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Application of WSM, WPM and TOPSIS Methods for the Optimization of Multiple Responses

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Abstract

Multi-criteria (or) attribute decision making (MCDM/MADM) methods have very high applications in industries for solving real world engineering problems. In the present work, MCDM methods of Weighted sum method (WSM), Weighted Product Method (WPM) and TOPSIS, have been employed for the computational analysis of multi-responses. AA7075 has been taken as work piece for the experimentation and the experiments were done on CNC lathe as per the Taguchi's standard L9 Orthogonal Array. The cutting parameters of speed, feed and depth of cut were taken as experimental inputs and Material Removal Rate (MRR) and Surface Roughness (R_a) were considered as responses. From the Weighted sum method (WSM) and Weighted Product Method (WPM) the optimal combination for multi-responses were found at ninth alternative, i.e. speed: 2000 rpm, feed: 0.4 mm/rev and depth of cut: 0.75 mm. Similarly, from the TOPSIS results, the optimal combination for multi-responses were found at seventh alternative, i.e. speed: 2000 rpm, feed: 0.2 mm/rev and depth of cut: 1 mm. Analysis of variance (ANOVA) has been done by using MINITAB-16 statistical software to find the influence of cutting parameters on the multi-responses. From the ANOVA results of WSM, WPM and relative closeness coefficient (C_i^+), it is found that feed rate has high influence (For WSM, WPM and C_i^+ the F values are 60.50, 60.30 and 91.42 respectively) in affecting the multi-responses.

Keywords*: Material Removal Rate (MRR), Surface Roughness (R_a), WSM, WPM, TOPSIS and ANOVA*

1. Introduction

In present days, multi criterion Decision-Making methods are gaining importance as potential tools for analyzing complex real problems due to their inherent ability to judge different alternatives on various criteria for possible selection of the best or suitable alternative. In the present study, various MCDM methods were used for the optimization of multi-responses. The weighted sum method (WSM) is the earliest and, most commonly used method of MCDM. To overcome the problems associated with WSM, Weighted product method (WPM) has been proposed. Other widely used methods are ELECTRE and TOPSIS. [1-6]WSM used for solving single dimensional problems. If there are m alternatives and n criteria, then the best alternative is the one that satisfies the following expression, $B^*WSM = \max \Sigma(r_{ij}W_j)$. Where, B^*WSM is the WSM score of the best alternative, n is the number of decision criteria, r_{ij} is the normalized value of the i^{th} alternative in terms of the j^{th} criterion, and W_j is the weight of importance of the j^{th} criterion. The assumption that governs WSM model is the additive utility assumption. That is the total value of each alternative is equal to the sum of the products of normal value and the weight of the criteria. In single-dimensional cases, where all the units are

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same, the WSM can be used without difficulty. The difficulty with this method emerges when it is applied to multi dimensional MCDM problems. To avoid this problem weighted product method (WPM) has been developed. It is very similar to the WSM but the main difference is that instead of adding in the model there are multiplication. The WPM can be used in single- and multi-dimensional MCDM problems. An advantage of the method is that instead of the actual values it can use relative ones. [7-8]TOPSIS is the technique for order preference by similarly to ideal solution. It was developed by Hwang and Yoon in 1980 as an alternative to the ELECTRE method and can be considered as one of its most widely accepted variants. The basic concept of this method is that the selected alternative should have the shortest distance from the ideal solution and the farthest distance from the negative-ideal solution in any geometrical sense. The TOPSIS method assumes that each criterion has a tendency of monotonically increasing or decreasing utility. Therefore, it is easy to define the positive ideal and negative-ideal solutions. The Euclidean distance approach was proposed to evaluate the relative closeness of the alternatives to the ideal solution. Thus, the preference order of the alternatives can be derived from a series of comparisons of these relative distances. The TOPSIS method first converts the various criteria, dimensions into non-dimensional criteria. Generally A^+ indicates the most preferable alternative or the ideal solution. Similarly, alternative A^- indicates the least preferable alternative or the negative ideal solution. [9-10]

Relative importance or weight of a criterion indicates the priority assigned to the criterion by the decision-maker while ranking the alternatives in a Multi criteria Decision-Making (MCDM) environment. A number of methods are available for computing the weights, commonly used are the Rating method and Entropy method. Rating method requires the decision-maker to express all the criterion weights on a numerical scale. A higher value for a given criterion represents its relative importance over the other criteria. The method is simple when there is a small number of a criterion, but may give erroneous results if the number of criteria is large. To avoid this entropy method has been employed. Entropy is a term that measures the uncertainty associated with random phenomena of the expected information content of a certain message and this uncertainty is represented by a discrete probability distribution. The Entropy Method estimates the weights of the various criteria from the given payoff matrix and is independent of the views of the decision-maker. [11-12]This method is particularly useful to explore contrasts between sets of data. These sets of data can be mapped as a set of alternative solutions in the payoff matrix where each alternative solution is evaluated in terms of its outcome. The philosophy of this method is based on the amount of information available and its relationship with the importance of the criterion. If the entropy value is high, the uncertainty contained in the criterion vector is high, diversification of the information is low and correspondingly the criterion is less important. This method is advantageous as it reduces the burden of the decision-maker for large sized problems. [13-15]

