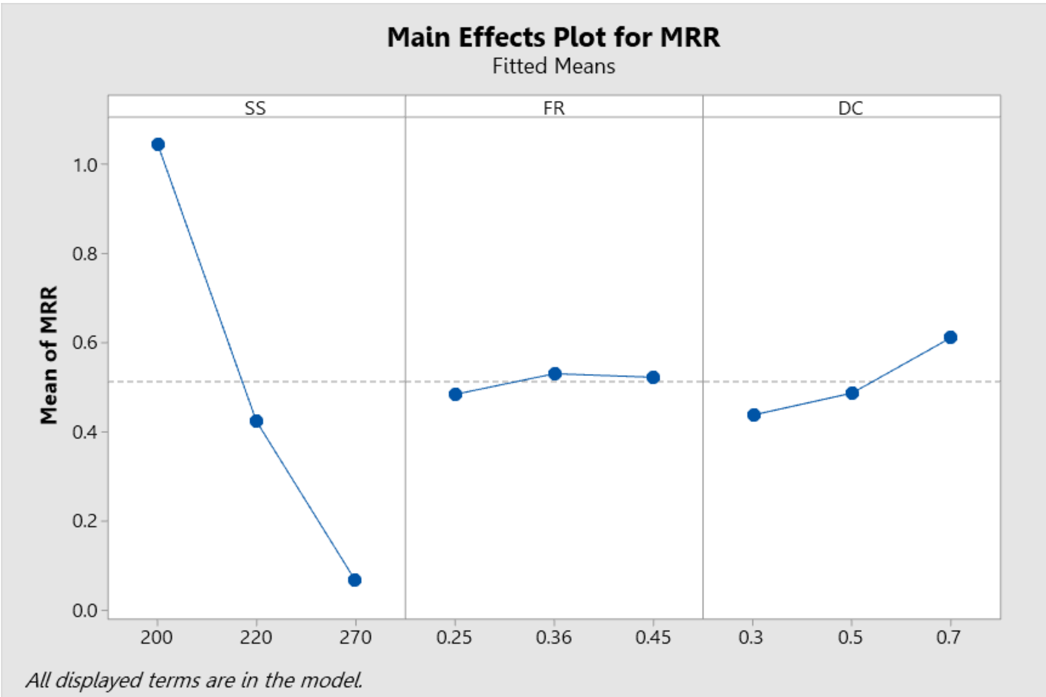

Figure 3 Main effects plot for MRR

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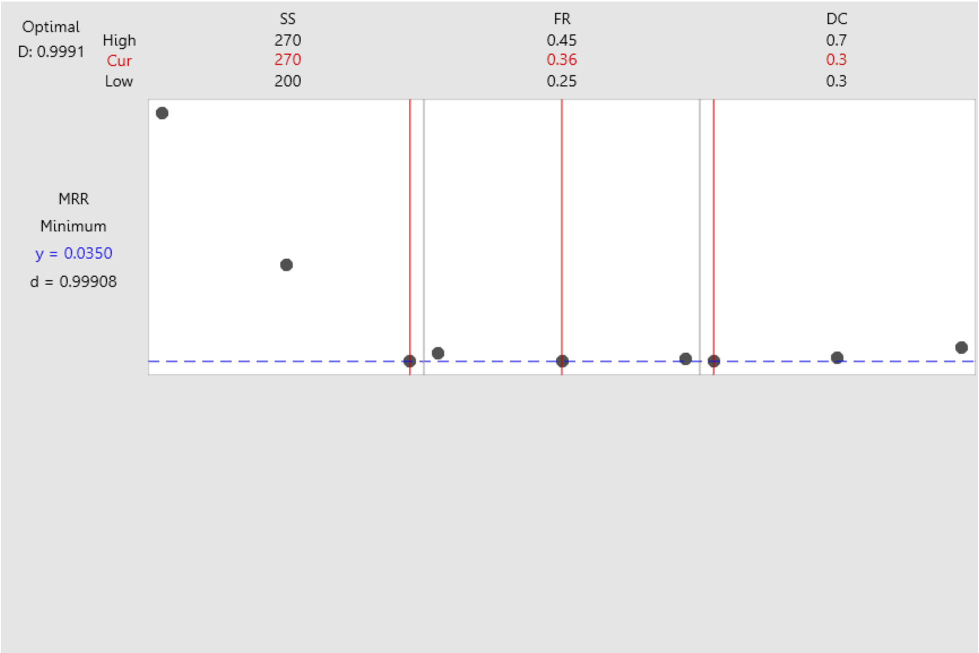

