A Comparison of RSM-DA and PSO-TOPSIS in optimizing the Finishing Turning of 9XC Steel under MQL Conditions

Thuy Duong Nguyen
School of Mechanical Engineering, Hanoi University of Science and Technology, Hanoi, Vietnam
duong.nguyenthuy@hust.edu.vn (corresponding author)

Khanh Huyen Nguyen
School of Mechanical Engineering, Hanoi University of Science and Technology, Hanoi, Vietnam
khanhhuyentto@gmail.com

Long Nguyen Ha
DHL-VNPT Express Co., Ltd, Vietnam
halong061295@gmail.com

Received: 20 February 2024 | Revised: 22 March 2024 | Accepted: 24 March 2024

 DOI: https://doi.org/10.48084/etasr.7100

ABSTRACT

This study compares the effectiveness of RSM-DA and PSO-TOPSIS in optimizing the finishing turning of 9XC steel under Minimum Quantity Lubrication. Experiments using the Box-Behnken Design were conducted. Depth of Cut (a_p), Feed Per Tooth (f_z), and Cutting Speed (V_c) served as the input parameters while the Material Removal Rate (MRR) and Surface Roughness (R_a) as the output responses. Fifteen experiments based on the Box-Behnken orthogonal array design were carried out. The RSM-DA method yielded optimized values of 3.35999 cm^3/min for MRR and 0.25367 µm for R_a when V_c, a_p, and f_z were set at 180 m/min, 0.2999 mm, and 0.06 mm/rev respectively. The Pareto solutions were obtained by PSO and TOPSIS identified the optimum set. The optimized MRR and R_a roughness values were found to be 4.320 cm^3/min and 0.474 µm, respectively when V_c = 180 m/min, a_p = 0.3 mm, and f_z = 0.10 mm/rev. The research results showed the suitability, strengths, and weaknesses of PSO-TOPSIS and RSM-DA for multi-objective optimization of the turning process of 9XC alloy under Minimum Quantity Lubrication conditions.

Keywords-MOPSO; TOPSIS; RSM-DA; optimization

I. INTRODUCTION

In manufacturing, finishing turning is crucial to producing high-quality components. However, traditional cooling and lubrication methods may be associated with both environmental and health issues as well as increased production costs. Occupational exposure to Metal Working Fluids (MWFs) may cause a variety of health effects. Furthermore, their use may lead to considerable environmental contamination. Therefore, the reduction of MWF usage is always considered [1]. Current research is focusing on Minimum Quantity Lubrication (MQL) as a sustainable green alternative to potentially damaging conventional approaches [3]. In MQL, a small quantity of lubricant is supplied along with high pressure air, resulting in an MQL mist at the cutting zone. This reduces the friction between the cutting tool and the workpiece [1]. Under flood cooling conditions, the amount of lubricating oil necessary for a quality product surface can be up to 60,000 ml per hour. MQL, only uses about 150 ml of liquid per hour [2]. Moreover, it has been shown to reduce the cutting forces therefore improving tool life [2]. The flood cooling lubricants can be re-circulated but this requires processing and maintenance, which raises costs [5]. Before MQL was employed, dry machining was used in conjunction with the flood cooling method. Dry machining produces a superior surface polish to coolant machining, but it has a few drawbacks such as inconsistent chip flush, high-temperature dissipation on the workpiece requiring special tooling to handle high temperatures, to name a few [6].

Product quality during processing is influenced by many factors. The Multi-Criteria Decision Analysis (MCDA) also known as Multi-Criteria Decision-Making (MCDM) is a suitable method to optimize and evaluate these factors [7]. Some commonly used MCDM methods are the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [4] the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) [8], the Analytic Hierarchy Process (AHP) [9], and the Complex Proportional Assessment (COPRAS) [10]. Those procedures give results that are less impacted by the subjective judgment of an expert [11]. Therefore, they are increasingly developed and applied to solve problems in many different fields such as healthcare, environmental and/or energy management, logistics, engineering and others.

This research aims to study the machining of high alloy 9XC steel, which is used to make highly wear-resistant complex-shaped tools and machine parts. The optimization of finishing turning of 9XC steel under MQL involves identifying the optimal cutting conditions to achieve desirable surface roughness (R_a) and material removal rate (MRR).