The objective of the present work is to optimize the multi-responses (MRR and R_a) under various alternatives. The experiments were carried out on CNC lathe for various process parametric combinations like speed, feed and depth of cut as per the Taguchi’s standard L9 orthogonal Array. [16-19] The MCDM/MADM methods of WSM, WPM and TOPSIS were employed to find the optimal combination of process parameters that yields high Material Removal Rate (MRR) and low Surface Roughness (R_a) simultaneously. Entropy-TOPSIS method is used to find the weights of the responses. Finally, the influence of process parameters on the multiple responses was studied using ANOVA by statistical software MINITAB-16. [20-21]

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2. Methodology

In the present work, AA7075 has been taken as work piece to conduct the experiments on CNC lathe as per the Taguchi's standard L9 Orthogonal Array. Optimization of multi-responses (MRR and R_a) has been carried out using MCDM approaches of WSM, WPM and TOPSIS methods.

Procedural steps of MCDM

- Defining the problem and fixing the criteria.
- Appropriate data collection.
- Establishment of feasible/efficient alternatives.
- Formulation of the payoff matrix (alternative versus criteria array) as given in the Table1.
- Selection of appropriate method to solve the problem. (WSM, WPM and TOPSIS)
- Incorporation of a decision-makers preference structure
- Choosing the best/suitable alternative.

Table 1. Payoff Matrix

Experiments (Alternatives)	Speed (v)	Feed (f)	Depth of cut (d)	Criteria 1 (MRR)	Criteria 2 (R_a)
A-1	1000	0.2	0.5	9.21	2.11
A-2	1000	0.3	0.75	24.85	5.023
A-3	1000	0.4	1	32.57	9.17
A-4	1500	0.2	0.75	20.57	2.036
A-5	1500	0.3	1	39	7.16
A-6	1500	0.4	0.5	24.85	11.59
A-7	2000	0.2	1	41.14	3.35
A-8	2000	0.3	0.5	27	7.25
A-9	2000	0.4	0.75	39.85	11.75

3. Results and Discussions

MCDM/MADM approaches of WSM, WPM and TOPSIS are most widely used methods in analyzing complex engineering problems. The results of MCDM methods were discussed below.

3.1. Weighted Sum Method (WSM)

Weighted sum method is used in single dimensional problems. For m number of alternatives and n criteria's the best alternatives are the one that satisfying

$$B^*_{WSM} = \max \sum_{i}^{j} r_{ij}\, W_j$$

Where, B^*_{WSM} is the weighted sum method score of the best alternatives. Calculated values of WSM with their S/N ratios and ranks were given in the Table 2.

Table 2. WSM Values and Ranking

Experiment No.	WSM	S/N of WSM	Rank
1	0.09596	-20.3582	9
2	0.23811	-12.4644	7
3	0.39244	-8.1245	3
4	0.13115	-17.6446	8

5	0.35122	-9.0884	4
6	0.44215	-7.0886	2
7	0.23990	-12.3994	6
8	0.31439	-10.0506	5
9	0.49665	-6.0790	1

ANOVA of WSM

ANOVA is applied to the values of WSM to determine the influence of process parameters on the multiple responses. From the ANOV A for WSM (Table 3), it is found that feed rate has high influence (F = 60.50) followed by speed (F = 8.66). Depth of cut has very low influence (F = 1.68) in affecting the multi-responses. Normal probability, versus fits and versus order plots for the residuals were drawn and shown in the Figures 1, 2 and 3.

Table 3. ANOVA for WSM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
v	2	0.017827	0.017827	0.008914	8.66	0.103
f	2	0.124487	0.124487	0.062243	60.50	0.016
d	2	0.003466	0.003466	0.001733	1.68	0.372
Error	2	0.002058	0.002058	0.001029		
Total	8	0.147838				

