# Multi-Objective Optimization of Surface Roughness and MRR in Milling of Hardened SKD 11 Steel under Nanofluid MQL Condition

The-Vinh Do and Thanh-Dat Phan
Thai Nguyen University of Technology, Thai Nguyen city,
Thai Nguyen Province, VIETNAM
Email: thevinh8880@tnut.edu.vn, leophanvn@tnut.edu.vn

***Abstract*— During the manufacturing process, high productivity and good quality are desired by every manufacturer. In this paper, the Response Surface Methodology (RSM) has been applied to optimize the surface roughness (Ra) and material removal rate (MMR) when milling hardened SKD 11 steel under nano-fluid MQL condition. The three cutting parameters including cutting speed, feed rate, and depth of cut were analyzed along with the hardness of the work-piece in order to build an empirical model that could predict the surface roughness as well as the material removal rate, hence easy to determine the optimum values of Ra and MMR. Experiments were conducted using the L27 orthogonal array of DOE method developed by G. Taguchi from three levels of four input factors above. Further analysis of variance (ANOVA) was used to evaluate the reliability of the method. Under optimal condition, Ra value is 0.249 µm and the MMR value is 1498.09 mm$^3$/min. In addition, the feed rate was identified as the most influential factor on surface roughness, followed by the depth of cut.**

***Index Terms*— surface roughness, hard milling, Hardened SKD 11 tool steel, multi-objective optimization, $SiO_2$ nanoparticles**

## I. Introduction

JIS SKD11 steel is a high-carbon and high-chromium alloy tool steel that has good wear resistance, high hardness, and strength, especially after heat treatment [1]. It is often used for stamping dies, plastic molds, and also widely used in cold work die steel. Due to its characteristics, hardened SKD11 steel is not suitable for traditional machining techniques such as turning, milling, grinding, drilling, and so forth. Therefore, it has been subjected mostly to electro-discharge machining (EDM) [2-4]. In [4], T.Y. Tai and S.J. Lu pointed out that EDM is one of the most effective methods to process materials with high brittleness, such as hard alloys, quenched steel, aluminum alloys, and ultra-hard ceramic materials.

Hard machining technology (i.e., hard milling) has been proved to be an effective alternative to traditional machining [5, 6]. The success of implementing systems including the CNC machine, cutting tools and tool holders, and the computer-aided design/manufacturing system with some characteristics found in a high-speed machining center allowed to perform milling process on material that has as high as 45 HRC up to 64 HRC [7]. Although the development of cutting tools has helped to increase the tool life and high precision of the machined parts in hard milling [8], still there is a challenge with the heat generated during the machining process which led to tool wear and less satisfaction in the surface roughness [9, 10]. The research of The-Vinh Do and Quang-Cherng Hsu [11] has shown that the Minimum Quantity Lubricant (MQL) application could remarkably help to increase the quality of surface roughness, improve tool life, reduce tool wear, decrease cutting temperature and reduce the cost of lubrication in hard milling.

In the MQL technique, a small amount of cutting fluid less than 50ml/h is prayed with high pressure at the cutting zone with the help of a nozzle (i.e., external delivery system) [12-14]. Moreover, nanoparticles have also been implemented into the lubricant/coolant as the state of the art method to enhance the efficiency of the cutting fluid or so called aerosol (i.e., mixer of lubricant/coolant with air) of MQL. AK Sharma et al. [15] reviewed many researches that used nanoparticles such as $Al_2O_3$, ND, $MoS_2$, $SiO_2$… in the varied machining process. They are proved to have extremely good thermal conductivity as well as tribological property and viscosity, which lead to the enhancement in the performance of MQL [16]. Moreover, using nanoparticles in MQL also reduces cost and negative effects on the environment [17]. $SiO_2$ nanoparticles, which can generate a thin protective film on the machined work-piece surface, carry many promising advantages in the milling process [15, 18]. Further work on optimizing task is to find suitable parameters and adjust other factors of the machining process to get the ultimate goal.

