Manufacturing Rev. **9**, 20 (2022)

https://doi.org/10.1051/mfreview/2022014

**Manufacturing Review**
Available online at:
https://mfr.edp-open.org

RESEARCH ARTICLE

OPEN ACCESS

# Application of MOORA & COPRAS integrated with entropy method for multi-criteria decision making in dry turning process of Nimonic C263

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Received: 17 September 2021 / Accepted: 12 May 2022

**Abstract.** This article presents an integrated multi-criteria decision making using Entropy, MOORA and COPRAS methods for turning Nimonic C263. Experiments were performed under L27 Taguchi orthogonal array. Dry turning was performed and cubic boron nitride (CBN) was used to turn the alloy. The variables speed, feed and depth of cut were chosen as factors. For each experiment, the shear force component was measured during on line. The insert flank wear was measured after every experiment. The main objective of this paper is to identify the suitable trial to ensure minimum force and flank wear simultaneously. Because of the cost reduction and quality improvement, the controlling factors level should be selected appropriately. Hence, the integrated MCDM technique using MOORA, COPRAS and Entropy was chosen to determine the best experiment out of 27 experiments. Alternatives were ranked and the results were evaluated. The best experiment for minimization of force and flank wear is found to be 125 m/min, 0.055 mm/rev and 0.25 mm. The experimental test were observed with lesser deviation and confirmed that proposal found is more suitable to obtain minimum force and flank wear.

**Keywords:** Nimonic C263 / MOORA / COPRAS / cutting force / flank wear

## 1 Introduction

Nickel alloy Nimonic C263 is found to be applied to manufacture aero parts owing to its inherent quality to resist the environmental changes and retention of its mechanical properties during usage. However, its fatigue life, creep limit and other mechanical properties are highly dependent on the quality of the machined surface and the machined surface should be free from residual stress and should have a great finish. These qualities are highly dependent upon the level of machining parameters, insert materials, mode of machining and also the above said qualities can be improved by controlling the generation of cutting force and flank wear during machining.

Machining of superalloys is still tough and a challenging task owing to process stress, strain and product quality requirements. The tool wear is found to be a main issue in machining the Nickel alloy due to low conductivity and the heat generated while machining is caused to insert. As a result, high insert tip temperature would cause extra wear on insert edge and part integrity directly affected. The generation of temperature in machining will be in the range of 1100 °C and 1300 °C [1]. The super alloys possesses a full range utilization in aero industry and other chemical and petrochemical factories.Howver,the machining factors impcts largely on machining thes alooys such as Inconel 718, Nimonic C263,

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Mnel metals etc. The factors such as speed, feed and depth of cut influence on force, surface roughness, integrity etc. The increase in speed cause temperature generation in the machining area and result in decreasing the force and roughness owing to loss of mechanical workpiece properties in the machining area [2]. The machinability issues pertaining to many super alloys were recharged by many researchers however, adequate research is to be carried out on Nimoni C263 alloy and optimium parameters are to be found out using various optimization tools to optimize the machining characteristics such as forces, surface roughness, integrity insert wear and temperature at machining area [3].

Therefore, modelling and multi-response optimization of parameters would be beneficial to study the impact of the parameters before the actual experiments and thereby the manufacturing, material and insert etc., the cost can be avoided. The MOORA is used to find a solution to calculate many complex decision-making issues in manufacturing sectors and it can also be called a multi-attribute optimization technique [4]. Various places such as product and process designs, finance, aircraft designs and manufacturing industries, automobile design and manufacturing, oil and gas industry are required effective decision support and also optimum decisions has to be identified among conflict intentions. There are several multi response optimization decision-making tools available such as Analytic hierarchy process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), analytic network process (ANP), MOORA and Multi-Objective Optimization On The Basis Of Simple Ratio Analysis (MOOSRA), ELimination et Choix Traduisant la REalite (ELECTRE),Complex Proportional Assessment Of Alternatives With Gray Relations (COPRAS-G), andVIekriterijumsko KOmpromisno Rangiranje (VIKOR) to handle multiple responses under conflicting criteria [5]. MOORA is an easy method comparing SVR, GA etc., since MOORA minimize the computational complexity. MOORA obtain feasible results even under conflicting criteria [6]. Zong-Liang Liang et al. developed a Multi-Objective Optimization model using MOORA-Taguchi and used in the gas metal arc welding process and validated with experimental results. Further, the developed MOORA was utilized to transform the correlated welding attributes into separate index-quality [7].

V. Anandan et al. [8] analysed the significance of graphene nanofluid while turning M42 steel using AHP and MOORA. MOORA is a versatile method and widely applied in the optimization of the parameters and sustainable machining to solve environmental issues like economic, social and environmental features [9,10]. Multiple Attribute Decision Making (MADM) tools like MOORA and Weighted Euclidean Distance Based Approach (WEDBA) are also found to be suitable in ranking the controlling factors and manufacturing activities [11].

The machining parameters were optimized in Electrical Discharge Machining (EDM) operation using MOORA technique and observed the optimum outputs such as material removal rate (MRR), plasma flushing efficiency (PFE), surface-roughness (SR) and recast layer thickness were achieved by intermingling MOORA with Weighted Principal Component Analysis (WPCA) [12].

