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Application of Grey Based Taguchi Method in Simultaneous Optimization of Surface Roughness and Material Removal Rate in Hard Milling under Nanofluid MQL Condition

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ABSTRACT

This paper presents the simultaneous optimization of cutting conditions in hard milling of JIS SKD 61 alloy steel using Grey based Taguchi method. Experiments were designed and carried out based on the L27 orthogonal array of the Taguchi method. The input parameters selected of the milling condition are cutting speed, feed rate, depth of cut, and nanoparticle concentration. The responses are surface roughness and material removal rate (MRR). The signal-to-noise ratio was calculated for the determination of a grey relation grade. An analysis was conducted to find out the effect of input factor on the grey relation grade by using the ANOVA. As result, the cutting speed is the factor having the strongest impact on multiple performance characteristics, followed by the nanoparticle concentration. Also, the optimal milling condition for the minimum surface roughness and maximum MRR is the condition consisting of cutting speed of 80m/min, feed rate of 0.02 mm/tooth, depth of cut of 0.6mm, and nanoparticle concentration of 4wt%.

KEYWORDS

surface roughness, MRR, hard milling, hardened SKD61 tool steel, SiO_2 nanoparticles, MQL, Grey based Taguchi method.

INTRODUCTION

Surface roughness is an important indicator that reflects the quality of a machined surface. In contrast, the material removal rate is characteristic of machining productivity. The simultaneous achievement of small machining roughness and high material removal rate in the metal cutting process has attracted many researchers as well as manufacturers. The multi-goal optimization process has been applied successfully in many metal cutting machining processes such as turning [1-3], milling [4,5], grinding [6-9], and so on. In experimental research, the Taguchi is a powerful method providing a simple, efficient, and systematic approach to optimize the designs for performance, quality, and cost [10, 11]. However, the Taguchi method cannot solve the problems of multi-goal optimization [12]. Therefore, the Taguchi method combined with Grey relational analysis is a good solution to this problem as suggested by Deng [13]. Nowadays, new technologies have been introduced to improve the productivity and quality of metal cutting machining. A new technology called nanofluid has also been successfully applied to lubrication and cooling process in machining. This method was introduced by Choi in 1995[14]. A colloidal mixture of nanometer-sized solid particles in base cutting fluid helps to overcome the weakness of the base fluid having a low heat conductivity [15]. Adding nanoparticles to the lubrication process increases the thermal conductivity, density, and viscosity of the nanofluid.

Hence, the efficiency of the heat transfer of the cutting liquid is improved. This point is in agreement with what was found in previous investigations [16-20]. In addition, the effectiveness in improving the roughness, reducing the cutting force, increasing the tool life, and reducing the tool wear of the nanofluid has also been demonstrated in many studies [21-23]. The effects achieved in metal cutting are due to the improved heat transfer efficiency when nanoscale solid particles are added [24, 25]. In addition, a series of effects such as ball/rolling bearing effect, third body effect, chemical mechanical protective film effect, mending effect, and polishing effect has had a positive effect on the cooling lubrication effect of the cutting fluid [26, 27]. There are some notable studies where roughness and MRR are output response. In a study by The-Vinh Do and Thanh-Dat Phan, the authors performed a multi-objective optimization to achieve the smallest roughness and the largest MRR in hard milling of SKD11[28]. In this study, the investigated cutting parameters include cutting speed, feed rate, depth of cut and hardness of workpiece. An optimal cutting mode has been proposed that satisfies the requirements of the lowest roughness and the highest MRR. Another targeted optimization study was performed by Okokpujie, IP et al.[4].