The response surface methodology (RSM) is a widely used mathematical and statistical method for modeling and analyzing a process in which the response of interest is affected by various variables (i.e., independent variables) and the objective of this method is to optimize the response (i.e., dependent variables) [18-21]. In the

Manuscript received September 9, 2020; revised January 11, 2021.
Corresponding author: thevinh8880@tnut.edu.vn.


doi: 10.18178/ijmerr.10.7.357-362

milling process, cutting speed, depth of cut, feed rate and the hardness of the work-piece can be considered the independent variables while the quality characteristic of the machined part like its surface roughness can be used as the response – the dependent variable. The data are collected via different experiments. After that, they are put into the regression analysis in the form of a quadratic model of RSM. The determined empirical model of RSM is capable of predicting the surface roughness (i.e., output) with a different set of independent variables (i.e., inputs). The adequacy of the model is then verified by statistical analysis (ANOVA). The ANOVA quantifies not only the effects of each individual but also the interaction effect of the inputs on the output. Therefore, this method can validate the statistical significance of factors in the machining process and draw further conclusions.

## II. Experiment Setup

A brief description of the experiment set up can be found in Table I. The milling processes were carried out on a Victor V-Center-4 vertical machining center. An SKD 11 work-piece was attached to the machining table for every experiment. The material compositions of SKD 11 are shown in Table II. Each work-piece block has dimensions of 150mm x 100mm x 40mm. The hardness of the work-piece (HRC) and the machining parameters including cutting speed (m/min), feed rate (mm/tooth), and depth of cut (mm) are presented in Table III. The cutting tool was Φ10 TiAlN coated end mill with four flutes, rake angle of $12^o$, and the helix angle of $35^o$. The based lubricant was cutting oil CT232. $SiO_2$ particles with a size of 100nm were chosen to enhance the performance of MQL. The flow rate of the mixture was set to 50 ml/h and the pressure was 3 kg/cm$^2$. The concentration of nanoparticles in the fluid was 2 wt%. A Noga–MC 1700 nozzle was used for MQL setup with an angle of $60^o$. Information on the MQL condition is given in Table IV. The surface roughness data was collected via Mitutoyo SJ-401 Surface Profilometer. Each experiment was repeated three times to eliminate the experimental error.

TABLE I. Hard-milling Process Information

| Items | Description |
|---|---|
| CNC Machine | Victor V-Center-4 |
| Surface roughness measuring instrument | Sj-401 |
| Cutting tool | Φ10 TiAlN |
| Work-piece material | SKD 11 |
| Work-piece dimensions | 150mm x 50mm x 40mm |
| MQL nozzle | Noga - MC 1700 |

TABLE II. Chemical Composition of SKD 11 Tool Steel.

| C | Si | Mn | Ni | Cr | Mo | W | V | Cu | P | S |
|---|---|---|---|---|---|---|---|---|---|---|
| 1.4 - 1.6 | 0.4 | 0.6 | 0.5 | 11.0 -13.0 | 0.8 -1.2 | 0.2 - 0.5 | ≤ 0.25 | ≤ 0.25 | ≤ 0.03 | ≤ 0.03 |

TABLE III. Cutting Parameters with Levels

| Input factor | Levels | | |
|---|---|---|---|
| | 1 | 2 | 3 |
| Cutting speed (m/min) | 40 | 60 | 80 |
| Feed-rate (mm/tooth) | 0.01 | 0.02 | 0.03 |
| Depth-of-cut (mm) | 0.2 | 0.4 | 0.6 |
| Hardness-of-workpiece (HRC) | 45 | 50 | 55 |

TABLE IV. Information of MQL Condition

| Items | Description |
|---|---|
| Fluid flow (ml/h) | 50 |
| Pressure (kg/cm$^2$) | 3 |
| Based Lubricant | Cutting oil CT232 |
| Nanoparticles | $SiO_2$ particle with a size of 100nm |
| Concentration of nanoparticle | 2wt % |

