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# USING VIKOR AND RSM-DA IN THE OPTIMIZATION OF DRY TURNING OF 9XC STEEL

**Nhat-Tan Nguyen[1], Anh-Thang Nguyen[1], Tien-Sy Nguyen[2]*, Nhu-Trang Le[3]**

[1] Mechanical Technology Department, Vietnam-Japan Center, Hanoi University of Industry, Hanoi, Vietnam
[2] Mechanical Technology Department, School of Mechanical and Automotive Engineering, Hanoi University of Industry, Hanoi, Vietnam
[3] Manufacturing Technology Department., Faculty of Mechanical Engineering, University of Economics - Technology for Industries, Hanoi, Vietnam

* nguyentiensy@haui.edu.vn

*Dry turning is an effective method for reducing the production costs and environmental impact of machining processes. In this study, the effect of cutting speed ($V_c$), feed rate ($f_z$), and depth of cut ($a_p$) on the surface roughness ($R_a$) and material removal rate (MRR) of 9XC steel during dry turning was investigated. A Box-Behnken experimental design was employed to analyze the main effects and interaction effects of these cutting parameters. In this research, the combining Response Surface Methodology - Desirability Approach (RSM-DA) and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method were both employed for solving multiple objective optimization problems, and their performance was compared. The results from both methods can be assessed based on their ability to identify the optimal set of parameters that simultaneously optimize surface quality and production rate, as well as their computational efficiency and ease of implementation. Both RSM-DA and VIKOR have been found effective for solving multi-objective optimization problems, such as optimizing cutting parameters in dry turning. While RSM-DA is a statistical tool that combines multiple objectives into a single function, VIKOR is a decision-making method that ranks alternatives based on multiple criteria. The choice of which method to use depends on the specific requirements of the problem and the availability of resources for implementation. The research results show that both VIKOR and RSM-DA are suitable for solving the multi-objective optimization problem of the turning process. According to the VIKOR method, the optimum cutting conditions were found to be a cutting speed $V_c$ of 120 m/min, a depth of cut $a_p$ of 0.1 mm a feed rate $f_z$ of 0.06 mm/rev, and, which resulted in a surface roughness of 0.209 um and a material removal rate of 0.72 cm$^3$/min. Meanwhile, RSM-DA predicts the optimal $R_a$ and MRR values of 0.254 um and 3.36 cm$_3$/min, respectively; corresponding to the Vc of 180m/min, $f_z$ of 0.06mm/rev and $a_p$ of 0.3mm; That means, the increasing the value of surface roughness by 21.5% will increase the MRR by 366.7%. The findings of this study can provide guidance for selecting the appropriate cutting parameters for dry turning of 9XC steel to achieve desired surface roughness $R_a$ and material removal rate MRR in the specific case.*

*Keywords: response surface methodology, RSM-DA, VIKOR, dry cutting, optimization, DFA*

## 1 INTRODUCTION

The machining process of steel involves the removal of material to create the desired shape and size [1]. The traditional cutting processes like as milling, turning, drilling…are the most popular. Turning, in particular, is a widely used machining process that involves the rotation of a workpiece combining with the suitable cutting tool to remove material from the workpiece surface. The selection of cutting parameters, tool geometry, and lubrication technique largely determines the efficiency of the turning process. Historically, cutting fluids have been conventionally used during turning to help with chip removal and minimize heat generated during the cutting process [2]. However, the use of cutting fluids can pose environmental and health hazards, and their disposal can also cause pollution [3]. This has led to the development of dry turning as an alternative to the conventional lubrication method. Dry turning involves the use of a cutting tool without the application of cutting fluids or other coolants [4]. This method is becoming increasingly popular due to its numerous advantages, including reduced costs associated with coolant purchase, disposal, and maintenance. Additionally, dry turning results in a cleaner and safer working environment due to the absence of cutting fluid mist, and the improved visibility of the cutting process [5], [6].