A suitable cutting mode is provided to achieve minimum roughness, maximum material removal rate and minimum cutting force. Jinhua Zhou et al used the grey relational analysis coupled with RBF neural network and PSO algorithm to perform multi-objective optimization in Inconel 718 steel milling [29]. The research results show that the new method, which is more effective than the original method, can be applied in multi-objective optimization in experimental studies. Taguchi coupled GRA was used in a study by Bhasha, A. Chinnamahammad, and K. Balamurugan [30]. In this study, an optimal mode was proposed to achieve the smallest Ra and the largest MRR. Overall, these are typical "case studies". It shows that multi-objective optimization studies to achieve minimum Ra and maximum MRR still need to be continued. Especially, multi-objective optimization studies in machining with nanofluid application. In this study, the simultaneous optimization of cutting conditions in hard milling of JIS SKD 61 alloy steel for minimizing the surface roughness and maximizing MRR was conducted by using Grey based Taguchi method. The input factors including cutting speed, feed rate, depth of cut, and nanoparticle concentration were selected to investigate their impact on multiple performance characteristics. The simultaneous achievement of small machining roughness and high material removal rate was achieved by using optimal milling conditions.

EXPERIMENTAL PROCEDURES

In the study, a Victor V-Center-4 vertical machining center was used for all experiments. The JIS SKD 61 alloy steel workpieces have a dimension of 200mm x 100mm x 50mm and a hardness of 50 HRC. The material compositions of the workpiece are shown in Table 1. In each experiment, a new Φ10 TiAlN coated end mill cutting tool was used. The surface roughness was measured via Mitutoyo SJ-401 surf-test. All tests were conducted under MQL cooling. The MQL condition fixed is as follows: flow rate is 50ml/h, air pressure is $3kg/cm^2$, and lubricating oil is CT232. SiO_2 nanoparticles with size 100nm were added in the cutting oil with 3 different concentrations of 0, 2, and 4 wt%. Cutting liquid is supplied in MQL cooling by using A Noga–MC 1700 nozzle. Each test was repeated three times to reduce the experimental errors. Figure 1 shows the experimental setup.

Table 1. Chemical compositions of the SKD61 steel workpiece

Element	C	Si	Mn	Cr	Mo	V	Ni
weight %	0.32 - 0.42	0.80 - 1.20	0.20 - 0.50	4.75 - 5.50	1.10 - 1.75	0.80 - 1.20	0 - 0.30

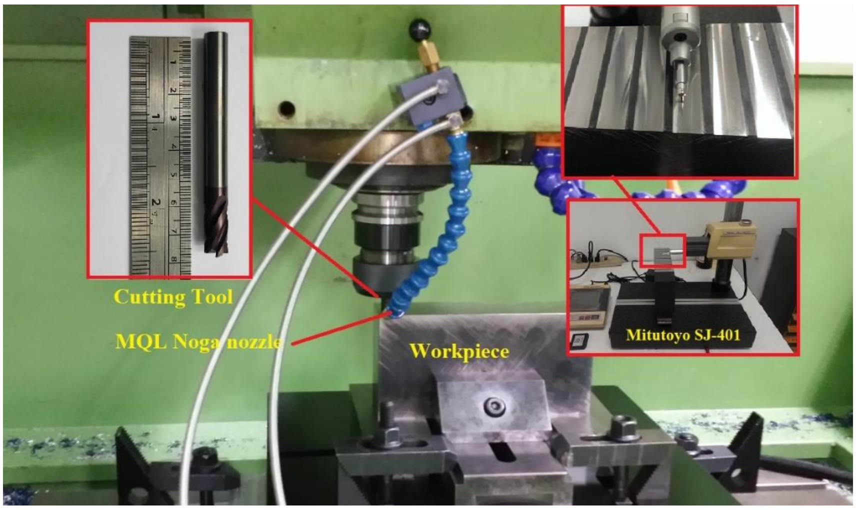

Figure 1. The experimental setup

The four inputs include cutting speed, feed rate, depth of cut, and nanoparticle concentration. Each factor has 3 levels. With four three-levels factors, the L27 array of Taguchi was used to design the experiment. Table 2 indicates the input factors with levels.

The material removal rate (MMR) is determined by the following formula (1) [23].

$$MRR = \frac{d \times a_e \times \mathrm{V} \times \mathrm{f} \times \mathrm{z} \times 1000}{3.14 \times D} \tag{1}$$

where *d* is the depth-of-cut (mm), a_e is the width-of-cut (mm), *v* is the cutting speed (m/min), *f* is the feed rate (mm/tooth), *z* is the flute of the cutter, *D* is the diameter of the cutting tool (mm).

