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Nguyen Thuy Duong
Hanoi University of Science and Technology, School of Mechanical Engineering, Hanoi, Vietnam

Hoang Tien Dung
Hanoi University of Industry, Faculty of Mechanical Engineering, Hanoi, Vietnam

Nguyen Van Canh
Hanoi University of Industry, Faculty of Mechanical Engineering, Hanoi, Vietnam

Dao Ngoc Hoanh
Hanoi University of Industry, Faculty of Mechanical Engineering, Hanoi, Vietnam

Do Minh Hien
Hanoi University of Industry, Faculty of Mechanical Engineering, Hanoi, Vietnam

Van Thien Nguyen
Hanoi University of Industry, Faculty of Mechanical Engineering, Hanoi, Vietnam

Key words: *grinding, minimum quantity lubricant, optimization, regression optimizer, multi-response optimization*
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PREDICTIONANDOPTIMIZATIONOFSURFACEROUGHNESS IN GRINDING OF S50C CARBON STEEL USING MINIMUM QUANTITY LUBRICATION OF VIETNAMESE PEANUT OIL

Nguyen Thuy Duong[1], Hoang Tien Dung[2], Nguyen Van Canh[2], Dao Ngoc Hoanh[2], Do Minh Hien[2], Van Thien Nguyen[2]*

[1]Hanoi University of Science and Technology, School of Mechanical Engineering, Hanoi, Vietnam
[2]Hanoi University of Industry, Faculty of Mechanical Engineering, Hanoi, Vietnam

This experimental research aimed to build the regression model of grinding S50C carbon steel based on a Regression Optimizer. The workpiece specimens were JIS S50C carbon steel that was hardened at 52HRC. Taguchi L27 orthogonal array was performed with 5 3-levels-factors. The studied factors were combining cutting parameters, such as cutting speed, feed rate, depth of cut, and lubricant parameters, including air coolant flow rate Q and air pressure P. The results show that cutting parameters includes workpiece velocity V_w, feed rate f, and depth of cut ap, influence the most on surface roughness R_a, Root Mean Square Roughness R_q, and Mean Roughness Depth R_z,. By contrast, the influence of lubrication parameters is fuzzy. Therefore, this present work focused on predicting and optimizing Ra, R_z, R_q in surface grinding of JSI S50C carbon steel using MQL of peanut oil. In this work, combining of grinding parameters and lubrication parameters were considered as input factors. The regression models of R_a, R_z, and R_q were obtained using Minitab 19 by Regression Optimizer tool, and then the multi-objective optimization problem was solved. The present findings have shown that Vietnamese vegetable peanut oil could be considered as the lubricant in the grinding process. The optimum grinding and lubricant parameters as following: the workpiece velocity Vw of 5 m/min, feed rate f of 3mm/stroke, depth of cut of 0.005mm and oil flow rate, air pressure of 91.94 ml/h, 1 MPa, respectively. Corresponding to the surface roughness R_a, Root Mean Square Roughness R_q, and Mean Roughness Depth R_z of 0.6512μm, 4.592μm, 0.8570μm, respectively.

Key words: grinding, minimum quantity lubricant, optimization, regression optimizer, multi-response optimization

INTRODUCTION

JIS S50C carbon steel is popular in the manufacturing industry due to its suitable characteristics. The S50C steel could be manufactured under metal forming processes such as hot forging, cold forging…or under metal cutting processes like grinding, turning, milling… the essential criteria that have to consider in the cutting of S50C is surface roughness. In traditional machining processes, metal cutting fluid (WMF) is often used to reduce the cutting zone's temperature, tool wear…and improve surface quality by reducing the friction between the cutting tool and workpiece [1]. Due to the increase of competition in the global market and forward to sustainable manufacturing, reducing cutting fluid was new wattage that was considered research. Many published research studies have shown that MQL is applied in grinding carbon steel and improves the surface quality contemporaneously [1]–[4]. Akash Subhash Awale et al. [5] carried out a multi-objective optimization in the grinding process assisted minimum quantity lubricant. The author claimed that controlling the cutting parameters and using optimal lubricant settings improves surface quality and reduces the tool wear.

