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Parametric analysis of dry machining process using a novel integrated multi-attribute decision making approach

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A B S T R A C T

In most of the machining processes, the complexity arises in the selection of the right process parameters, which influence the machining process and output responses such as machinability and surface roughness. In such situations, it is important to estimate the inter-relationships among the output responses. One such method, Decision-Making Trial and Evaluation Laboratory (DEMATEL) is applied to study the inter-relationships of the output responses. Estimation of proper weights is also crucial where the output responses are conflicting in nature. In the current study, DEMATEL technique is used for estimating the inter-relationships for output responses in machining of EN 24 alloy under dry conditions. CRiteria Importance Through Inter-criteria Correlation (CRITIC) method is used to estimate the weights and finally the optimal selection of machining parameters is carried out using Techniques for Order Preference by Similarity to an Ideal Solution (TOPSIS) method. The model developed guides the decision maker in selection of precise weights, estimation of the inter relationships among the responses and selection of optimal process parameters.

1. Introduction

During the machining process, the friction developed at the tool-workpiece contact, which is generally reduced using a coated cutting tool or a coolant. Using coolants might affect the operator's health, hence dry machining, with coated cutting tool, (Viswanathan et al., 2018) is preferred and is widely used. The primary objective of machining is to obtain high quality and reliable products. Machining is a complex process (Akkuş & Yaka, 2021); machining parameters optimization is quite important to achieve the desired dimensions of the machined part, and it increases productivity (Shastri et al., 2021). Therefore, in the literature the focus of researchers in machining is on the modeling and optimization of the machining process (Sabiya et al., 2019). It is essential to conduct many machining trials in optimizing the process parameters, which increases manufacturing costs (Shilpa et al., 2020). To avoid these manufacturing costs, the Design of Experiments (DoE) methodology is applied. Some DoE methods based on Taguchi Orthogonal Array (OA) (Gaitonde et al., 2009) and Response Surface Methodology (RSM) (Mir & Wani, 2018) allow the user to conduct least number of experiments, as well as they are helpful in analyzing the effect of each factor, interaction effects between the process parameters. They also aid to study the effect of each factor and generate mathematical models such as regression equations and predict the optimal process parameters. As machining involves multiple conflicting criteria, it is preferred to adopt Multi Criteria Decision-Making (MCDM) methods for performing optimization. MCDM (Rao & Patel, 2010) is further divided as Multi-Objective Decision-Making (MODM) and Multi-Attribute Decision-Making (MADM) methods (Venkata Ajay Kumar G et al., 2019). MODM

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has continuous decision variables, whereas MADM has discrete decision variables. Most commonly used MADM methods are Analytical Hierarchy Process (AHP) (Saaty, 2002), Simple Additive Weighting (SAW) (Kaliszewski & Podkopaev, 2016), TOPSIS (Lai et al., 1994) and Grey Relational Analysis (GRA) (Julong, 1988).