Table 2. The input factor of the experiment

Levels	Input factors			
	Cutting speed (m/min)	Feed rate (mm/tooth)	Depth of cut (mm)	Nanoparticle concentration (wt%)
1	40	0.01	0.2	0
2	60	0.02	0.4	2
3	80	0.03	0.6	4

RESULTS AND DISCUSSIONS

The results of the experiment are shown in Table 3.

Table 3. The result of the experiment

Run	*c*	*v*	*d*	*f*	Ra (µm)	MRR (mm^3/min)
1	0	40	0.2	0.01	0.2	101.9108
2	0	40	0.4	0.02	0.248	407.6433
3	0	40	0.6	0.03	0.312	917.1975
4	0	60	0.2	0.02	0.224	305.7325
5	0	60	0.4	0.03	0.276	917.1975
6	0	60	0.6	0.01	0.181	458.5987
7	0	80	0.2	0.03	0.257	611.465

8	0	80	0.4	0.01	0.167	407.6433
9	0	80	0.6	0.02	0.214	1222.93
10	2	40	0.2	0.02	0.179	203.8217
11	2	40	0.4	0.03	0.295	611.465
12	2	40	0.6	0.01	0.176	305.7325
13	2	60	0.2	0.03	0.255	458.5987
14	2	60	0.4	0.01	0.228	305.7325
15	2	60	0.6	0.02	0.263	917.1975
16	2	80	0.2	0.01	0.128	203.8217
17	2	80	0.4	0.02	0.19	815.2866
18	2	80	0.6	0.03	0.272	1834.395
19	4	40	0.2	0.03	0.26	305.7325
20	4	40	0.4	0.01	0.138	203.8217
21	4	40	0.6	0.02	0.155	611.465
22	4	60	0.2	0.01	0.098	152.8662
23	4	60	0.4	0.02	0.137	611.465
24	4	60	0.6	0.03	0.21	1375.796
25	4	80	0.2	0.02	0.128	407.6433
26	4	80	0.4	0.03	0.2	1222.93
27	4	80	0.6	0.01	0.126	611.465

In this paper, Taguchi and Grey methods were applied to optimize the results simultaneously to achieve the minimum roughness and maximum material removal rate. After the data collection process, the Grey-based Taguchi method is applied for simultaneous optimization. The basic steps of the optimization process by the Grey-based Taguchi method are given as follows:

In the first step, the signal to noise (S/N) is calculated for corresponding responses. The goal is to reduce the surface roughness and increase the *MRR*. Thus, the smaller is the better S/N calculated in (2) is the suitable type for surface roughness and the larger is the better S/N calculated in (3) is the suitable type for *MRR*:

The smaller is the better S/N:

$$SN = -10log_{10}(\frac{1}{n}\sum_{i=1}^{n} y_i^2) \tag{2}$$

The larger is the better S/N:

$$SN = -10log_{10}(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}) \tag{3}$$

Where: y_i is the data received by the experiment. n is the number of experiments

A data preprocessing for raw data (S/N data) normalization is performed in the second step. The linear normalization of the S/N ratio is performed by the grey relational generating (a range between zero and unity). The normalized S/N ratio Zij for the i^{th} performance characteristic in the j^{th} experiment can be calculated by equation (4). Table 4 indicates the calculated values of S/N. normalized Zij and Δj(k).

$$Z_{ij} = \frac{SN_{ij} - \min(SN_{ij}, j=1,2,..k)}{\max(SN_{ij}, j=1,2,..n) - \min(SN_{ij}, j=1,2,..n)} \tag{4}$$