Metal machining process output is highly dependent on the input variables [12]. The cutting conditions that are investigated in this paper include cutting speed (V_c), depth of cut (a_p), and feed rate (f_z). The response variables studied are surface roughness (R_a) and Material Removal Rate (MRR). Several steel alloys similar to 9XC have already been studied. Authors in [13] examined the influence of machining parameters on surface roughness and dimensional accuracy when turning EN24 steel using Cubic Boron Nitride (CBN) cutting tools. They found that the spindle rotation speed has the greatest effect on surface roughness, while the depth of cut significantly influences the dimensional accuracy. Authors in [14] optimized the cutting parameters using MQL with nanoparticles, when turning AISI 4340. The experiment was carried out based on parameters derived from the Taguchi method and showed that the feed rate, depth of cut, and cutting speed affected the surface roughness in a decreasing direction when machining under MQL with nanoparticles. In addition, the MQL with nanoparticles was shown to be more effective than the flood cooling method.

This study aims to build on these foundational insights by applying RSM-DA [11] and PSO-TOPSIS in a novel context, offering a fresh perspective on optimizing machining parameters for 9XC steel under MQL conditions. The experiments herein are constructed using the Box-Behnken method [12]. Our primary objective is to minimize the surface roughness (R_a) while maximizing the MRR by identifying the optimal cutting conditions driven by the cutting speed (V_c), feed rate (f_z), and depth of cut (a_p). Such an optimization offers reduced production costs and improved product quality. This study endeavors not only to identify the most efficient cutting conditions for the turning of 9XC steel under MQL but also to contribute to the broader understanding of machining optimization. The outcome of this research is expected to offer significant insights for industrial applications, especially in contexts where both environmental sustainability and manufacturing efficiency are of paramount importance.

II. MATERIALS AND METHODS

A. Workpiece Material and Cutting Tool

The workpiece is a 9XC steel alloy which has been heat-treated to a hardness of 60 HRC (Figure 1). It has a 25 mm diameter and a 50 mm length. The chemical composition at 20 ^{o}C of 9XC steel is shown in Table I. Table II depicts the mechanical and physical characteristics of the alloy at 20 ^{o}C.

Fig. 1. 9XC alloy steel before and after heat treatment.

The 9XC steel alloy turning is performed on the Mori Seiki 253 CNC lathe. The workpiece is rough turned by insert KBN25M (Kyocera) and finishing turned by insert DCGT11T304 (CK), both made from CBN. CBN processes high hardness and superior thermal conductivity [15]. The tool holders used are SDOCR2020K11 and SDJCR2525M11 as shown in Figure 2.

Fig. 2. Carbide cutting tool for turning 9XC alloy steel.

TABLE I THE CHEMICAL COMPOSITION OF THE 9XC ALLOY

Element	Weight (%)
C	0.90
Si	1.50
Mn	0.55
Ni	0.38
S	0.15
P	0.02
Cr	1.15
Mo	0.18
W	0.16
V	0,15
Ti	0.03
Cu	0.25

TABLE II MECHANICAL AND PHYSICAL CHARACTERISTICS OF 9XC ALLOY AT 20^{0}C

Elastic modulus (GPa)	200-210
Elongation (%)	12
Poission's ratio	0.29
Tensile strength (MPa)	790
Yield strength (MPa)	445
Coefficient of thermal expansion (1/K)	1.2 × 10-5
Specific heat capacity (J/kg.K)	450
Thermal conductivity (W/m.K)	44.5

B. Experimental Design

In this research, the experiments were carried out in MQL conditions when turning on the CNC lathe. The MQL system consisted of an oil flow control assembly, a pneumatic pressure regulator valve, an oil tank with a capacity of 3 lt, a pipeline system, and an MQL nozzle. The layout of the MQL system with a CNC lathe is shown in Figure 3. The relevant specifications are shown in Table III. Appropriate testing of the system showed that the flow accuracy level achieved was more than 95%.