S = 0.0320746, R^2 = 98.61%, R^2 (Adj) = 94.43%

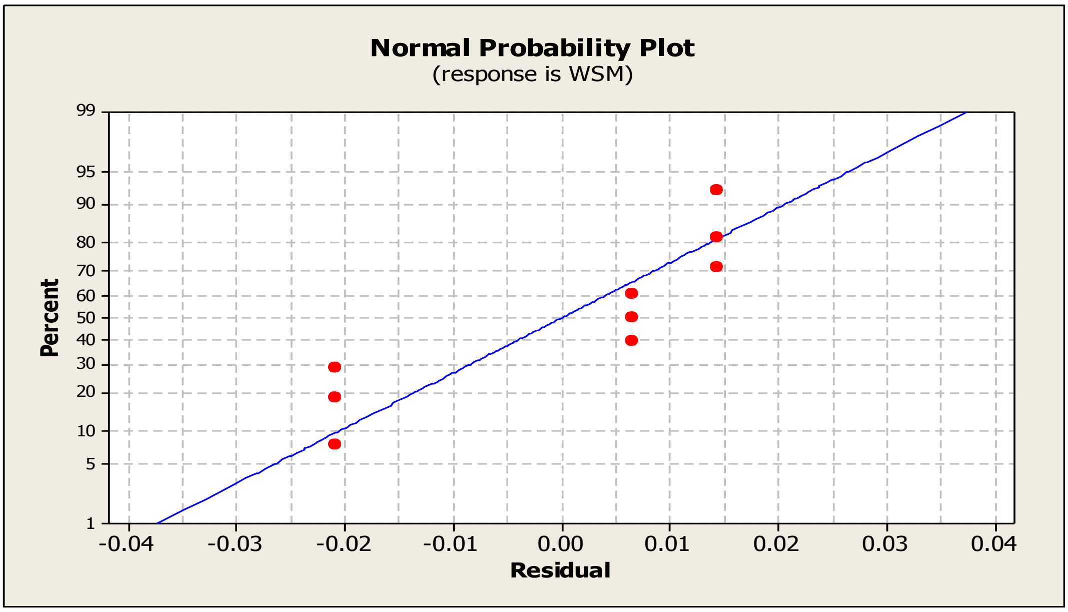

Figure 1. Normal Probability Plot for WSM

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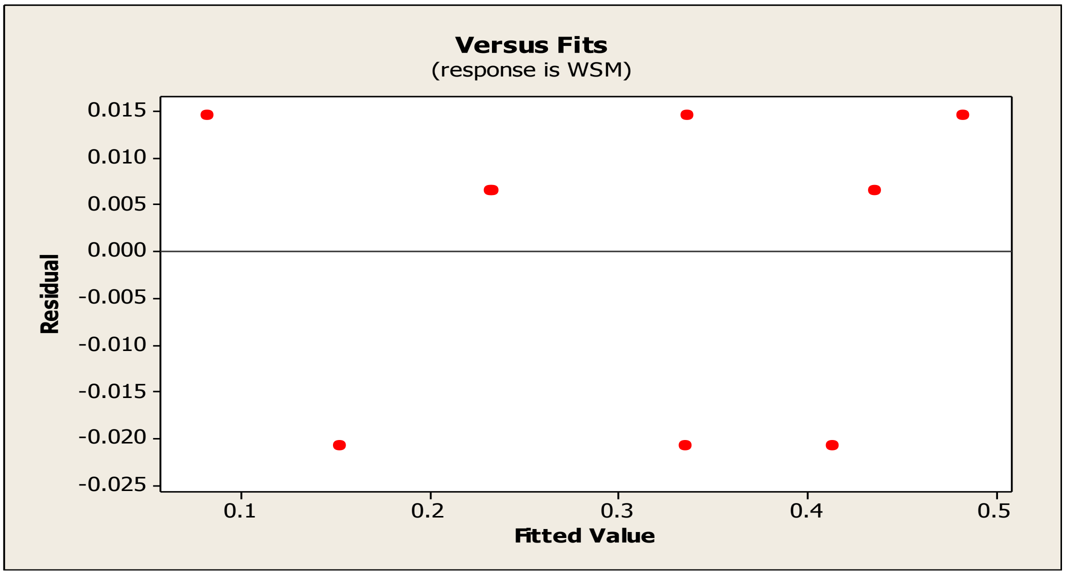

Figure 2. Versus Fits Plot for WSM

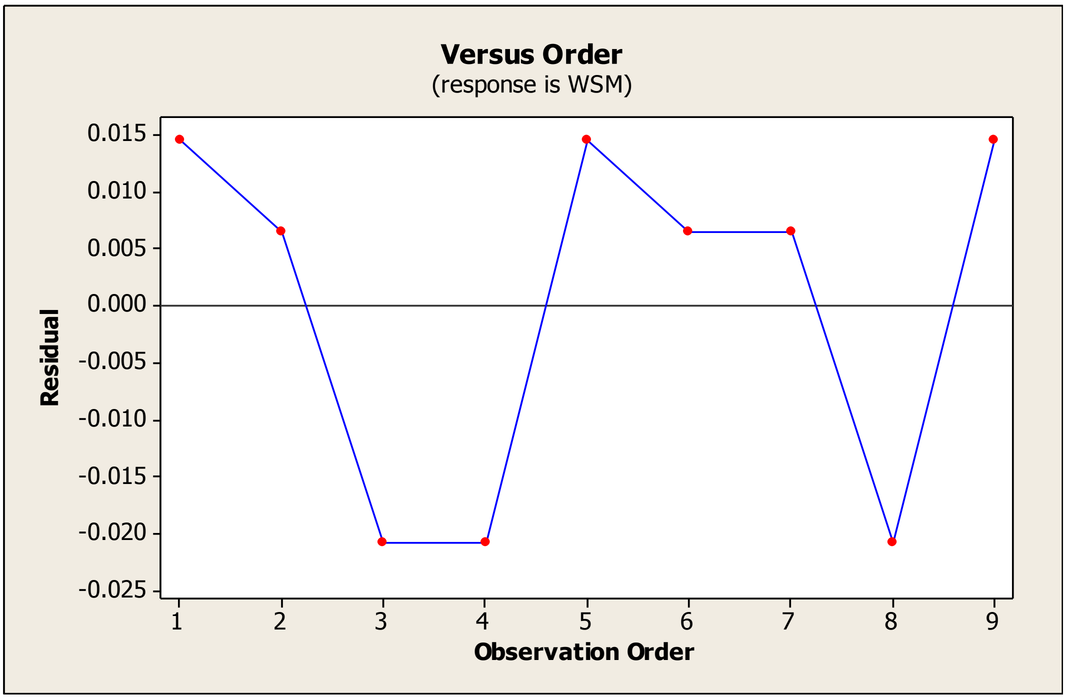

Figure 3. Versus Order Plot for WSM

3.2. Weight Product Method (WPM)

The Weighted Product Method (WPM) is also similar to WSM. The main difference is that instead of addition in WPM multiplication has to be done. The overall performance score is computed as

$$R_i = \prod_{j=1}^{n} |r_{ij}|^{w_j}$$

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Here, r_{ij} is the normalized values of decision matrix and W_j is the weight of the response. The best alternative is the one having the highest R_i value. The calculated values of R_i were given in the Table 4.