DEMATEL is used to estimate the interrelationships among the responses and identifying the cause and effects was proposed and designed at the Geneva Research Centre - Battelle Memorial Institute (Si et al., 2018). The researchers (Das & Chakraborty, 2020) applied the DEMATEL to estimate the interrelationships among the responses of the green electric discharge machining process. The CRITIC method proposed by Diakoulaki, Mavrotas, and Papayannakis (Diakoulaki et al., 1995) is used mainly to determine the objective weights of the responses based on the decision matrix. In machining of ultra-high-strength steel 300 M using four various ceramic tool combinations, (Wang & Zhao, 2016a) AHP-CRITIC method is applied for mechanical properties optimization of ceramic tool materials. TOPSIS is used for finding out the optimal parametric combination and is widely used in the sustainable turning of 17-4 Precipitated Hardened (PH) stainless steel (Sivaiah & Uma, 2019) and dry machining of EN AW-2011 alloy (Jozić et al., 2020). Researchers have investigated Surface Roughness (SR), tool wear (flank wear & crater wear) and chip coefficient reduction in machining of titanium grade 5 alloy using Physical Vapor Deposition (PVD) AlTiN coated carbide as a cutting insert (Pradhan & Maity, 2018). They have optimized the machining parameters with desirability function approach, and found cutting speed is the most significant parameter. (Aouici et al., 2017) compared the TiN coated and uncoated ceramic tools especially on the cutting force in machining of AISI H11 steel by Taguchi method and RSM. Depth of cut was found as the most contributing factor on axial force. Uncoated carbide inserts show better performance in terms of cutting force and tool wear. Optimum conditions are estimated by using desirability function approach, quadratic models are estimated by RSM. Researchers have (Parida & Routara, 2014) applied the multi-response optimization technique TOPSIS in machining of GFRP composite and this method led to more reliable solutions when compared to experimental results. Cutting speed is significant for SR and depth of cut is significant for the material removal rate (MRR). The authors (Balasubramaniyan Singaravel, 2015) simultaneously optimized microhardness, SR and MRR in machining of EN 25 steel with coated carbide using TOPSIS methodology. (Tic & Steel, 2018) improved the surface quality and productivity of turning AISI D3 steel with mixed ceramic tools under dry condition. Feed rate is most significant for the SR and depth of cut for MRR, applied GRA for simultaneous optimization, grey relational grade was also improved and had a good agreement with the experimental value. (Kuntoglu et al., 2020) modelling the machining parameters in machining of AISI 5140 steel under dry conditions using coated carbide tools. Prediction of parameters estimated for SR and vibration for three components viz axial, radial and tangential showed a good agreement to the measured values. Feed rate is more effective for the SR and axial vibration followed by cutting-edge angle for radial vibration and cutting speed for tangential vibration. (Bouzid et al., 2018) optimized the flank wear in turning of AISI 304 stainless steel with multilayer $TiCN/Al_2O_3/TiN$ coated carbide using Desirability Function Analysis (DFA). Cutting time is identified as the most influential factor on SR and cutting speed significantly influences the tool lifespan. Increased cutting speed and feed rate reduces the tool life to about 77%. Further, different optimization techniques as applied to dry turning are summarized in Table 1.

In the literature, Precise weight allocation for the output responses is not addressed; formulation of the inter-relationships between the responses is important when more responses are measured. In this paper, DEMATEL method is applied to dry machining of alloy steel to identify the relationships among the responses; CRITIC method is used to identify the weights for the responses, and TOPSIS employed for optimal process parameters estimation. This is a novel integrated MADM approach, which combines the three techniques: DEMATEL-CRITIC-TOPSIS.

Table 1
Summary of different optimization techniques in dry turning for alloy steels

Work material	DoE used	Optimization technique applied
AISI H11 (Aouici et al., 2017)	L36 OA	Desirability function approach
EN 25 steel (Singaravel et al., n.d.)	L18 OA	AHP-TOPSIS
AISI D3 steel (Tic & Steel, 2018)	L18 OA	GRA
AISI 52100 steel (Alok & Das, 2019)	20 experiments, Central Composite Design (CCD)	RSM
AISI 304 stainless steel (Bouzid et al., 2018)	RSM – two full factorial designs – 27 runs	Desirability function approach
ultra-high-strength steel 300M (Wang & Zhao, 2016b)	12 experiments with three levels of cutting speed (no DoE used)	AHP-CRITIC
17-4 PH stainless steel (Sivaiah & Uma, 2019)	L9 OA	TOPSIS

2. Methodology

The methodology employed for estimation of interrelationships between the output responses, weight and optimal parameters in machining of EN24 steel under dry condition is presented in Fig. 1.

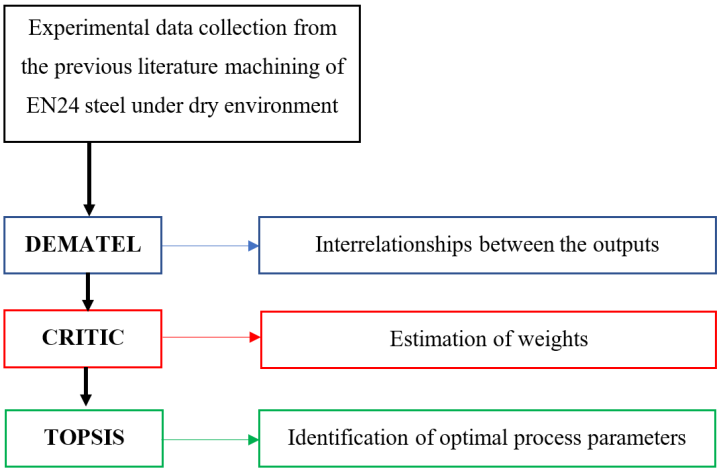

Fig. 1. Methodology employed

3. MADM approaches

This section presents the various approaches involved in MADM.

