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A combination method for multi-criteria decision making problem in turning process

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Abstract. This paper presents a multi-criteria decision making (MCDM) for a turning process. An experimental process was performed according to the sequence of a matrix using the Taguchi method with nine experiments. The parameters including workpiece speed, feed rate, depth of cut, and nose radius were selected as the input variables. At each experiment, three cutting force components that were measured in the three directions X, Y, and Z, were F_x, F_y, and F_z, respectively. The value of Material Removal Rate (*MRR*) was also calculated at each experiment. The main purpose of this study is determination of an experiment in total performed experiments simultaneously ensuring the minimum F_x, F_y, and F_z and the maximum *MRR*. The Entropy method was applied to determine the weights for parameters F_x, F_x, F_x, and *MRR*. Eight MCDM methods were applied for multi-criteria decision making, this has not been performed in any studies. The implementation steps of each method were also presented in this paper. Seven ones of these eight methods determined the best experiment in total nine performed experiments. A new multi-criteria decision-making method as well as orientation for the further works were also proposed in this study.

Keywords: MCDM / Taguchi / weight / entropy / multi-criteria decision making methods / turning

1 Introduction

The concept of "multi-criteria decision making – *MCDM*" is used to make a decision for selecting an option related to multiple criteria, of which the criteria may be contradictory. There are many mathematical tools to support the multi-criteria decision making such as *SAW* (simple additive weighting) [1], *WASPAS* (weighted aggregates sum product assessment) [2], *TOPSIS* (preference by similarity to ideal solution) [3], *VIKOR* (vlsekriterijumska optimizacija i kompromisno resenje in Serbian) [4], *MOORA* (multiobjective optimization on the basis of ratio analysis) [5], *COPRAS* (complex proportional assessment) [6], *PIV* (proximity indexed value) [7], *PSI* (preference selection index) [8], etc. These methods were applied for multi-criteria decision making in many studies, under many different fields. Only considering in the turning process, these methods were also applied in many studies. The following is a summary of main contents of a number of studies on multi-criteria decision-making in turning processes that were published.

The *TOPSIS* method was used for multi-criteria decision making when turning EN8 steel [9]. The experimental matrix was designed according to the Taguchi method with 27 experiments. In this study, the cutting velocity, feed rate, and depth of cut were selected as the input parameters. The output parameters that were selected included surface roughness (*Ra*) and Material Removal Rate (*MRR*). The weights of the criteria were determined by the Entropy method. This study determined an experiment that simultaneously ensured the minimum surface roughness and the maximum *MRR*.

Multi-criteria decision making when turning EN25 steel was also carried out using the *TOPSIS* method [10]. In this study, the experimental matrix of 18 experiments was also designed according to Taguchi method. The parameters including the type of cutting tool materials, cutting velocity, feed rate, and depth of cut were selected as the input parameters. The hardness of workpiece surface, surface roughness, and *MRR* were selected as the output parameters. The weights of criteria were determined using the Analytic Hierarchy Process (*AHP*) method. This study determined an experiment where the minimum values of hardness of workpiece surface and surface roughness, and the maximum value of *MRR* were simultaneously ensured.

The *TOPSIS* method was also used for multi-criteria decision making when turning AISI 52100 steel [11]. The cutting velocity, feed rate, depth of cut, nose radius, and negative rake angle were selected as the input parameters. The experimental matrix was also designed according to

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the Taguchi method with 32 experiments. The surface roughness and cutting force were measured at each experiment. This study determined an experiment where the minimum surface roughness and minimum cutting force were simultaneously ensured.

In turning processes of EN19 steel, the multi-criteria decision making was also performed by the *TOPSIS* method [12]. A matrix (nine experiments) was designed according to the Taguchi method with the input parameters including cutting velocity, feed rate, and depth of cut. *MRR*, *Ra* (the arithmetic mean roughness), and *Rz* (the maximum roughness) were selected as the criteria for assessing the turning process. The Entropy method was also used to determine the weight for each criterion. This study has determined an experiment where the minimum *Ra* and *Rz*, and the maximum *MRR* were ensured simultaneously.

The *TOPSIS* method was also applied to make a multi-criteria decision when turning AISI D2 steel [13]. In this study, an experimental matrix was also designed according to the Taguchi method with 20 experiments. The cutting velocity, feed rate, and depth of cut were also selected as the input parameters. Surface roughness and *MRR* were selected as the output parameters. The weights of criteria were calculated using the Entropy method. This study determined an experiment where the minimum surface roughness and the maximum *MRR* were simultaneously ensured.

The authors also used the *TOPSIS* method for multi-criteria decision making when turning Pure Titanium material [14]. They also designed an experimental matrix according to the Taguchi method with nine experiments. The cutting velocity, feed rate, and depth of cut were selected as the input parameters. The cutting force, surface roughness, tool life, and *MRR* were selected as the criteria to assess the turning process. The weight of each criterion was selected by the authors of this paper. Finally, they determined an experiment where the minimum cutting force and surface roughness, the maximum tool life and *MRR* were simultaneously ensured.

The *TOPSIS* and *MOORA* methods were used for multi-criteria decision making when turning ASTM A558 steel [15]. The spindle speed, feed rate, and depth of cut were selected as the input parameters. An experimental matrix was designed according to the Taguchi method with 27 experiments. The cutting power, surface roughness, and tool vibration frequency were determined in each experiment. The weights of the criteria were determined by the Principal Component Analysis (*PCA*) method. The ranking results of the performed experiments by these two methods were completely different. The authors explained that the ranking of options by the *TOPSIS* method based on the Euclidean distance function is not related to the machining characteristics and cutting power.

The *TOPSIS* and *SAW* methods were applied for multi-criteria decision making when turning Ti-6Al-4V steel [16]. In this study, they selected cutting velocity, feed rate, and depth of cut as the input parameters. An experimental matrix was designed according to the Taguchi method with 27 experiments. The surface roughness, tool wear, cutting temperature, and cutting force were selected as the output parameters. The purpose of this study is determination of an experiment in total 27 performed experiments that simultaneously ensured all four output parameters with the minimum values. The weights of criteria were determined by the *AHP* method. The ranking results according to the two methods coincided with 16/27 options (with of 11 different options). However, both methods have consistent results in determining the best and worst experiments.

The *VIKOR* method was applied for multi-criteria decision making when turning EN 10503 steel [17]. In this study, they also designed an experimental matrix according to the Taguchi method with nine experiments. The spindle speed, feed rate, and depth of cut were selected as the input parameters. The weight of *MRR* was selected to be 0.5, the weight of remaining criteria (surface roughness and three cutting force components) has also been selected to be 0.5. The authors of this study determined an experiment that simultaneously ensures the minimum surface roughness, three minimum cutting force components, three minimum vibration components and the maximum *MRR*.