## III. Results and Discussions

The data collected throughout the experiments are presented in Table V. The preset machining parameter including the cutting speed ($v$), the feed rate ($f$), the depth of cut ($d$), and the hardness of the work-piece ($h$) are selected by the L27 orthogonal array of Taguchi method. Accordingly, 27 experiments were carried out to study the effect of these parameters on the surface roughness $Ra$. Meanwhile, the values of material removal rate $MMR$ can be calculated by the following formula (1) [22].

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

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 V. THE RESULT OF THE EXPERIMENT

| Runs | *v* (m/min) | *f* (mm/tooth) | *d* (mm) | *h* (HRC) | *Ra* (μm) | *MRR* (mm3/min) |
|---|---|---|---|---|---|---|
| 1 | 40 | 0.01 | 0.2 | 45 | 0.142 | 101.911 |
| 2 | 40 | 0.01 | 0.4 | 50 | 0.19 | 203.822 |
| 3 | 40 | 0.01 | 0.6 | 55 | 0.31 | 305.732 |
| 4 | 40 | 0.02 | 0.2 | 50 | 0.2 | 203.822 |
| 5 | 40 | 0.02 | 0.4 | 55 | 0.31 | 407.643 |
| 6 | 40 | 0.02 | 0.6 | 45 | 0.288 | 611.465 |
| 7 | 40 | 0.03 | 0.2 | 55 | 0.29 | 305.732 |
| 8 | 40 | 0.03 | 0.4 | 45 | 0.287 | 611.465 |
| 9 | 40 | 0.03 | 0.6 | 50 | 0.448 | 917.197 |
| 10 | 60 | 0.01 | 0.2 | 50 | 0.132 | 152.866 |
| 11 | 60 | 0.01 | 0.4 | 55 | 0.234 | 305.732 |
| 12 | 60 | 0.01 | 0.6 | 45 | 0.188 | 458.599 |
| 13 | 60 | 0.02 | 0.2 | 55 | 0.259 | 305.732 |
| 14 | 60 | 0.02 | 0.4 | 45 | 0.211 | 611.465 |
| 15 | 60 | 0.02 | 0.6 | 50 | 0.311 | 917.197 |
| 16 | 60 | 0.03 | 0.2 | 45 | 0.238 | 458.599 |
| 17 | 60 | 0.03 | 0.4 | 50 | 0.35 | 917.197 |
| 18 | 60 | 0.03 | 0.6 | 55 | 0.49 | 1375.796 |
| 19 | 80 | 0.01 | 0.2 | 55 | 0.13 | 203.822 |
| 20 | 80 | 0.01 | 0.4 | 45 | 0.171 | 407.643 |
| 21 | 80 | 0.01 | 0.6 | 50 | 0.21 | 611.465 |
| 22 | 80 | 0.02 | 0.2 | 45 | 0.18 | 407.643 |
| 23 | 80 | 0.02 | 0.4 | 50 | 0.23 | 815.287 |
| 24 | 80 | 0.02 | 0.6 | 55 | 0.37 | 1222.930 |
| 25 | 80 | 0.03 | 0.2 | 50 | 0.302 | 611.465 |
| 26 | 80 | 0.03 | 0.4 | 55 | 0.41 | 1222.930 |
| 27 | 80 | 0.03 | 0.6 | 45 | 0.328 | 1834.395 |

In this research, the goal is to minimize the surface roughness while maximizing the material removal rate. However, the value of *MRR* can be calculated as in (1) after using a set of initial parameters. Therefore, the RSM model was focused on predicting the dependent variable *Ra*. The mathematical equation was determined as below:

$$Ra = 0.831 + 0.00057\,v - 16.58\,f - 0.569\,d - 0.0261\,h - 0.000004\,v{*}v + 73.3\,f{*}f + 0.042\,d{*}d + 0.000200\,h{*}h + 0.0374\,v{*}f - 0.00353\,v{*}d + 0.000004\,v{*}h + 5.44\,f{*}d + 0.344\,f{*}h + 0.01871\,d{*}h \quad (2)$$

