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Decision Framework For Selecting Cutting Fluids Under Diverse Machining Conditions

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ABSTRACT
This study presents an optimization-based approach for selecting suitable cutting fluids in turning operations using multi-criteria decision-making methods–TOPSIS and VIKOR. Key parameters such as feeding resistance, tool–work interaction force, surface texture, and side force are analyzed to evaluate fluid performance. Microsoft Excel is employed for parametric modeling, enabling designers to vary input conditions and instantly determine the most appropriate cutting fluid without manual calculations.
Experiments were conducted on mild steel using a single-point cutting tool, and the results were visualized through comparative graphs showing the relative performance of different fluids. The study highlights the significant impact of coolant flow and other cutting parameters on surface finish and machining efficiency. The proposed model serves as a practical tool for manufacturers and designers to optimize cutting fluid selection under various machining conditions.
Keyword: *- Metalworking Coolants, Tool Load Analysis Surface Finish Evaluation*

1. INTRODUCTION

Reducing cutting forces through the optimization of machining parameters is crucial, as excessive force can negatively affect the machining process. High cutting forces often lead to increased energy consumption, shortened tool life, degraded surface finish, and elevated surface roughness. These forces directly influence key machining factors penetration depth, feed per unit time, rake inclination, spindle speed, and wear of cutting tool. As a result, accurate measurement and control of cutting forces have become a priority in machining research and practice.
To measure these forces effectively during turning operations, a variety of dynamometers have been developed, utilizing technologies like load-cell, piezoelectric, thermo-electric, and photoelectric transducers. In addition to direct measurement methods, researchers have conducted several experimental investigations and predictive studies that estimate cutting forces based on machining conditions. Simplified analytical models have also been applied to present the significance of process inputs, including feed rate and cutting velocity —on the magnitude of cutting forces.

1.1 Cutting Force Measurement

Three principal forces act on a single-point cutting tool while it engages with the work piece, as illustrated in Figure 1.1.

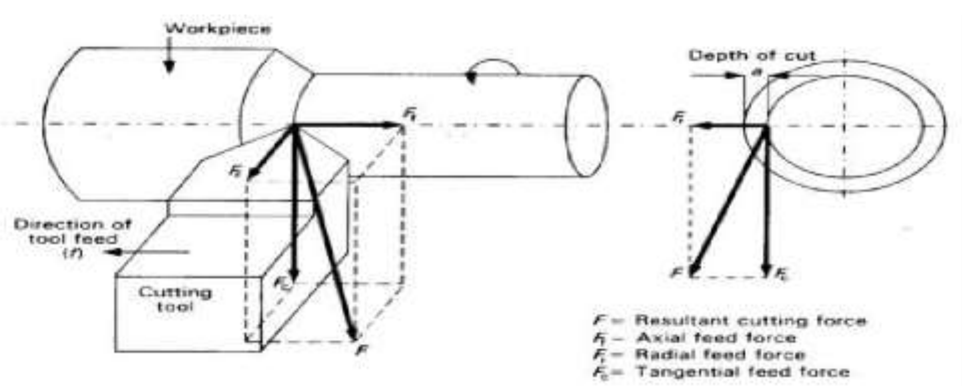

Fig 1: Cutting Forces Acting on Cutting Tool [1]

The force Fx, represents the feed force along the X-axis, Fy corresponds to the cutting force in the Y-axis direction, and Fz denotes the radial force acting along the Z-axis. These cutting forces were recorded by employing the dynamometer illustrated in Figure 1.5.

1.2 Cutting Fluid [6]

Various types of cutting fluids are used in machining. These fluids can be derived from sources such as oils of plant origin, fats from animals, petroleum fractions, water, and air or a combination of these components.

2. METHODOLOGY

The methodology section includes a flowchart illustrating the laboratory arrangement. This process flow diagram provides a successive stages overview of the operation of the setup, offering a comprehensive grasp of how the experiment functions. By presenting the overall process visually, the flowchart simplifies comprehension, followed by a detailed explanation of each step involved.

The proposed study follows these steps to determine the most suitable cutting fluid.

The study focuses on assessing the major turning process parameters under the influence of various cutting fluids and determining the most suitable fluid through the application of Multi-Criteria Decision-Making (MCDM) techniques. Furthermore, it involves a comparative analysis of different MCDM approaches to evaluate their effectiveness in decision-making. To ensure the reliability of the results, a sensitivity analysis is also carried out for the selection of cutting fluids.