The practice of dry cutting has been widely adopted in a range of cutting operations, such as milling, turning,ect. In a study by Khatri et al. [7], dry cutting was applied in the milling of aluminium alloy and compared with traditional wet-cutting methods. According to the results, dry cutting has led to higher material removal rates and lower cutting forces, thus improving surface quality and reducing tool wear.

Wu Ze et al. [8] conducted a study that revealed the benefits of textured tools with elliptical grooves on their rake face during machining operations. These tools provide self-lubrication, which has resulted in a decrease of both the tool-chip friction coefficient and the chip thickness ratio. Studies have also indicated that textured tools can prolong tool life compared to conventional tools. However, the effectiveness of these self-lubricating textured tools is influenced by the specific cutting parameters utilized during the machining process.

Overall, the application of dry cutting has shown promising results in various machining operations, and further research is needed to determine its feasibility in different materials and cutting conditions.

The aim of this study was to develop a regression model between technological parameters and surface roughness and material removal rate (MRR) during the dry turning process of 9XC steel. Based on this, multi-objective optimization methods RSM-DA and VIKOR [9] were also used to simultaneously optimize $R_a$ and MRR. The optimization results from these two methods were compared and evaluated to determine the advantages, disadvantages, and suitability of each method in the multi-objective optimization process of cutting in general and turning in particular. Therefore, recommendations can be made for researchers or manufacturers when dry-turning 9XC steel.

## 2 MATERIALS AND METHOD

### 2.1 Workpiece material and cutting tool.

The workpiece material used is 9XC alloy steel that has been heat-treated to achieve a hardness of 60 HRC. The workpiece is prepared with a diameter of 25mm and a length of 50mm (Fig.1b). The chemical makeup of 9XC alloy steel is characterized by its high carbon and high chromium content, making it a durable and high-performing tool steel. The composition includes carbon in the range of 0.85-0.95%, chromium in the range of 8.00-9.50%, molybdenum in the range of 0.20-0.50%, vanadium in the range of 0.15-0.30%, and silicon in the range of 0.15-%.

Turning of 9XC alloy steel was performed on a Mori Seiki 253 CNC lathe (Fig.1a). The rough turning was carried out using a KBN25M insert (Kyocera), and the finish turning was done with a DCGT11T304 insert (CK), both coated with cubic boron nitride (CBN). CBN is known for its high hardness and superior thermal conductivity [10]. The tool holders used were coded SDOCR2020K11 and SDJCR2525M11.

(a) Experimental machine (b) Experimental workpieces

Fig. 1. Experimental setup

### 2.2 Experimental data acquisition

Following the turning process, the workpiece specimens were evaluated for surface roughness $R_a$ using surftest SV-2100 surface roughness tester (Mitutoyo, Japan). The tester's probe was moved along a length of 25mm on the surface of the machined blank to calculate and record the surface roughness data. To ensure accuracy, the surface roughness was measured three times at three different positions, and the final result was the average value of the three measurements. Figure 2 illustrates the image of the turned workpieces and the measurement process, while Table 1 presents the experimental results data.

Fig. 2. Roughness testing and measurement result

Table 1. Data pertaining to the experimental machining parameters and results

| Exp. No. | Cutting speed (m/min) | Feed (mm/rev) | Depth of cut (mm) | $R_a$ (µm) | MRR ($cm^3$/min) |
|---|---|---|---|---|---|
| 1 | 180 | 0.08 | 0.3 | 0.42 | 4.32 |
| 2 | 180 | 0.08 | 0.1 | 0.29 | 1.44 |
| 3 | 60 | 0.1 | 0.2 | 0.47 | 1.2 |
| 4 | 120 | 0.08 | 0.2 | 0.34 | 1.92 |
| 5 | 120 | 0.06 | 0.1 | 0.21 | 0.72 |
| 6 | 180 | 0.06 | 0.2 | 0.22 | 2.16 |
| 7 | 120 | 0.1 | 0.3 | 0.48 | 3.6 |
| 8 | 120 | 0.06 | 0.3 | 0.21 | 2.16 |
| 9 | 60 | 0.06 | 0.2 | 0.30 | 0.72 |
| 10 | 180 | 0.1 | 0.2 | 0.43 | 3.6 |
| 11 | 120 | 0.08 | 0.2 | 0.31 | 1.92 |
| 12 | 60 | 0.08 | 0.1 | 0.32 | 0.48 |
| 13 | 60 | 0.08 | 0.3 | 0.33 | 1.44 |
| 14 | 120 | 0.1 | 0.1 | 0.44 | 1.2 |
| 15 | 120 | 0.08 | 0.2 | 0.46 | 1.92 |