Hamdy et al. [13] have conducted a plasma arc welding on mild steel and welding parameters were optimized by MOORA-Standard deviation (SDV)-Genetic Algorithm (GA), in which SDV and MOORA were used to allocate weight criteria for all objects and to transform all responses into a single attribute index respectively. GA was used to model the all responses using attribute index. Durwesh Jhodkar et al. [14] conducted a turning operation based on an $L_{27}$ array on titanium alloy and the controlling parameters were optimized using a hybrid MOORA-FUZZY approach. Further, it was proved that MOORA can be used to optimize many conflicting outputs which are related to certain constraints. MOORA has two things such as reference and ration points and these were considered as main to evaluate the overall performance of each alternative. This COPRAS is used to convert a more number of outputs into one index which can be called as Multi Performance characteristics Index (MPCI) [14].

The levels of machining parameters are important as these impact the responses; therefore these process impacts are needed to be monitored and controlled. The force signals were used to correlate the tool wear and it was reported that the force signals have shown a good correlation with flank wear [15]. The cutting force has changed in magnitude depending upon the cutting edge status irrespective of the cutting time. The forces are increases as the edge worn, it is owing to an increase in contact surface in-between the workpiece and cutting edge in the machining operation. Therefore, optimized condition of the parameters is to be found to optimize the magnitude of the force and wear [16].

Shoujin et al. [17] conducted dry turning on titanium alloy and investigated the change of cutting forces concerning change in the level of cutting speeds and matched up with the flank wear. The flank wear was found significant with volume material removed at both the speed 150 m/min and 220 m/min, but different wear mechanisms were reported. Further, they have reported that the magnitude of the cutting forces was found to be low at speed 220 m/min then the forces observed at 150 m/min. It would be owing to softening the machine zone due to high heat at high-level speed hence low forces.

COPRAS (Complex Proportional Assessment) method was introduced by Zavadskas and Kaklauskas in 1994 [18]. It is also used to identify the best possible alternative among the set of all alternatives. The proportional ratios of the best and worst ideal solutions are compared in COPRAS method to determine a solution with the ratio to the best solution. Varathrajulu et al. [19] have used the multi criteria decision making (MCDM) methods like TOPSIS and COPRAS to optimize the drilling parameters in drilling magnesium alloys (Mg). In both the methods identical sequence order were noted in TOPSIS and COPRAS method. Further, it was confirmed that the COPRAS method consumes less time in optimization. Do Duc Trung [20] has conducted turning experimental trails on 150Cr14 steel using TiAiN coated insert and compared eight MCDM methods (SAW, MOORA, COPRAS,

**Table 1.** Turning factors and their levels.

| Factor | Symbol | Unit | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|---|
| Cutting speed | V | m/min | 80 | 190 | 250 |
| Feed rate | S | mm/rev | 0.055 | 0.096 | 0.159 |
| DOC | $a_p$ | mm | 0.25 | 0.50 | 0.75 |

WASPAS, TOPSIS, VIKOR, PIV and PSI) to get optimum parameters to obtain minimum of cutting force, feed force, axial force and maimum of MRR. Out of eight methods, seven methods perfomed similarly to obtain the best experiment.

Seyed Hadi Mousavi-Nasab et al. [21] demonstrated clearly the MCDM framework using four parameters such as Attributes or decision factors (criteria), optionsor choices (Alternatives), comparative significance of criterion (Weight of attribute) and performance ratings of options regarding the criteria.

From the state of the art, it is observed that the application of MCDM techniques obtain best possible values to optimize the outputs. Many researchers have developed several models to predict the optimum results in the machining of alloys, however, no study is found in optimization of the parameters in turning Nimonic C263 alloy using MCDM. Therefore, an attempt is taken to optimize the machining parameters using the MCDM methods MOORA and COPRAS to obtain minimum of cutting force and flank wear.

## 2 Turning experiment

The parameters including cutting speed, feed rate and depth of cut were choosen as input factors to carry out the experiment process.The turning trails were done using NAGAMATI175 lathe. The lathe's specifications: Height: 165 mm, swing: 305 mm, speed: 54–1200 revolution/minute, feed: 0.048–0.716 mm/rev, power: 1HP. The Taguchi technique was utilized to design the experiment. The input factors was choosen with three levels as given in Table 1. The $L_{27}$ orthogonal array is shown in Table 2. The cutting forces directly impact the surface roughness and tool wear during machining process. The cutting force generation were observed using Kistler piezo-electric tool post dynamometer: coupled with amplifier. The flank wear was recorded for every preset time interval with help of tool maker's microscope. The experimental results are given in Table 2. The experimental details are shown in Figure 1. CBN (Cubic boron nitride) insert was used during the machining process. It has high hardness and it is found to be suitable for high-speed machining of superalloys. Dry turning is carried out. The experimental results were given in Table 2. MCDM tools such as MOORA and COPRAS were used to find best experiment to minimize the cutting force and flank wear simultaneously. Entropy method was used to obtain the weight of the criteria in order to reduce the influence of decision maker's intuition and perception.

## 3 Determine the weights using the Entropy method

Entropy method generates weight for each criteria considering the importance of criteria between and within using the response value. The weights obtained will be used for both MCDM methods MOORA and COPRAS. The determination of the criterion weight using Entropy method is done as follows [22,23].

Step 1: Obtain Normalised values.

$$P_{ij} = \frac{y_{ij}}{m + \sum_{i=1}^{m} y_{ij}^2}. \tag{1}$$

Step 2. Calculate the value of the Entropy measurement degree for each criterion.

$$e_j = -\sum_{i=1}^{m}\left[P_{ij} \times \ln(P_{ij})\right] - \left(1 - \sum_{i=1}^{m} P_{ij}\right) \times ln\left(1 - \sum_{i=1}^{m} P_{ij}\right). \tag{2}$$

Step 3. Calculate the weight for each criterion.