Then the predicted values of *Ra* and *MRR* are determined and compared to the measured values as shown in Fig. 1. Fig. 1a visualized the correlation between the predicted and the measured values of Ra while Fig. 1b visualized the correlation between the predicted and the calculated values of *MMR*. As shown in Fig. 1, the experimental and predicted results have a fine correlation. Therefore, the mathematical models established in the study are reliable.

Further analysis of variance (ANOVA) was conduct in Minitab 17 software to analyze the influence of input parameters and the fitness of the model. The P-value column in Table VI indicates the significant of each parameter of the milling process to the response (i.e., the surface roughness) of the model. As long as that value is less than 0.05, the corresponding parameter has statistic significant. Hence, the feed rate (*f*) clearly has the most effect with a 50.2% contribution to the model, following by the depth of cut (*d*) and the hardness of the work-piece (*h*) with 27.9% and 14.4%, respectively. The total coefficient of determination R-sq of the model is 98.3%. It means that the model perfectly fits with the measured *Ra*.

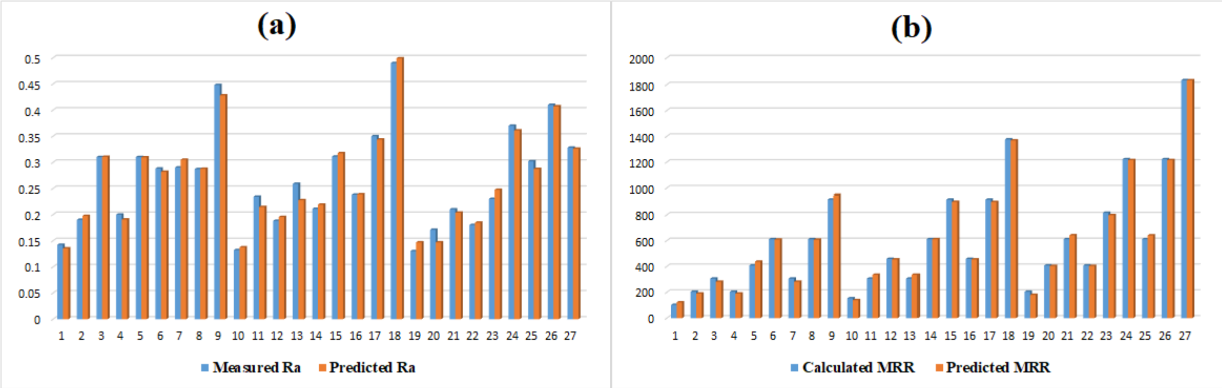


Figure 1. (a) Measure Ra vs Predicted Ra; (b) Calculated MMR vs Predicted MMR

TABLE VI. ANOVA STATISTICAL TABLE

| Source | DF | Adj_SS | Adj_MS | F-Value | P-Value | %C |
|---|---|---|---|---|---|---|
| Model | 14 | 0.224267 | 0.016019 | 48.90 | 0.000[a] | 98.3 |
| Linear | 4 | 0.212103 | 0.053026 | 161.86 | 0.000[a] | 92.9 |
| v | 1 | 0.000998 | 0.000998 | 3.04 | 0.107 | 0.4 |
| f | 1 | 0.114561 | 0.114561 | 349.69 | 0.000[a] | 50.2 |
| d | 1 | 0.063606 | 0.063606 | 194.15 | 0.000[a] | 27.9 |
| h | 1 | 0.032939 | 0.032939 | 100.54 | 0.000[a] | 14.4 |
| Square | 4 | 0.000506 | 0.000126 | 0.39 | 0.815 | 0.2 |
| v*v | 1 | 0.000017 | 0.000017 | 0.05 | 0.825 | 0.0 |
| f*f | 1 | 0.000323 | 0.000323 | 0.98 | 0.341 | 0.1 |
| d*d | 1 | 0.000017 | 0.000017 | 0.05 | 0.825 | 0.0 |
| h*h | 1 | 0.000150 | 0.000150 | 0.46 | 0.511 | 0.1 |