In the recent few decades, many different optimization methods were presented to optimize surface roughness in the machining process, including milling, turning, grinding. However, the manufacturers have to consider improving the product's quality while reducing the cost due to the highly competitive market. Hence, multiple objective optimizations were more popular recently. Many researchers performed Taguchi and Taguchi-based optimization techniques because of their advantages [6]–[8], minimizing the number of experiments. Hung-Chang Liao et al. [6] successfully applied the DEAR-based Taguchi method in multiple optimization issues and compared it to the PCA method. The work-study has shown that Taguchi and other Taguchi based techniques are a powerful tool to solve multi-criteria optimization, where the DEAR approach performed better than Taguchi and PCA techniques. Mia et al. [7] carried out research applying Taguchi S/N (signal/Noise) ratio in multiple optimizations in the hard assisted MQL turning of AISI 1060 steel process, concentrate on increasing material removal rate and minimizing surface roughness and tool wear at the same time. The research's results revealed that selecting a grinding parameter set: Vc of 90m/min, feed rate f of 0.2mm/rev, and ap at 1.5mm provides the best quality surface and maximum production rate. Many other study results have shown that Taguchi based techniques are robust and easy to use to solve multi-objective optimization. But the disadvantage of these methods can be used to rank and find the best alternative instead of predicting the exact parameter set. Due to the lack of these methods, some new techniques, formulas…were announced

*nguyenvancanh@haui.edu.vn

to solve multiple criteria problems, such as coupling method of response surface (CMRS) [9], Artificial Neural Network (ANN) [10]–[13]… or computer software to build the regression model then predict the parameter sets corresponding to the optimum desired manufacturing responses. In this present work, computing software namely regression optimizer was selected to build the regression models then solve the multi-objective optimization problems. The Vietnamese peanut oil was used as the MQL lubricant.

RESEARCH METHODOLOGY

Experimental material

Experimental workpiece is S50C carbon steel with 52 HRC hardness after heat treatment. The chemical composition of S50C steel is present in Table 1.

Table 1: S50C steel Chemical Composition

C(%)	Si(%)	Mn(%)	P(%)	S(%)	Cr(%)	Ni(%)	Cu(%)
			max	max	max	max	max
0.47-0.55	0.17-0.37	0.50-0.80	0.035	0.035	0.25	0.25	0.25

The experimental machine and measurement equipment

The machine grinding APSG-820/2A was used for this experiment procedure. The surface roughness Ra, Root Mean Square Roughness R_q and Mean Roughness Depth R_z were measured by Surftest JS-201 of Mitutoyo (Japan).

Figure 1: Experimental grinding machine

Figure 2: Mitutoyo Surftest JS-210

Each experimental was measured 3 times at 3 separate positions, the measured results were filled in Table 3.

MQL lubrication

Vegetable peanut oil was used for MQL Lubrication in this experimental procedure according to the results of previous publication.

The experimental design

In this study work, Taguchi Orthogonal Array was applied to design the experimental matrix. The five three-level input factors and their values werelisted in Table 2.

According to the number of input factors and the level of each factor, the Taguchi's orthogonal array L27(313) was used. The experimental matrix designed by Minitab 19, and has shown as Table 2.

The grinding parameters were selected according to the specification of grinding machine, where the level 1 and level 3 are the lower and upper limitation of parameter, respectively. And, level 2 are the average value of level 1 and level 3 values.

R_a is surface roughness; the values were determined by the formula (1), according to EN ISO 4287:1997 [14]

$$R_a=\frac{1}{l}\int_0^l |Z(x)|dx \quad (1)$$

Where: Z(x) is the arithmetic mean of the absolute ordinate within the sampling length.

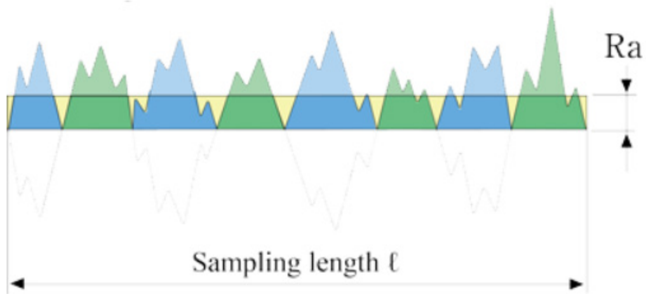

Figure 3: Surface Roughness Ra and RMS Roughness Rq [14]