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m}(1 - e_j)}. \tag{3}$$

### 3.1 MOORA method

The MOORA method was firstly introduced in 2004 [8], the steps are presented as follows. The following are the steps involved in Ratio MOORA:

Step 1: Form a decision matrix $X = x_{ij}$ with '$m$' alternatives and '$n$' criteria, $i = 1, 2.3, \ldots, m$ and $j = 1, 2.3, \ldots, n$

$$X = [x_{ij}]_{m \times n}. \tag{4}$$

Step 2: Normalise the decision matrix:

$$n_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1, 2, 3, \ldots, m \text{ and } j = 1, 2.3, \ldots, n. \tag{5}$$

where $i$ = number of trials, $j$ = number of responses and $n_{ij}$ = normalized value of the $i$th experimental run related with the $j$th responses.

**Table 2.** Summary results of processing factors and attributes data of turning process.

| Exp. Trails | Controlling factors | | | Machining attributes | |
|---|---|---|---|---|---|
| | V-m/min | S-mm/rev | ap-mm | $F_z$-N | VB-mm |
| 1 | 80 | 0.055 | 0.25 | 400 | 0.3 |
| 2 | 80 | 0.055 | 0.50 | 440 | 0.32 |
| 3 | 80 | 0.055 | 0.75 | 490 | 0.34 |
| 4 | 80 | 0.096 | 0.25 | 450 | 0.33 |
| 5 | 80 | 0.096 | 0.50 | 500 | 0.35 |
| 6 | 80 | 0.096 | 0.75 | 540 | 0.36 |
| 7 | 80 | 0.159 | 0.25 | 460 | 0.38 |
| 8 | 80 | 0.159 | 0.50 | 520 | 0.39 |
| 9 | 80 | 0.159 | 0.75 | 550 | 0.40 |
| 10 | 125 | 0.055 | 0.25 | 300 | 0.29 |
| 11 | 125 | 0.055 | 0.50 | 330 | 0.31 |
| 12 | 125 | 0.055 | 0.75 | 380 | 0.33 |
| 13 | 125 | 0.096 | 0.25 | 325 | 0.30 |
| 14 | 125 | 0.096 | 0.50 | 345 | 0.345 |
| 15 | 125 | 0.096 | 0.75 | 390 | 0.365 |
| 16 | 125 | 0.159 | 0.25 | 420 | 0.32 |
| 17 | 125 | 0.159 | 0.50 | 440 | 0.36 |
| 18 | 125 | 0.159 | 0.75 | 495 | 0.41 |
| 19 | 190 | 0.055 | 0.25 | 265 | 0.42 |
| 20 | 190 | 0.055 | 0.50 | 290 | 0.38 |
| 21 | 190 | 0.055 | 0.75 | 300 | 0.42 |
| 22 | 190 | 0.096 | 0.25 | 310 | 0.39 |
| 23 | 190 | 0.096 | 0.50 | 360 | 0.45 |
| 24 | 190 | 0.096 | 0.75 | 410 | 0.46 |
| 25 | 190 | 0.159 | 0.25 | 430 | 0.45 |
| 26 | 190 | 0.159 | 0.50 | 465 | 0.44 |
| 27 | 190 | 0.159 | 0.75 | 480 | 0.47 |

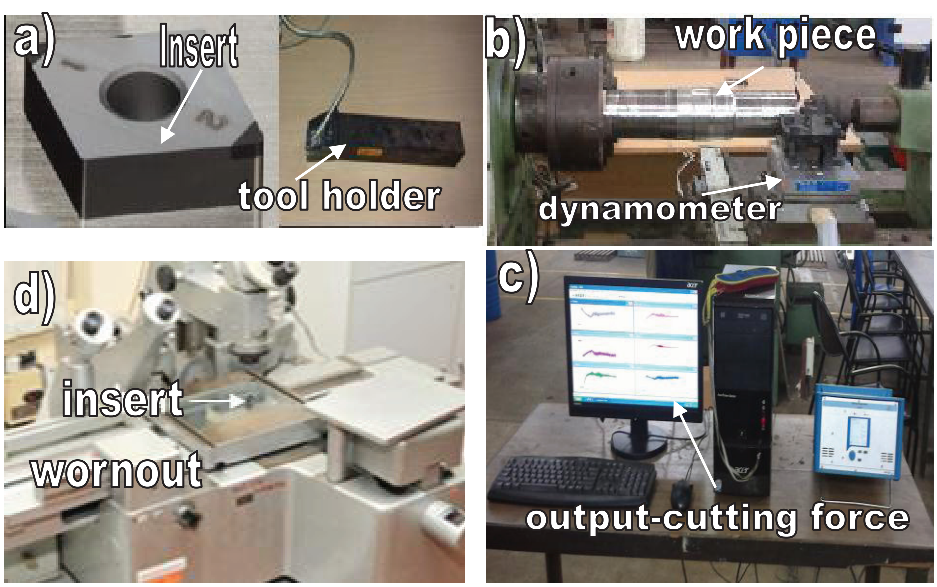


**Fig. 1.** Experimental details. (a) Insert & tool holder, (b) experimental set-up; (c) Flank wear measurement; (d) Dyanaware output-cutting force measurement.