Table 4. Values of SN ratio. normalized SN ratio. and the absolute

TT	S/N		Z_{ij}		$\Delta j(k)$	
			Ra	MRR		
	Ra	*MRR*	$Z_0(k)$		*Ra*	*MRR*
			1.000	1.000		
1	13.9794	40.16441	0.384	0	0.616	1
2	12.11097	52.20561	0.198245	0.479625	0.801755	0.520375
3	10.11691	59.24926	0	0.760188	1	0.239812
4	12.99504	49.70683	0.286137	0.380094	0.713863	0.619906
5	11.18182	59.24926	0.105871	0.760188	0.894129	0.239812
6	14.84643	53.22866	0.470198	0.520375	0.529802	0.479625
7	11.80134	55.72743	0.167462	0.619906	0.832538	0.380094
8	15.54567	52.20561	0.539715	0.479625	0.460285	0.520375
9	13.39172	61.74803	0.325575	0.859719	0.674425	0.140281
10	14.94294	46.18501	0.479793	0.239812	0.520207	0.760188
11	10.60356	55.72743	0.048382	0.619906	0.951618	0.380094
12	15.08975	49.70683	0.494388	0.380094	0.505612	0.619906
13	11.8692	53.22866	0.174208	0.520375	0.825792	0.479625
14	12.8413	49.70683	0.270853	0.380094	0.729147	0.619906
15	11.60089	59.24926	0.147534	0.760188	0.852466	0.239812
16	17.8558	46.18501	0.769383	0.239812	0.230617	0.760188
17	14.42493	58.22621	0.428293	0.719437	0.571707	0.280563
18	11.30862	65.26986	0.118477	1	0.881523	0
19	11.70053	49.70683	0.15744	0.380094	0.84256	0.619906
20	17.20242	46.18501	0.704425	0.239812	0.295575	0.760188
21	16.19337	55.72743	0.604108	0.619906	0.395892	0.380094
22	20.17548	43.68623	1	0.140281	0	0.859719
23	17.26559	55.72743	0.710705	0.619906	0.289295	0.380094
24	13.55561	62.77108	0.341868	0.900469	0.658132	0.099531
25	17.8558	52.20561	0.769383	0.479625	0.230617	0.520375
26	13.9794	61.74803	0.384	0.859719	0.616	0.140281
27	17.99259	55.72743	0.782982	0.619906	0.217018	0.380094

In third step, the grey relation coefficient is determined as the equation (5)

$$\gamma(k) = \frac{\Delta min + \zeta \Delta max}{\Delta_j(k) + \zeta \Delta max} \qquad (5)$$

Where j=1. 2…n; k=1. 2…m; n is the number of experiments; k is the number of object.

$\Delta j(k)$ is the deviation sequence and determined as the equation: $\Delta_{j(k)} = \|Z_0(k) - Z_j(k)\|$. And: $\Delta\min = \min_{\forall j \in i} \min_{\forall k} \|Z_0(k) - Z_j(k)\|$; $\Delta\max = \max_{\forall j \in i} \max_{\forall k} \|Z_0(k) - Z_j(k)\|$.

ζ is the distinguishing coefficient $0 \le \zeta \le 1$. In this case. $\zeta = 0.5$.

After the third step, the grey relational grade γ_i is calculated as equation (6).

$$\overline{\gamma_j} = \frac{1}{k}\sum_{i=1}^{m}\gamma_{ij} \tag{6}$$

Where γ_j is the grey relational grade for the jth experiment; k is the number of objectives (in this study. k=2)

Table 5 indicates the grey relational coefficient and the grey relational grade.

Table 5. Values of Grey relational coefficient and grey relational grade

No.	Grey relational co-efficient γ_i		$\bar{\gamma}$
	Ra	Fl	
1	0.448	0.333	0.391
2	0.384	0.490	0.437
3	0.333	0.676	0.505
4	0.412	0.446	0.429
5	0.359	0.676	0.517
6	0.486	0.510	0.498
7	0.375	0.568	0.472
8	0.521	0.490	0.505
9	0.426	0.781	0.603
10	0.490	0.397	0.443
11	0.344	0.568	0.456
12	0.497	0.446	0.472
13	0.377	0.510	0.444
14	0.407	0.446	0.427
15	0.370	0.676	0.523
16	0.684	0.397	0.541
17	0.467	0.641	0.554
18	0.362	1.000	0.681
19	0.372	0.446	0.409
20	0.628	0.397	0.513
21	0.558	0.568	0.563
22	1.000	0.368	0.684
23	0.633	0.568	0.601
24	0.432	0.834	0.633
25	0.684	0.490	0.587
26	0.448	0.781	0.614
27	0.697	0.568	0.633