Rz is Mean Roughness Depth. The values were calculated as [14]:

$$R_z=R_p+R_v \quad (2)$$

Rq is Root Mean Square (RMS) Roughness. The RMS Values were determined as [14]:

$$R_q=\sqrt{\frac{1}{l}\int_0^l Z^2(x)dx} \quad (3)$$

Table 2: MQL parameters, Grinding parameters and their level

Parameters	Symbol	Dimension	Level 1	Level 2	Level 3
Flow rate	Q	ml/h	50	100	150
Air pressure	P	MPa	2	4	6
Workpiece Velocity	Vw	m/min	5	10	15
Feed rate	f	m/stroke	3	5	7
Depth of cut	ap	mm	0.005	0.010	0.015

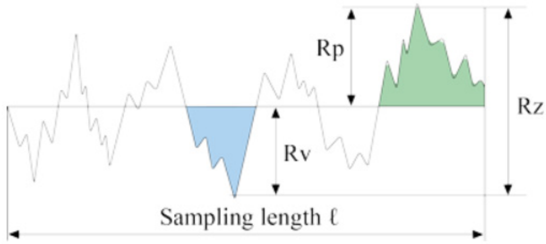

Figure 4: Ten point height of irregularities, Rz [14]

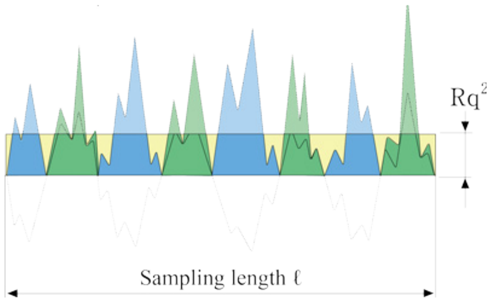

Figure 5: Root mean square roughness [14]

Experimental procedure

Each workpiece specimen was grinded following by the run of experimental matrix. The surface roughness were measured by JS-210 surftest and the results were listed in Table 3.

RESULTS AND DISCUSSION

Taguchi Analysis

Influence of input factors on surface roughness R_a

Table 4: Response table for signal to noise ratios for R_a

Level	Q	P	V_w	F	t
1	0.25905	0.59043	0.52979	1.98365	0.97511
2	0.15145	0.02601	0.28287	-0.22556	0.09922
3	0.12136	-0.08457	-0.28079	-1.22622	-0.54246
Delta	0.13769	0.67500	0.81058	3.20987	1.51757
Rank	5	4	3	1	2

Table 3: Experimental and prediction results

			Experimental Results			Prediction Results			
Runs	V_w	f	a_p	R_q	R_z	R_a	R_q	R_z	R_a
1	5	3	0.005	0.857	4.555	0.502	0.79092	4.56008	0.61358
2	5	3	0.010	0.890	5.672	0.540	0.94996	5.30668	0.7008
3	5	3	0.015	0.988	5.266	0.864	1.08595	5.9605	0.78803
4	10	5	0.005	1.331	6.341	0.939	1.18578	6.30386	0.89735
5	10	5	0.010	1.323	6.767	1.020	1.29728	6.86332	0.98458
6	10	5	0.015	1.368	7.144	1.215	1.39993	7.3805	1.07181
7	15	7	0.005	1.559	7.543	1.036	1.47871	7.66048	1.18113
8	15	7	0.010	1.644	8.460	1.343	1.56954	8.12709	1.26836
9	15	7	0.015	1.684	8.342	1.231	1.65539	8.56832	1.35558
10	10	7	0.005	1.425	7.094	0.929	1.37392	7.31399	1.05746
11	10	7	0.010	1.366	8.085	1.136	1.47123	7.80135	1.14469
12	10	7	0.015	1.454	7.837	1.220	1.56249	8.26	1.23191
13	15	3	0.005	1.266	5.399	0.928	0.9308	5.17306	0.73713
14	15	3	0.010	1.325	5.733	0.888	1.06923	5.84184	0.82435
15	15	3	0.015	1.245	6.634	0.814	1.19169	6.44156	0.91158
16	5	5	0.005	1.195	6.324	0.943	1.16348	6.35368	0.89274
17	5	5	0.010	1.286	7.214	0.938	1.27693	6.90912	0.97997
18	5	5	0.015	1.278	7.770	1.395	1.38109	7.42311	1.06719
19	15	5	0.005	1.252	6.030	0.985	1.16101	6.36525	0.89724
20	15	5	0.010	1.295	7.103	1.083	1.27468	6.91975	0.98446
21	15	5	0.015	1.337	7.263	1.049	1.37902	7.43301	1.07169
22	5	7	0.005	1.348	7.509	1.071	1.35471	7.35698	1.05285
23	5	7	0.010	1.398	7.807	1.095	1.45331	7.84167	1.14007
24	5	7	0.015	1.362	8.512	1.239	1.54563	8.29809	1.2273
25	10	3	0.005	1.125	5.434	0.791	0.90221	5.23366	0.73251
26	10	3	0.010	1.139	5.335	0.683	1.04444	5.89558	0.81974
27	10	3	0.015	1.149	6.153	0.665	1.1695	6.49033	0.90697