**Table 3.** Normalized value for criteria.

| Exp. | Responses | | | Normalised ($n_{ij}$) | |
|---|---|---|---|---|---|
| | CF | FW | | CF | FW |
| e1 | 409 | 0.30 | | 0.188 | 0.153 |
| e2 | 451 | 0.32 | | 0.208 | 0.164 |
| e3 | 496 | 0.34 | | 0.229 | 0.174 |
| e4 | 433 | 0.33 | | 0.200 | 0.169 |
| e5 | 476 | 0.35 | | 0.219 | 0.179 |
| e6 | 521 | 0.37 | | 0.240 | 0.189 |
| e7 | 476 | 0.36 | | 0.219 | 0.184 |
| e8 | 519 | 0.38 | | 0.239 | 0.194 |
| e9 | 565 | 0.41 | | 0.260 | 0.210 |
| e10 | 290 | 0.29 | | 0.134 | 0.148 |
| e11 | 327 | 0.31 | | 0.151 | 0.159 |
| e12 | 366 | 0.33 | | 0.169 | 0.169 |
| e13 | 335 | 0.32 | | 0.154 | 0.164 |
| e14 | 372 | 0.33 | | 0.171 | 0.169 |
| e15 | 412 | 0.36 | | 0.190 | 0.184 |
| e16 | 401 | 0.34 | | 0.185 | 0.174 |
| e17 | 439 | 0.36 | | 0.202 | 0.184 |
| e18 | 479 | 0.39 | | 0.221 | 0.199 |
| e19 | 255 | 0.39 | | 0.117 | 0.199 |
| e20 | 283 | 0.41 | | 0.130 | 0.210 |
| e21 | 314 | 0.43 | | 0.145 | 0.220 |
| e22 | 329 | 0.41 | | 0.152 | 0.210 |
| e23 | 358 | 0.43 | | 0.165 | 0.220 |
| e24 | 389 | 0.45 | | 0.179 | 0.230 |
| e25 | 428 | 0.43 | | 0.197 | 0.220 |
| e26 | 458 | 0.45 | | 0.211 | 0.230 |
| e27 | 490 | 0.48 | | 0.226 | 0.245 |
| | | Hi | | 2.549 | 2.575 |
| $k = -0.699$ | | 1-Hi | | –1.549 | –1.575 |
| Sum (Hi) = 5.124 | | Weight | | 0.496 | 0.504 |

Step 3: Determine the weighted normalised matrix using

$$v_{ij} = n_{ij} \times w_j \tag{6}$$

where $w_j$ indicates the weight of $j$th criterion.

Step 4: Calculate the final preference values ($p_i^*$) by

$$p_i^* = \sum_{j=1}^{s} v_{ij} - \sum_{j=s+1}^{n} v_{ij} \tag{7}$$

where $j = 1, 2, 3, \ldots, s$ are those criteria which needs to be maximised and $j = s+1, s+2, \ldots, n$ are the remaining criteria to be minimised.

The alternatives are ranked based on the values of preference values ($p_i^*$) in descending order.

Step 5: Find the utility degree $N_i$ in terms of '%' using

$$N_i = \left(\frac{p_i^*}{Max\, p_i^*}\right) \times 100. \tag{8}$$

Table 3 shows the normalized values of eaxh criteria using equation (7). Table 4 shows the Relative closeness ($N_i$) and preference rank. The ANOVA was given in Table 5, in which, the feed rate was identified as dominant factor followed speed and depth of cut on the responses.

## 3.2 COPRAS method

The COPRAS method was firstly introduced in 1994 [6]. The steps are presented as follows. The mathematical formulation of the COPRAS method is given below:

**Table 4.** MOORA grade, relative closeness ($N_i$) and rank.

| Exp. | MAX | MIN | ($p_i^*$) MOORA GRADE | Ni | RANK |
|---|---|---|---|---|---|
| e1 | 0.000 | 0.171 | –0.171 | 83% | 8 |
| e2 | 0.000 | 0.186 | –0.186 | 76% | 13 |
| e3 | 0.000 | 0.201 | –0.201 | 70% | 18 |
| e4 | 0.000 | 0.184 | –0.184 | 77% | 12 |
| e5 | 0.000 | 0.199 | –0.199 | 71% | 17 |
| e6 | 0.000 | 0.214 | –0.214 | 66% | 23 |
| e7 | 0.000 | 0.202 | –0.202 | 70% | 19 |
| e8 | 0.000 | 0.217 | –0.217 | 65% | 24 |
| e9 | 0.000 | 0.235 | –0.235 | 60% | 26 |
| e10 | 0.000 | 0.141 | –0.141 | 100% | 1 |
| e11 | 0.000 | 0.155 | –0.155 | 91% | 2 |
| e12 | 0.000 | 0.169 | –0.169 | 84% | 5 |
| e13 | 0.000 | 0.159 | –0.159 | 89% | 4 |
| e14 | 0.000 | 0.170 | –0.170 | 83% | 6 |
| e15 | 0.000 | 0.187 | –0.187 | 75% | 14 |
| e16 | 0.000 | 0.179 | –0.179 | 79% | 9 |
| e17 | 0.000 | 0.193 | –0.193 | 73% | 16 |
| e18 | 0.000 | 0.210 | –0.210 | 67% | 22 |
| e19 | 0.000 | 0.159 | –0.159 | 89% | 3 |
| e20 | 0.000 | 0.170 | –0.170 | 83% | 7 |
| e21 | 0.000 | 0.183 | –0.183 | 77% | 11 |
| e22 | 0.000 | 0.181 | –0.181 | 78% | 10 |
| e23 | 0.000 | 0.193 | –0.193 | 73% | 15 |
| e24 | 0.000 | 0.205 | –0.205 | 69% | 20 |
| e25 | 0.000 | 0.209 | –0.209 | 68% | 21 |
| e26 | 0.000 | 0.221 | –0.221 | 64% | 25 |
| e27 | 0.000 | 0.236 | –0.236 | 60% | 27 |