Table 4. R_i Values of WPM and Ranking

Experiment No.	WPM	S/N of WPM	Rank
1	0.09594	-20.3600	9
2	0.23717	-12.4988	6
3	0.39180	-8.1387	3
4	0.11921	-18.4737	8
5	0.34800	-9.1684	4
6	0.42530	-7.4261	2
7	0.20805	-13.6366	7
8	0.31422	-10.0553	5
9	0.49508	-6.1065	1

ANOVA of WPM

Analysis of variance is applied for calculated WPM values and from the ANOVA given in the Table 5, it is clear that the feed rate has high influence (F = 60.30) followed by cutting speed (F = 6.56). Depth of cut has less influence (F = 1.13) in affecting the multi-responses. The Residual plots were drawn and shown in the Figures 4, 5 and 6.

Table 5. ANOVA for WPM

Source	DF	Seq SS	Adj SS	Adj MS	F	P
v	2	0.014355	0.014355	0.007178	6.56	0.132
f	2	0.131938	0.131938	0.065969	60.30	0.016
d	2	0.002464	0.002464	0.001232	1.13	0.470
Error	2	0.002188	0.002188	0.001094		
Total	8	0.150945				

S = 0.0330753, R^2 = 98.55%, R^2 (Adj) = 94.2%

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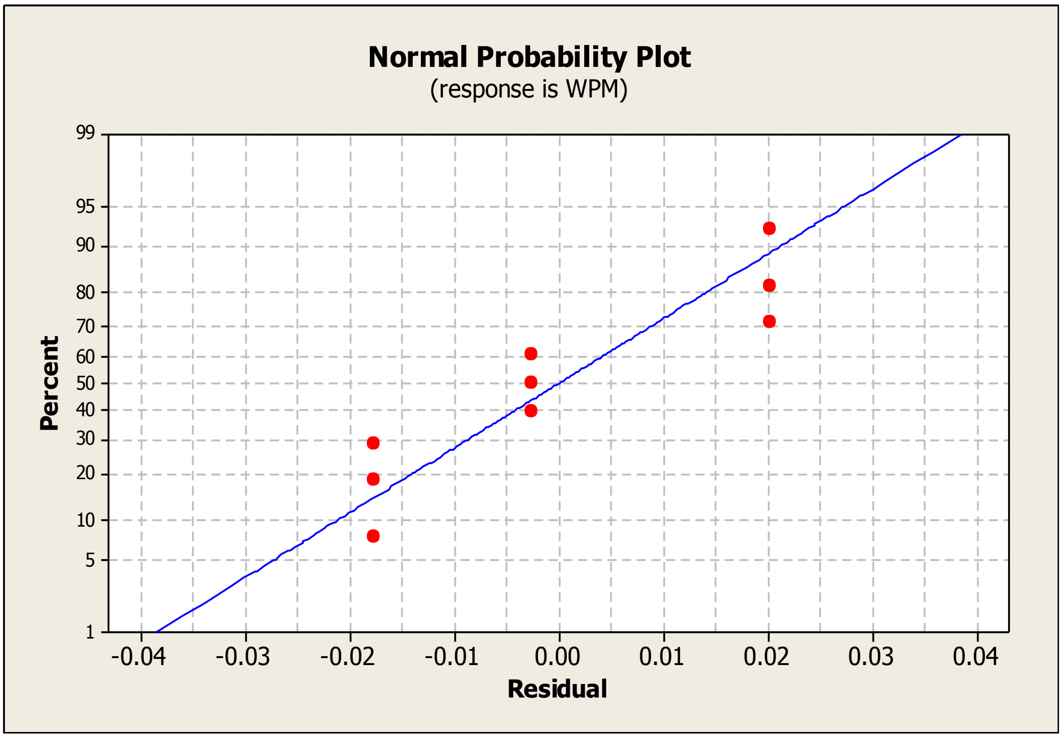