Table 5: Response table for means for Ra

Level	Q	P	V_w	F	t
1	0.9999	0.9544	0.9630	0.8005	0.9058
2	0.9924	1.0053	0.9787	1.0297	1.0040
3	0.9967	1.0293	1.0473	1.1588	1.0792
Delta	0.0075	0.0749	0.0843	0.3583	0.1733
Rank	5	4	3	1	2

Figure 6: Main effects plot for means of R_a

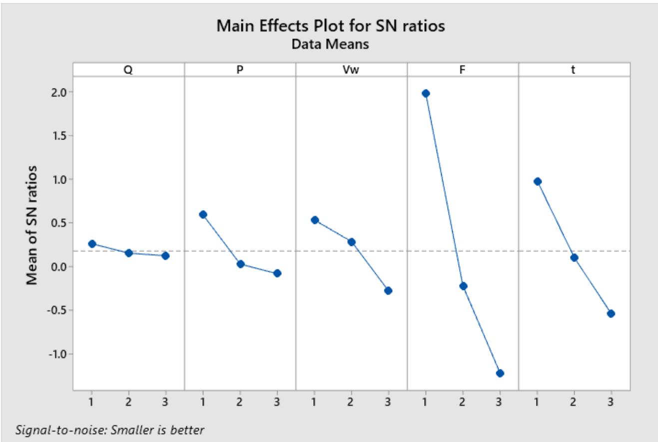

Figure 7: Main effects plot for SN ratios of R_a

The data in table 4, table 5 depict the influence of cutting and lubrication parameters on the surface roughness R_a. The cutting parameters, namely V_w, F, and t affect surface roughness R_a significantly. The influence of F is the most, followed by a_p and V_w. The lubricant parameters include P and Q influence on surface roughness insignificantly. When figures 6,7 present the interaction between cutting parameters with surface roughness value. The value of feed rate f rising from level 1 to level 3, the surface roughness increases quickly from 0.8µm to around 1.15µm, an increase of 50%. Similarly, the surface roughness rising significantly from 0.9µm to 1.1µm when the workpiece velocity V_w increase from level 1 to level 3. The figure for the cutting depth is fluctuating around 0.9µm to 1.0µm, respectively.

The data in tables 6,7 illustrate the influence of cutting and lubrication parameters on the mean roughness depth R_z. Where, the cutting parameters influence surface roughness more significantly than the lubrication parameters. The cutting parameters include Vw, f, and t effect surface roughness significantly. The influence of f is the most, followed by t and V_w. The lubricant parameters include P and Q influence on surface roughness insignificantly.

Influence of input factors on mean roughness depth R_z

Table 6: Response table for signal to noise ratios for R_z

Level	Q	P	V_w	F	t
1	-16.33	-16.18	-16.40	-14.88	-15.81
2	-16.70	-16.66	-16.42	-16.73	-16.68
3	-16.54	-16.73	-16.74	-17.95	-17.07
Delta	0.37	0.55	0.33	3.07	1.27
Rank	4	3	5	1	2

Table 7: Response table for means for R_z

Level	Q	P	V_w	F	t
1	6.677	6.545	6.737	5.576	6.248
2	6.899	6.872	6.688	6.884	6.908
3	6.794	6.953	6.945	7.910	7.213
Delta	0.222	0.408	0.257	2.334	0.966
Rank	5	3	4	1	2