TABLE III SPECIFICATIONS OF THE MQL SYSTEM

Item	Specifications
Structure	2 nozzles
Metal cutting fluid	Treated vegetable oil
Flow	Q = 5 ÷ 500 ml/h
Air pressure	P = 1 ÷ 8 bar
Spray angle	$0 \div 45^o$

The experimental input parameters derived from the Taguchi experimental matrix, are cutting speed (V_c), depth of cut (a_p), and feed rate (f_z), each with three possible values. These were (60, 120, 180) m/min for V_c, (0.1, 0.2, 0.3) mm for a_p and (0.06, 0.08, 0.1) mm/rev for f_z. This strategic choice of values for the input parameters was designed to comprehensively evaluate the effects of varying cutting conditions on the machining outcome. At each test turn, the cutting depth remained constant at 0.5 mm for the rough turning while the depth of cut was changed for the finishing turning at each test turn (Table IV). The cutting length, coolant flow rate, and air pressure (for MQL) were fixed at 25 mm, 150 ml/h, and 4 bar, respectively.

C. Experimental Data Acquisition

After completing the turning, the surface roughness of the workpiece was measured using the Mitutoyo SV - 2100 roughness meter. Three measurements of surface roughness were performed at three different locations. Their mean value was assumed to be the surface roughness R_a of the workpiece shown in Table IV.

TABLE IV EXPERIMENTAL MACHINING PARAMETER VALUES AND RESULTS

Run	V_c (m/min)	f_z (mm/rev)	a_p (mm)	R_a (μm)	MRR (cm^3/min)
1	180	0.08	0.3	0.409	4.32
2	180	0.08	0.1	0.405	1.44
3	60	0.1	0.2	0.32	1.20
4	120	0.08	0.2	0.362	1.92
5	120	0.06	0.1	0.325	0.72
6	180	0.06	0.2	0.405	2.16
7	120	0.1	0.3	0.366	3.60
8	120	0.06	0.3	0.363	2.16
9	60	0.06	0.2	0.315	0.72
10	180	0.1	0.2	0.409	3.60
11	120	0.08	0.2	0.362	1.92
12	60	0.08	0.1	0.315	0.48
13	60	0.08	0.3	0.320	1.44
14	120	0.1	0.1	0.362	1.20
15	120	0.08	0.2	0.362	1.92

Fig. 3. MQL-assisted CNC lathe experimental setup.

D. RSM-DA Method

RSM-DA is a combination of RSM (Response Surface Methodology) and DA (Desirability Function Approach). RSM is a collection of mathematical and statistical methodologies used for modeling and analyzing complex systems. The main purpose of RSM is to identify the relationship between the input variables and the output variable, which is typically a measure of the system's performance. RSM is commonly used in experimental design and process optimization. DA, on the other hand, is a statistical method used for the classification and prediction of data. The main idea of DA is to identify a linear combination of factors that can discriminate between different groups or classes of data. DA is commonly used in pattern recognition and data analysis. The combination of RSM and DA in RSM-DA allows for the optimization and classification of complex systems with multiple variables and responses. The RSM part of the method creates a model that describes the connection between the input variables and the outcome variables, while the DA part of the method uses this model to classify the data into different groups based on the values of the input variables.

E. Combining of PSO-TOPSIS

PSO (Particle Swarm Optimization) is an optimization algorithm inspired by the behavior of bird flocks and social groups. The algorithm begins by considering a set of potential solutions to an optimization problem as particles. Each particle is, then, transferred through the search space and updated based on its own experience and that of its neighbors. The main idea of PSO is to enhance a candidate solution repeatedly with respect to a specific quality measure to optimize a problem. The algorithm works by preserving a pool of potential solutions and shifting these solutions about in the search space, using simple mathematical calculations.

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a decision-making procedure with multiple criteria that assists in determining the best option from a collection of accessible options.

The combined method PSO-TOPSIS has the advantage of improving solution accuracy albeit with a higher complexity, compared to using each method individually. It finds and selects the best solution with high accuracy while minimizing evaluation and selection errors.