In the next step, the Taguchi method is applied to determine the effect of input factors on the grey relational grade. Figure 2 shows the effect of the input factors on the grey relational grade. With the help of Figure 2, the optimal machining process for minimum roughness and maximum material removal rate is the nanoparticle concentration of 4%, cutting speed of 80m/min, depth of cut of 0.6mm, and feed rate of 0.02 mm/tooth. To obtain minimum roughness and highest MRR, the highest concentration of nanoparticles is applied. It makes sense that nanofluid is a good solution for the hard milling of SKD61 tool steel.

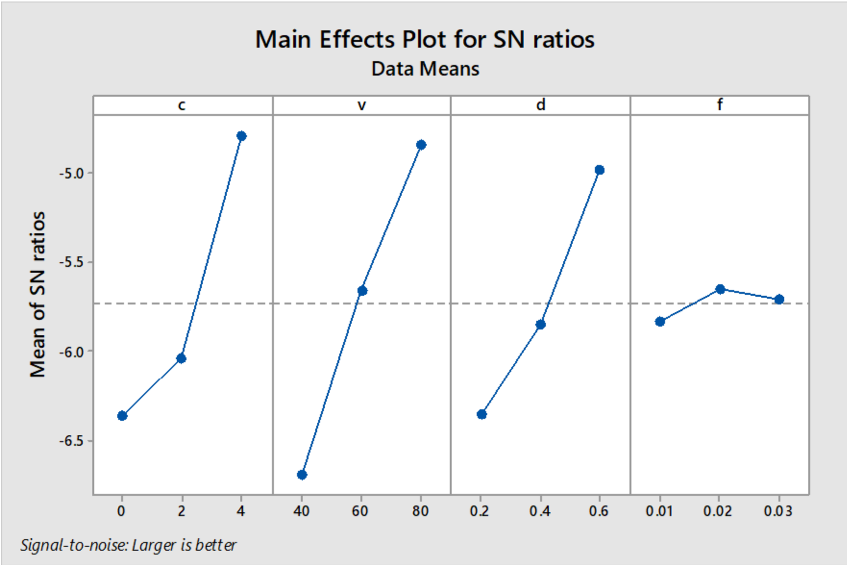

Figure 2. Main effects plot for the grey relational grade

Table 6. The result of the analysis of variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%
c	1	0.043023	0.043023	17.08	0.000[a]	23.59
v	1	0.055638	0.055638	22.09	0.000[a]	30.51
d	1	0.028034	0.028034	11.13	0.003[a]	15.37
f	1	0.000265	0.000265	0.11	0.749	0.15
Error	22	0.055422	0.002519	-	-	-
Total	26	0.182381	-	-	-	-

By using the values of the grey relational grade, the analysis of variance (ANOVA) is formulated to identify the significant factors. The results of ANOVA are shown in Table 6. From the ANOVA result, it is clear that the cutting speed (30.51%) influences more on multiple performance characteristics followed by the nanoparticle concentration (23.59%) and the depth of cut (15.37%). The feed rate has a negligible effect on the multiple performance characteristics with 0.15%. The effects of *c*, *v*, and *d* were statistically significant (P value <0.05).

CONCLUSION

In the study, the simultaneous optimization of cutting conditions for minimizing the surface roughness and maximizing MRR in hard milling of JIS SKD 61 alloy steel using grey-based Taguchi method. Some of the main results can be presented as follows:

- The optimal cutting condition for the minimum surface roughness and maximum MRR is the nanoparticle concentration of 4%, cutting speed of 80m/min, depth of cut of 0.6mm, and feed rate of 0.02 mm/tooth.
- The cutting speed is the input factor that influences more on multiple performance characteristics with 30.51% in total effect followed by the nanoparticle concentration (23.59%) and the depth of cut (15.37%).
- Nanofluid is a good solution in reducing machining roughness and improving MRR during hard milling of SKD61 steel.