Figure 8: Main effects plot for means of R_z

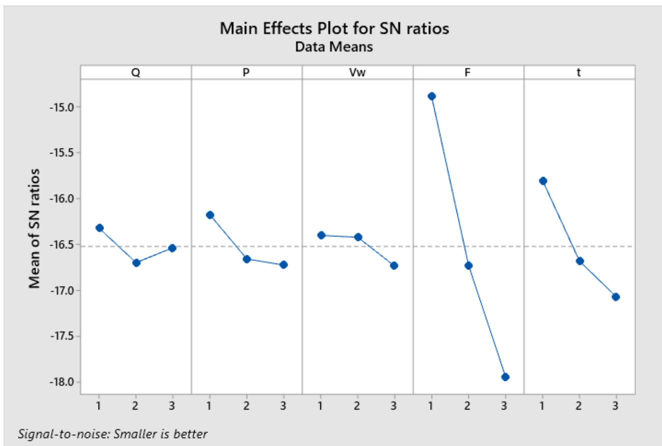

Figure 9: Main effects plot for SN Ratios of R_z

Besides, figures 8, 9 outline the interaction between cutting parameters with surface roughness value. The value of feed rate f increase from level 1 to level 3 causes quickly increasing from 5.5µm to around 8.0µm of mean roughness depth R_z, an increase of around 40%. Similarly, the surface roughness rising significantly from 6.2µm to 7.2µm when the depth of cut ap rising from level 1 to level 3. By contrast, the maximum height R_z increases slightly from 6.9µm when V_w rising from Level 1 to level 2, then went down significantly when the V_w rising to the level 3 value.

Influence of input factors on root mean square roughness R_q

The data in tables 8 and 9 present the influence of cutting parameters, namely V_w, f, t, and lubrication parameters includes P, Q on the Root Mean Square Roughness (RMS Roughness) Rq. Where, the cutting parameters influence surface roughness more significantly than the lubrication parameters. By contrast, the lubricant parameters influence surface roughness insignificantly.

Figures 9 and 10 show that the values of P, V_w, F, and t are proportional to RMS Roughness. That means, increasing P, V_w, F, and t causes the rising value of RSM Roughness. When the values of F and Vw increase from level 1 to level 3, the RMS roughness goes up quickly from 1.1µm to 1.5µm and 1.2µm to 1.4µm, respectively. Similarly, when the depth of cut t rising from level 1 to level 3, the RMS roughness goes slightly from 1.28µm to 1.32µm.

Table 8: Response table for signal to noise ratios of R_q

Level	Q	P	V_w	F	t
1	-1.9862	-1.4773	-1.2879	-0.8100	-1.9147
2	-2.3656	-2.4680	-2.2251	-2.2459	-2.1505
3	-2.0292	-2.4356	-2.8679	-3.3250	-2.3158
Delta	0.3795	0.9907	1.5800	2.5150	0.4010
Rank	5	3	2	1	4

Table 9: Response Table for Means of R_q

Level	Q	P	V_w	F	t
1	1.294	1.207	1.178	1.109	1.262
2	1.315	1.329	1.298	1.296	1.296
3	1.267	1.340	1.401	1.471	1.318
Delta	0.048	0.133	0.223	0.362	0.056
Rank	5	3	2	1	4

By contrast, the influence of flow rate Q is not stable. When Q rising from level 1 to level 2, meaning from 50ml/h to 100ml/h, the RMS roughness rose slightly from 1.3µm to 1.31. However, with the continued increase of flow rate to 150ml/h (level 3), the RSM roughness reduces to 1.28µm.

Fig. 8, 10 and 12 also shown that each individual responses R_a, R_z, R_q reach to optimal point at the same combination of input factors.

Figure 10: Main effects plot for means of R_q

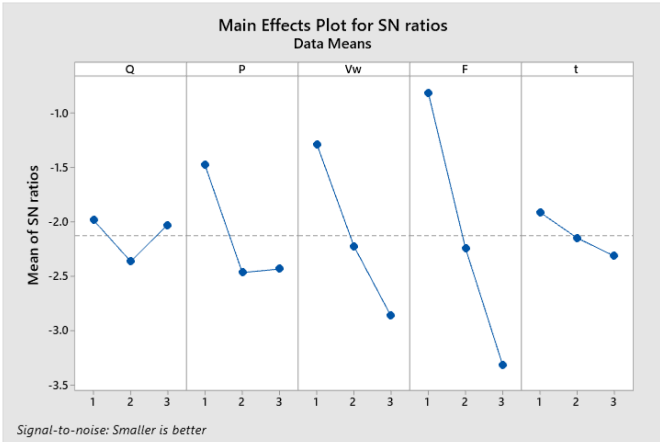

Figure 11: Main effects plot for SN Ratios of R_q

Regression model

The regression model for Surface roughness R_a, mean roughness depth R_z, Root Mean Square (RMS) Roughness R_q were generated with the regression optimizer tool in Minitab 19, with the Box-Cox transformation selection. The regression modelsare shown as (4), (5), and (6). The regression models were applied to calculate the predicted value of R_a, R_z, R_q. The summarize of prediction and measurement of R_a, R_z, R_q were shown in Table 3.