Figure 4. Normal Probability Plot for WPM

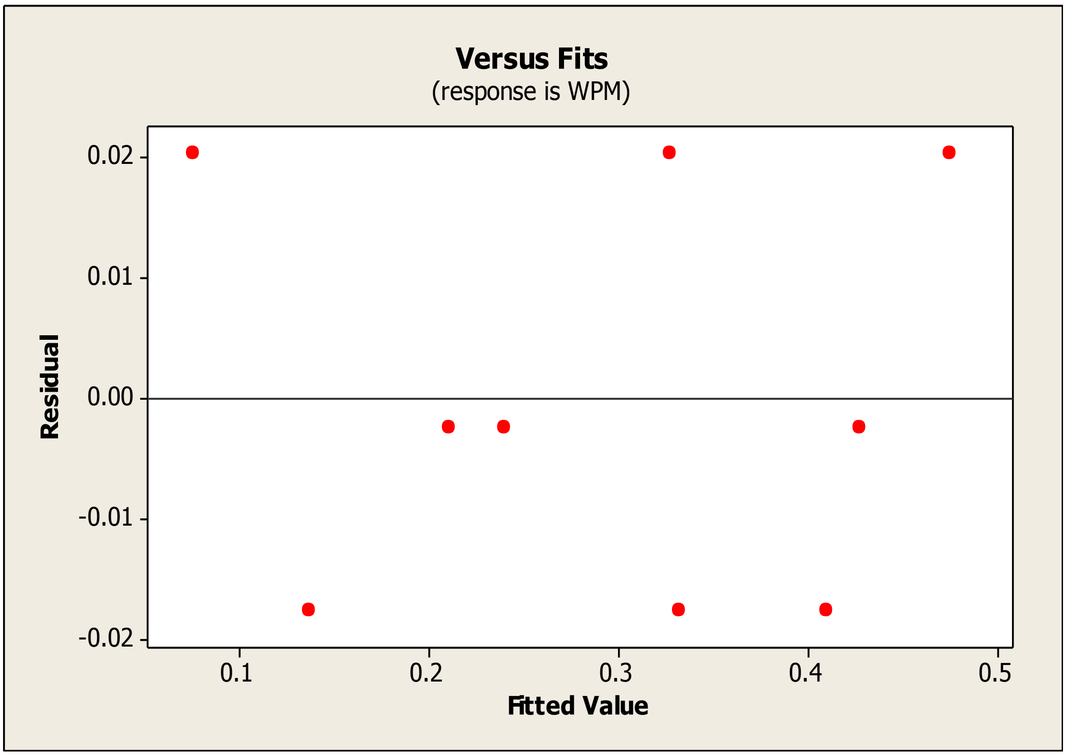

Figure 5. Versus Fits Plot for WPM

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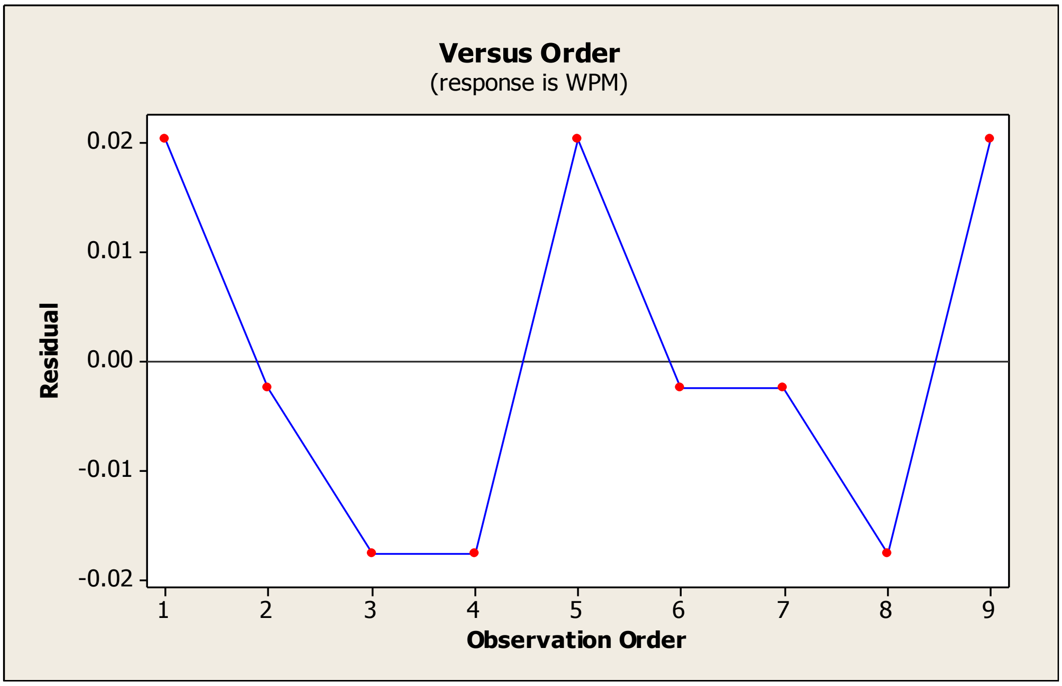

Figure 6. Versus Order Plot for WPM

3.3. TOPSIS Method

TOPSIS decision making method is a technique introduced by Yoon and Hwang. It is a worldwide accepted approach to finding the best alternative that is closest to the ideal solution. The basic principle in this method is that chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. In TOPSIS method of decision making problems, first step is to determine the weights using entropy approach.

3.3.1. Calculations of Weights Using Entropy Approach

Calculation of weights using entropy method involves in four steps they are

Step1. Determination of the decision matrix.

In decision matrix, the rows are assigned to available alternatives and the columns are assigned to characteristics. The general decision matrix can be shown as

$$D = \begin{array}{c} A_1 \\ A_i \\ A_m \end{array} \begin{bmatrix} Y_{11} & Y_{12} & .. & Y_{1j} & Y_{1n} \\ Y_{i1} & Y_{i2} & .. & Y_{ij} & .. \\ Y_{m1} & Y_{m2} & .. & Y_{mj} & Y_{mn} \end{bmatrix}$$

Here, A_i (i = 1,2,3...m) signifies the potential alternatives, Y_j (J = 1,2,3........n) signifies the attributes and Y_{ij} is the performance of A_i with respect to characteristic Y_j. The actual decision matrix is given in the Table 6.