3.1 DEMATEL method

The DEMATEL method is widely used to identify the cause and effect of the responses. Major steps involved are identifying the threshold value, estimating the cause and effects and finally the formulation of the diagraph or causal relationships diagram

Step 1: Establishing the direct-relation matrix
The decision maker needs to establish the correlation between the criteria on a scale of 0 to 4 (Diakoulaki et al., 1995).
Step 2: Normalizing the direct-relation matrix

$$Y = k \,.\, A \tag{1}$$

$$where\ k = \frac{1}{\max\limits_{1 \le i \le n}\left(\sum\limits_{j=1}^{n} a_{ij}\right)} \quad (i, j = 1,2,.....,n)$$

Step 3: Calculate the total-relation matrix (T)

$$T = \left[t_{ij}\right]_{n\,x\,n} \quad (i,\ \ j = 1,2,\ .....,n) \tag{2}$$

where $T \ = \ Y(I-Y)^{-1}$

Here, I is identity matrix; t_{ij} is indirect effect of the i^{th} criterion on j^{th} criterion.
Step 4: Evaluate the sum of rows (R) and columns (C) of the matrix T. The vectors R and C obtained using the equations

$$R_i = \left[\sum_{j=1}^{n} t_{ij}\right]_{n\,x\,1} = \left[t_i\right]_{n\,x\,1}, \quad i=1,2,....,n \tag{3}$$

$$C_j = \left[\sum_{i=1}^{n} t_{ij}\right]_{1\,x\,n} = \left[t_j\right]_{n\,x\,1}, \quad i=1,\ 2,\ldots,n \tag{4}$$

Step 5: Derive the threshold value (α), which obtained by averaging of the elements in the T matrix. Here N represents the number of elements in the T matrix.

$$\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}[t_{ij}]}{N} \tag{5}$$

Step 6: Construction of the causal diagram

The prominence vector ($R_k + C_k$) on the horizontal axis when added with R and C values gives the importance of the criterion; the relation vector ($R_k - C_k$) divides the cause group and effect group. If ($R_k - C_k$) is positive then cause group, ($R_k - C_k$) is negative, then it is effect group. By establishing the causal diagram, the most important criteria for a problem can be identified.

3.2 CRITIC Method

The CRITIC method is an objective weight estimation based on the responses. After formulating the decision matrix, it is required to normalize and estimate the linear correlation coefficient between the criteria's. Finally, the individual weights of the responses are calculated.

Step 1: Determining the normalized decision making matrix using the Eq. (6)

$$r_{ij} = \begin{cases} \dfrac{x_{ij} - x_j^{\max}}{x_j^{\max} - x_j^{\min}} & x_{ij}\ \text{is a beneficial attribute} \\ \dfrac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} & x_{ij}\ \text{is a non-beneficial attribute} \end{cases} \tag{6}$$

Step 2: Estimating the criterion information

$$C_j = \sigma_j \sum_{k=1}^{m} 1 - r_{jk} \tag{7}$$

Here σ_j is the standard deviation of the each criterion and r_{jk} linear correlation coefficient between the criteria's

Step 3: Determining the weights of the individual output

$$W_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \tag{8}$$

3.3 TOPSIS

TOPSIS method uses the compromise ranking methodology and ranks the alternatives. Here the major step is to frame the positive and negative ideal solutions. TOPSIS method is explained as follows:

Step1: Decision matrix normalized based on the output responses

$$R_{ij} = \frac{m_{ij}}{\sqrt{\sum_{j=1}^{M} m_{ij}^2}} \tag{9}$$

Step 2: Estimated weights multiplied to the normalized decision matrix

$$V_{ij} = w_j * R_{ij} \tag{10}$$

Step 3: Identifying the positive (A^+) and negative (A^-) ideal solutions

$$A^+ = \left\{v_1^+, v_2^+, \ldots, v_n^+\right\}$$
$$A^- = \left\{v_1^-, v_2^-, \ldots, v_n^-\right\} \tag{11}$$

Step 4: Estimating the separation measures for the alternatives

$$D_j^+ = \sqrt{\sum_{i=1}^{n} \left(v_j^+ - v_{ij} \right)^2} \quad ; \quad D_j^- = \sqrt{\sum_{i=1}^{n} \left(v_j^- - v_{ij} \right)^2} \tag{12}$$

Step 5: Calculating the Relative closeness value (C_{Ci})

$$C_{ci} = \frac{D_j^-}{D_j^+ + D_j^-} \tag{13}$$

Step 6: Ranking of the alternatives in the descending order of (C_{Ci}).