The R-squared for Regression Model of R_a, R_z, R_q are 89.08%, 92.42%, and 95.36%, respectively. That means the regression models could be applied topredict the value of surface roughness R_a, mean roughness depth R_z, and Root Mean Square Roughness R_q. The regression models were used to solve multiple optimization problems.

Regression model for surface roughness average R_a

$$R_a=0.2190-000032Q+0.0375P+0.00843V_w+0.0895f+17.33t \quad (4)$$

Regression model for mean roughness depth R_z

$$R_z^2=-13.83+0.0105Q+2.270P+0.231V_w+7.846f+1307t \quad (5)$$

Regression model for root mean square roughness R_q

$$R_q^2=-0.345-0.0147Q+0.1679P+0.05625V_w+0.2310f+14.11t \quad (6)$$

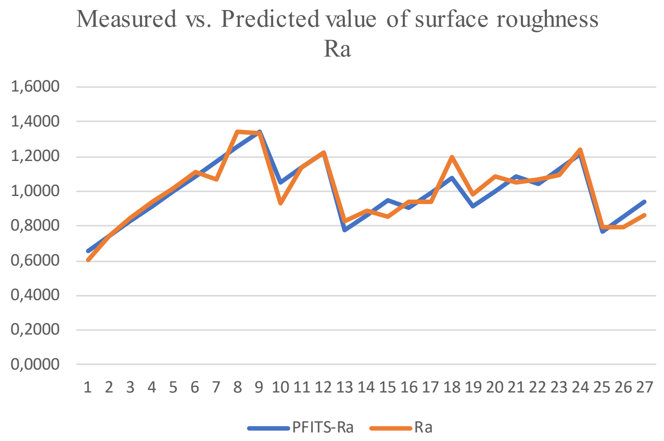

Figure 12: Measured vs. predicted value of surface roughness R_a

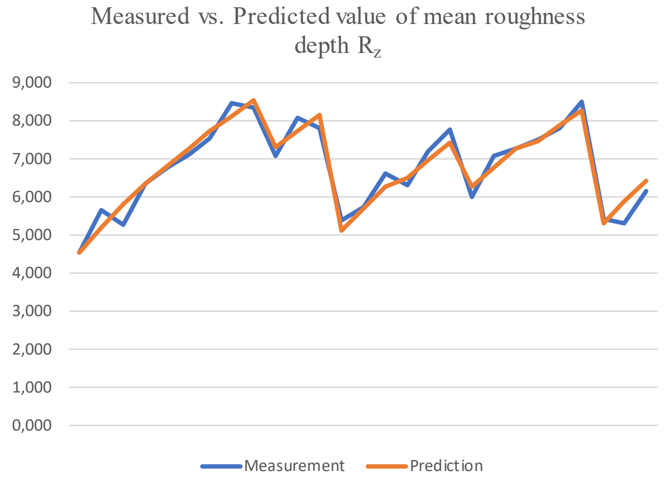

Figure 13: Measured vs. predicted value of mean roughness depth R_z

Multiple response optimization

In this work, the regression optimizer tool of Minitab was used to solve the multiple optimization problems, with

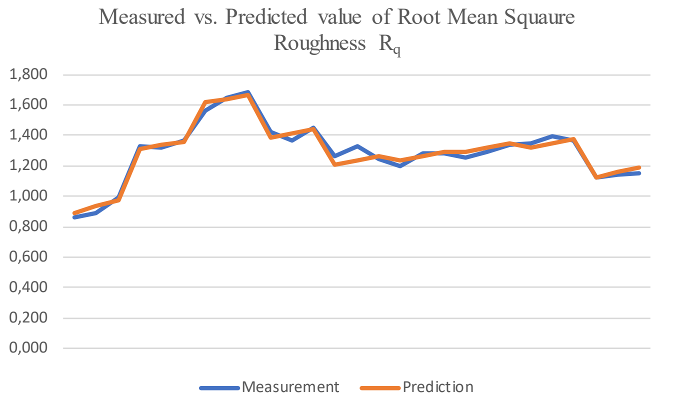

Figure 14: Measured vs. predicted value of root mean squaure roughness R_q

the minimizing of R_a, R_z, R_q approach. The results are shown in Tables 10, 11, 12 and Figure 15.