**Table 5.** MOORA ANNOVA.

| MOORA ANOVA | | | | | |
|---|---|---|---|---|---|
| Factor | SS | dof | MS | *F* | Contribution |
| Cutting speed | 0.0037 | 2 | 0.0018 | 113.0 | 24.4 |
| Feed rate | 0.0075 | 2 | 0.0038 | 230.2 | 49.6 |
| Depth of cut | 0.0036 | 2 | 0.0018 | 110.7 | 23.9 |
| Error | 0.0003 | 20 | 0.0000 | | 2.2 |
| Total | 0.0152 | 26 | | | 100 |

Step 1: Form a decision matrix

$$D = \begin{pmatrix} x_{11} & x_{12} & \dots & x_{1m} \\ x_{21} & x_{22} & \dots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n1} & \dots & x_{nm} \end{pmatrix}, \quad i = 1, 2, \dots, n \quad \text{and} \quad j = 1, 2, \dots, m \tag{9}$$

where '$m$' refers the number of attributes and '$n$' refers the number of alternatives.

Step 2: Determine the weight of the attributes '$q_j$'.

Step 3: Since each attribute is different, the elements of the decision matrix are normalized using

$$\overline{x}_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{n} x_{ij}^2}}, \tag{10}$$

$i = 1, 2, \ldots, n$ and $j = 1, 2, \ldots, m$; and shown as

$$\overline{D} = \begin{pmatrix} \overline{x}_{11} & \overline{x}_{12} & \ldots & \overline{x}_{1m} \\ \overline{x}_{21} & \overline{x}_{21} & \ldots & \overline{x}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \overline{x}_{n1} & \overline{x}_{n1} & \ldots & \overline{x}_{nm} \end{pmatrix}, \quad i = 1, 2, \ldots, n \quad \text{and} \quad j = 1, 2, \ldots, m. \tag{11}$$

The weighted normalized decision matrix $\hat{D}$ using $\hat{x}_{ij} = \overline{x}_{ij} * q_j$

$$\hat{D} = \begin{pmatrix} \hat{x}_{11} & \hat{x}_{12} & \ldots & \hat{x}_{1m} \\ \hat{x}_{21} & \hat{x}_{21} & \ldots & \hat{x}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \hat{x}_{n1} & \hat{x}_{n1} & \ldots & \hat{x}_{nm} \end{pmatrix}, \quad i = 1, 2, \ldots, n \quad \text{and} \quad j = 1, 2, \ldots, m. \tag{12}$$

Step 4: Calculate the summation $\boldsymbol{P_i}$ of those attributes need to be maximized:

$P_i = \sum_{j=1}^{k} \hat{x}_{ij}$,where '$k$' indicates the number of attributes requires maximization.

Step 5: Calculate the summation $\boldsymbol{R_i}$ of those attributes need to be minimized:

$R_i = \sum_{j=k+1}^{m} \hat{x}_{ij}$, where '$m$-$k$' indicates the number of attributes requires minimization.

Step 6: Calculate the minimum value of $R_i$: $R_{\min} = \min_i R_i$, $i = 1, 2, \ldots, n$

Step 7: Determine the relative weight $Q_i$ for each alternative using:

$$Q_i = P_i + \frac{R_{\min} \sum_{i=1}^{n} R_i}{R_i \frac{R_{\min}}{R_i}} \quad \text{(OR)}$$

$$Q_i = P_i + \frac{\sum_{i=1}^{n} R_i}{R_i \sum_{i=1}^{n} \frac{1}{R_i}}. \tag{13}$$

Step 8: The maximum value $Q_i$ among all alternatives will be considered as the best alternative under priority.

Step 9: Determine the utility degree $N_i$ in terms of '%' using

$$N_i = \left( \frac{Q_i}{\text{Max } Q_i} \right) * 100. \tag{14}$$

Using the equations [9–14], relative weight, utility degree and its rank were calculated. The results are shown in Table 6. The ranking results of the solutions were also presented in Table 6. Further, the ANOVA was given in Table 7, in which, it is seen that feed rate contribute much on the responses followed by speed and depth of cut. From the ranking results of the options according to MOORA and COPRAS methods (Tabs 4 and 6), these two methods, including MOORA and COPRAS indicate that the experimental trial 10 is the best one. From this result, it is observed that, if we want to minimize simultaneously the cutting force and flank wear, the cutting speed is 125 mm/rev, feed rate is 0.055 and depth of cut is 0.25 mm.

## 4 MCDM method for the turning experiment

### 4.1 Weight calculation for outputs with help of the entropy method

The cutting force is assigned as $Y_1$ and flank wear is assigned as $Y_2$. The normalized value for criteria, entropy measure degree for the criteria and weights for the criteria were determined and given in Table 3. It was determined using the equations (1)–(3) respectively.

### 4.2 Multi-Criteria decision making using the MOORA method

The calculated results such as MOORA grade ($p_i^*$), relative closeness ($N_i$) and rank were presented in Table 4, where the weights of the criteria were calculated using entropy method. The ranking results also presented in Table 4. Further, MOORA ANOVA was done and it is observed that the feed rate contribute more on the criteria followed by cutting speed and feed rate and it is presented in Table 5.

### 4.3 Multi-criteria decision making using the COPRAS method

The values of $R_i$, $Q_i$ and $N_i$ and rank were presented in Table 6, Further, COPRAS ANOVA was done and it is observed that the feed rate contribute more on the criteria followed by cutting speed and feed rate and it is presented in Table 7.

## 5 Experimental results and discussions

The experimental results were given in Table 2. In this, cutting force has the minimum value at experiment 19 and flank wear is the minimum value at experiment number 10. Thus it is very clear that there is no an experiment that simultaneously confirm the minimum values of flank wear and surface roughness. Hence, we need to find an experiment where cutting force and flank wear are considered as minimum. Therefore, MCDM techniques was used to find out an experiment to obtain the cutting force and flank wear.