### 2.3 Multi-response optimization

In this study, to solve this Multiple objective Optimization (MO) problem, two methods including VIKOR and DFA were used, and their obtained results will be compared with each other. In this experimental research, we will be discussing multi-attribute optimization, which can be described as follows:

$$find\ x = [V_c, f_z, a_p]\, to\ minimize\ R_a\ and\ maximize\ MRR \tag{1}$$

$$\text{Where: } \begin{cases} 60 \le V_c \le 180 \\ 0.06 \le f_z \le 0.08 \\ 0.1 \le a_p \le 0.3 \end{cases} \tag{2}$$

#### 2.3.1 VIKOR method

The VIKOR method was originally designed for multi-criteria optimization of complex systems. This method calculates the compromise ranking list and solution, as well as weight stability intervals for preference stability based on the initial weights provided. The method's development started with the $L_{p\text{-metric}}$ criterion form, expressed as follows:

$$L_{p,k} = \left\{\sum_{j=1}^{n}\left[\frac{w_j\left(f_j^* - f_{kj}\right)}{f_j^* - f_j^-}\right]^p\right\}^{\frac{1}{p}}, \quad 1 \le p \le \infty;\ k = 1, 2, \ldots, n \tag{3}$$

The VIKOR method aims to achieve the goal of obtaining the maximum group utility for $\min_k S_k$ (represented as an average gap when p=1) and the minimum individual regret of the "opponent" for $\min_k S_k$. To formulate a ranking measure that satisfies these objectives, the method uses $L_{1,k}$ and $L_{\infty,k}$. The compromise solution, denoted as $F^c$, is a feasible solution that is closest to the ideal $F^*$. The method establishes compromise through mutual concessions, with $\Delta f_1 = f_1^* - f_1^c$ and $\Delta f_2 = f_2^* - f_2^c$. The compromise ranking ordering in the VIKOR method follows the steps outlined below:

$$f_j^* = \max_k f_{kj} \tag{4}$$

$$f_j^- = \min_k f_{kj} \tag{5}$$

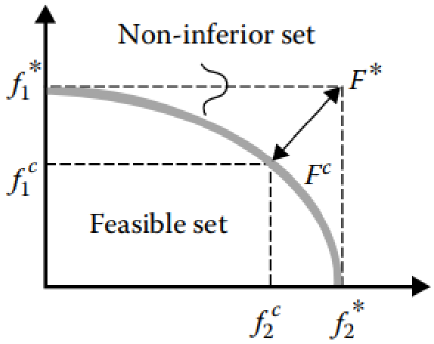


Fig. 3. Ideal solution and compromise [11]

**Step 2:** The values for $S_k$ and $R_k$ are determined through the application of the following mathematical expressions (k = 1, 2,…, n)

$$S_k = \sum_{j=1}^{m} w_j \frac{|f_j^* - f_{kj}|}{|f_j^* - f_j^-|} \tag{6}$$

$$R_k = \max_j \left\{ \frac{|f_j^* - f_{kj}|}{|f_j^* - f_j^-|}, j = 1, 2, \dots, m \right\} \tag{7}$$

The weights of criteria, which represent their relative importance, are denoted as $w_j$.