When turning the CP-Titanium Grade 2 material, the authors also designed an experimental matrix according to the Taguchi method with 27 experiments [18]. In this study, they selected cutting velocity, feed rate, and depth of cut as the input parameters. They measured surface roughness, *MRR*, and cutting force for each experiment. The *VIKOR* method was applied to determine an experiment where simultaneously ensured the minimum surface roughness, maximum *MRR* and minimum cutting force. In which the authors also selected the weight of *MRR* to be 0.5, and the weight of remaining criteria (surface roughness and cutting force) was also selected to be 0.5.

The *VIKOR* method also was used for multi-criteria decision making when turning AISI 316L material [19]. The cutting parameters including workpiece speed, feed rate, and depth of cut were selected as the input parameters for each experiment. An experimental matrix was also designed according to the Taguchi method with 16 experiments. Surface roughness, tool wear, and *MRR* were determined for each experiment. The weight of *MRR* was selected to be 0.5, the weight of remaining criteria (surface roughness and tool wear) was also selected to be 0.5. This study determined an experiment where simultaneously ensured the minimum surface roughness, the minimum tool wear and the maximum *MRR*.

In study [20], the *VIKOR* method has also been used for multi-criteria decision making when turning mild steel. In this study, an experimental matrix was also designed according to the Taguchi method with 9 experiments. The cutting velocity, feed rate, depth of cut, and coolant flow were selected as the input parameters. The surface roughness, *MRR,* and energy consumption were determined in each experiment. The weight of *MRR* was selected to be 0.5, the weight of remaining criteria (surface roughness and energy consumption) was also selected to be 0.5. This study has selected an experiment where simultaneously ensures the minimum surface roughness and energy consumption, and the maximum *MRR*.

The authors also designed an experimental matrix according to the Taguchi method for turning AA7075 aluminum alloy [21]. They also selected cutting velocity, feed rate, and depth of cut as the input parameters for the experimental process. At each experiment, they determined *MRR, Ra, Rz,* and *Rq* (the root-mean-square roughness). They also applied the *VIKOR* method to determine an experiment which simultaneously ensured the maximum *MRR*, the minimum *Ra*, *Rq* and *Rz* parameters. In this study, the weight of each criterion was selected to be 0.25.

The *MOORA* method was used for multi-criteria decision making when turning EN 10503 steel [22]. The authors of this study also designed an experimental matrix according to the Taguchi method with nine experiments. The cutting velocity, feed rate, depth of cut, and nose radius were also selected as the input parameters. The surface roughness, three cutting force components, and *MRR* were determined for each experiment. The weights of these output parameters were calculated by the Entropy method. This study determined an experiment where simultaneously ensured the minimum surface roughness, the three minimum cutting force components and the maximum *MRR*.

The *MOORA* method for multi-criteria decision making when turning EN25 steel [23]. In this study, the parameters including nose radius, cutting velocity, feed rate, and depth of cut were selected as the input parameters. The surface roughness, workpiece hardness after turning, and *MRR* were determined for each experiment. An experimental matrix was also designed according to the Taguchi method with 18 experiments. The weight of each output parameter was calculated using the Entropy method. Finally, they determined an experiment at which the minimum surface roughness and minimum workpiece surface hardness and the maximum *MRR* were simultaneously ensured.

The *MOORA* method has also been used for multi-criteria decision making when turning Al6026-T9 aluminum alloy [24]. The cutting velocity, feed rate, depth of cut, positive rake angle, and cutting conditions (Dry and *MQL*) were selected as input parameters. An experimental matrix was also designed according to the Taguchi method with sixteen experiments. At each experiment, the feed force, tangential force, radial force, resultant cutting force, and shape deviations were measured. The weights of responses were determined according to the CRriteria Importance Through Inter-criteria Correlation (*CRITIC*) method. This study determined an experiment that ensured all response having a minimum value.

The authors also used *MOORA* method for multi-criteria decision making when turning Commercially Pure Titanium (Cp-Ti) [25]. A matrix including 27 experiments was also designed according to the Taguchi method. The cutting velocity, feed rate, and depth of cut were selected as the input parameters. The cutting force, surface roughness, and tool wear were determined in each experiment. The weights of these output parameters were determined using the Fuzzy logic method. Finally, they have determined an experiment that ensured all three responses having a minimum value simultaneously.

The *MOORA* and *WASPAS* methods were used for multi-criteria decision making when turning Al 6063 aluminum alloy [26]. The cutting speed, feed rate, depth of cut, and percentage of TiC (additive in materials) were selected as input parameters. The cutting force, surface roughness, and *MRR* were selected as responses of each experiment. The Entropy method was selected to determine the weight of responses. The results of ranking options according to the two methods completely coincided in 27 experiments. Finally, this study has determined an experiment where the minimum cutting force and surface roughness, and the maximum MRR were simultaneously ensured.

The authors combined the *COPRAS* method with the Grey decision-making system method (*COPRAS-G* method) for multi-criteria decision making when turning ASTM A36 steel [27]. In this study, they designed an experimental matrix according to the Taguchi method with 27 experiments. The input parameters included spindle speed, feed rate, and depth of cut. At each experiment, the cutting power, tool vibration, and surface roughness were determined. The weights of output parameters were calculated according to the "relative weights for each option" method. Finally, they determined an experiment that simultaneously ensured all three output parameters having a minimum value.

The *PSI* method is known as a multi-criteria decision making method without determining the weights for criteria [8]. This method was used for multi-criteria decision making when turning EN24 steel [28]. In this study, an experimental matrix was also designed according to Taguchi method with sixteen experiments. The spindle speed, feed rate, depth of cut, and nose radius were selected as the input parameters. The surface roughness and *MRR* were selected as the output parameters. This study determined an experiment that simultaneously ensured the minimum surface roughness and the maximum *MRR*.

Through the above studies on the multi-criteria decision making of the turning process, it is shown that:

Firstly, the experimental matrix is usually designed according to the Taguchi method. This is also easy to understand because this is a method that allows to design a matrix with a small number of experiments with a large number of input parameters and each input parameter has many value levels. Another outstanding advantage of the Taguchi method is that it allows the selection of input parameters with the qualitative parameters [29].

Secondly, spindle speed (cutting velocity), feed rate, depth of cut, and nose radius are often selected as the input parameters. This is also easy to understand as these are parameters that can be easily adjusted by the machine operator.