The data from Table 10, 11, 12 and Figure 15 shown that optimum cutting parameters as: workpiece velocity V_w, feed rate f, depth of cut ap are 5m/min, 3mm/stroke, 0.005mm, respectively, corresponding to the optimum lu-

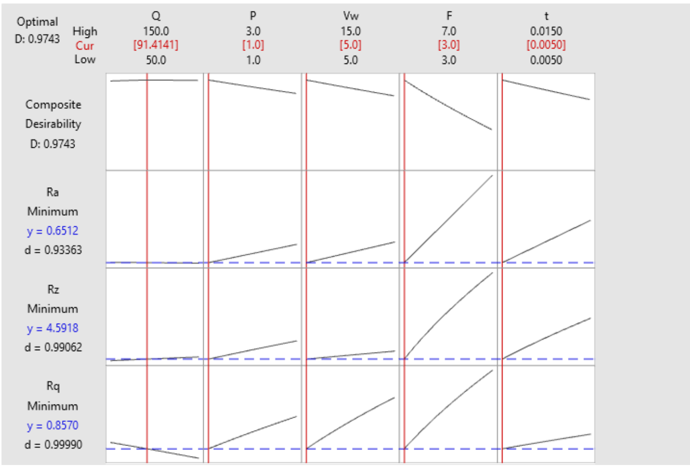

Figure 15: Multiple optimization of R_a, R_z, R_q

Table 10: Parameters of multiple optimization problems

Response	Goal	Lower	Target	Upper	Weight	Importance
R_a	Minimum		0.60200	1.34267	1	1
R_z	Minimum		4.55467	8.51200	1	1
R_q	Minimum		0.85690	1.68420	1	1

Table 11: The solution of multiple optimization problems

Solution	Q	P	V_w	F	a_p	R_aFit	R_zFit	R_qFit	Composite Desirability
1	91.4141	1	5	3	0.005	0.651159	4.59178	0.856980	0.974272

Table 12: The multiple response prediction of multiple optimization

Variable	Setting	Response	Fit	SE Fit	95% CI	95% PI
Q	91.4141	R_a	0.6512	0.0342	(0.5799, 0.7224)	(0.4946, 0.8077)
P	1	R_z	4.592	*	(4.092, 5.042)	(3.399, 5.533)
V_w	5	R_q	0.8570	*	(0.7891, 0.9199)	(0.6991, 0.9900)
f	3					
a_p	0.005					

brication parameters as oil flow rate of 91.94ml/h and air pressure of 1 MPa. Corresponding to the surface roughness R_a, root mean square roughness R_q, and mean roughness depth R_z of 0.6512μm.

CONCLUSION

In summary, this paper argued that:

- The feed rate f effect the most on the whole surface roughness R_a, Root Mean Square Roughness R_q, and Mean Roughness Depth R_z, followed by workpiece velocity V_w. The depth of cut ap effect on the roughness values insignificant.
- The lubricant variants had an insignificant influence on R_a, R_z, R_q
- In this experimental study, grinding of hardened S50C carbon steel was the first performed with assisted Vietnamese peanut oil as minimum quantity lubricant.
- The present findings confirm vegetable oil's ability based as the lubricant in the cutting process, including grinding. The combining grinding and lubricant parameters as following: The workpiece velocity Vw of 5 m/min, feed rate f of 3mm/stroke, depth of cut of 0.005mm and oil flow rate, air pressure of 91.94 ml/h, 1 MPa, respectively. Corresponding to the surface roughness R_a, Root Mean Square Roughness R_q, and Mean Roughness Depth R_z of 0.6512μm, 4.592μm, 0.8570μm.
- Computing software Minitab could be applied to generate the regression models and solve the multiple objective optimization problems.
- The effects of the combinations of input variables on Ra, Rz, Rq are quite similar. Hence, It's sufficient to research only one of response R_a, R_z or R_q.

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