**Step 3:** The value of $Q_k$ is computed using the following relation (k = 1, 2,…, n):

$$R_k = \max_j \left\{ \frac{|f_j^* - f_{kj}|}{|f_j^* - f_j^-|}, j = 1, 2, \dots, m \right\} \tag{8}$$

$$Q_k = v \frac{S_k - S^*}{S^- - S^*} + (1 - v) \frac{R_k - R^*}{R^- - R^*} \tag{9}$$

k = 1, 2, …, m (alternatives)

where

$$S^* = \min_k S_k, \qquad S^- = \max_k S_k \tag{10}$$

$$R^* = \min R_j, \qquad R^- = \max R_j \tag{11}$$

A weight parameter, denoted as v, is introduced in the VIKOR method to represent the strategy of "the majority of criteria" or "the maximum group utility". In this study, the value of *v* is set to 0.5.

**Step 4:** The values of S, R, and Q are sorted in decreasing order to obtain three ranking lists.

**Step 5:** The alternative $(a_1)$ is recommended as the compromise solution if it is ranked the best by the measure Q (minimum), provided that the following two conditions are met.

***Condition 1:*** "Acceptable advantage"

$$Q(a_2) - Q(a_1) \geq DQ \tag{12}$$

$$DQ = \frac{1}{J-1} \tag{13}$$

Let *a'* be the alternative ranked second on the list by Q, where 'J' represents the total number of alternatives.

***Condition 2:*** "Acceptable stability in decision making"

For a compromise solution to be considered stable in a decision-making process, alternative $a_1$ must be the highest-ranked option according to S and/or R values, in addition to being the best-ranked according to Q. The decision-making process may involve voting by majority rule, where a threshold $v > 0.5$ must be reached, or by consensus, where *v* is approximately 0.5, or with a vote, where ($v < 0.5$). The weight of the decision-making strategy is determined by the majority of criteria or the maximum group utility.

In cases where the conditions mentioned above are not met, it may be necessary to consider a set of compromise solutions. For instance, if only condition 2 is not met, alternatives $a_1$ and $a_2$ may be recommended. If condition 1 is not met, a set of alternatives including a1, a2, and possibly up to a maximum of a(n) may be suggested, where a(n) is the alternative that satisfies the relation $Q(a_n) - Q(a_1) < DQ$ for maximum n, based on the proximity of their positions.

The best alternative is determined based on the lowest value of *Q*, and it is ranked at the top of the list. The final result of the ranking process is a list of compromise alternatives, along with the corresponding compromise solution that corresponds to the "advantage rate".

### *2.3.2 RSM-DA:*

RSM-DA [12], [13] is a combination of both RSM (Response Surface Method) and DFA (Desirability Function Approach) methods, which are used to optimize the process parameters for achieving the desired performance in the process. RSM is used to build a response surface model to predict the response variables based on the input variables, while DFA is used to optimize the input variables based on multiple desirable criteria. Multi-objective optimization techniques commonly use combining Response Surface Methodology with Desirability technique (RSM-DA). It is used to optimize a response function that has multiple input variables, such as the process parameters of a cutting operation. In this method, a desired function (D) is constructed based on the requirements and preferences of the user. Each desired value, such as surface roughness $R_a$, and Material Removal Rate MRR, corresponds to a unique set of process parameters, which are converted into a single desired value $d_i$. The value of $d_i$ is calculated using formulas (14) and (15).

$$d_i(y_i) = \begin{cases} 0, y_i < L \\ \left(\frac{y_i - L}{H - L}\right)^r & , L \le y_i \le H \\ 1, y_i \ge H \end{cases} \quad (14)$$

$$d_i(y_i) = \begin{cases} 0, y_i < L \\ \left(\frac{H - y_i}{H - L}\right)^r & , L \le y_i \le H \\ 1, y_i > H \end{cases} \quad (15)$$

In these formulas, L and H correspond to the low and high values within the value range of the parameters $y_i$.

In this experimental study, these are the threshold values of $R_a$, and MRR. And r is a parameter defined by the user (r>0) to describe the shape of the corresponding $d_i$.