| 2-Way_Interaction | 6 | 0.011658 | 0.001943 | 5.93 | 0.004[a] | 5.1 |
| v*f | 1 | 0.000631 | 0.000631 | 1.93 | 0.190 | 0.3 |
| v*d | 1 | 0.002247 | 0.002247 | 6.86 | 0.022[a] | 1.0 |
| v*h | 1 | 0.000002 | 0.000002 | 0.01 | 0.936 | 0.0 |
| f*d | 1 | 0.001334 | 0.001334 | 4.07 | 0.067 | 0.6 |
| f*h | 1 | 0.003328 | 0.003328 | 10.16 | 0.008[a] | 1.5 |
| d*h | 1 | 0.003939 | 0.003939 | 12.02 | 0.005[a] | 1.7 |
| Error | 12 | 0.003931 | 0.000328 | - | - | 1.7 |
| Total | 26 | 0.228198 | - | - | - | 100.0 |
| R-sq=98.28% | | | | | | |

[a] Significant

TABLE VII. THE RESULTS OF MULTI-OBJECTIVE OPTIMIZATION

| Response | Goal | Optimal values | | | | Predicted | Measured | Error (%) |
|---|---|---|---|---|---|---|---|---|
| | | *V* | *f* | *d* | *h* | | | |
| Roughness | Min. | 80 | 0.0245 | 0.6 | 45 | 0.278 | 0.249 | 11.65 |
| MRR | Max. | | | | | 1517.54 | 1498.09 | 1.3 |
| Composite desirability = 0.6936 | | | | | | | | |

Based on the empirical model, the desirability function was applied to extract the optimum values for both *Ra* and *MMR* as shown in Table VII.

Since the multi-objective optimization is the goal of the research, the achieved result is a trade-off where the min value of surface roughness is 0.249 μm and the max value of material removal rate is 1498.09 $mm^3$/min. The machining parameters are set to 80m/min for the cutting speed, 0.0245 mm/tooth for the feed rate, 0.6 mm for the depth of cut, and the hardness of the SKD 11 work-piece is 45 HRC. The composite desirability of 0.69 is a reasonable value for the two optimum targets. Additional comparison between the predicted and measured/calculated values of *Ra* and *MRR* shows the percentage of error at 11.65% and 1.3% respectively. More information on the optimization work can be observed in Fig. 2.

The plot helps to visualize and analyze how different experimental settings affect the predicted responses of the model. The vertical red lines on this graph and the red parameter values are fixed on the composite optimal value. The trade-off characteristic of this value is clearly shown when comparing the two curves of the depth of cut (*d*).