4. Parametric analysis of a dry machining on EN 24 alloy steel

A hard turning of EN 24 alloy steel experiments are (A. Das et al., 2019) conducted on the specimen of 40mm diameter and 500 mm length under dry machining conditions. Based on Taguchi L9 Orthogonal Array (OA) with Cutting speed at three levels (80, 100, 120 m/min), feed at three levels (0.05, 0.1, 0.15 mm/rev) and depth of cut at three levels (0.1, 0.2, 0.3 mm) the layout for experimentation is created. The five output responses estimated are cutting force (F_Z) (in N), flank wear (VB_C) (in mm), crater wear width (K_W) (in mm), surface roughness (R_a) (in μm) and micro-hardness of the chip (MH) (in HV) which are summarized in the Table 2.

Table 2
Experimental details of EN 24 machining using coated cermet under dry machining environment (A. Das et al., 2019)

Exp. Run no.	Cutting speed (v)	Feed (f)	Depth of cut (d)	Fz (N)	VBc (mm)	Kw (mm)	Microhardness, MH (HV)	Surface roughness, Ra (μm)
1	1	1	1	104	0.18932	0.29341	280	1.20
2	1	2	2	118	0.12932	0.24437	420	1.29
3	1	3	3	159	0.11223	0.18621	519	1.34
4	2	1	2	99	0.13996	0.24753	395	1.60
5	2	2	3	123	0.05178	0.18762	530	1.67
6	2	3	1	76	0.08036	0.23672	452	1.82
7	3	1	3	119	0.16833	0.19902	458	2.10
8	3	2	1	71	0.11132	0.2639	416	2.39
9	3	3	2	88	0.13894	0.19832	516	2.61

In DEMATEL method, the initial step is to establish the direct relation matrix on the integer scale ranging from 0 to 4. The developed direct-relation matrix for the five output responses shown in the Table 3. By using the Eq (1), the matrix then normalized as given in Table 4. Then, Eq. (2) applied to estimate the T matrix consequently the summation of rows and columns of the developed T matrix defined as R and C vectors by applying the Eq. (3) and Eq. (4) shown in Table 5. The net effect of the responses (R+C) and (R-C) is also estimated and grouped as cause and effect, as shown in Table 6. The threshold value (α) is calculated using Eq. (5). Based on the cause and effect, the causal diagram is constructed and depicted in Fig 2. Flank wear has the highest net influence followed by surface roughness followed by cutting force in dry machining (turning) of EN 24 alloy steel.

Table 3
Formulated initial direct-relation matrix

Output responses	Fz	VBc	Kw	MH	Ra
Fz	0	3	2	3	3
VBc	3	0	1	2	3
Kw	2	1	0	1	3
MH	3	2	3	0	1
Ra	3	2	3	3	0

Table 4
Normalized values for the direct-relation matrix

Output responses	Fz	VBc	Kw	MH	Ra
Fz	0	0.272727	0.181818	0.272727	0.272727
VBc	0.272727	0	0.090909	0.181818	0.272727
Kw	0.181818	0.090909	0	0.090909	0.272727
MH	0.272727	0.181818	0.272727	0	0.090909
Ra	0.272727	0.181818	0.272727	0.272727	0

Table 5
Total relational-matrix for the output responses

Output responses	Fz	VBc	Kw	MH	Ra
Fz	1.418133*	1.322915*	1.368454*	1.440178*	1.524426*
VBc	1.452701*	0.971393	1.14941*	1.229787*	1.359118*
Kw	1.136204*	0.855682	0.850714	0.94289	1.133699*
MH	1.379839*	1.065618	1.215897*	1.002587	1.180604*
Ra	1.609812*	1.243221*	1.418547*	1.419685*	1.294039*