In that case, the value of D is calculated using formula (13):

$$D = \left(\prod_{i=1}^{n} D_i^{w_i}\right)^{\frac{1}{\sum w_i}} \quad (16)$$

Where, $w_i$ is the weight set, $\sum w_i = 1$, i=1÷n

## *3 RESULTS AND DISCUSSION*

### *3.1 Predictive models and model fitness*

The following equation represents the fully developed model of $R_a$ and MRR, which were generated using Design Expert (version 13). The Quandric model is chosen to generate a model of $R_a$ because of its higher reliability compared to other models. The comparison results between regression models obtained by Linear, 2FI, Quadratic and Cubic are shown in table 3.

$$R_a = 0.3867 - 0.0017V_c + 0.1047f_z + 0.0216a_p + 0.0018V_cf_z + 0.0247V_ca_p - 0.0054V_c^2 - 0.0064f_z^2 - 0.0481a_p^2 \quad (17)$$

$$MRR = 1.92 + 0.9600V_c + 0.4800f_z + 0.9600a_p + 0.2400V_cf_z + 0.2400f_za_p + 0.4800V_ca_p \quad (18)$$

Table 2. Regression models for response $R_a$

| Source | Sequential p-value | Lack of Fit p-value | Adjusted $R^2$ | Predicted $R^2$ | |
|---|---|---|---|---|---|
| Linear | < 0.0001 | 0.0119 | 0.8454 | 0.7693 | |
| 2FI | 0.5302 | 0.0103 | 0.8362 | 0.6255 | |
| Quadratic | 0.0099 | 0.0426 | 0.9683 | 0.8236 | Suggested |
| Cubic | 0.0426 | | 0.9977 | | Aliased |

While the regression model of MRR was generated based on the Linear model, Table 4.

Table 3. Regression models for response MRR

| Source | Sequential p-value | Lack of Fit p-value | Adjusted $R^2$ | Predicted $R^2$ | |
|---|---|---|---|---|---|
| Linear | < 0.0001 | | 0.9021 | 0.8353 | Suggested |
| 2FI | - | - | 1 | - | |
| Quadratic | - | - | - | - | |
| Cubic | - | - | - | - | Aliased |

### 3.2 Effects of dry-turning pameters on $R_a$ and MRR

Table 1. Analysis of Variance (ANOVA) for a quadratic model of the response variable $R_a$

| Source | SS* | df | MS** | F-value | p-value | |
|---|---|---|---|---|---|---|
| Model | 0.1029 | 9 | 0.0114 | 48.58 | 0.0002 | significant |
| $V_c$ | 0.0000 | 1 | 0.0000 | 0.1023 | 0.7621 | |
| $f_z$ | 0.0877 | 1 | 0.0877 | 372.49 | < 0.0001 | |
| $a_p$ | 0.0037 | 1 | 0.0037 | 15.93 | 0.0104 | |
| $V_c f_z$ | 0.0000 | 1 | 0.0000 | 0.0539 | 0.8256 | |
| $V_c . a_p$ | 0.0024 | 1 | 0.0024 | 10.37 | 0.0235 | |
| $f_z . a_p$ | 0.0005 | 1 | 0.0005 | 1.92 | 0.2246 | |
| $V_c^2$ | 0.0001 | 1 | 0.0001 | 0.4524 | 0.5310 | |
| $f_z^2$ | 0.0002 | 1 | 0.0002 | 0.6415 | 0.4595 | |
| $a_p^2$ | 0.0085 | 1 | 0.0085 | 36.24 | 0.0018 | |
| Residual | 0.0012 | 5 | 0.0002 | | | |
| Lack of Fit | 0.0011 | 3 | 0.0004 | 22.66 | 0.0426 | significant |
| Pure Error | 0.0000 | 2 | 0.0000 | | | |
| Cor Total | 0.1041 | 14 | | | | |

The Model F-value of 48.58 indicates the model's significance, with only a 0.02% probability of such a high F-value occurring due to noise. P-values below 0.0500 demonstrate significant model terms, including $f_z$, $a_p$, $V_c . a_p$ and $a_p^2$, whereas values exceeding 0.1000 suggest insignificant model terms. In cases where the model contains several insignificant terms (excluding those required for hierarchy), simplifying the model may be advantageous. A significant lack of fit, as indicated by a Lack of Fit F-value of 22.66 and a probability of 4.26% for such a high F-value occurring due to noise, is unfavourable as it suggests that the model may not fit the data accurately. The goal is to achieve an accurate model fit, which may require further adjustments to the model to address the lack of fit.