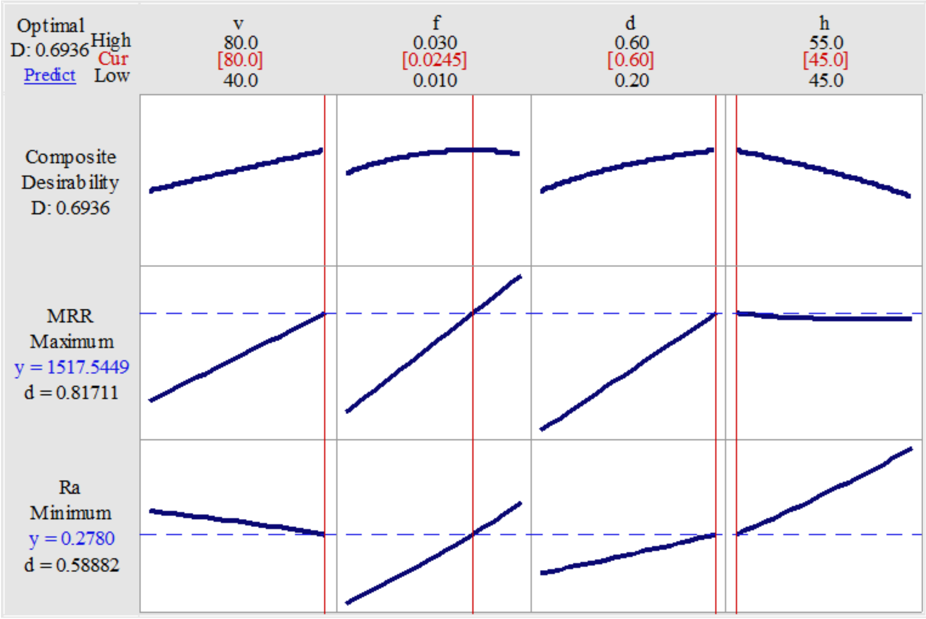


Figure 2. Optimization plot for surface roughness and *MRR*

## IV. Conclusion

This research mainly focused on optimizing the surface roughness and material removal rate in hard milling of hardened SKD 11 steel under nanofluid MQL condition by applying the Taguchi method and Response Surface methodology. The experimental results indicate that:

- The mathematical model of Response Surface methodology built to find the minimum value of the surface roughness can obtain the reliability of up to 98.28%.
- The feed rate is the most influential factor in *Ra* value, following by the depth of cut.
- The multi-objective optimization for the surface roughness *Ra* and the material removal rate *MMR* can only be achieved with a trade-off. The composite desirability value of 0.69 is acceptable as the *Ra* value is only 0.249 µm and the *MMR* value is 1498.09 mm$^3$/min.

## Conflict of Interest

The authors declare no conflict of interest.

## Author Contributions

The first author carried out the experiment, analyzed data, and edited the manuscript. The second author processed the data and wrote the manuscript.

## Acknowledgment

The authors wish to thank Thai Nguyen University of Technology. This work was supported by Thai Nguyen University of Technology.

## References

[1] J. L. Li, L. L. Jing, and M. Chen, "An FEM study on residual stresses induced by high-speed end-milling of hardened steel SKD11," *Journal of Materials Processing Technology*, vol. 209, pp. 4515-4520, 2009.

[2] W. Ming, Z. Zhang, S. Wang, H. Huang, Y. Zhang, Y. Zhang, et al., "Investigating the energy distribution of workpiece and optimizing process parameters during the EDM of Al6061, Inconel718, and SKD11," *The International Journal of Advanced Manufacturing Technology*, vol. 92, pp. 4039-4056, 2017.

[3] G. Zhang, Z. Zhang, W. Ming, J. Guo, Y. Huang, and X. Shao, "The multi-objective optimization of medium-speed WEDM process parameters for machining SKD11 steel by the hybrid method of RSM and NSGA-II," *The International Journal of Advanced Manufacturing Technology*, vol. 70, pp. 2097-2109, 2013.

[4] T. Tai and S. Lu, "Improving the fatigue life of electro-discharge-machined SDK11 tool steel via the suppression of surface cracks," *International Journal of Fatigue*, vol. 31, pp. 433-438, 2009.

[5] M. P. GC, G. R. Chate, M. B. Parappagoudar, and K. Gupta, "Studies on machining of hard materials," in *Machining of Hard Materials*, ed: Springer, 2020, pp. 25-51.

[6] T. V. Do, "Empirical model for surface roughness in hard milling of AISI H13 steel under nanofluid-MQL condition based on analysis of cutting parameters," *Journal of Mechanical Engineering Research and Developments*, vol. 43, pp. 89-94, 2020.

[7] V. P. Astakhov, "Machining of hard materials – definitions and industrial applications," pp. 1-32, 2011.