Initially, the turning operation is performed on plain carbon steel, during which force data is collected using a load cell dynamometer. Following this, key machining parameters are calculated for various cutting fluids. These results are then evaluated using Multi-Criteria Decision-Making (MCDM) techniques. Specifically, the AHP and TOPSIS methods are employed to identify the most suitable cutting fluid based on multiple performance criteria.

2.1 Problem Statement

The literature review highlights the critical role of cutting fluid selection in machining operations, particularly turning, as it directly influences key parameters such as surface finish, cutting forces, and depth of cut. Optimizing these process parameters often requires the application of numerical methods and optimization algorithms. In general, an optimization problem involves maximizing or minimizing one or more objective functions while adhering to multiple, often conflicting, constraints. Given the significant impact of cutting fluids on machining performance, there is a clear need for a systematic optimization approach to select the most appropriate cutting fluid for turning operations. Moreover, the review suggests that using suitable cutting fluids under varying cutting conditions can significantly enhance surface quality and overall machining efficiency. It also emphasizes the potential benefits of incorporating environmentally friendly cutting fluids as sustainable alternatives to conventional coolants.

In the present study, various scenarios involving different cutting fluids have been considered, as recommended in reference [1].

Case I:

Table -1: Observed Outcomes at 240 rpm

SN	**RPM**	**Feed (mm/ min)**	**MR Depth (mm)**	**Lubricant Used**	**F_{+X}**	**F_{+Y}**	**F_{+Z}**	**Surface texture (μm)**
1				**Sun flow. seed oil**	29	221	40	10

2	220	100	0.1	**Coc. oil**	20	200	30	18
3				**Simple Coolant**	33	150	30	13
4				**Dry**	40	200	49	21

Case II:
Table -2: Observed Outcomes at 360 rpm

SN	**RPM**	**Feed (mm/ min)**	**MR Depth (mm)**	**Lubricant Used**	**F_{+X}**	**F_{+Y}**	**F_{+Z}**	**Surface texture (μm)**
1	350	150	0.14	**Sun flow. seed oil**	21	271	21	7
2				**Coc. oil**	52	342	61	14
3				**Simple Coolant**	42	382	40	12
				Dry	78	382	71	28

Case III:
Table -3: Observed Outcomes at 560 rpm

SN		**RPM**	**Feed (mm/ min)**	**MR Depth (mm)**	**Lubricant Used**	**F_{+X}**	**F_{+Y}**	**F_{+Z}**	**Surface texture (μm)**
1		560	250	0.22	**Sun flow. seed oil**	112	412	84	4
2					**Coc. oil**	182	122	62	6
3					**Simple Coolant**	82	202	42	4
4					**Dry**	172	342	71	11

2.2 Calculation

A. Analytic Hierarchy Process [18]

The method of the AHP can be defined as:

In this approach, the decision-making problem is structured into a hierarchy consisting of a goal, main criteria, supporting factors, and possible options. At each level of the hierarchy, comparisons are made by evaluating how much each element contributes to the element above it. Decision-makers assess these relationships using qualitative judgments such as equal, slightly stronger, strong, very strong, and extremely strong preferences. These qualitative assessments are then translated into numerical values based on a predefined scale (as shown in Table 4).

The resulting pairwise comparisons for each criterion are arranged into a sq. matrix, where the diag. elements are always 1, indicating self-comparison. If the element in row i and column j is greater than 1, it indicates that the i-th factor is considered more important than the j-th factor. Conversely, if the value is less than 1, the j-th criterion is preferred. Each entry in the matrix is reciprocated across the diagonal; that is, the element in position (j, i) is the inverse of the element in (i, j).

Table -4: Pairwise Comparison Matrix

Alternative	Num. value(s)
Equal	2
Marginally strong	2
Strong	6
Very strong	8
Extremely strong	10

The normalized right eigenvector of the comparison matrix, along with its principal eigenvalue, is used to determine the relative importance of the criteria under evaluation. Each element of the normalized eigenvector represents the **weight** assigned to a specific criterion or sub-criterion, and in the context of alternatives, these values are interpreted as **ratings**.

Since the AHP method involves subjective judgments, some degree of inconsistency may arise due to redundancy or conflicting inputs. To assess the reliability of the pairwise comparisons the matrix should be checked for consistency. This is done by calculating the **Consistency Index (CI)**, which reflects how consistent the judgments are in the matrix.