Therefore, MOORA and COPRAS were used to find out an experiment for minimum of cutting force anf flank wear. The experimental results in Table 2 show that it is difficult to determine which of the experiment in 27 performed experiments have simultaneously the minimum value of cutting forces, flank wear. This is explained as follows. With the results in Table 2, for example, in experiment 19, the cutting force was a minimum value (equal to 265N), but in this experiment, the values of flank wear are not a small one. Another example is experiment 1,

**Table 6.** Relative weight, utility degree and its rank.

| Exp. | Ri | 1/Ri | ($Q_i$) COPRAS GRADE | Ni | RANK |
|---|---|---|---|---|---|
| e1 | 0.171 | 5.855 | 0.208 | 82% | 8 |
| e2 | 0.186 | 5.390 | 0.191 | 76% | 13 |
| e3 | 0.201 | 4.976 | 0.176 | 70% | 18 |
| e4 | 0.184 | 5.435 | 0.193 | 76% | 12 |
| e5 | 0.199 | 5.025 | 0.178 | 71% | 17 |
| e6 | 0.214 | 4.664 | 0.165 | 66% | 23 |
| e7 | 0.202 | 4.961 | 0.176 | 70% | 19 |
| e8 | 0.217 | 4.618 | 0.164 | 65% | 24 |
| e9 | 0.235 | 4.259 | 0.151 | 60% | 26 |
| e10 | 0.141 | 7.091 | 0.252 | 100% | 1 |
| e11 | 0.155 | 6.467 | 0.229 | 91% | 2 |
| e12 | 0.169 | 5.928 | 0.210 | 83% | 5 |
| e13 | 0.159 | 6.288 | 0.223 | 88% | 4 |
| e14 | 0.170 | 5.880 | 0.209 | 83% | 6 |
| e15 | 0.187 | 5.349 | 0.190 | 75% | 14 |
| e16 | 0.179 | 5.578 | 0.198 | 79% | 9 |
| e17 | 0.193 | 5.178 | 0.184 | 73% | 16 |
| e18 | 0.210 | 4.762 | 0.169 | 67% | 22 |
| e19 | 0.159 | 6.297 | 0.223 | 89% | 3 |
| e20 | 0.170 | 5.870 | 0.208 | 83% | 7 |
| e21 | 0.183 | 5.477 | 0.194 | 77% | 11 |
| e22 | 0.181 | 5.529 | 0.196 | 78% | 10 |
| e23 | 0.193 | 5.191 | 0.184 | 73% | 15 |
| e24 | 0.205 | 4.881 | 0.173 | 69% | 20 |
| e25 | 0.209 | 4.793 | 0.170 | 67% | 21 |
| e26 | 0.221 | 4.532 | 0.161 | 64% | 25 |
| e27 | 0.236 | 4.243 | 0.150 | 60% | 27 |

**Table 7.** COPRAS ANOVA.

| COPRAS ANOVA | | | | | |
|---|---|---|---|---|---|
| Factor | SS | dof | MS | F | Contribution |
| Cutting speed | 0.0042 | 2 | 0.0021 | 76.3 | 25.9 |
| Feed rate | 0.0076 | 2 | 0.0038 | 139.6 | 47.5 |
| Depth of cut | 0.0037 | 2 | 0.0019 | 68.2 | 23.2 |
| Error | 0.0005 | 20 | 0.0000 | | 3.4 |
| Total | 0.0160 | 26 | | | 100 |

in this experiment, flank wear is the smallest one, but in this experiment, the value of the cutting force is not a small one (equal 400N). The above analysis showed that it is difficult to select/choose one experiment from 27 experiments to ensure simultaneously the minimum of cutting force and flank wear. Therefore, it is essential to compute the multi-criteria decision matrix techniques to decide the experiment with minimum cutting force and flank wear.

The MOORA possesses four steps as Decision matrix construction, Input data-Normalization, Weight calculation of each attribute, Determination of the Normalized assessment determination for ranking the alternatives [17].

The decision matrix construction is showing the effect of various choices in respect of different objectives. The decision matrix equation is shown in equation (1). The process factors are to be normalized based on the formula of normalization. It transforms the attributes into non-dimensional numbers and it is given in equation (2). Higher the better for any attributes, the normalized performances are added and subtracted incase of lower the better attributes. Priorities are may be given to some of the attributes, in this situation, the weights are multiplied with it and it is given in equation (3). The suitable/best choice of parameters is chosen based on the rank order of $p_i$ and the good alternative has more value of $p_i$, whereas the bad choice of alternative has a low value of $p_i$ [9,13].The best alternative is chosen based on $N_i$ relative closeness value and it is given in Table 3. Table 4 shows the normalized and weight normalized values and its rank.

Based on the calculated results using MOORA, the experimental trails are ranked and it is identified as: 8–13–18–12–17–23–19–24–26–1–2–5–4–7–14–9–16–22–3–6–11–10–15–20–21–25–27. The best design experiment trail is ordered as: 10–11–19–13–12–20–14–1–16–22–21–4–2–15–23–17–5–3–7–24–25–18–6–8–26–9–27. It is meant that the best combination of the controlling factors is in run 10 and the worst is in run 27. The experimental run 10 has 100% relative closeness and run 27 has 60% relative closeness. The best combination of controlling factors to obtain minimum of the output are identified in run 10 followed by run 11 and 19. The best combination of controlling factors were identified as spindle speed of 125 m/min, feed rate 0.055 mm/rev and depth of cut 0.25 mm. Hence, the above said sequence order is recommended to omit the manufacturing cost and also augment the component's quality.