*tij > 1.0916

Table 6
Computation of vectors D and K and net effects of response

Output responses	Rk	Ck	R+C	R – C	Criteria group
Fz	7.074105	6.996688	14.07079	0.077417	Cause
VBc	6.162409	5.458828	11.62124	0.703581	Cause
Kw	4.919189	6.003022	10.92221	-1.08383	Effect
MH	5.844546	6.035127	11.87967	-0.19058	Effect
Ra	6.985303	6.491886	13.47719	0.493418	Cause

The threshold value (α) is 1.0916 which is obtained by averaging the all the elements in the T matrix of Table 5. In the Table 5 the t_{ij} × represents the elements of T matrix which are greater than 1.0916, it represents the significant interaction between the two output responses. For example t_{12} × (1.322915) > α (1.0916), so in the diagraph an arrow shows the interaction of cutting force and micro hardness (unidirectional) as depicted in the Fig. 3. There are further bi-directional interactions between the output responses like flank wear to cutting force, cutting force to surface roughness, surface roughness to micro hardness, cutting force to crater wear width and cutting force to micro hardness.

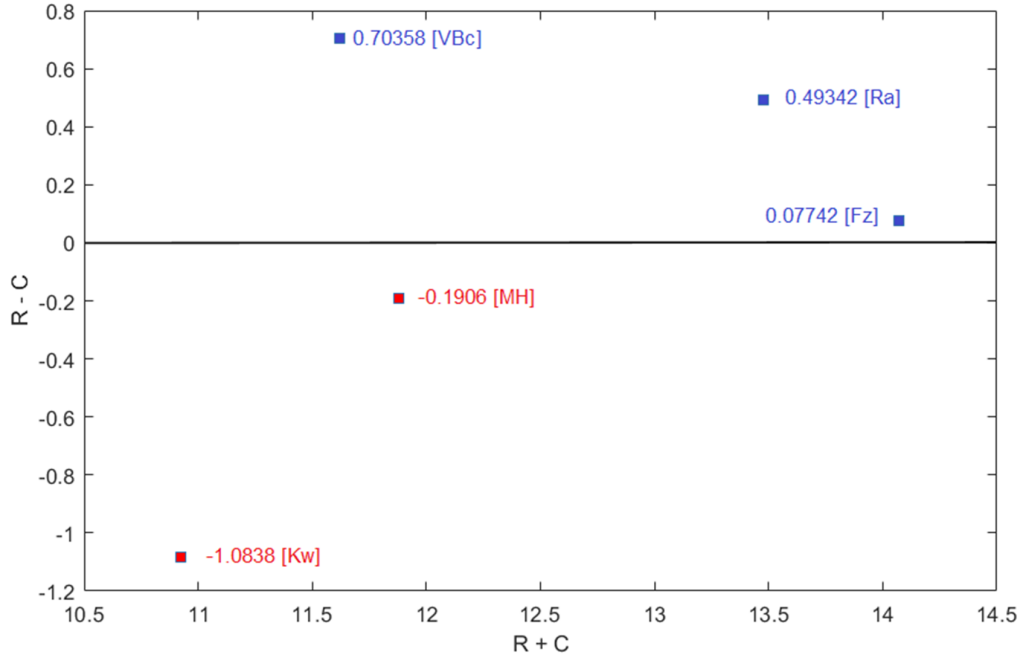

Fig. 2. DEMATEL causal diagram for the output responses

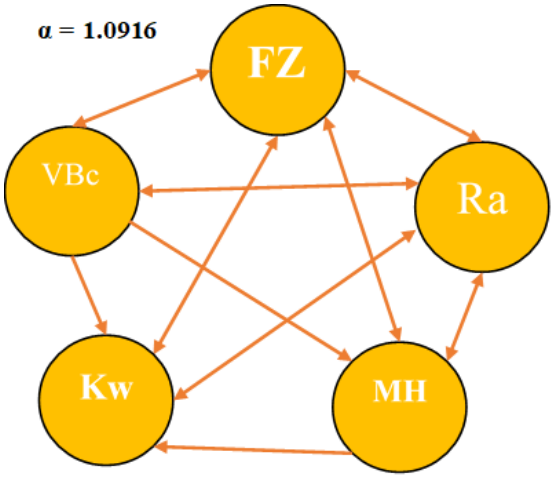

Fig. 3. DEMATEL diagraph for responses

In MCDM problems, weights of the responses play important role; for this purpose CRITIC methodology is employed. The five output responses from the Table 2 is normalized using the Eq. (6), the normalized values are shown in Table 7. The criterion information calculated using Eq. (7) and correlation values are tabulated in table 8. The weights of the five output responses are estimated using Eq. (8) and are presented in the last column of Table 9.