Thirdly, the determination of weights for the criteria was performed by several methods (Entropy, *AHP*, *PCA*, etc.) or by the selection of decision makers. However, it must also be said that, if the weighting of the criteria is performed according to a subjective opinion of the decision maker, it is an act that lacks the necessary reliability. The weighting of each criterion is performed by expert opinions also depends a lot on the knowledge of experts, and sometimes is also greatly influenced by the designing of questionnaires. The fact shows that the Entropy method has been used more than other methods. This provides us a solid confidence in the accuracy of this method.

Fourthly, although the above MCDM methods have been applied in many studies. However, no studies have applied all above methods in multi-criteria decision making for the turning process. If the multi-criteria decision-making for a machining process is performed by multiple methods that indicate the same best option too, the confidence level of the obtained results will be increased.

Fifthly, PIV is a method for multi-criteria decision making, firstly introduced in 2018 [7]. This method has been successfully applied in multi-criteria decision making in some cases, such as in the ranking and selection of E-learning sites [30], for the selection of materials to manufacture some parts of automobiles [31], for the selection of elements in logistics activities of the EU countries [32], for the selection of additives in a production process [33]. However, up to now, no studies have been found to apply this method for multi-criteria decision making in the turning process.

From the above analysis, this paper will inherit and develop to fill the gaps that previous studies have not done. In particular, the Taguchi method will be applied to design an experimental matrix with input parameters including spindle speed, feed rate, depth of cut, and nose radius. Three components of cutting force F_x, F_y, F_z, and *MRR* are selected as the criteria for evaluating the turning process. The weights of criteria will be determined by the Entropy method. All eight methods including *SAW*, *WASPAS*, *TOPSIS*, *VIKOR*, *MOORA*, *COPRAS*, *PIV*, *PSI*, are applied for multi-criteria decision making. The objective of this study is determination of an experiment that simultaneously ensures three minimum components of cutting force and the maximum *MRR*.

2 Determine the weights using the Entropy method

Determining the weights of criteria by the Entropy method is performed according to the following steps [34–36].

Step 1. Determine the normalized value for the criteria.

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

where y_{ij} is the value of the criterion j corresponding to the option i; m is the number of options (solutions).

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

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

Step 3. Calculate the weight for each criterion.

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

3 MCDM methods

3.1 SAW method

The *SAW* method was firstly recommended in 2006 [1]. The implementation steps according to this method are presented as follows.

Step 1. Establish an initial decision-making matrix (Y) as shown in equation (4). Where m is the number of options ($(A_1, A_2,..., A_m)$, n is the number of criteria ($C_1, C_2, ..., C_n$).

$$Y = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \cdots \\ A_m \end{array} & \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & xy_{22} & \cdots & y_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \end{array} \tag{4}$$

Step 2. Determine the normalized matrix according to the following formula.

$$n_{\mathrm{ij}} = \frac{y_{\mathrm{ij}}}{\max y_{ij}} \quad \text{for} \quad C_1, C_2, ..., C_n \in B \tag{5}$$

$$n_{\mathrm{ij}} = \frac{\min y_{\mathrm{ij}}}{y_{ij}} \quad \text{for} \quad C_1, C_2, ..., C_n \in C \tag{6}$$

where B represents the criterion as large as better, C represents the criterion as small as better.

Step 3. Calculate the preference value for each option.

$$V_i = \sum_{j=1}^{n} w_j \cdot n_{ij} \tag{7}$$

where w_j is the weight of the criterion j.

Step 4. Rank the options according to the principle that the best solution is the solution having the maximum V_i.

3.2 WASPAS method

The *WSPAS* method was firstly recommended in 2012 [2], the performing steps are presented as follows.

Step 1 and **Step 2**: The same step 1 and step 2 of the *SAW* method.

Step 3. Develop a weight matrix by multiplying the initial matrix by the weights of criteria with w_j is the weight of the criterion j.

$$\nu_n = \left[\nu_{\mathrm{ij}}\right]_{m \times n} \tag{8}$$

$$\nu_{ij} = w_j \times n_{ij}, \quad i = 1, 2, \ldots, m \quad j = 1, 2, \ldots, n \tag{9}$$

Step 4. Calculate the sum the values ν_{ij} in each row for each solution.

$$Q_i = \left[q_{\mathrm{ij}}\right]_{1 \times m} \tag{10}$$

$$q_{\mathrm{ij}} = \sum_{j=1}^{n} \nu_{\mathrm{ij}} \tag{11}$$

Step 5. Calculate the product the values $(\nu_{ij})^{wj}$ in each the row for each solution.

$$P_i = [p_{\mathrm{ij}}]_{1\times m} \tag{12}$$

$$p_{\mathrm{ij}} = \prod_{j=1}^{n} (\nu_{\mathrm{ij}})^{\mathrm{w}_j} \tag{13}$$

Step 6. Determine the relative values A_i of the options.

$$A_i = [a_{\mathrm{ij}}]_{1\times m} \tag{14}$$

$$A_i = \lambda \times Q_i + (1-\lambda) \times P_i \tag{15}$$

where the factor λ can be choose one of the following values: 0; 0.1; 0.2; ...; 1.0

Step 7. Rank the options according to the principle that the best option is the solution having the maximum A_i.

3.3 TOPSIS method

The implementation steps of the *TOPSIS* method are described as follows [3].

Step 1: The same step 1 of the *SAW* method.

Step 2: Determine the converted values according to the formula.

$$y'_{ij} = \frac{y_{ij}}{\sqrt{\sum_{i=1}^{n} y_{ij}^2}} \tag{16}$$

Step 3: Calculate a normalized matrix according to the formula.

$$Y = w_j.y'_{ij} \tag{17}$$

where w_j is the weight of the criterion *j*.

Step 4: Determine the best solution $A+$ and the worst solution A- for the criteria according to the following formulas.

$$A^+ = \left\{y_1^+, y_2^+, \ldots, y_j^+, \ldots, y_n^+\right\} \tag{18}$$

$$A^- = \left\{y_1^-, y_2^-, \ldots, y_j^-, \ldots, y_n^-\right\} \tag{19}$$

where y_j^+ and y_j^- are the best and worst values of the criterion *j*, respectively.

Step 5: Determine the values S_i^+ and S_i^- according to the following two formulas.

$$S_i^+ = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^+\right)^2} \quad \mathrm{i} = 1,\ 2, \ldots,\ \mathrm{m} \tag{20}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(y_{ij} - y_j^-\right)^2} \quad \mathrm{i} = 1,\ 2, \ldots,\ \mathrm{m} \tag{21}$$

Step 6: Determine the values C_i^* according to the formula.

$$C_i^* = \frac{S_i^-}{S_i^+ + S_i^-} \quad \mathrm{i} = 1,\ 2, \ldots,\ \mathrm{m};\quad 0 \le C_i^* \le 1 \tag{22}$$

Step 7: Rank the options according to the principle that the option with the maximum value of C_i^* is the best solution.