MOORA ANOVA is shown in Table 5, in which the feed rate was found to be in 1st rank in affecting the outputs followed by the depth of cut and cutting speed. The. Further, the percentage contribution in affecting the outputs are shown in Table 5 and the percentage contribution such as 49.6%, 23.8% and 24.3% was reported for feed rate, depth of cut and cutting speed respectively.

The same best combination of controlling factors were also identified as spindle speed of 125 m/min, feed rate 0.055 mm/rev and depth of cut 0.25 mm using COPARAS techniques. Based on the calculated results using COPRAS, the experimental trails are ranked and it is identified as: 8–13–18–12–17–23–19–24–26–1–2–5–4–7–14–9–16–22–3–6–11–10–15–20–21–25–27. The best design experiment trail is as follows as shown in Table 6: 10–11–19–13–12–20–24–1–16–22–21–4–2–15–23–17–5–3–7–24–25–18–6–8–26–9–27. It is meant that the best combination of the controlling factors is in run 10 and the worst is in run 27. The experimental run 10 has 100% utility degree and run 27 is the worst alternative with 60% utility degree (Tab. 6). The best combination of controlling factors to obtain minimum of the output are identified in run 10 followed by run 11 and 19.

The best combination was identified as speed 125 m/min. feed rate 0.055 mm/rev and depth of cut 0.25 mm. Therefore, it is suggested to select the above sequence in order to diminish the manufacturing cost and to augment the quality of the component. The best combination of controlling factors were identified both the MCDM techniques such as spindle speed of 125 m/min, feed rate 0.055 mm/rev and depth of cut 0.25 mm. Hence, the above said sequence order is recommended to omit the manufacturing cost and also augment the component's quality. The ranking order found by MOORA is very well agreed with COPRAS technique. Both techniques ranking order coincide with 100%. The notable similitude among the two rank orders are seen. Both the techniques possess easiest computation to compute alternatives and the best controlling factors in turning this alloy using CBN insert for minimizing the cutting force and flank wear simultaneously.

Table 6 shows the relative weight, utility degree and its rank. Table 7 indicates the COPRAS ANOVA, in which the feed rate was found to be in 1st rank in affecting the outputs followed by the cutting speed and depth of cut. Further, the percentage contribution in affecting the criteria were reported as 47.5%, 25.9% and 23.2% was reported for feed rate, cutting speed and depth of cut respectively.

The cutting force alone was found to be smaller in experiments 10, 11, 12, 13, 14, 15, 19, 20, 21, 22, 23 and ranged in 300N to 390N; however, the flank wear was found to be higher in the above-said experimental trails as shown in Table 2.

The cutting force in experiment 19 was found to be minimum (equal to 265N) and this cutting force is at rank number 3 (Tabs 4 and 6) (this cutting force value is lower but flank wear value is higher compare to other experiments).

The flank wear was found to be smaller in experiments 1, 2, 3, 4, 5, 10, 11, 12, 13, 14, 16 and ranged from 0.29 mm to 0.35 mm; however, the cutting force was found to be higher in the above said experiments. Therefore, best combination of factors such as V-125 m/min, 0.055 mm/rev and 0.25 mm was chosen for minimizing the criterias simultaneously using MOORA and COPRAS methods.

In this work, only three input factors are considered and have not considered insert's signature, tool material, lubrication condition etc., these additional factors can be considered by considering multiple criteria/objectives like surface roughness, temperature generation at the cutting zone, surface integrity and change in the microstructure. These additional inputs and outputs need to be considered in the next research to bring the turning process on Nimonic C263 alloy in a better comprehensive way.

## 6 Conclusions

Nimonic C263 alloy was turned in dry condition using CBN insert. MOORA and COPRAS techniques were used for to calculate the combination of controlling factors such as cutting speed, feed rate and depth of cut for simultaneous minimization of cutting force and flank wear.

- According to the relative closeness values in the MOORA technique, the machining attributes are sorted as follows: 8–13–18–12–17–23–19–24–26–1–2–5–4–7–14–9–16–22–3–6–11–10–15–20–21–25–27. The optimium sequence is found as follows: 10–11–19–13–12–20–14–1–16–22–21–4–2–15–23–17–5–3–7–24–25–18–6–8–26–9–27.

- The COPRAS techniques's rank list of experimental trails is as follows: 8–13–18–12–17–23–19–24–26–1–2–5–4–7–14–9–16–22–3–6–11–10–15–20–21–25–27. optimium sequence is found as follows: 10–11–19–13–12–20–24–1–16–22–21–4–2–15–23–17–5–3–7–24–25–18–6–8–26–9–27.
- Based on both the techniques, the foremost combination of factors is identified in run 10 and the worst is in run 27. The sequencing order of MOORA ad COPRAS techniques are found to be identical.
- The best combination factors observed based on MOORA and COPRAS of turning parameters for simultaneous minimization of all the outputs are identified with a cutting speed of 125 m/min, feed rate 0.055 mm/rev and depth of cut 0.50 mm.
- The percentage contribution of cutting speed, feed rate and depth of cut on from ANOVA table was observed as 24.3%, 49.6% and 23.8% respectively.
- Feed rate was identified as a dominant factor in affecting the force and flank wear followed by cutting speed and depth of cut.
- Cutting force was affected owing to a change in the level of speed and feed rate, whereas flank wear was increased as the level of all factors increased.