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Table 6. Actual Decision Matrix of Responses

Experiment No. (Alternatives)	MRR	R_a
A-1	9.21	2.11
A-2	24.85	5.023
A-3	32.57	9.17
A-4	20.57	2.036
A-5	39	7.16
A-6	24.85	11.59
A-7	41.14	3.35
A-8	27	7.25
A-9	39.85	11.75

Step2. Formation of Normalized decision matrix ($\bar{Y}_{ij}$):

In matrix D, Y_{ij} is the I^{th} alternative to the J^{th} factor. The normalised decision matrix is calculated by using below formula and given in the Table 7.

$$\bar{Y}_{ij} = \frac{Y_{ij}}{\sum_{i=1}^{m} Y_{ij}} \quad (1 \le i \le m,\ 1 \le j \le n)$$

Table 7. Normalized Decision Matrix

Experimental No.	MRR	R_a
1	0.03555	0.03549
2	0.09593	0.08450
3	0.12573	0.15427
4	0.07940	0.03425
5	0.15055	0.12045
6	0.09593	0.19498
7	0.15881	0.05636
8	0.10423	0.12197
9	0.15383	0.19768

Step3. Calculation of output entropy ($\acute{\varepsilon}_j$) using the formula below and the calculated values was given in the Table 8.

$$\acute{\varepsilon}_j = \frac{-1}{\ln(m)} \sum_{i=1}^{m} \bar{Y}_{ij} \ln \bar{Y}_{ij}$$

Table 8. Output Entropy Values

Criteria	MRR	R_a
$\acute{\varepsilon}_j$	0.96991	0.93027

Step4. Calculation of the weight (W_j) by using the formula

$$W_j = \frac{1 - \acute{\varepsilon}_j}{\sum_{i=1}^{m}(1 - \acute{\varepsilon}_j)}$$

Where, $\sum_{i=1}^{m} W_j = 1$ and (1- $\acute{\varepsilon}_j$) is called uncertainty. The calculated values of weights were given in the Table 9.

Table 9. Weights of Responses

Criteria	MRR	R_a
W_j	0.3014	0.6985

3.3.2. TOPSIS Calculations

TOPSIS calculations involves in 6 steps they are

Step1. Determine the Normalized decision making matrix.

Normalize the decision matrix of r_{ij} can be determined by using the below formula, and the calculated normalized values were given in the Table 10.

$$rij = \frac{Y_{ij}}{\sqrt{\sum_{i=1}^{n} Y_{ij}^2}};$$

Where, r_{ij} represents the normalized performance of A_i with respect to characteristic Y_j.

Table 10. Normalized Decision Matrix

Experiment No.	MRR	R_a
1	0.10088	0.09386
2	0.27220	0.22344
3	0.35676	0.40791
4	0.22531	0.09056
5	0.42719	0.31850
6	0.27220	0.51556
7	0.45063	0.14902
8	0.29575	0.32250
9	0.43650	0.52268

Step2. Construction of a weighted normalized decision matrix by

$$V_{ij} = W_j \, r_{ij}$$

Where, W_j represents the relative weight of the J^{th} criteria. The calculated values of V_{ij} are given in the Table 11.

Table 11. Weighted Normalized Decision Matrix

Experiment No.	MRR	R_a
1	0.03040	0.06556
2	0.08204	0.15607
3	0.10752	0.28492
4	0.06790	0.06325
5	0.12875	0.22247
6	0.08204	0.36011
7	0.13581	0.10409
8	0.08913	0.22526
9	0.13156	0.36509

Step3. Determine the Positive ideal solution and Negative ideal solution by using

$$A^{+} = \{(\max_i V_{ij} \mid j \in J), (\min V_{ij} \mid j \in j)\, i = 1,2 \ldots .m)\}$$
$$= \{v_1^{+}, v_2^{+}, \ldots .. v_j^{+}, \ldots \ldots v_n^{+}\}$$
$$A^{-} = \{(\min_i V_{ij} \mid j \in J), (\max V_{ij} \mid j \in j)\, i = 1,2, \ldots \ldots \ldots .m\}$$

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$$= \{v_1^-, v_2^-, \dots \dots v_j^-, \dots \dots v_n^-\}$$

J = 1, 2, 3........n, associated with the beneficial attributes.

J = 1, 2, 3...n, associated with non-beneficial adverse attributes. The PIS and NIS values were given in the Table 12.

Table 12. PIS and NIS Values

Criteria	MRR	R_a
PIS	0.13581	0.06325
NIS	0.0304	0.36509

Step4. Calculation of separation values from the PIS and NIS.

The separation of each alternative from PIS is given by $S_i^+ = \sqrt{\sum_{j=1}^{n}\left(v_i^+ - v_{ij}\right)^2}$; Where, i = 1, 2 ...m.

The separation of each alternative from NIS is given by $S_i^- = \sqrt{\sum_{j=1}^{n}\left(v_j^- - v_{ij}\right)^2}$; Where, i = 1, 2 ...m.