$CI = (\lambda_{max} - n)/(n - 1)$

B. Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [16]

Initially, a decision matrix is formed where *i* indicates the criterion and *j* represents the alternative ($j = 1, 2, \ldots, n$). The matrix is then normalized to obtain the Normalized Decision Matrix, which reflects the relative performance of the considered alternatives.

Next, the weighted decision matrix is derived by multiplying each value of the normalized matrix with its respective criterion weight, thereby incorporating the importance of each criterion into the evaluation of alternatives.

The **Positive Ideal Solution** (A^+) and the **Negative Ideal Solution** (A^-) are determined based on the **weighted decision matrix**. Here, the set JJJ corresponds to the **beneficial (maximization) criteria**, while J′J′J′ refers to the **non-beneficial (minimization) criteria**

$V = V_{ij} = W_j \times R_{ij}$

Identify the Positive and Negative Ideal Solution

$PIS = A^{+} = \{V^{+}1, ... Vn^{+}\}$

$NIS = A^{-} = \{V^{-}1, ... Vn^{-}\}$

.

Once the ideal and non-ideal solutions are identified, the next step is to **measure the separation distance** of each alternative from both A+A⁺A+ and A−A⁻A−. These distances indicate how close or far each alternative is from the optimal and least-preferred solutions, respectively, and are used to rank the alternatives.

$S^{+} = \sqrt{\sum^{n}j = 1 (Vj^{+} - Vij)^{2}}$ i=1,2,3....,m

$S^{-} = \sqrt{\sum^{n}j = 1 (Vj^{-} - Vij)^{2}}$ i=1,2,3......,m

The proximity of each alternative to the ideal solution is then determined. For every competing option, this measure indicates how close the potential location is to the positive ideal solution when compared with its distance from the negative. This value serves as the basis for ranking the alternatives, where a higher relative closeness signifies a more preferable choice.

$C_i = S_i^{-}/(S_i^{+}+S_i^{-})$, $0 \le C_i \le 1$

Finally, the alternatives are arranged in descending order according to their relative closeness scores. (Ci). A higher Ci indicates greater proximity to the ideal solution, which corresponds to a higher preference ranking. Thus, the alternative with the largest Ci value is considered to demonstrate the best performance, while lower values represent less desirable options.

C. Vikor Method [17]

Determine the best fi* and worst fi— values for all criterion functions i=1,2,...n If the ith function is a benefit criterion, then:

$f_i^{*} = \max_j f_{ij}$, $f_i^{-} = \max_j f_{ij}$

Calculate the values S_j and R_j; j = 1,2...........,n., by the equations

$S_j = \sum^{n}_{j=1} wi\, (f_i^{*} - f_{ij})/(f_i^{*} - f_{ij})$, $R_j = \max_j [wi(f_i^{*} - f_{ij})/(f_i^{*} - f_{ij})]$

Where w_i are the weights of criteria, expressing their relative importance.

Calculate the values of Qj where j = 1,2,3,4.....J-1,J., by the relation

$Qj = v *(S_j - S^{*})/(S_{-} - S^{*}) + (1 - v)*(R_j - R^{*})/(R_{-} - R^{*})$

$S^{*} = \min j\ Sj$, $S_{-} = \max j\ S_j$

$R^{*} = \min j\ Rj$, $R_{-} = \max j\ R_j - R^{*}$

And v is considered as the weight reflecting the balance between maximum group utility and individual regret, where v=0.5v = 0.5v=0.5.

Preference ranking is obtained by arranging the values of S, R, and Q in descending order.

3. Outcomes and Interpretation

The outcomes derived from AHP and TOPSIS are discussed in the following section. The table below shows the factor weights assigned through AHP, reflecting the designer's or manufacturer's assessment of the parameters influencing the cutting process.

Table -5: Weights of Parameters Influencing Cutting

Factors influence Cutting	**F_{+X}**	**F_{+Y}**	**F_{+Z}**	**Surface texture (μm)**
Weightage	0.14	0.2043	0.0491	0.6064

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Findings from the Chart 1: The graph illustrates that the highest relative closeness value is **0.817**, identifying **C1*** as the most suitable cutting fluid. Conversely, the lowest relative closeness value of **0.049** designates **C4*** as the least preferred cutting fluid at **220 rpm**, based on the criterion weightage provided in **Table 5**.