Table 7
Normalized values of output responses by CRITIC method

Exp. Run no.	Fz	VBc	Kw	MH	Ra
1	0.625	0	0	0	1
2	0.465909	0.436237	0.457463	0.56	0.93617
3	0	0.560491	1	0.956	0.900709
4	0.681818	0.358877	0.427985	0.46	0.716312
5	0.409091	1	0.986847	1	0.666667
6	0.943182	0.792206	0.528825	0.688	0.560284
7	0.454545	0.15261	0.880504	0.712	0.361702
8	1	0.567108	0.27528	0.544	0.156028
9	0.806818	0.366293	0.887034	0.944	0

Table 8
Correlation coefficient of the output responses

	Fz	VBc	Kw	MH	Ra
Fz	1	0.00311	-0.5283	-0.31981	-0.57292
VBc	0.00311	1	0.434201	0.645073	-0.07848
Kw	-0.5283	0.434201	1	0.936909	-0.25513
MH	-0.31981	0.645073	0.936909	1	-0.38717
Ra	-0.57292	-0.07848	-0.25513	-0.38717	1

Table 9
Weights for the output responses estimated by using CRITIC method

	Cj	Wj
Fz	1.673678	0.25214
VBc	0.91627	0.138037
Kw	1.200947	0.180923
MH	0.979384	0.147545
Ra	1.8676	0.281355

For finding the optimal set of parameters using TOPSIS, Table 2 output responses normalized with Eq. (9). The weights estimated using CRITIC method are utilized here and multiplied with the normalized values using the Eq. (10). Estimation of positive and negative ideal solutions is obtained by using Eq. (11). Further the separation measures using Eq. (12) and the closeness coefficient using Eq. (13). Now, the ranking of alternatives in descending order is carried out based on the closeness coefficient and ranking is established to identify the optimal parameters, which is presented in Table 10.

Table 10
Dj^+ , Dj^- , C_{Ci} and Rank by using the TOPSIS

Exp. Run no.	Dj+	Dj-	C_{Ci}	Rank
1	0.067199	0.083348	0.553632	5
2	0.049444	0.079748	0.617284	3
3	0.071254	0.079931	0.528697	6
4	0.048115	0.073328	0.603805	4
5	0.046584	0.083134	0.64088	2
6	0.03688	0.087924	0.704498	**1**
7	0.072235	0.051577	0.416573	9
8	0.068418	0.075712	0.525304	7
9	0.079273	0.067627	0.460363	8

From TOPSIS, run number six is identified as optimum parameter level combinations where in cutting speed is 100 m/min, feed is 0.15 mm/rev and depth of cut is 0.1 mm under dry machining. In dry machining, the depth of cut influences the cutting force, feed influences the flank wear, depth of cut influence the crater wear, feed influences the micro hardness of chip, and cutting speed influences the surface roughness. The tool is continuously in contact with the work piece in turning operation, where the tool wear is more profound. In dry machining, the tool wears out quickly because of the absence of coolant in the cutting zone. The surface roughness of the material affects further because of tool wear. The worn out particles damage the surface integrity of the work piece. If the cutting forces in the cutting zone are reduced the work piece will have a better surface finish. In dry machining, the tool wear, surface roughness and cutting forces are the main factors in the machining of alloy steels. As the hardness of the chip increases, there will be an increase in tool wear too.

5. Conclusions

In this work, a Hybrid technique by combining the DEMATEL-CRITIC-TOPSIS methods has been applied to estimate the interrelationship between the output parameters and finally we have found the optimal parametric combination in machining on EN 24 alloy steel under the dry machining. The cause and effects have been identified by DEMATEL as cutting forces, flank wear, and surface roughness. All the parameters finally affect the surface roughness of the machined part, and CRITIC method has shown the highest weightage to surface roughness. Finally, TOPSIS determined the optimal combination of parameters in dry machining of EN 24 alloy steel. The data obtained for verifying the proposed model are collected from the literature, as there is no scope for conducting the confirmation test. This method can be applied to other machining processes to estimate optimal parameters and improve the performance of machining.

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