III. RESULTS AND DISCUSSION

A. Predictive Models and Model Fitness

The regression analysis and model construction for R_a and MRR as functions of V_c, f_z, and a_p were conducted using the statsmodels [14] library in Python [15]. The results are shown below:

$$R_a = 0.2333 + 0.0007V_c + 0.03062f_z + 0.0637a_p \quad (1)$$

$$MRR = -3.84 + 0.016V_c + 24f_z + 9.6a_p \quad (2)$$

The regression analysis revealed that the MRR model, with an R^2 value of 0.923, could explain 92.3% of MRR variability. Similarly, the R_a model, with an R^2 value of 0.957, accounted for 95.7% of R_a variability.

The regression functions (1) and (2) were used to find the ideal set of cutting parameters V_c, f_z, and a_p. The multiple objective optimization problem for R_a and MRR involved estimating the $\{V_c, f_z, a_p\}$ that minimize R_a and maximize MRR under the following constrains:

$$\begin{cases} 60 \le V_c \le 180 \\ 0.06 \le f_z \le 0.1 \\ 0.1 \le a_p \le 0.3 \end{cases} \quad (3)$$

B. Optimization Results by RSM-DA

The desirability function approach converts each response into a dimensionless desirability value, ranging from 0 to 1.0, with 1.0 being the optimum value. The analysis reveals that there is an optimal cutting speed (V_c) that maximizes desirability, with a discernible peak indicating the preferred operating condition. As for the feed rate (f_z) and depth of cut (a_p), higher levels are favored to meet the combined objectives (Figure 4).

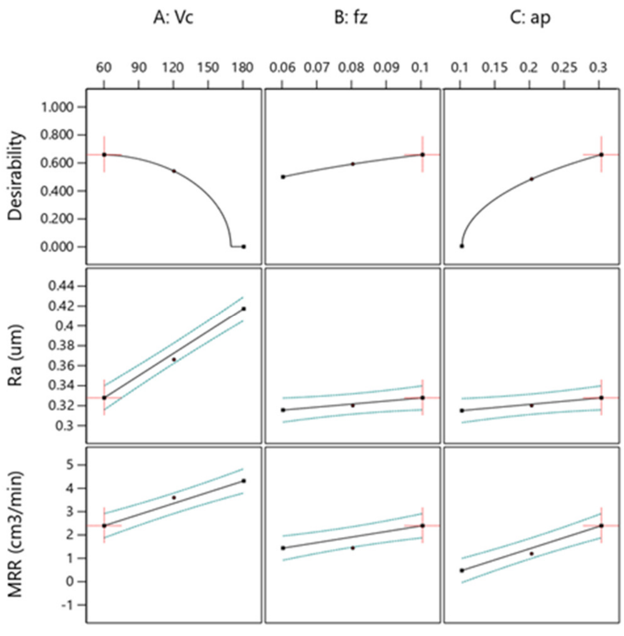

Fig. 4. Optimization results by the RSM-DA method.

Regarding surface roughness (R_a), the data indicates a direct relationship with both f_z and a_p. As one can see from Figure 4, increasing a_p and f_z contributes to a rougher surface finish. The impact of V_c on R_a is more pronounced and suggests a significant increase in R_a at higher speeds.

Regarding the Material Removal Rate (MRR), it responds positively to increases in V_c, f_z, and a_p, which aligns with expectations that more aggressive cutting conditions enhance material removal. The optimal settings would depend on the RI assigned to each objective in the desirability function. From this analysis, the optimal set of turning parameters $\{V_c, f_z, a_p\}$ are found to be 180 m/min, 0.06 mm/rev and 0.299 mm, respectively, corresponding to Ra = 0.2537 μm and MRR = 3.360 cm^3/min.

C. Optimization Results by PSO-TOPSIS

Two hundred possible optimization solutions were calculated by the PSO algorithm in Matlab. Three of them are, indicatively, presented in Table V.

TABLE V OPTIMIZATION SOLUTIONS BY PSO

Run	V_c	a_p	f_z	R_a	MRR	D_k^+	D_k^-	C_k^+	Ranking
A1	180.00	0.30	0.10	0.457	4.247	0.0018	0.0414	0.9581	11
…									
A125	180.00	0.30	0.10	0.474	4.320	0.0000	0.0430	1.0000	1
…									
A200	179.71	0.30	0.06	0.274	3.446	0.0216	0.0251	0.5372	105

The entropy weights computed using the TOPSIS method, for Ra and MRR were $w_1 = 0.427$ and $w_2 = 0.573$, respectively. The ideal solution of the TOPSIS approach corresponds to the highest C_k^+ value. As seen from Table V, the best selection of cutting parameters comes from run 125 (i.e. V_c = 180 m/min, a_p = 0.3 mm, and f_z = 0.10 mm/rev). Then, the R_a becomes 0.474 μm and the MRR, 4.320 cm^3/min.

