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A Comprehensive Solution Approach for CNC Machine Tool Selection Problem

Yusuf SAHIN[1,*], Erdal AYDEMIR[2]

[1] *Department of Business Administration, Burdur Mehmet Akif Ersoy University, Turkey*
[2] *Department of Industrial Engineering, Suleyman Demirel University, Turkey*
e-mail: ysahin@mehmetakif.edu.tr, erdalaydemir@sdu.edu.tr

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Abstract. A proper CNC machine selection problem is an important issue for manufacturing companies under competitive market conditions. The selection of an improper machine tool can cause many problems such as production capabilities and productivity indicators considering time and money industrially and practically. In this paper, a comprehensive solution approach is presented for the CNC machine tool selection problem according to the determined criteria. Seven main and thirteen sub-criteria were determined for the evaluation of the seven alternatives. To purify the selection process from subjectivity, instead of a single decision-maker, the opinions of six different experts on the importance of the criteria were taken and evaluated using the Best-Worst method. According to the evaluations, the order of importance of the main criteria has been determined as cost, productivity, flexibility, and dimensions. After the weighting of the criteria, three different ranking methods (GRA, COPRAS, and MULTIMOORA) were preferred due to the high investment costs of the selected alternatives. The findings obtained by solving the problem of selection of the CNC machine are close to those obtained by past researchers. As a result, using the suggested methodology, effective alternative decision-making solutions are obtained.

Key words: machine tool selection, BWM, GRA, COPRAS, MULTIMOORA.

1. Introduction

Companies need to have many plans related to marketing, financing, and production in today's competitive markets. On the other hand, companies, based on these strategies, have to take a series of decisions, especially at the stage of establishment and when making growth decisions. One of these decisions is the selection of machines and equipment to be used in manufacturing. Identifying the appropriate machine or equipment from among the alternatives available is also a very important decision which, in the long run, affects the efficiency of the production system. The use of suitable machinery improves the manufacturing process, ensures the effective use of manpower, increases productivity, and enhances the versatility of the system (Dağdeviren, 2008). Also, the characteristics of the chosen machine have a considerable effect on prices, efficiency, and performance numbers, which are the key objectives of the production strategy.

*Corresponding author.

Generally, computer numerical control (CNC) machines, which can be used with high precision to perform repetitive, challenging, and unsafe production jobs, are considered cost-effective equipment (Athawale and Chakraborty, 2010). CNC machines are regarded as cost-effective instruments that can be used to perform routine, demanding, and dangerous manufacturing tasks by offering a high degree of precision to eliminate human errors. CNC machines are also used in innovative fields such as the production of molds for phase change material (PCM) (Lim *et al.*, 2018). A very complex decision problem is the purchase of such a technological machine tool, as it requires a large investment and has many alternative and selection criteria. There is a large amount of data to be analysed by the decision-maker and many features to consider for an appropriate and effective evaluation of the selection of machine tools. To choose the most suitable one, the decision-maker must be an expert or be familiar with the technical specifications of the machines (Rao, 2006).

The scope of this paper, which is based on these needs, is to select a proper machine tool using Best-Worst weighted GRA, COPRAS, and MULTIMOORA methods. These methods are used to determine the order of priority with managerial insights and implications. However, this paper tries to answer the following questions:

(1) What are the criteria of the most used features in the CNC machine tool selection process?
(2) Which alternative CNC machine tool may be more suitable under variable weighted uncertainties?
(3) How different weights of expert opinions will affect this selection problem on the Best-Worst methodology?

The rest of this study is organized as follows: a related literature review is given in Section 2. In Section 3, at first, the problem definition is given and then, Best-Worst, Grey Relational Analysis (GRA), COPRAS, and MULTIMOORA methodologies are explained. The proposed solution approach and its implementation are placed in Section 4 with the numerical case study. In Section 5, the conclusion and discussions are presented for considering future studies.

2. Literature Review

For several years, machine tool selection has been an important decision problem for manufacturing firms. The primary explanation for this is that there are several issues with the selection of an inappropriate machine that affects overall efficiency and production capabilities in the long run (Taha and Rostam, 2012). A detailed literature review is given in Table 1 and some selected studies are summarized in the following.

Since there is more than one criterion, Multi-Criteria Decision Making (MCDM) methods are widely used in the solution of the Machine Tool Selection (MTS) problem. Several options and criteria are evaluated in these studies to decide the best alternative. It is considered as the most suitable option for the decision-maker who, after rating the alternatives, gets the highest score (Ayağ and Özdemir, 2006). The researchers have used various approaches to solve the MTS problem until today. The Analytical Hierarchy Process (AHP) and TOPSIS Method are the most commonly used methods among these techniques.

Due to uncertainties in the decision-maker's decisions, a fuzzy AHP instead of traditional AHP was used for the evaluation and justification of an advanced production system (Ayag and Ozdemir, 2006) with developing a software (Durán and Aguilo, 2008). To analyse the structure of the equipment selection problem and evaluate the weights of the parameters, Dağdeviren (2008) suggested an integrated approach using AHP and the PROMETHEE approach for obtaining the final rating and conducting sensitivity analysis by adjusting weights. Önüt *et al.* (2008) suggested a fuzzy TOPSIS based approach for the evaluation and selection of vertical CNC machining centres, where weights were determined by fuzzy AHP.