### 3.3 Optimization results

#### 3.3.1 VIKOR method

The multiple objective optimization problems were solved using the VIKOR method, the result is shown in Table 5.

The compromise solution was selected after analyzing the $Q_k$ values of all available alternatives.

The first, *DQ* values were obtained by Eq. (13):

$$DQ = \frac{1}{j-1} = \frac{1}{15-1} = 0.07142$$

$$Q(a_2)\text{-}Q(a_1)= 0.044\text{-}0.012=0.4473 > DQ$$

Based on Eq.(12), condition 1-Acceptable advantage is satisfied, meaning. According to the calculation results using the VIKOR method, the optimal solution is the 6th alternative with corresponding cutting parameters ($V_c$, $f_z$, $a_p$) of 120 m/min, 0.06 (mm/tooth), and 0.1 (mm), respectively. This corresponds to surface roughness values of $R_a$ = 0.201 µm, and machining productivity of MRR = 0.720 ($cm^3$/h).

Table 2. Multiple objective optimization problems can be solved using the VIKOR method

| Alt* | $V_c$ | $f_z$ | $a_p$ | $R_a$ | MRR | $S_k$ | $R_k$ | $Q_k$ | Rank |
|---|---|---|---|---|---|---|---|---|---|
| | *(m/min)* | *(mm/tooth)* | *(mm)* | *(µm)* | *($cm^3$/min)* | | | | |
| 1 | 180 | 0.06 | 0.2 | 0.283 | 2.160 | 3.672 | 3.539 | 0.428 | 12 |
| 2 | 120 | 0.1 | 0.1 | 0.408 | 1.200 | 2.158 | 1.797 | 0.195 | 4 |

| Alt* | $V_c$ | $f_z$ | $a_p$ | $R_a$ | MRR | $S_k$ | $R_k$ | $Q_k$ | Rank |
|---|---|---|---|---|---|---|---|---|---|
| 3 | 120 | 0.06 | 0.3 | 0.235 | 2.160 | 3.586 | 3.539 | 0.422 | 11 |
| 4 | 60 | 0.1 | 0.2 | 0.464 | 1.200 | 2.259 | 1.797 | 0.202 | 5 |
| 5 | 180 | 0.1 | 0.2 | 0.485 | 3.600 | 6.650 | 6.150 | 0.828 | 14 |
| **6** | **120** | **0.06** | **0.1** | **0.209** | **0.720** | **0.927** | **0.927** | **0.044** | **1** |
| 7 | 60 | 0.08 | 0.3 | 0.340 | 1.440 | 2.471 | 2.233 | 0.248 | 7 |
| 8 | 60 | 0.06 | 0.2 | 0.269 | 0.720 | 1.035 | 0.927 | 0.052 | 3 |
| 9 | 60 | 0.08 | 0.1 | 0.351 | 0.480 | 0.748 | 0.491 | 0.012 | 2 |
| 10 | 120 | 0.08 | 0.2 | 0.391 | 1.920 | 3.433 | 3.103 | 0.380 | 10 |
| 11 | 180 | 0.08 | 0.3 | 0.365 | 4.320 | 7.740 | 7.456 | 1.000 | 15 |
| 12 | 120 | 0.1 | 0.3 | 0.477 | 3.600 | 6.636 | 6.150 | 0.827 | 13 |
| 13 | 180 | 0.08 | 0.1 | 0.277 | 1.440 | 2.355 | 2.233 | 0.240 | 6 |
| 14 | 120 | 0.08 | 0.2 | 0.383 | 1.920 | 3.418 | 3.103 | 0.378 | 8 |
| 15 | 120 | 0.08 | 0.2 | 0.387 | 1.920 | 3.425 | 3.103 | 0.379 | 9 |
| **Best** $f_j^*$ | | | | 0.209 | 4.320 | 0.748 | 0.491 | | |
| **Worst** $f_j^-$ | | | | 0.485 | 0.480 | 7.740 | 7.456 | | |

*Alt*: Alternative*

It is noticeable that 0.480 cm³/min is the highest value of MRR among the 15 experiments. The optimal result calculated by the VIKOR method has chosen the option with the best suitable MRR at 0.720 cm³/h to achieve the lowest surface roughness value $R_a$=0.201 µm, in comparison with the 11th alternative, where the MRR is highest, at 4.320 cm³/h, an increase of 800%. Meanwhile, the surface roughness value rises to 0.365 µm.