[8] E. Abele, B. Schramm, C. Berger, and H. Scheerer, "Dry machining using CrAlYN coated carbides," *Plasma Processes and Polymers*, vol. 4, pp. S622-S627, 2007.

[9] B. Denkena, J. Köhler, and B. Bergmann, "Development of cutting edge geometries for hard milling operations," *CIRP Journal of Manufacturing Science and Technology*, vol. 8, pp. 43-52, 2015.

[10] Q. C. Hsu, T. V. Do, and T. N. Nguyen, "Minimum quantity lubricant: A beneficial application in hard-milling of AISI H13 steel," *Universal Journal of Mechanical Engineering*, vol. 7, pp. 411-423, 2019.

[11] 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.

[12] A. K. Sharma, A. K. Tiwari, and A. R. Dixit, "Effects of Minimum Quantity Lubrication (MQL) in machining processes using conventional and nanofluid based cutting fluids: A comprehensive review," *Journal of Cleaner Production*, vol. 127, pp. 1-18, 2016.

[13] T. Walker, "MQL Handbook," ed: Unist company, 2013.

[14] T. V. Do, Q. M. Nguyen, and M. T. Pham, "Optimization of cutting parameters for improving surface roughness during hard

milling of AISI H13 steel," *Key Engineering Materials*, 2020, pp. 35-39.
[15] A. K. Sharma, A. K. Tiwari, and A. R. Dixit, "Progress of nanofluid application in machining: a review," *Materials and Manufacturing Processes*, vol. 30, pp. 813-828, 2015.
[16] P. Q. Dong, T. M. Duc, and T. T. Long, "Performance evaluation of MQCL hard milling of SKD 11 tool steel using MoS2 nanofluid," *Metals*, vol. 9, p. 658, 2019.
[17] J. P. Davim, *Green Manufacturing Processes and Systems*, Springer, 2013.
[18] T. Singh, P. Singh, J. Dureja, M. Dogra, H. Singh, and M. S. Bhatti, "A review of near dry machining/minimum quantity lubrication machining of difficult to machine alloys," *International Journal of Machining and Machinability of Materials*, vol. 18, pp. 213-251, 2016.
[19] Z. Hessainia, A. Belbah, M. A. Yallese, T. Mabrouki, and J. F. Rigal, "On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations," *Measurement*, vol. 46, pp. 1671-1681, 2013.
[20] E. Kilickap, A. Yardimeden, and Y. H. Çelik, "Mathematical modelling and optimization of cutting force, tool wear and surface roughness by using artificial neural network and response surface methodology in milling of Ti-6242S," *Applied Sciences*, vol. 7, p. 1064, 2017.
[21] T. V. Do and N. A. V. Le, "Optimization of surface roughness and cutting force in MQL hard-milling of AISI H13 steel," in *Proc. the International Conference, Advances in Engineering Research and Application*, ICERA 2018, 2019, pp. 448-454.
[22] A. Y. Nee, *Handbook of Manufacturing Engineering and Technology*, Springer, 2015.



**The-Vinh Do** is a lecturer of the Faculty of Mechanical Engineering and a researcher of Research Development Institute of Advanced Industrial Technology, Thai Nguyen University of Technology, Viet Nam. He graduated with a Ph.D. in mechanical engineering from National Kaohsiung University Applied Sciences, Taiwan. He has research in areas such as machining process optimization, nanoparticle application in metal cutting, cooling, and lubricant in machining. Besides, he is also interested in the field of optimization methods.

**Thanh-Dat Phan** is a lecturer in the Faculty of International Training, Thai Nguyen University of Technology, Viet Nam. He graduated with a Master of Science degree in Mechanical engineering from Feng Chia University, Taiwan. His researches mainly focus on Applications of Artificial Intelligent and also covers areas such as machining process optimization, nanoparticle application in metal cutting, cooling, and lubricant in machining.