Moreover, in order to measure the level of benefit provided by using fuzzy numbers in multi-criteria decision models, Yurdakul and Ic (2009) solved the problem of MTS and compared the solutions of TOPSIS and Fuzzy TOPSIS techniques. The TOPSIS method was used by Athawale and Chakraborty (2010) to evaluate CNC machines in terms of system features and costs. Then, as the consecutive studies, fuzzy numbers were used for pairwise comparison with an Analytic Network Process (ANP) which was proposed to improve the imprecise ranking of the company's requirements which is based on the conventional ANP for machine tool selection problem. The proposed methodology was developed to eliminate the effects of vagueness and uncertainty on the judgments of a decision-maker (Ayağ and Özdemir, 2011). The next one is TOPSIS and ANP methods which are commonly used MCDM methods for performance analysis on the machine tool selection problem (Ayağ and Özdemir, 2012). Similarly, Fuzzy ANP and Fuzzy PROMETHEE-II techniques were integrated by Samanlioglu and Ayağ (2016) to solve the problem of machine tool selection. Chen *et al.* (2021) proposed an approach consisting of DEMANTEL, ULOWA, and PROMETHEE methods for mechanical product optimization design based on meta-action reliability. An example of the application and feasibility of their proposed method is demonstrated with an automatic pallet changer (APC) of a CNC machine tool.

Methods such as SAW (Patel *et al.*, 2012; Özdağoğlu *et al.*, 2017), Multi-Moora-Interval Value Grey Number Sets (IVGN) (Sahu *et al.*, 2014), MOORA-MOOSRA (Sarkar *et al.*, 2015), VIKOR (Jing *et al.*, 2015), Fuzzy ANP-Promethee (Özceylan *et al.*, 2016), QFD (Perçin and Min, 2013; Prasad and Chakraborty, 2015), Axiomatic Design (Kulak *et al.*, 2005; Cakir, 2018), a neutrosophic MOORA method (Zaied *et al.*, 2019) and entropy weighted fuzzy DEMATEL with VIKOR defuzzification (Li *et al.*, 2020) were used for the selection problem in the literature in addition to these studies. In addition to the studies with details, the studies in the literature regarding machine selection, tool selection, and technology selection are shown in Table 1.

In this study, a new solution approach is proposed where criteria weights are determined by the Best-Worst method, and rankings are determined by considering with GRA, COPRAS, and MULTIMOORA methods. Within the scope of the study, a new solution approach in which weighting and ranking methods are used together has been tried to be

Table 1
Detailed literature review.

Source	Application area			Method			Uncertainty	
	Machine selection	Tool selection	Technology selection	MCDM Method	Integrated method	Others	Crisp	Fuzzy
Arslan *et al.* (2004)		√		√			√	
Yurdakul (2004)		√			√		√	
Kulak *et al.* (2005)		√			√			√
Ayağ and Özdemir (2006)		√			√			√
Ayağ (2007)		√			√		√	
Çimren *et al.* (2007)		√		√			√	
Dağdeviren (2008)		√			√		√	
Önüt *et al.* (2008)		√		√				√
Durán and Aguilo (2008)		√		√				√
Yurdakul and Ic (2009)		√		√				√
Rao and Parnichkun (2009)	√				√		√	
Athawale and Chakraborty (2010)		√			√		√	√
Qi (2010)		√		√				√
Özgen *et al.* (2011)		√			√		√	√
Paramasivam *et al.* (2011)		√			√		√	
Ayağ and Özdemir (2011)		√		√				√
İç *et al.* (2012)	√			√			√	
Ayağ and Özdemir (2012)		√			√		√	√
Taha and Rostam (2012)		√			√		√	
İç (2012)			√		√		√	
Samvedi *et al.* (2012)		√			√			√
Ilangkumaran *et al.* (2012)		√			√			√
Aghdaie *et al.* (2013)		√			√		√	
Perçin and Min (2013)		√			√			√
Tho *et al.* (2013)		√			√		√	√
Sahu *et al.* (2014)		√			√		√	√
Vatansever and Kazancoglu (2014)	√				√		√	√
Prasad and Chakraborty (2015)	√					√	√	
Izadikhah (2015)		√		√				√
Nguyen *et al.* (2015)		√			√		√	√
Sahu *et al.* (2015a)		√		√				√
Sahu *et al.* (2015b)		√		√				√
Sarkar *et al.* (2015)		√				√	√	
Jing *et al.* (2015)		√		√			√	
Kumar *et al.* (2015)		√		√			√	
Kumru and Kumru (2015)	√			√				√
Samanlioglu and Ayağ (2016)		√			√			√
Özceylan *et al.* (2016)		√			√		√	√
Wu *et al.* (2016)		√		√				√
Karim and Karmaker (2016)		√			√		√	√
Chakraborty and Boral (2017)		√				√	√	
Özdağoğlu *et al.* (2017)	√				√		√	
Cakir (2018)	√			√				√
Liu *et al.* (2018)		√			√	√	√	
Zaied *et al.* (2019)	√			√				√
Li *et al.* (2020)		√		√	√			√
Chen *et al.* (2021)			√	√	√		√	√
Villa Silva *et al.* (2021)		√		√	√			√

put forward. The methods used are powerful methods that have not been used before in the machine tool selection problem and their effectiveness has been shown in previous studies in the literature and this study.