## References


1. E. Kaya, B. Akiiz, Effects of cutting parameters on machinability characteristics of Ni-based superalloys: a review, Open Eng. **7** (2017) 330–342
2. F.S. Ben Sal, A. Haddad, M. Athmane Yallese, Optimization of machining parameters in turning of Inconel 718 Nickel-base super alloy, Mech. Ind. **21** (2020) 203
3. S. Senthil Kuma, M. Ponnusamy Sudeshkumar, C. Ezilarasan, S. Palani, J. Veerasundaram, Modelling and simulation of machining attributes in dry turning of aircraft materials Nimonic C263 using CBN, Manufactur. Rev. **8** (2021) 30
4. L.B. Abhang, M. Iqbal, M. Hameedullah, Optimization of machining process parameters using Moora method, Defect Diffus. Forum **402** (2020) 81–89
5. A. Sarkara, S.C. Panja, D. Das, B. Sarkar, Developing an efficient decision support system for non-traditional machine selection: an application of MOORA and MOOSRA, Product. Manufactur. Res. **3** (2015) 324–342
6. V.S. Gadakh, V.B. Shinde, N.S. Khemnar, Optimization of welding process parameters using MOORA method, Int. J. Adv. Manuf. Technol. **69** (2013) 2031–2039
7. Z.-L. Liang, T.-J. Yun, W.-B. Oh, B.-R. Lee, I.-S. Kim, A study on MOORA-based taguchi method for optimization in automated GMA welding process, Mater. Today **22** (2020) 1778–1785
8. V. Anandan, M. Naresh Babu, M. Vetrivel Sezhian, C. Vakkas Yildirim, M. Dinesh Babu, Influence of graphene nano fluid on various environmental factors during turning of M42 steel, J. Manufactur. Process. **68** (2021) 90–103
9. S.V. Wankhede, J.A. Hole, MOORA and TOPSIS based selection of input parameter in solar powered absorption refrigeration system, Int. J. Ambient Energy (2020). DOI: 10.1080/01430750.2020.1831600
10. G.R. Chate, M. Patel, G.C. Harsha, H.M. Shubham, U. Urankar, S.A. Sanadi, A.P. Jadhav, S. Hiremath, A.S. Deshpande, Sustainable machining: modeling and optimization using Taguchi, MOORA and DEAR methods, Mater. Today Proc. (2021)
11. V. Jain, P. Ajmera, Application of MADM methods as MOORA and WEDBA for ranking of FMS flexibility, Int. J. Data Netw. Sci. **3** (2019) 119–136
12. P. Chaudhury, S. Samantaray, Multi-optimization of process parameters for machining of a non-conductive SiC ceramic composite by non-conventional machining method, Manufactur. Rev. **7** (2020) 32
13. A. Hamdy, M. Fattouh, S. Abaas, R. Masoud, Multi-objective optimization of plasma arc cutting process using Moora combined with GA, Eng. Res. J. **42** (2019) 219–230
14. D. Jhodkar, A. Khan, K. Gupta, Fuzzy-MOORA based optimization of machining parameters for machinability enhancement of Titanium, Math. Model. Eng. Probl. **8** (2021) 189–198
15. P.J. Arrazola, A. Garay, E. Fernandez, K. Ostolaza, Correlation between tool flank wear, force signals and surface integrity when turning bars of Inconel 718 in finishing conditions, Int. J. Mach. Mach. Mater. **15** (2014) 84–100
16. M. Safavi Marek Balazinski, H. Mehmanparast, S. Ali Niknam, Experimental characterization of tool wear morphology and cutting force profile in dry and wet turning of titanium metal matrix composites (Ti-MMCs), Metals **10** (2020) 1459
17. S. Sun, M. Brandt, J.P.T. Mo, Evolution of tool wear and its effect on cutting forces during dry machining of Ti-6Al-4V alloy, Proc. IMechE B **228** (2014) 191–202
18. E.K. Zavadskas, A. Kaklauskas, V. Sarka, The new method of multicriteria complex proportional assessment of projects, Technol. Econ. Dev. Econ. **1** (1994) 131–139
19. M. Varathrajulu, M. Duraiselvam, M. Bhuvanesh Kumar, G. Jayaprakash, N. Baskar, Multi criteria decision making through TOPSIS and COPRAS on drilling parameters of magnesium AZ91, J. Magn. Alloys **4** (2021) 1–18
20. D.D. Trung, A combination method for multi-criteria decision making problem in turning process, Manufactur. Rev. **8** (2021) 1–26
21. S.H. Mousavi-Nasab, A. Sotoudeh-Anvari, Comprehensive MCDM-based approach using TOPSIS, COPRAS and DEA as an auxiliary tool for material selection problems, Mater. Des. **121** (2017) 237–253
22. D.D. Trung, N.-T. Nguyen, D. Van Duc, Study on multi-objective optimization of the turning process of En 10503 steel by combination of Taguchi method and Moora technique, EUREKA: Phys. Eng. **2** (2021) 52–65
23. S. Thamizhmanii, S. Hasan, Relationship between Flank wear and Cutting Force on the Machining of Hard Martensitic Stainless Steel by Super Hard Tools, in *Proceedings of the World Congress on Engineering 2010 Vol III, WCE* 2010, *June 30-July* **2** (2010) London, UK


**Cite this article as**: Munuswamy Krishna, Sathuvachari Devarajan Kumar, Chakaravarthy Ezilarasan, Perumalsamy Vishnu Sudarsan, Viswanathan Anandan, Sivaprakasam Palani, Veerasundram Jayaseelan, Application of MOORA & COPRAS integrated with entropy method for multi-criteria decision making in dry turning process of Nimonic C263, Manufacturing Rev. **9**, 20 (2022)