3.4 VIKOR method

The implementation steps of the *VIKOR* method are presented as follows [4].

Step 1: Determine the best value y^*_j and the worst value y^-_j of all criteria.

–If the criterion j is a positive one, then: $y^*_j = \max y_{ij}$, and $y^-_j = \min y_{ij}$.

– If the criterion j is a negative one, then: $y^*_j = \min y_{ij}$, and $y^-_j = \max y_{ij}$.

Step 2: Calculate the values r_{ij}, S_i, R_i according to the following formulas.

$$r_{ij} = \left(|y_j^* - y_{ij}|\right) / \left(|y_j^* - y_j^-|\right) \tag{23}$$

$$S_i = \sum_{j=1}^{n} w_j \left(|y_j^* - y_{ij}|\right) / \left(|y_j^* - y_j^-|\right) = \sum_{j=1}^{n} w_j r_{ij} \tag{24}$$

$$R_i = \max\left[w_j \left(|y_j^* - y_{ij}|\right) / \left(|y_j^* - y_j^-|\right)\right] = \max\left[w_j r_{ij}\right] \tag{25}$$

Step 3: Calculate Q_i

$$Q_i = \nu(S_i - S^*)/(S^- - S^*) + (1-\nu)(R_i - R^*)/(R^- - R^*) \tag{26}$$

with $0 \le \nu \le 1$ where ν is the weight of the positive group. Normally $\nu = 0.5$ [4].

$1-\nu$ is the weight of the negative group.

$$S^* = \min S_i \tag{27}$$

$$S^- = \max S_i \tag{28}$$

$$R^* = \min R_i \tag{29}$$

$$R^- = \max R_i \tag{30}$$

Step 4: Rank the options according to the principle that the option with the minimum Q_i is the best one.

3.5 MOORA method

The *MOORA* method was firstly introduced in 2004 [5], the steps are presented as follows.

Step 1 and **Step 2**: The same step 1 and step 2 of the *SAW* method.

Step 3: Calculate a normalized decision making matrix $[X_{ij}]_{m\times n}$ according to the formula.

$$X = [X_{ij}]_{m\times n}, \quad \text{with} \quad X_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}^2} \tag{31}$$

Step 4: Calculate the decision making matrices after normalizing the weights according to the formula.

$$W_{ij} = w_j \times y_{ij} \tag{32}$$

Step 5: Calculate P_i and R_i according to the following two formulas.

$$P_i = \frac{1}{|B|}\sum_{j\in B} W_{ij} \tag{33}$$

$$R_i = \frac{1}{|NB|}\sum_{j\in NB} W_{ij} \tag{34}$$

where B and NB are the number of the criterion as large as better and the criterion as small as better, respectively.

Step 6: Calculate the values Q_i according to the formula.

$$Q_i = P_i - R_i \tag{35}$$

Step 7: Rank the options according to the principle that the option with the minimum Q_i is the best one.

3.6 COPRAS method

The *COPRAS* method was firstly introduced in 1994 [6]. The steps are presented as follows.

Step 1 and **Step 2**: The same step 1 and step 2 of the *SAW* method.

Step 3, Step 4, and **Step 5**: The same step 3, step 4, and step 5 of the *MOORA* method.

Step 6: Calculate the values Q_i according to the formula.

$$Q_i = P_i + \frac{\sum_{i=1}^{m} R_i}{R_i \times \sum_{i=1}^{m} \frac{1}{R_i}} \tag{36}$$

Step 7: Rank the options according to the principle that the option with the minimum Q_i is the best one.

3.7 PIV method

The *PIV* method was firstly introduced in 2018 [7]. The implementation steps for multi-criteria decision making according to this method are presented as follows:

Step 1 and **Step 2**: The same step 1 and step 2 of the *SAW* method.

Step 3: Determine the normalized decision-making matrix using the formula.

$$R_j = \frac{y_j}{\sqrt{\sum_{i=1}^{m} y_j^2}} \tag{37}$$

Of which Yi is the actual decision value of option i.

Step 4: Determine the weighted normalized decision-making matrix according to the formula.

$$\nu_j = W_j \times R_j \tag{38}$$

Of which w_j is the weight of the criterion j.

Step 5: Evaluate the weighted proximity index according to the following formula.

$$u_i = \begin{cases} \nu_{\max} - \nu_i & \text{for the criterion as large as better} \\ \nu_i - \nu_{\min} & \text{for the criterion as small as better} \end{cases} \tag{39}$$

Step 6. Determine the overall proximity value according to the following formula.

$$d_i = \sum_{j=1}^{n} u_i \tag{40}$$

Step 7. Rank the options according to the principle that the option with the minimum d_i is the best one

3.8 PSI method

The *PSI* method was firstly introduced in 2010 as the one for multi-criteria decision making without determining the weight of the criteria [8]. The implementation steps according to this method are presented as follows.

Step 1: Normalize the attributes.

$$N_{ij} = \frac{y_{ij}}{y_j^{\max}} \text{ for the criterion as large as better} \tag{41}$$

$$N_{ij} = \frac{y_j^{\min}}{y_{ij}} \text{ for the criterion as small as better} \tag{42}$$

Step 2: Calculate the mean value of the normalized data.

$$N = \frac{1}{n}\sum_{i=1}^{n} N_{ij} \tag{43}$$

Step 3: Determine the preference value from the mean value.

$$\varphi_j = \sum_{i=1}^{n} [N_{ij} - n]^2 \tag{44}$$

Step 4: Determine the deviation in the preference value.

$$\emptyset_j = [1 - \varphi_j] \tag{45}$$

Table 1. Input parameters.

Parameters	Symbol	Unit	Value at the level		
			1	2	3
Workpiece speed	n_w	rev/min	460	650	910
Feed rate	f_d	mm/rev	0.08	0.194	0.302
Depth of cut	a_p	mm	0.15	0.30	0.45
Nose radius	r	mm	0.4	0.6	1.2

Table 2. Experimental matrix.

Trial.	Coded value				Actual value			
	x_1	x_2	x_3	x_4	n_w (rev/min)	f_d (mm/rev)	a_p (mm)	r (mm)
1	1	1	1	1	460	0.08	0.20	0.4
2	1	2	2	2	460	0.194	0.35	0.6
3	1	3	3	3	460	0.302	0.50	1.2
4	2	2	3	3	650	0.08	0.35	1.2
5	2	3	1	1	650	0.194	0.50	0.4
6	2	1	2	2	650	0.302	0.20	0.6
7	3	3	2	2	910	0.08	0.50	0.6
8	3	1	3	3	910	0.194	0.20	1.2
9	3	2	1	1	910	0.302	0.35	0.4

Step 5: Determine the overall preference value for the criteria.

$$\beta_j = \frac{\text{Ø}_j}{\sum_{j=1}^{m} \text{Ø}_j} \tag{46}$$

Step 6: Calculate the Preference Selection Index (PSI) of each option.

$$\theta_j = \sum_{j=1}^{m} y_{ij}.\beta_j \tag{47}$$

Step 7: Rank the options according to the principle that the solution with with the maximum θ_i is the best one.