Figure 4 Response optimization for MRR

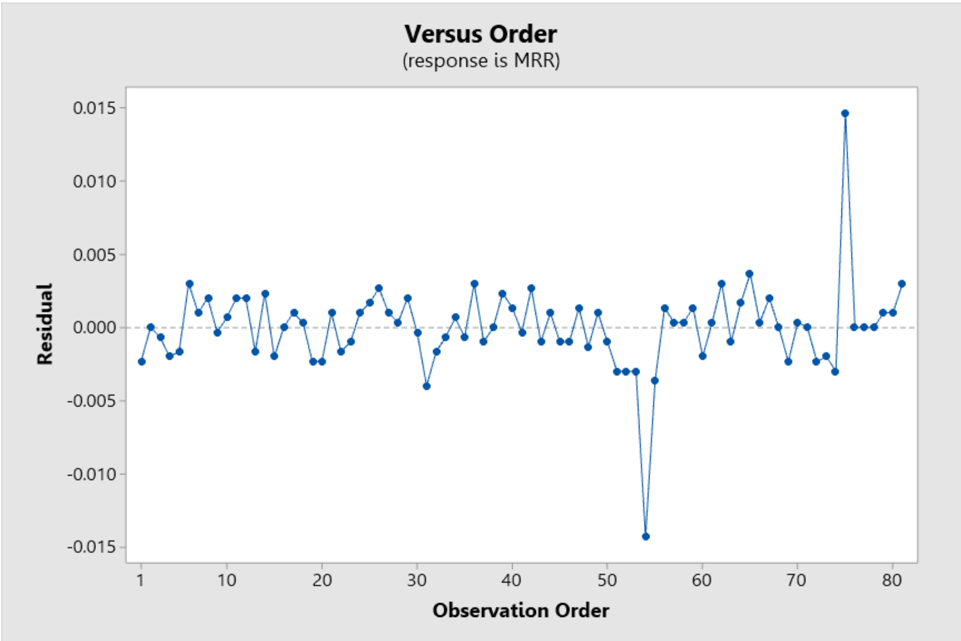

Figure 5 Residual versus observation order

There is no significant evidence of model at a = 0.00. Therefore, this study can conclude that the true response surface is explained by the linear model. To study the effects of three factors, total runs = 81 runs are required. Due to space limitations, the treatments, factor values,and the corresponding responses are not shown. Analysis of variance method (ANOVA) is used to find factors with significant effects. Effects x1, x2, x3, x1x2, x1x3, x2x3, and x1x2x3 respectively. Degree of freedom (DF) are found to be significant, that is the most significant effect, has significant interactions with all other factors.
Alternatively, these results can be obtained visually from the mean versus fits probability plot of interaction shown in Figure 2, main effects shown in Figure 3, response optimization shown in Figure 4, and residual versus observation order plot the range of the residuals looks essentially constant across the levelsof the predictor variable, spindle of speed, flow rate and depth of cut. The scatter in the residuals at SS, FR, and DC and 3 type and 200, 220 and 270 rpm and 0.2, 0.36, and 0.45 mm/rev, and 0.3,0.5 and 0.7 mm. respectively.
That the standard deviation of the random errors is the same for the responses observed at each spindle of speed, flow rate, and depth of cut respectively according (S. Phanphet, N. Sukprasert, A. Wangmai, S. Bangphan, and P. Bangphan.,2018). Result of estimated regression coefficients for the response (material removal rate) function as surface weight of workpieces is presented shown in Table 5. This analysis is carried out for a significance level of 5%, i.e., for a confidence level of 95%.
The model adequacies were checked by adjusted-R2 (adj-R2) of 99.99% according (S. Phanphet, N. Sukprasert, A. Wangmai, S. Bangphan, and P. Bangphan.,2018). The check of the normality assumptions of the data is then conducted, it can be seen in Figure 3 that all the points on the main effect plot come close to forming a straight line. This implies that the data are fairly normal and there is no deviation from the normality. The response taken from Table revealed that the square coefficients of SS (x1), FL(x2) and DC(x3), have a remarkable effect on the material removal rate yield. Moreover, all the linear and interaction terms of three factor and three level presented in significant effects on the material removal rate at 5% probability level according (S. Phanphet, N. Sukprasert, A. Wangmai, S. Bangphan, and P. Bangphan.,2018).

Conclusion

The results of this study have clearly indicated full factorial design is an effective method for optimization of material removal rate. Response surface methodology was successfully applied to optimize spindle of speed, flow rate and depth of cut on turning machine that was not a carbide tool. When productions into the formulation, the optimized levels of R-Squire (adjust) was 99.99 % and standard deviation was 0.0035189 yielded lowest material removal rate. The predicted value produced 0.0473 grams of MRR is in close agreement with turning machine activity produce from experiment, which is 0.034 grams of MRR and the confidence interval between 0.0432-0.0514 grams. This study clearly showed that full factorial design was one of the suitable methods to optimize the best operating conditions to maximize the lath removing. Graphical response surface and contour plot were used to locate the optimum point. The statistical fitted models and the contour plot of responses can be used to predict values of responses at any point inside the experimental space and can be successfully used to optimize the production process by turning machine. Applying the principles of design of experiments using full factorials can build confidence in the practice and can be further expanded.

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