### *3.3.2 RSM-DA method*

The calculation results using the DFA method by Design Expert software (version 13) are presented in table 6 and figure 4. Thus, the calculated set of optimized parameters corresponds to $V_c$ = 180 m/min, $f_z$ = 0.06 (mm/tooth), and $a_p$ = 0.3 mm. These parameters resulted in $R_a$ = 0.254 µm and MRR = 3.36 cm³/h

Table 3. Multiple objective optimization problems solving by RSM-DF method

| No. | $V_c$ *(m/min)* | $f_z$ *(mm/tooth)* | $a_p$ *(mm)* | $R_a$ *(µm)* | MRR *(cm³/min)* | D | Ranking |
|---|---|---|---|---|---|---|---|
| 1 | 180 | 0.06 | 0.3 | 0.254 | 3.36 | 0.792 | 1 |
| 2 | 180 | 0.06 | 0.3 | 0.254 | 3.36 | 0.792 | 2 |
| 3 | 179.48 | 0.06 | 0.3 | 0.254 | 3.35 | 0.79 | 3 |
| 4 | 179.61 | 0.06 | 0.3 | 0.255 | 3.359 | 0.79 | 4 |
| 5 | 180 | 0.06 | 0.3 | 0.257 | 3.382 | 0.79 | 5 |
| 6 | 180 | 0.06 | 0.299 | 0.256 | 3.359 | 0.789 | 6 |
| 7 | 179.999 | 0.061 | 0.3 | 0.259 | 3.393 | 0.788 | 7 |
| 8 | 178.561 | 0.06 | 0.3 | 0.254 | 3.331 | 0.788 | 8 |
| 9 | 180 | 0.06 | 0.299 | 0.257 | 3.368 | 0.788 | 9 |
| 10 | 180 | 0.061 | 0.3 | 0.26 | 3.4 | 0.788 | 10 |
| 11 | 179.4 | 0.061 | 0.3 | 0.259 | 3.382 | 0.787 | 11 |
| 12 | 180 | 0.06 | 0.298 | 0.256 | 3.336 | 0.786 | 12 |
| 13 | 177.747 | 0.06 | 0.3 | 0.254 | 3.315 | 0.786 | 13 |
| 14 | 179.898 | 0.061 | 0.3 | 0.263 | 3.424 | 0.785 | 14 |
| 15 | 177.281 | 0.06 | 0.3 | 0.255 | 3.311 | 0.784 | 15 |