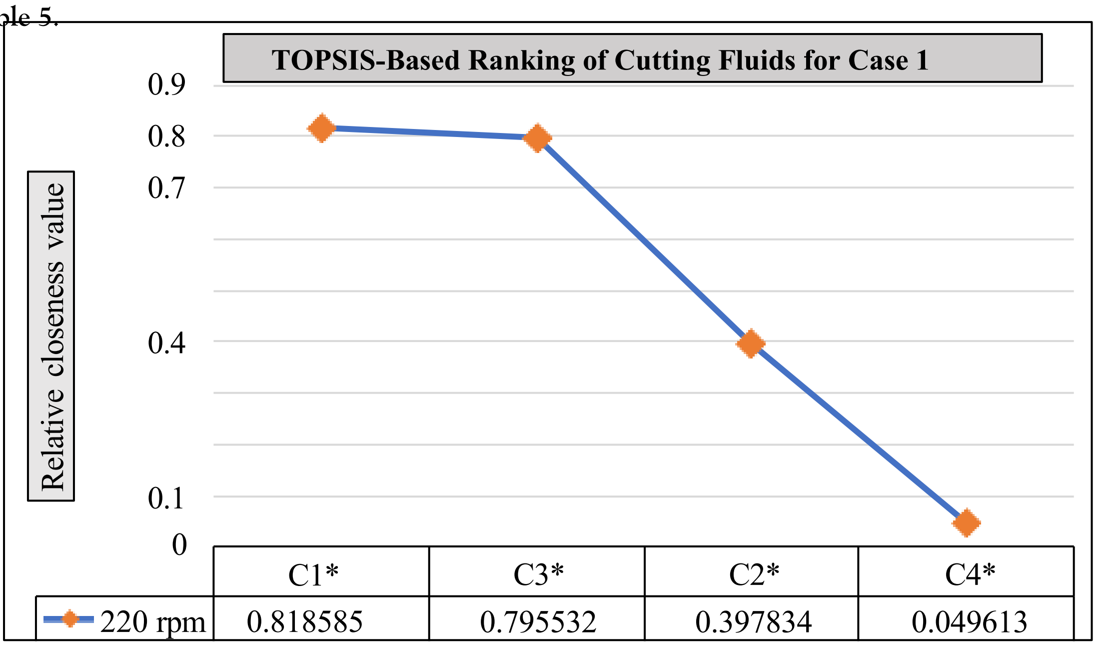


Chart -1: Cutting Fluids V/S Relative Closeness Value

Conclusion of Chart 2: The graph shows that the **lowest relative closeness value** (-0.0796) corresponds to **Q3**, identifying it as the best cutting fluid. In contrast, the **highest relative closeness value** (0.550) corresponds to **Q4**, making it the least preferred option at **220 rpm**, based on the criterion weights given in **Table 5**.