The calculated S_i+ and S_i^- values are given in the Table 13.

Table 13. Distance Measures

Experiment No.	S_i^+	S_i^-
1	0.10543	0.29953
2	0.10726	0.21530
3	0.22346	0.11124
4	0.06791	0.30416
5	0.15937	0.17324
6	0.30169	0.05187
7	0.04084	0.28148
8	0.16860	0.15166
9	0.30186	0.10116

Step5. Calculation of relative closeness to the ideal solutions and corresponding Signal to noise (S/N) ratios.

$$\text{Relative closeness coefficient, } C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-}; \text{ Where i = 1,2......m}$$

The larger the C_i^+value, the better the performance of the alternatives. S/N ratios for C_i^+ values were calculated by using Taguchi's Higher-the-Better characteristic.

Step6. Rank the preference order. The relative closeness coefficient values and their corresponding Signal-to-Noise ratios were given in the Table 14.

Table 14. Relative Closeness Values and Ranking

Experiment No.	C^+	S/N of C^+	Rank
1	0.73965	-2.6195	3
2	0.66747	-3.5114	4
3	0.33235	-9.5681	7
4	0.81748	-1.7505	2
5	0.52085	-5.6657	5
6	0.14670	-16.6714	9
7	0.87329	-1.1768	1

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8	0.47355	-6.4927	6
9	0.25100	-12.0065	8

ANOVA of relative closeness coefficient (C_i^+)

Analysis of variance has been done to find the influence of cutting parameters on the multiple responses. ANOVA of C_i^+ is given in the Table 15. From the Table, it is clear that feed rate is the high influencing parameter (F = 91.42) which affects the multi-responses. The Normal probability plot, versus fits and versus order plots of C_i^+ shown in the Figures 7, 8 and 9, signifies that the residuals are following the normal distribution and does not follow any particular pattern.

Table 15. ANOVA for C_i^+

Source	DF	Seq SS	Adj SS	Adj MS	F	P
v	2	0.010836	0.010836	0.005418	2.05	0.328
f	2	0.483357	0.483357	0.241679	91.42	0.100
d	2	0.030655	0.030655	0.015327	5.80	0.147
Error	2	0.005287	0.005287	0.002644		
Total	8	0.530135				