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REFERENCES

[1] A. K. Sahoo, A. N. Baral, A. K. Rout, and B. Routra, "Multi-objective optimization and predictive modeling of surface roughness and material removal rate in turning using grey relational and regression analysis," Procedia Engineering, vol. 38, pp. 1606-1627, 2012.

[2] S. Raykar, D. D'Addona, and A. Mane, "Multi-objective optimization of high speed turning of Al 7075 using grey relational analysis," Procedia Cirp, vol. 33, pp. 293-298, 2015.

[3] R. Kumar, P. S. Bilga, and S. Singh, "Multi objective optimization using different methods of assigning weights to energy consumption responses, surface roughness and material removal rate during rough turning operation," Journal of cleaner production, vol. 164, pp. 45-57, 2017.

[4] I. Okokpujie, O. Ohunakin, and C. Bolu, "Multi-objective optimization of machining factors on surface roughness, material removal rate and cutting force on end-milling using MWCNTs nano-lubricant," Progress in Additive Manufacturing, vol. 6, pp. 155-178, 2021.

[5] A. Kumbhar, R. Bhosale, A. Modi, S. Jadhav, S. Nipanikar, and A. Kulkarni, "Multi-objective optimization of machining parameters in CNC end milling of stainless steel 304," International Journal of Innovative Research in Science, Engineering and Technology, vol. 4, pp. 8419-8426, 2015.

[6] M. Janardhan and A. G. Krishna, "Multi-objective optimization of cutting parameters for surface roughness and metal removal rate in surface grinding using response surface methodology," International Journal of Advances in Engineering & Technology, vol. 3, p. 270, 2012.

[7] L. X. Hung, V. N. Pi, T. T. Hong, V. T. Lien, L. A. Tung, and B. T. Long, "Multi-objective optimization of dressing parameters of internal cylindrical grinding for 9CrSi aloy steel using taguchi method and grey relational analysis," Materials Today: Proceedings, vol. 18, pp. 2257-2264, 2019.

[8] T. T. Hong, D. T. Vinh, T. V. Hung, T. N. Giang, N. T. Tu, L. X. Hung, et al., "Multi-objective Optimization of Surface Roughness and MRR in Surface Grinding of Hardened SKD11 Using Grey-Based Taguchi Method," in International Conference on Engineering Research and Applications, 2020, pp. 584-593.

[9] D. Trung, N. Thien, and N. Nguyen, "Application of TOPSIS Method in Multi-Objective Optimization of the Grinding Process Using Segmented Grinding Wheel," Tribology in Industry, vol. 43, 2021.

[10] T.-V. Do and Q.-C. Hsu, "Optimization of minimum quantity lubricant conditions and cutting parameters in hard milling of AISI H13 steel," Applied Sciences, vol. 6, p. 83, 2016.

[11] T.-V. Do, N.-C. Vu, and Q.-M. Nguyen, "Optimization of cooling conditions and cutting parameters during hard milling of AISI H13 steel by using Taguchi method," in 2018 IEEE International Conference on Advanced Manufacturing (ICAM), 2018, pp. 396-398.

[12] J. Saedon, N. Jaafar, M. A. Yahaya, N. Saad, and M. S. Kasim, "Multi-objective optimization of titanium alloy through orthogonal array and grey relational analysis in WEDM," Procedia Technology, vol. 15, pp. 832-840, 2014.

[13] D. Julong, "Introduction to grey system theory," The Journal of grey system, vol. 1, pp. 1-24, 1989.

[14] S. Choi and A. Jeffrey, "Eastman, enhancing thermal conductivity of fluids with nanoparticles," Developments and Applications of Non-Newtonian Flows, vol. 231, pp. 99-105, 1995.

[15] N. A. C. Sidik, S. Samion, J. Ghaderian, and M. N. A. W. M. Yazid, "Recent progress on the application of nanofluids in minimum quantity lubrication machining: A review," International Journal of Heat and Mass Transfer, vol. 108, pp. 79-89, 2017.