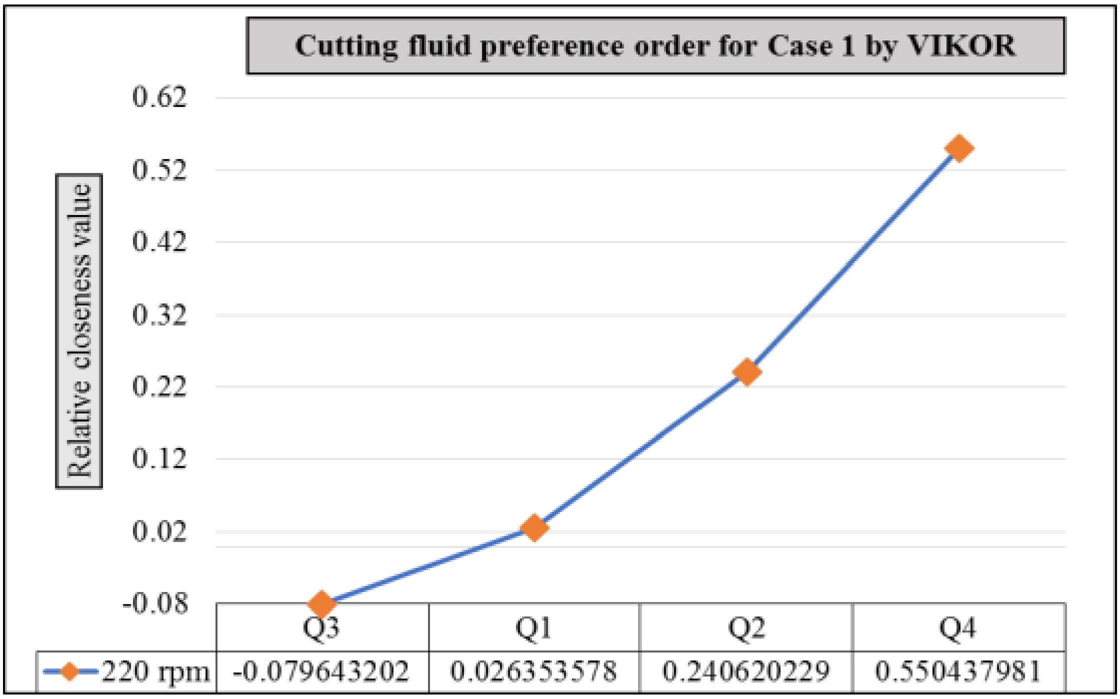


Chart -2: Relative Closeness Values of Cutting Fluids

Conclusion of Chart 3: The graph indicates that the **highest relative closeness value (1.000)** corresponds to **C1***, identifying it as the best cutting fluid, while the **lowest value (0.000)** corresponds to **C4***, making it the least preferred option at **350 rpm**, based on the criterion weights provided in **Table 5**.

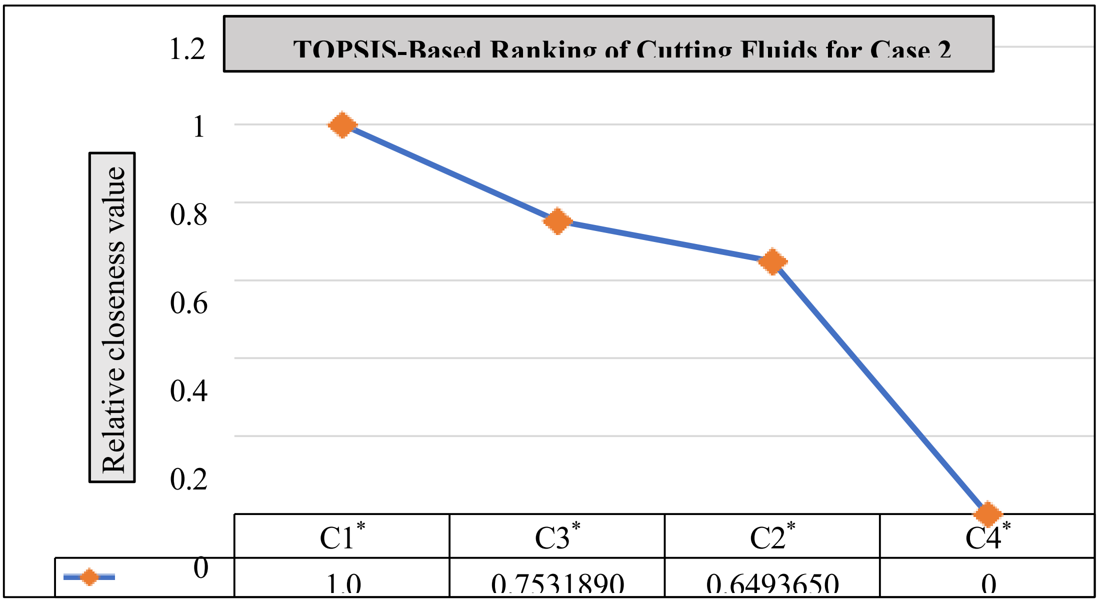


Chart -3: Cutting Fluids V/S Relative Closeness Value

Conclusion of Chart 4: The graph shows that the **lowest relative closeness value (0.000)** corresponds to **Q1**, making it the best cutting fluid, while the **highest value (0.803)** corresponds to **Q4**, identifying it as the least preferred option at **350 rpm**, based on the criterion weights given in **Table 5**.