S = 0.0514162, R^2 = 99.00%, R^2 (Adj) = 96.01%

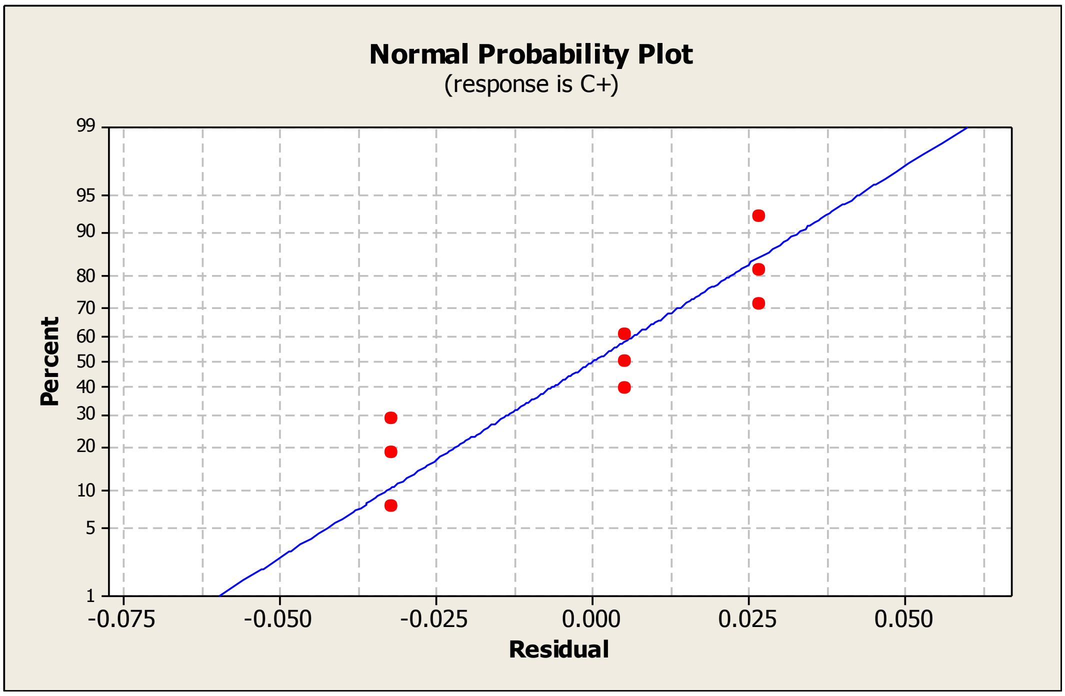

Figure 7. Normal Probability Plot for C_i+

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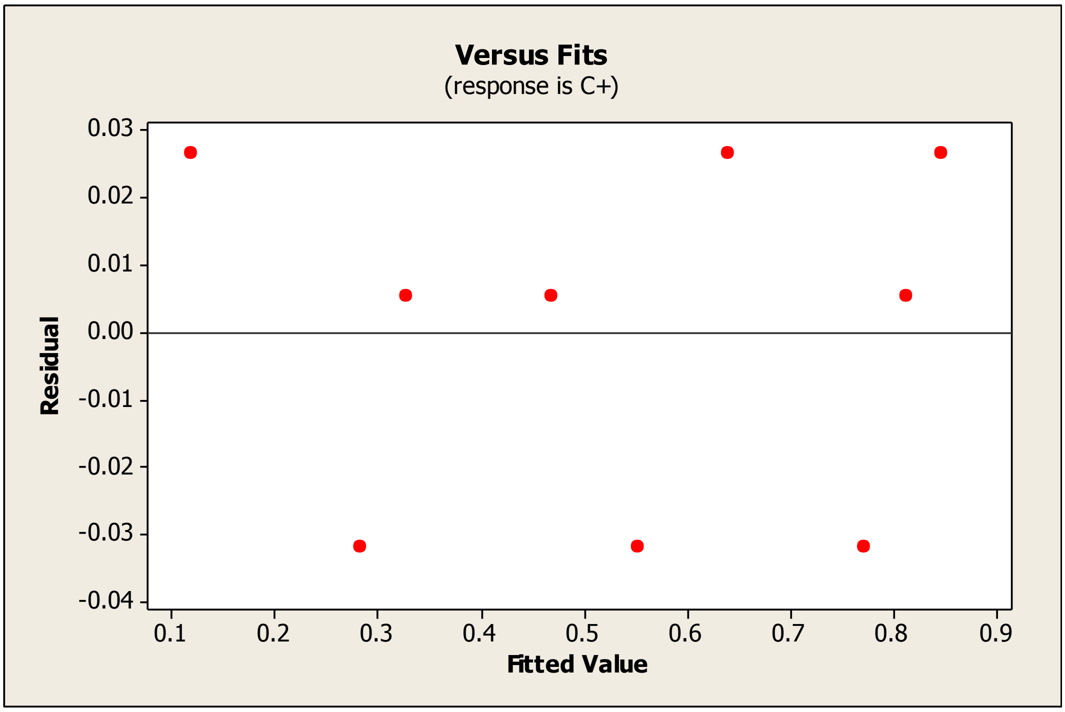

Figure 8. Versus Fits Plot for C_i+

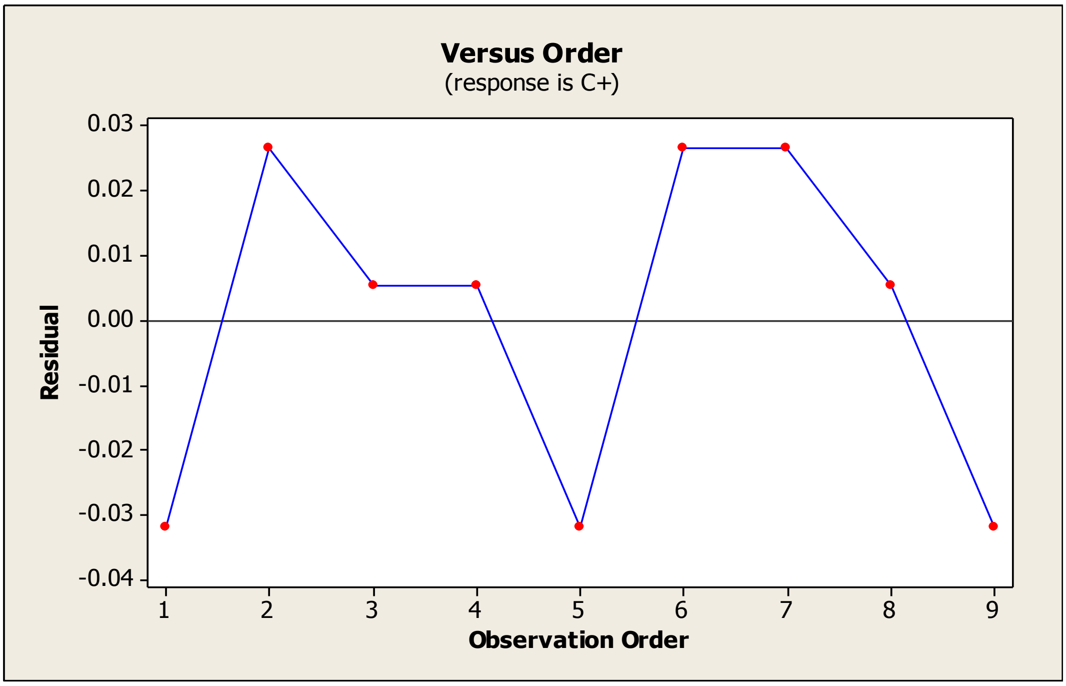

Figure 9. Versus Order Plot for C_i+

4. Conclusions

- From the TOPSIS method, the optimal combination of process parameters is found at the Speed: 2000 rpm, Feed: 0.2 mm/rev and Depth of cut: 1 mm.

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- From the Weighted Sum Method (WSM) and Weighted Product Method (WPM), the optimal combination of process parameters is found at the Speed: 2000 rpm, Feed: 0.4 mm/rev and Depth of cut: 0.75 mm.
- From the ANOVA results of WSM, WPM and relative closeness coefficient (C^+), it is found that feed rate has high influence in affecting the multi-responses.

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