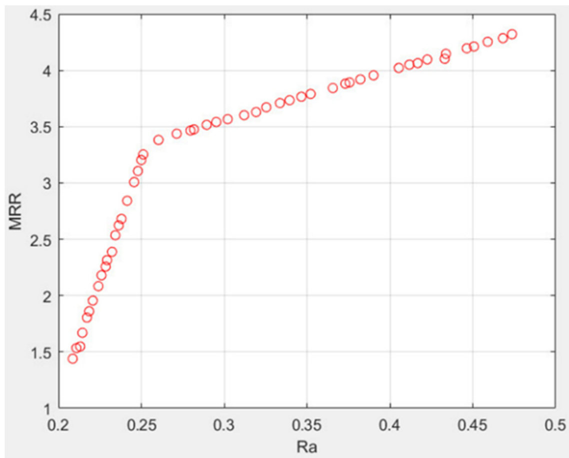

Fig. 5. Pareto front curve of efficient solutions.

The non-linear relationship indicated by the Pareto φront (Figure 5) suggests that reducing surface roughness might reduce the MRR. The 'bending' part of the curve highlights the trade-off between enhanced cutting efficiency and lower surface roughness. The upper right region, where both R_a and

MRR are high, may represent more aggressive cutting conditions optimizing both factors. This Pareto Front provides valuable insights for selecting cutting conditions, balancing between surface finish and material removal based on specific production requirements.

IV. CONCLUSION

In this research, the optimization of finishing turning of 9XC steel under Minimum Quantity Lubrication (MQL) conditions was investigated, with RSM-DA and PSO-TOPSIS being the two optimization techniques employed. The motivation was driven by the urgent need to reduce the environmental impact and enhance manufacturing efficiency in the machining industry. Our aim was to identify the most effective method by which optimal surface roughness and material removal rate could be achieved. These factors are crucial for the quality and cost-effectiveness of the manufacturing process.

As seen in Table VI, both RSM-DA and PSO-TOPSIS are highly suitable for the multi-objective optimization challenge posed by the turning process of 9XC steel.

TABLE VI COMPARISON OF OPTIMIZATION RESULTS OBTAINED BY RSM-DA AND PSO-TOPSIS

Method	Optimal πarameters set			Response	
	V_c	f_z	a_p	R_a	MRR
RSM-DA	180.00	0.06	0.299	0.25467	3.3599
PSO-TOPSIS	180.00	0.10	0.300	0.47400	4.3200
Comparison between the two methods				↑46.3%	↑22.2%

Through the detailed experimental procedure and rigorous analysis, it was determined that each approach offers valuable insights, possessing unique strengths and applicability depending on the specific optimization goals. The RSM-DA method was readily utilized to pinpoint where the optimal balance between the MRR and the surface roughness is achieved. Furthermore, as the MRR and surface roughness are, often, conflicting objectives in machining processes, the investigation into the complex trade-offs between them was efficiently carried out by PSO-TOPSIS.

ACKNOWLEDGMENT

This research is funded by the Hanoi University of Science and Technology (HUST) under project number T2022-PC-014.

REFERENCES

[1] "DIN 69090-1:2011-12, MMS-Bearbeitungstechnologie_- Teil_1: Begriffe und Definitionen." Beuth Verlag GmbH, https://doi.org/10.31030/1812924.

[2] B. Sen, M. Mia, G. M. Krolczyk, U. K. Mandal, and S. P. Mondal, "Eco-Friendly Cutting Fluids in Minimum Quantity Lubrication Assisted Machining: A Review on the Perception of Sustainable Manufacturing, " *International Journal of Precision Engineering and Manufacturing-Green Technology*, vol. 8, no. 1, pp. 249–280, Jan. 2021, https://doi.org/10.1007/s40684-019-00158-6.