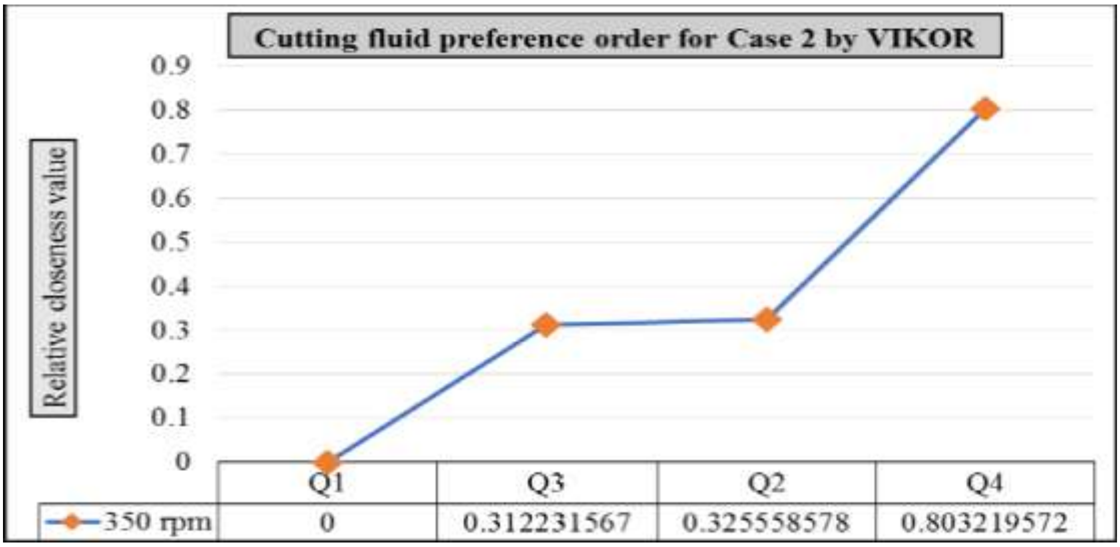


Chart -4: Comparison of Cutting Fluids and Relative

Conclusion of Chart 5: The graph indicates that the **highest relative closeness value (0.913)** corresponds to **C3***, making it the best cutting fluid, while the **lowest value (0.072)** corresponds to **C4***, identifying it as the least preferred option at **560 rpm**, based on the criterion weights provided in **Table 5**.