4 Turning process experiment

The experimental workpiece is 150Cr14 steel with a diameter of 30 mm and a length of 280 mm. This is a martensitic steel, and this steel was commonly used to make wear-resistant parts such as shafts, gears, turbines, rolling shafts, etc.

The TiAlN coated insert was used during the experimental process. This cutter insert type has high hardness, high wear resistance as well as high toughness. So, this type of cutting tool has capable of reducing chipping during the machining process.

Four parameters including cutting velocity (n_w), feed rate (f_d), depth of cut (a_p), and nose radius (r) were selected as the input parameters of the experimental process. These parameters can be easily adjusted by the machine operator.

The Taguchi method was applied to design an experimental matrix. Each input parameter was selected with three value levels as shown in Table 1. These values were selected according to the recommendations of the cutting tool manufacturer and according to the technological capabilities of the experimental machine. The orthogonal matrix with nine experiments is presented in Table 2.

Cutting forces directly influence on the machined surface roughness and tool life, and cutting forces are also influenced by many factors in machining processes [37,38]. In this study, three cutting force components in three directions (X, Y, Z) were determined at each experimental point. The experiments were performed in a conventional lathe. The force sensor (Kistler type 9139AA) was used to measure three components of the cutting force. The force sensor is placed on the carriage, then the tool holder is fixed on the force sensor (Fig. 1). The value of the cutting force in each direction in each experiment is calculated as its average value during the cutting time.

MRR is the most important measure to evaluate the productivity of the cutting process [39]. *MRR* is calculated according to formula (48). Where n_w is the number of revolutions of the workpiece per minute, d is the diameter

Table 3. Experimental results.

Trial.	F_x (N)	F_y (N)	F_z (N)	MRR (mm^3/s)
1	59.844	187.437	44.165	11.561
2	87.943	199.762	99.125	49.062
3	78.913	127.456	69.874	109.108
4	54.816	172.714	60.19	28.588
5	63.117	180.361	68.869	99.039
6	68.79	113.951	70.694	61.669
7	46.654	116.88	92.222	57.177
8	44.989	162.337	63.25	55.462
9	54.846	167.837	74.165	151.09

Table 4. The normalized values p_i for the criteria.

Solotions	p_{ij}			
	y_1	y_2	y_3	y_4
1	0.00164	0.00080	0.00092	0.00020
2	0.00241	0.00085	0.00206	0.00085
3	0.00216	0.00054	0.00145	0.00188
4	0.00150	0.00074	0.00125	0.00049
5	0.00173	0.00077	0.00143	0.00171
6	0.00189	0.00049	0.00147	0.00106
7	0.00128	0.00050	0.00192	0.00098
8	0.00123	0.00069	0.00132	0.00096
9	0.00150	0.00071	0.00154	0.00260

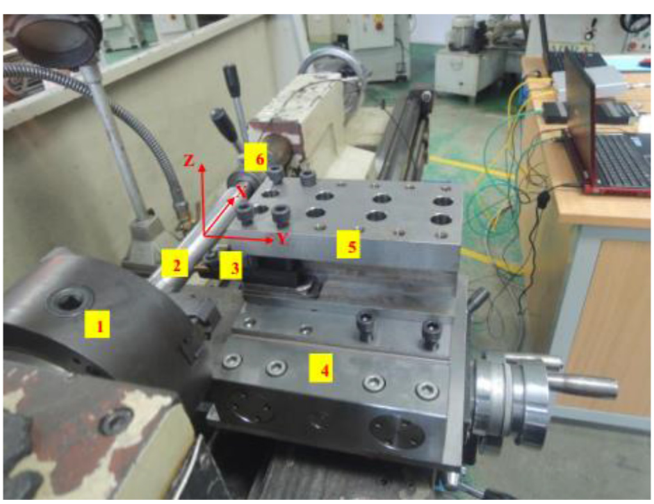

Fig. 1. Setting the experimental system. 1. Three-jaw chuck, 2. Workpiece, 3. Tool, 4. Force sensor, 5. Tool holder, 6. Center.

of the workpiece, f_d is the feed rate, and a_p is the depth of cut.

$$MRR = \frac{1}{60} \cdot n_w \cdot \pi \cdot d \cdot f_d \cdot a_p \left(mm^3/s\right) \quad (48)$$

5 Experimental results and discussions

The experimental results were presented in Table 3. In this table, F_x has the minimum value at experiment #8, F_y is the minimum at experiment #6, F_z is the minimum at experiment #1, and MRR is the maximum at experiment #9. Thus, it is clear that there is not an experiment that simultaneously ensures the minimum values of F_x, F_y, F_z and the maximum value of MRR. Therefore, we can only find an experiment where F_x, F_y, F_z are considered as the "minimum" and MRR is considered as the "maximum", and of course this must be done by the $MCDM$ method.

6 Multi-criteria decision making for the turning process

6.1 Determine the weight of responses using the entropy method

To facilitate the calculation, we assign the following criteria: $F_x = y_1$, $F_y = y_2$, $F_z = y_3$, and $MRR = y_4$. Applying formula (1), we can determine the normalized value for criteria, the results are as shown in Table 4.

Table 5. Entropy measure of the criteria.

e_j			
y_1	y_2	y_3	y_4
0.11271	0.05037	0.10007	0.08099

Table 6. The weight of criteria.

w_j			
y_1	y_2	y_3	y_4
0.2427	0.25976	0.24616	0.25138

Table 7. Normalized matrix.

Solotions	n_{ij}			
	y_1	y_2	y_3	y_4
1	0.75177	0.60794	1.00000	0.07652
1	0.51157	0.57043	0.44555	0.32472
2	0.57011	0.89404	0.63207	0.72214
4	0.82073	0.65977	0.73376	0.18921
5	0.71279	0.63179	0.64129	0.65550
6	0.65400	1.00000	0.62473	0.40816
7	0.96431	0.97494	0.47890	0.37843
8	1.00000	0.70194	0.69826	0.36708
9	0.82028	0.67894	0.59550	1.00000

Applying formula (2), we can determine the entropy measure degree for the criteria, the results are shown in Table 5.