[16] B. Li, C. Li, Y. Zhang, Y. Wang, D. Jia, M. Yang, et al., "Heat transfer performance of MQL grinding with different nanofluids for Ni-based alloys using vegetable oil," Journal of Cleaner Production, vol. 154, pp. 1-11, 2017.

[17] T. V. Do and T.-D. Phan, "An empirical investigation of SIO2 nano concentration under MQL on surface roughness in hard milling of jis SKD61 steel," Journal of Applied Engineering Science, vol. 18, pp. 432-437, 2020.

[18] L. Godson, B. Raja, D. M. Lal, and S. Wongwises, "Enhancement of heat transfer using nanofluids—an overview," Renewable and sustainable energy reviews, vol. 14, pp. 629-641, 2010.

[19] S. Sharma and S. M. Gupta, "Preparation and evaluation of stable nanofluids for heat transfer application: a review," Experimental Thermal and Fluid Science, vol. 79, pp. 202-212, 2016.

[20] T.-D. Phan, T. V. Do, T.-L. Pham, and H.-L. Duong, "Optimization of Cutting Parameters and Nanoparticle Concentration in Hard Milling for Surface Roughness of JIS SKD61 Steel Using Linear Regression and Taguchi Method," in International Conference on Engineering Research and Applications, 2020, pp. 628-635.

[21] M. Sayuti, A. A. Sarhan, and M. Hamdi, "An investigation of optimum SiO 2 nanolubrication parameters in end milling of aerospace Al6061-T6 alloy," The International Journal of Advanced Manufacturing Technology, vol. 67, pp. 833-849, 2013.

[22] M. Sayuti, A. A. Sarhan, and F. Salem, "Novel uses of SiO2 nano-lubrication system in hard turning process of hardened steel AISI4140 for less tool wear, surface roughness and oil consumption," Journal of Cleaner Production, vol. 67, pp. 265-276, 2014.

[23] T.-V. Do, "Effect of Cutting Parameters on Cutting Force of Hard Milling of SKD 61 Steel under Nanofluid-MQL Condition," International Journal of Mechanical Engineering and Robotics Research, vol. 9, pp. 1104-1109, 2020.

[24] W. Yu, H. Xie, L. Chen, and Y. Li, "Investigation of thermal conductivity and viscosity of ethylene glycol based ZnO nanofluid," Thermochimica Acta, vol. 491, pp. 92-96, 2009.

[25] A. Moghadassi, S. M. Hosseini, D. Henneke, and A. Elkamel, "A model of nanofluids effective thermal conductivity based on dimensionless groups," Journal of Thermal Analysis and Calorimetry, vol. 96, pp. 81-84, 2009.

[26] P.-H. Lee, J. S. Nam, C. Li, and S. W. Lee, "An experimental study on micro-grinding process with nanofluid minimum quantity lubrication (MQL)," International Journal of Precision Engineering and Manufacturing, vol. 13, pp. 331-338, 2012.

[27] S. Oh and B. Rhee, "Effects of Tribological Characteristics on Lubricant Proper-Ties (the 2nd)," The Korean Society of Tribologists and Lubrication Engineers, vol. 17, pp. 334-340, 2001.

[28] T.-V. Do; and T.-D. Phan, "Multi-Objective Optimization of Surface Roughness and MRR in Milling of Hardened SKD 11 Steel under Nanofluid MQL Condition," International Journal of Mechanical Engineering and Robotics Research, vol. 10, pp. 357-362, 2021.

[29] J. Zhou, J. Ren, and C. Yao, "Multi-objective optimization of multi-axis ball-end milling Inconel 718 via grey relational analysis coupled with RBF neural network and PSO algorithm," Measurement, vol. 102, pp. 271-285, 2017.

[30] A. C. Bhasha and K. Balamurugan, "Multi-objective optimization of high-speed end milling on Al6061/3% RHA/6% TiC reinforced hybrid composite using Taguchi coupled GRA," in 2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE), pp. 1-6, 2020.