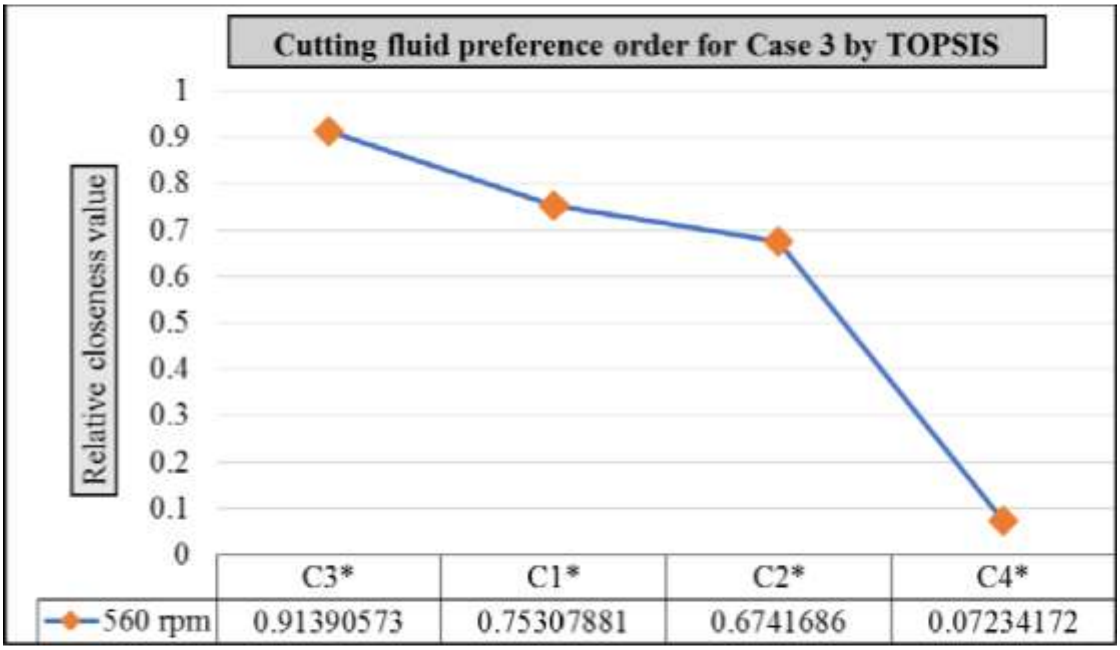
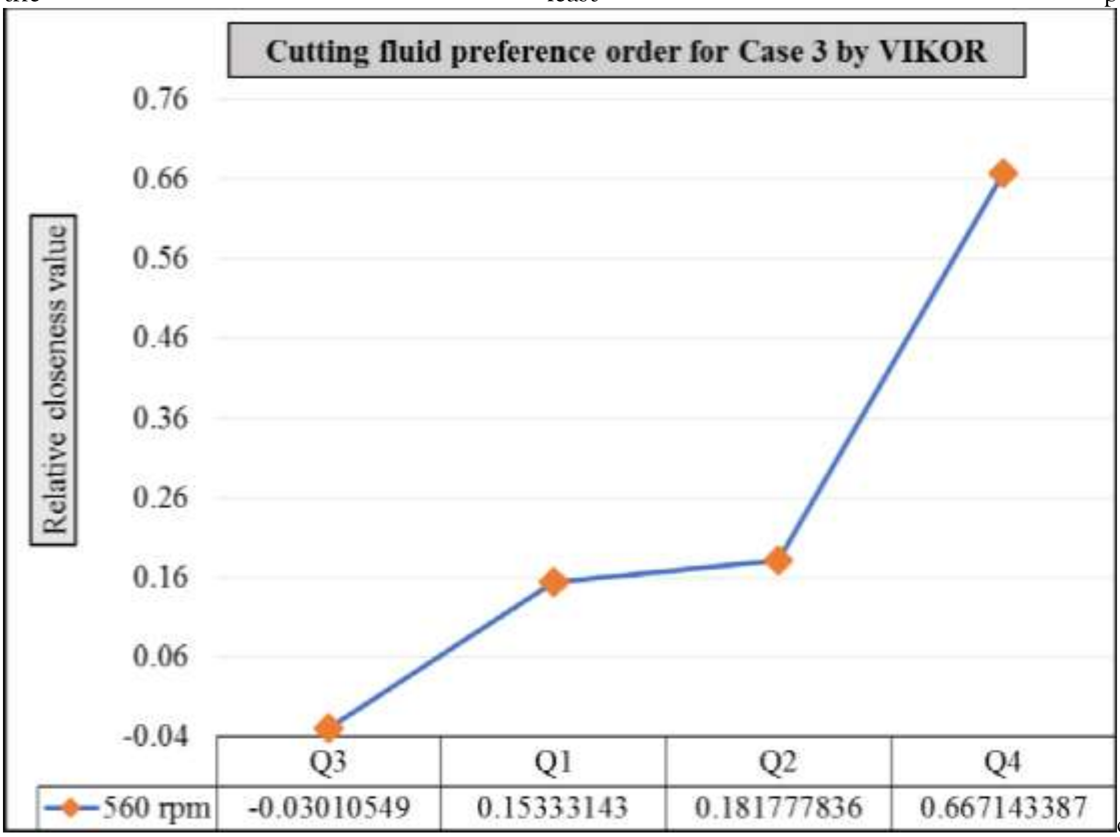


Chart -5: Relative Closeness Values of Cutting Fluids

Conclusion of Chart 6: The graph shows that the lowest relative closeness value (-0.030) corresponds to Q3, identifying it as the best cutting fluid, while the highest value (0.667) corresponds to Q4, making it the least preferre



d option at 560 rpm, based on the criterion weights provided in Table 5.

4. CONCLUSIONS

From the literature review and experimental results, it is evident that analyzing thrust force, radial force, and surface roughness enables the development of an optimization model to support designers and manufacturers in identifying the most appropriate cutting fluid for the turning process. This model improves surface quality while optimizing process parameters. The final selection of the cutting fluid was performed using a Multi-Criteria Decision-Making (MCDM) approach, evaluated across three different cases under defined criterion weights.

5. FUTURE SCOPE

The values of different cutting forces were measured by varying the cutting fluids. These forces were obtained using a **load cell dynamometer**, which allowed the calculation of cutting forces under different machining conditions such as depth of cut, cutting speed, and feed rate. The load cell dynamometer and the experimental setup can thus be effectively utilized for analyzing and determining suitable machining parameters that ensure better surface finish, improved accuracy, and reduced production cost.

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