Applying formula (3), we can determine the weights for the criteria, the results are presented in Table 6.

6.2 Multi-Criteria decision making using the SAW method

Establish an initial decision-making matrix (Y). This matrix is the last 4 columns in Table 3 (table of experimental results).

Normalize the initial matrix according to formulas (5) and (6). The results are presented in Table 7.

Calculate the preference value for each option according to formula (7). The results are presented in Table 8. The ranking of options according to the values V_i has also been carried out, the results were also added in this table. The ranking of options was also performed in this table.

Table 8. V_i values of each option and ranking of options.

Solotions	V_i	Ranking
1	0.60577	7
2	0.46364	9
3	0.70772	2
4	0.59876	8
5	0.65975	6
6	0.67487	5
7	0.70030	3
8	0.68920	4
9	0.77341	1

6.3 Multi-criteria decision making using the WASPAS method

Develop a weighted matrix by multiplying the initial matrix by the weights of criteria according to formulas (8) and (9), where the weight of criteria was determined (in Tab. 6). The results are presented in Table 9.

Calculate the sum of all the values v_{ij} of the criteria in each option according to formulas (10) and (11). The results are included in Table 10.

Calculate the product of all values $(v_{ij})^{wj}$ of the criteria in each option according to formulas (12) and (13). The results were also added in Table 10.

Determine the relative values A_i of options according to formulas (14) and (15). The results are shown in Table 10.

The ranking of options according to the value A_i was also added in Table 10.

6.4 Multi-criteria decision making using the TOPSIS method

Applying the formula (16) to determine the converted values for the criteria as shown in Table 11.

Table 9. Weighted matrix.

Solotions	v_{ij}			
	y_1	y_2	y_3	y_4
1	0.18246	0.15792	0.24616	0.01923
2	0.12416	0.14817	0.10968	0.08163
3	0.13837	0.23223	0.15559	0.18153
4	0.19919	0.17138	0.18062	0.04756
5	0.17300	0.16411	0.15786	0.16478
6	0.15873	0.25976	0.15378	0.10260
7	0.23404	0.25325	0.11789	0.09513
8	0.24270	0.18233	0.17188	0.09228
9	0.19908	0.17636	0.14659	0.25138

Table 10. Several parameters in *WASPAS*.

Solotions	q_i	p_i	A_i	Ranking
1	0.60577	0.10746	0.35662	8
2	0.46364	0.11347	0.28855	9
3	0.70772	0.17443	0.44108	2
4	0.59876	0.13046	0.36461	7
5	0.65975	0.16481	0.41228	6
6	0.67487	0.16040	0.41764	5
7	0.70030	0.16091	0.43061	3
8	0.68920	0.16231	0.42575	4
9	0.77341	0.18972	0.48156	1

Table 11. Converted values in TOPSIS.

Solutions	y'_{ij}			
	y_1	y_2	y_3	y_4
1	0.3134	0.3868	0.2015	0.0480
2	0.4605	0.4122	0.4523	0.2036
3	0.4132	0.2630	0.3188	0.4529
4	0.2870	0.3564	0.2746	0.1187
5	0.3305	0.3722	0.3143	0.4111
6	0.3602	0.2352	0.3226	0.2560
7	0.2443	0.2412	0.4208	0.2373
8	0.2356	0.3350	0.2886	0.2302
9	0.2872	0.3464	0.3384	0.6271

Applying formula (17), we can determine a normalized matrix as shown in Table 12. where the weights of criteria have been determined by the entropy method (in Tab. 6).

From the data in Table 12, the best solution $A+$ and worst solution A- for the options have been determined according to formulas (18) and (19), presented in Table 13.

The values S_i^+, S_i^- and C_i^* are calculated according to the respective formulas (20), (21) and (22), which are presented in Table 14. The ranking of options was also performed in Table 14.

Table 12. Normalized matrix $Y = w_j \cdot y'_{ij}$.

Solutions	$w_j \cdot y'_{ij}$			
	y_1	y_2	y_3	y_4
1	0.0761	0.1005	0.0496	0.0121
2	0.1118	0.1071	0.1113	0.0512
3	0.1003	0.0683	0.0785	0.1138
4	0.0697	0.0926	0.0676	0.0298
5	0.0802	0.0967	0.0774	0.1033
6	0.0874	0.0611	0.0794	0.0643
7	0.0593	0.0627	0.1036	0.0597
8	0.0572	0.0870	0.0710	0.0579
9	0.0697	0.0900	0.0833	0.1576

Table 13. The best and worst solutions.

	y_1	y_2	y_3	y_4
$A+$	0.0572	0.0611	0.0496	0.1576
$A-$	0.1118	0.1071	0.1113	0.0121

Table 14. Several values in TOPSIS.

Solutions	Si^+	Si^-	C^*_i	Ranking
1	0.1745	0.0716	0.2910	8
2	0.1683	0.0391	0.1887	9
3	0.0921	0.1143	0.5539	2
4	0.1559	0.0649	0.2939	7
5	0.1116	0.1029	0.4797	3
6	0.1163	0.0804	0.4087	4
7	0.1254	0.0840	0.4012	5
8	0.1302	0.0843	0.3929	6
9	0.0912	0.1551	0.6295	1

Table 15. Minimum and maximum values of the criteria.

	y_1	y_2	y_3	y_4
Min y_{ij}	87.9430	199.7620	99.1250	11.5610
Max y_{ij}	44.9890	113.9510	44.1650	151.0900

6.5 Multi-criteria decision making using the VIKOR method

Determine the best value y^*_j and worst value y^-_j of all criteria, the results are presented in Table 15. Where for the criteria y_1, y_2, and y_3 is the best value is the minimum one, and for the criterion y_4 is the best value is the maximum one.

The calculated results of r_{ij} according to formula (23) are presented in Table 16.

The calculated results of S_i, R_i, and Q_i according to the formulas from (24) to (30) are presented in Table 17. Where the weight of MRR (the bigger the better) is also selected as 0.5, the weight of remaining criteria (F_x, F_y, F_z – the smaller the better) is also selected as 0.5 [4]. The results of ranking options according to the value Q_i have also been shown in this table.

6.6 Multi-criteria decision making using the MOORA method

Using equation (31) to calculate the normalized matrix, the calculated results were presented in Table 18.

Table 16. Values r_{ij}.

Solutions	r_{ij}			
	y_1	y_2	y_3	y_4
1	0.6542	0.1436	1.0000	0.0000
2	0.0000	0.0000	0.0000	0.2688
3	0.2102	0.8423	0.5322	0.6991
4	0.7712	0.3151	0.7084	0.1220
5	0.5780	0.2260	0.5505	0.6270
6	0.4459	0.9996	0.5173	0.3591
7	0.9612	0.9655	0.1256	0.3269
8	1.0000	0.4360	0.6527	0.3146
9	0.7705	0.3719	0.4541	1.0000

Table 17. Values Si, R_i, and Q_i and ranking.