[3] P. Sandhu, G. S. Goindi, and S. Chopra, "Evaluation of dry machining, air-cooling conditions and MQL techniques as sustainable manufacturing processes for turning of aluminium 6061," *Materials Today: Proceedings*, vol. 68, pp. 791–798, Jan. 2022, https://doi.org/10.1016/j.matpr.2022.06.154.

[4] A. Tecle and L. Duckstein, "Concepts of multicriterion decision making"in J.J. Bogardi & H.P. Nachtnebel, (Eds.) (1993). Multicriteria decision making in water resources management. IHP of UNESCO, Paris, pp 33–62, 1994

[5] V. C. Nguyen, T. D. Nguyen, and D. H. Tien, "Cutting Parameter Optimization in Finishing Milling of Ti-6Al-4V Titanium Alloy under MQL Condition using TOPSIS and ANOVA Analysis," *Engineering, Technology & Applied Science Research*, vol. 11, no. 1, pp. 6775–6780, Feb. 2021, https://doi.org/10.48084/etasr.4015.

[6] G.-H. Tzeng and J.-J. Huang, "TOPSIS and VIKOR," in *Multiple Attribute Decision Making*, Chapman and Hall/CRC, 2011, https://doi.org/10.1201/b11032.

[7] J. Becker, A. Becker, and W. Sałabun, "Construction and Use of the ANP Decision Model Taking into Account the Experts' Competence," Procedia Computer Science, vol. 112, pp. 2269–2279, Jan. 2017, https://doi.org/10.1016/j.procs.2017.08.145.

[8] R. Krishankumar, H. Garg, K. Arun, A. Saha, K. S. Ravichandran, and S. Kar, "An integrated decision-making COPRAS approach to probabilistic hesitant fuzzy set information," *Complex & Intelligent Systems*, vol. 7, no. 5, pp. 2281–2298, Oct. 2021, https://doi.org/10.1007/s40747-021-00387-w.

[9] M. H. El-Axir, M. M. Elkhabeery, and M. M. Okasha, "Modeling and Parameter Optimization for Surface Roughness and Residual Stress in Dry Turning Process," *Engineering, Technology & Applied Science Research*, vol. 7, no. 5, pp. 2047–2055, Oct. 2017, https://doi.org/10.48084/etasr.1560.

[10] T. P. Gundarneeya, V. D. Golakiya, S. D. Ambaliya, and S. H. Patel, "Experimental investigation of process parameters on surface roughness and dimensional accuracy in hard turning of EN24 steel," *Materials Today: Proceedings*, vol. 57, pp. 674–680, Jan. 2022, https://doi.org/10.1016/j.matpr.2022.02.104.

[11] P. B. Patole and V. V. Kulkarni, "Optimization of Process Parameters based on Surface Roughness and Cutting Force in MQL Turning of AISI 4340 using Nano Fluid," *Materials Today: Proceedings*, vol. 5, no. 1, Part 1, pp. 104–112, Jan. 2018, https://doi.org/10.1016/j.matpr.2017.11.060.

[12] V. Canh Nguyen, T. Duong Nguyen, and V. Thao Le, "Optimization of sustainable milling of SKD11 steel under minimum quantity lubrication," Proceedings *of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, vol. 237, no. 3, pp. 907–916, Jun. 2023, https://doi.org/10.1177/09544089221110978.

[13] S. L. C. Ferreira et al., "Box-Behnken design: An alternative for the optimization of analytical methods," *Analytica Chimica Acta*, vol. 597, no. 2, pp. 179–186, Aug. 2007, https://doi.org/10.1016/j.aca.2007.07.011.

[14] N. Qian, Y. Fu, F. Jiang, W. Ding, J. Zhang, and J. Xu, "CBN grain wear during eco-benign grinding of nickel-based superalloy with oscillating heat pipe abrasive wheel," *Ceramics International*, vol. 48, no. 7, pp. 9692–9701, Apr. 2022, https://doi.org/10.1016/j.ceramint.2021.12.170.

[15] S. Seabold and J. Perktold, "Statsmodels: Econometric and Statistical Modeling with Python," *Proceedings of the 9th Python in Science Conference*, vol. 2010, Jan. 2010.