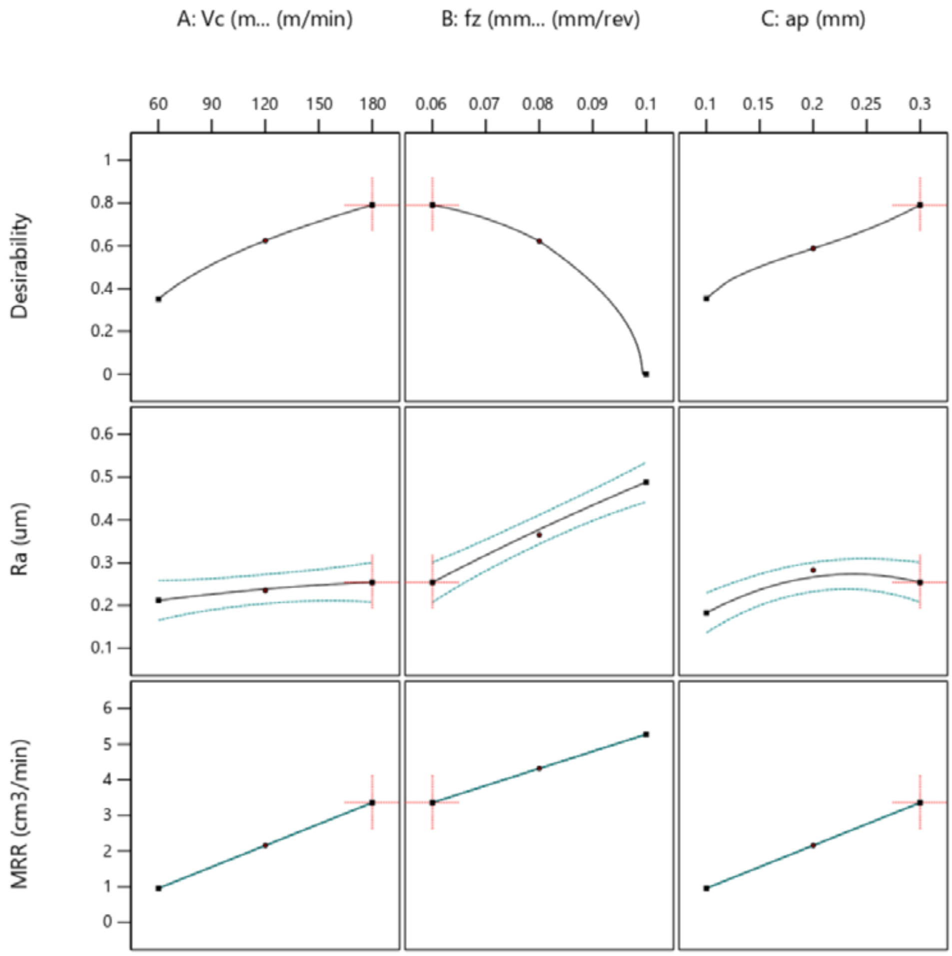


Fig. 4. Optimization result calculated by RSM-DA method

## *4 CONCLUSIONS*

As aforementioned, Table 7 presents the summarized results obtained from applying the VIKOR and RSM-DA methods for solving MO problems.

Table 7. Comparing the results of the optimization

| Methods | Parameters | | | Responses | |
|---|---|---|---|---|---|
| | $V_c$ *(m/min)* | $f_z$ *(mm/tooth)* | $a_p$ *(mm)* | $R_a$ *(µm)* | MRR *(cm³/min)* |
| VIKOR | 120 | 0.06 | 0.1 | 0.209 | 0.720 |
| RSM-DA | 180 | 0.06 | 0.3 | 0.254 | 3.36 |
| Comparison between RSM-DA versus VIKOR methods | | | | ↑21.5 | ↑366.7% |

The comparison between the two methods shows a clear difference between RSM-DA and VIKOR methods. Each method has its cons and pro. If the change in surface roughness value is still within an acceptable range, then the proposed values by RSM-DA may be accepted.

In this research, the VIKOR method provides an optimal set of parameters with the lowest surface roughness value, at 0.209 µm. However, the expected MRR value is about 6 times lower than the value obtained by RSM-DA. That means RSM-DA proposed increasing the surface roughness value by 21.5% (which means decreasing the surface quality) to achieve a productivity increase of about 6 times.

These methods were used to find the optimal set of input parameters that can satisfy multiple objectives simultaneously. The results show that both methods were effective in achieving the desired outcomes. The VIKOR method provided a set of compromise solutions that could satisfy all the objectives, while the RSM-DA method provided the optimal combination of input parameters that could satisfy the objectives with a high degree of accuracy. The results indicate that the RSM-DA method outperformed the VIKOR method in terms of accuracy, as it was able to identify the optimal solution with a higher level of precision. Overall, both methods are valuable tools for solving multiple objective optimization problems, and the choice of method depends on the specific requirements of the problem and the resources available for implementation. In practical manufacturing, processed products always need to meet a certain range of surface roughness values. If the change in surface roughness value is still within the allowable range, then the RSM-DA result seems to provide a better optimal result.

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