Solutions	S_i	R_i	Q_i	Ranking
1	0.0676	0.3333	0.5977	8
2	0.0676	0.3333	0.0000	9
3	0.0676	0.3333	0.8455	5
4	0.0676	0.3333	0.7485	6
5	0.0676	0.3333	0.6135	7
6	0.0676	0.3333	0.9725	3
7	0.0676	0.3333	0.9663	4
8	0.0676	0.3333	0.9942	2
9	0.0676	0.2598	0.9924	1

Table 18. Normalized matrix X.

Solutions	$X = [X_{ij}]_{m\times n}$			
	y_1	y_2	y_1	y_2
1	0.3134	0.3868	0.2015	0.0480
2	0.4605	0.4122	0.4523	0.2036
3	0.4132	0.2630	0.3188	0.4529
4	0.2870	0.3564	0.2746	0.1187
5	0.3305	0.3722	0.3143	0.4111
6	0.3602	0.2352	0.3226	0.2560
7	0.2443	0.2412	0.4208	0.2373
8	0.2356	0.3350	0.2886	0.2302
9	0.2872	0.3464	0.3384	0.6271

Using equation (32) to calculate the normalized matrix with weight. Where the weights of the criteria were determined using Entropy method in Table 6. The calculated results were presented in Table 19.

Applying the equation (33) to caltulate the value of P_i, using equation (34) to calculated the value of R_i, and using equation (35) to calculate the value of Q_i, the calculated results were listed in Table 20. The ranking results of the solutions were also presented in this table.

6.7 Multi-criteria decision making using the COPRAS method

The values P_i and R_i are calculated in the same way as the *MOORA* method. Using formula (36) to calculate the

Table 19. Normalized matrix with the weight.

Solutions	$W_{ij} = w_j \cdot y_{ij}$			
	y_1	y_2	y_1	y_2
1	14.5244	48.6879	10.8717	2.9062
2	21.3441	51.8894	24.4006	12.3332
3	19.1525	33.1074	17.2002	27.4276
4	13.3041	44.8635	14.8164	7.1865
5	15.3187	46.8498	16.9528	24.8964
6	16.6956	29.5994	17.4020	15.5024
7	11.3231	30.3603	22.7014	14.3732
8	10.9190	42.1680	15.5696	13.9420
9	13.3113	43.5967	18.2565	37.9810

Table 20. Calculated results of P_i, R_i, Q_i and the ranking results.

Solutions	P_i	R_i	Q_i	Ranking
1	24.6946	2.9062	21.7884	9
2	32.5447	12.3332	20.2115	8
3	23.1534	27.4276	–4.2742	2
4	24.3280	7.1865	17.1415	7
5	26.3738	24.8964	1.4774	3
6	21.2324	15.5024	5.7300	4
7	21.4616	14.3732	7.0884	5
8	22.8855	13.9420	8.9435	6
9	25.0548	37.9810	–12.9262	1

values Q_i, the calculated results are presented in Table 21. The ranking results of the solutions were also presented in this table.

6.8 Multi-criteria decision making using the PIV method

Evaluate the weighted proximity index according to the formula (39). The results are presented in Table 22.

Determine the overall proximity value according to the formula (40). The results are presented in Table 23. The ranking of options according to the value d_i is also presented in this table.

6.9 Multi-criteria decision making using the PSI method

The normalized values of attributes are calculated according to the formulas (41) and (42), as presented in Table 24.

The mean of normalized values is calculated according to formula (43). This value was also added in Table 24.

Determine the preference value from the mean according to the formula (44): $\varphi_{y1} = 0.21784$; $\varphi_{y2} = 0.21564$; $\varphi_{y3} = 0.20693$; $\varphi_{y4} = 0.65516$.

Determine the deviation in the preference value according to the formula (45): $\emptyset_{y1} = 0.78216$; $\emptyset_{y2} = 0.78436$; $\emptyset_{y3} = 0.79307$; $\emptyset_{y4} = 0.34484$.

Determine the overall preference value according to the formula (46): $\beta_{y1} = 0.2892$, $\beta_{y2} = 0.2900$, $\beta_{y3} = 0.2932$; $\beta_{y4} = 0.1275$.

Calculate the preference selection index θ (*PSI*) of each option according to the formula (47), the calculated results are presented in Table 25.

From the ranking results of the options according to above methods (in Tabs. 8, 10, 14, 17, 20, 21, 23, 25), all seven methods, including *SAW*, *WASPAS*, *TOPSIS*, *VIKOR*, *MOORA*, *COPRAS*, *PIV* indicate that the option number 9 is the best one. Particularly for the *PSI* method, it is determined that the option number 2 is the best one. Another special thing is that option number 2 is determined as the worst option when applying the *SAW*, *WAPSAS*, *TOPSIS*, *VIKOR*, and *PIV* methods, while the *PSI* method determines that option 2 is the best one. This creates a feeling of unreliability when using the *PSI* method. This difference is explained that seven methods (*SAW*, *WASPAS*, *TOPSIS*, *VIKOR*, *MOORA*, *COPRAS*, *PIV*) use the weight of criteria according to the entropy method too, while the PSI method uses the "*preference*

Table 21. Results of calculating P_i, R_i, Qi and ranking.

Solutions	P_i	R_i	Q_i	Ranking
1	24.6946	2.9062	86.3909	9
2	32.5447	12.3332	47.0828	7
3	23.1534	27.4276	29.6907	2
4	24.3280	7.1865	49.2780	8
5	26.3738	24.8964	33.5757	4
6	21.2324	15.5024	32.7985	3
7	21.4616	14.3732	33.9364	5
8	22.8855	13.9420	35.7461	6
9	25.0548	37.9810	29.7756	1

Table 22. Evaluate the weighted proximity index.

Solotions	u_{ij}			
	y_1	y_2	y_3	y_4
1	0.01888	0.03940	0.00000	0.14558
2	0.05459	0.04600	0.06173	0.10645
3	0.04312	0.00724	0.02887	0.04380
4	0.01249	0.03150	0.01800	0.12781
5	0.02304	0.03560	0.02775	0.05431
6	0.03025	0.00000	0.02980	0.09330
7	0.00212	0.00157	0.05398	0.09798
8	0.00000	0.02594	0.02143	0.09977
9	0.01253	0.02889	0.03369	0.00000

value from the mean value", "*the deviation in the preference value*", and "*the overall preference value*".

From this problem, a new idea is proposed, that is combining the *PSI* method with the entropy determination weight method and called the *PSIe* method. In the *PSIe* method, instead using the "*preference value from the mean value*", the "*deviation in the preference value*", and "*overall preference value*", the entropy weight was used. That means the "*preference selection index θ*" will be calculated as the sum of the products between the value of this criterion and its weight as described by equation (49).

$$\theta_j = \sum_{j=1}^{m} y_{ij}.w_j. \tag{49}$$

Applying the formula (49) to the calculation of θ_i in the *PSIe* method, the results are shown in Table 26. The results of ranking options according to the value θ_i are also presented in Table 26.

A summary of the ranking of options according to 9 methods (*SAW*, *WASPAS*, *TOPSIS*, *VIKOR*, *MOORA*, *COPRAS*, *PIV*, *PSI*, and *PSIe*) is presented in Table 27.

According to the results of ranking options in Table 27, there are 8/9 methods determining that option 9 is the best one (except for the *PSI* method as mentioned above). The worst option is determined by the *PSIe* method is also consistent with the *MOORA* and *COPRAS* methods. These results provide us with more confidence in using the *PSIe* method than using the *PSI* method. The application of the entropy method to determine the weight of the criteria was helped the multi-criteria decision making

Table 23. Overall proximity values and ranking of options.

Solotions	d_i	Ranking
1	0.20385	8
2	0.26878	9
3	0.12304	2
4	0.18981	7
5	0.14070	3
6	0.15335	5
7	0.15565	6
8	0.14715	4
9	0.07511	1

Table 24. Normalized value of attributes.

Solutions	N_{ij}			
	y_1	y_2	y_3	y_4
1	0.7518	0.6079	1.0000	0.0765
2	0.5116	0.5704	0.4455	0.3247
3	0.5701	0.8940	0.6321	0.7221
4	0.8207	0.6598	0.7338	0.1892
5	0.7128	0.6318	0.6413	0.6555
6	0.6540	1.0000	0.6247	0.4082
7	0.9643	0.9749	0.4789	0.3784
8	1.0000	0.7019	0.6983	0.3671
9	0.8203	0.6789	0.5955	1.0000
Mean	0.7562	0.7466	0.6500	0.4580

Table 25. Values θ in PSI and rankings.

Solutions	θ	Ranking
1	86.0950	6
2	118.6949	1
3	94.1912	4
4	87.2412	5
5	103.3881	3
6	81.5383	9
7	81.7260	8
8	85.7135	7
9	105.5537	2

Table 26. Values θ in PSIe and ranking.

No.	θ	Ranking
1	76.9901	9
2	109.9673	2
3	96.8877	4
4	80.1704	6
5	104.0178	3
6	79.1994	7
7	78.7579	8
8	82.5987	5
9	113.1455	1

Table 27. Ranking of options according to the MCDM methods.

Solutions	Ranking								
	SAW	*WASPAS*	*TOPSIS*	*VIKOR*	*MOORA*	*COPRAS*	*PIV*	*PSI*	*PSIe*
1	7	8	8	8	9	9	8	6	9
2	9	9	9	9	8	7	9	1	2
3	2	2	2	5	2	2	2	4	4
4	8	7	7	6	7	8	7	5	6
5	6	6	3	7	3	4	3	3	3
6	5	5	4	3	4	3	5	9	7
7	3	3	5	4	5	5	6	8	8
8	4	4	6	2	6	6	4	7	5
9	1	1	1	1	1	1	1	2	1

methods to identify the best solution among the implemented ones. From that, it can be seen that when the weight of the criteria is determined by the entropy method, the stability in determining the best solution is very high. In the particular case of this study, the level of stability was absolute. Thus, not only for the turning process but also for other machining processes, in determination process of the best solution, in order to have the high reliability for the best solution, it is necessary to apply many multi-criteria decision making methods. In these cases, the entropy method should be chosen to determine the weights for the criteria.

From this result, we also come to the conclusion that if we wish to simultaneously ensure the "minimum" F_x, F_y, and F_z, and the "maximum" *MRR*, the spindle speed is 910 rev/min, the feed rate is 0.302 mm/ rev, the depth of cut is 0.35 mm, and the nose radius is 0.4 mm.

7 Conclusion

In this study, the turning experimental process of 150Cr14 steel was performed using TiAlN coated cutting insert. An experimental matrix was designed according to the Taguchi method with four input parameters including spindle speed, feed rate, depth of cut, and nose radius. At each experiment, four output parameters of the turning process were determined including three components of the cutting force in three directions (F_x, F_y, and F_z), and *MRR*. The Entropy method was applied to determine the weights of criteria. Eight methods including *SAW, WASPAS, TOPSIS, VIKOR, MOORA, COPRAS, PIV, PSI* were applied to rank the options. Several conclusions are drawn as follows:

– This is the first time that the *PIV* method is applied to make the multi-criteria decision for the turning process. This study is also the first study that applied all eight methods including *SAW*, *WASPAS*, *TOPSIS*, *VIKOR*, MOORA, *COPRAS*, *PIV*, *PSI* for multi-criteria decision making. Seven of these eight methods determined the same best solution (except for the *PSI* method).
– The multi-criteria decision making methods all determine the best solution if the weight of the criteria is determined by the Entropy method. This leads to the promotion of the use of the Entropy method in determining the weights for the criteria.
– The *PSI* method does not use entropy weights, so the ranking results are very different from the other ones. This means that there must be careful considerations in deciding whether or not to use the *PSI* method for multi-criteria decision making.
– A new method proposed in this study is the combination of the *PSI* method with the Entropy weight method, called the *PSIe* method. The *PSIe* method also determined the best experiment like the other seven ones including *SAW, WASPAS, TOPSIS, VIKOR, MOORA, COPRAS, PIV*.
– The weight of the four parameters F_x, F_y, F_z, and *MRR* are 0.24270, 0.25976, 0.24616, and 0.25138, respectively.
– To simultaneously ensure the criteria including three minimum components of the cutting forces and the maximum *MRR*, the spindle speed is 910 (rev/min), the feed rate is 0.302 (mm/rev), the depth of cut is 0.35 (mm), and the nose radius is 0.4 (mm).
– The combination of all methods, *Taguchi − Entropy − SAW − WASPAS − TOPSIS − VIKOR − MOORA − COPRAS − PIV*, and *PSI* was applied for the first time, and was succeeded in selecting the best experiment in this study. This combination also promises to be successful when applied to other machining processes.
– It is required to perform further studies to apply the *PSIe* method in multi-criteria decision making, then compare the results with other methods. Thereby, it is possible to decide whether to use the *PSIe* method or not. These are the tasks that the author will perform in near future.

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