3. Material and Methods

3.1. *Problem Definition (CNC Machine Selection Process)*

In the machine tool market, there are hundreds of CNC machine alternatives. In the first step, machine tool alternatives that can satisfy the company's needs should be identified. In the second stage, the defined alternatives are evaluated using any decision model. When comparing various machine tools, decision-makers use a set of criteria. These criteria are generally related to the technological features of the machine, but they also include criteria such as productivity, flexibility, cost, maintenance, and service. Ayağ and Özdemir (2006), as well as Ayağ (2007), defined 8 key criteria and 19 sub-criteria for machine tool selection. Productivity, flexibility, space adaptability, precision, reliability, safety and environment, and maintenance and service are the main criteria used in these studies. Taha and Rostam (2012) used literature information and expert opinion to develop 5 key and 27 sub-criteria that represent the technological characteristics of a machine tool. In their fuzzy-based decision-support system, Özceylan *et al.* (2016) used "*cost*", "*quality*", "*flexibility*", and "*performance*" as the main criteria. These four criteria are subdivided into 15 sub-criteria. Due to differences in manufacturing facilities and decision makers' viewpoints, different criteria have been used in machine tool selection in previous research. As shown by the examples in this section, technological features and cost elements are commonly used in machine selection.

3.2. *Methods*

In this paper, the Best-Worst method is applied for determining the criteria weights using the mean of the expert opinions via taking advantage of pairwise comparison from best to worst. This method has been preferred for reasons such as making less and more consistent comparisons, being able to be used with other methods to be used for sorting, and not having to deal with fractional numbers. On the other hand, the choice of CNC machine tool is one of the decision problems that require a very high investment. For this reason, alternatives and decisions can be compared by using more than one method rather than a single method for ranking the alternatives. As for the choice of alternatives, GRA is selected with reference series, COPRAS is also selected to evaluate the performance of each alternative, taking into account the contradictory situations, and MULTIMOORA is preferred to apply dominance solution in terms of the subordinate ranking methods for this study. These alternative selection methods are used with the determined criteria weights from the Best-Worst method. Consequently, the whole solution procedure is designed for the proper decision-making process on the CNC selection research problem.

3.2.1. *Best-Worst Method*

The method proposed by Rezaei (2015) is a multi-criteria decision-making method based on pairwise comparison. In areas such as supplier selection (Rezaei *et al.*, 2016), assessment of the social sustainability of supply chains (Ahmadi *et al.*, 2017), evaluation of service quality in the aviation industry (Gupta, 2018), and evaluation of companies' RandD performance (Salimi and Rezaei, 2018) applications have been made. The steps of the method are presented below (Kheybari *et al.*, 2019).

Step 1: Evaluation criteria $[c_1, c_2, \dots, c_n]$ are determined.

Step 2: The best (most important) and the worst (least important) criteria are determined.

Step 3: A pairwise comparison is made between the best criterion and other criteria using a scale of 1-9 and the BO vector $A_B = (a_{B1}, a_{B2}, \dots, a_{Bj}, \dots, a_{Bn})$ is obtained. (Here 1 means equally important, 9 means much more important.)

Step 4: A binary comparison is made between the other criteria and the worst criterion, again using the scale 1–9, and the OW vector $(A_w = (a_{1w}, a_{2w}, \dots, a_{jw}, \dots, a_{nw}))$ is obtained.

Step 5: Optimal weights $(w_1^*, w_2^*, \dots, w_n^*)$ are calculated for each criterion.

Here, the status $\frac{w_B}{w_j} = a_{Bj}$ and $\frac{w_j}{w_w} = a_{jw}$ must be provided for each pair of w_B/w_j and w_j/w_{jw}. The following mathematical model has been created to minimize the maximum differences $(|\frac{w_B}{w_j} - a_{Bj}|$ and $|\frac{w_j}{w_w} - a_{jw}|)$ for all j's.

$$\min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_w} - a_{jw} \right| \right\} \tag{1}$$

st:

$$\sum_{j=1}^{n} w_j = 1, \tag{2}$$

$$w_j \geqslant 0, \quad \text{for all } j.$$

Then the expressions here are converted into the mathematical model shown below:

$$\min \xi \tag{3}$$

s.t.:

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \leqslant \xi, \quad \text{for all } j, \tag{4}$$

$$\left| \frac{w_j}{w_w} - a_{jw} \right| \leqslant \xi, \quad \text{for all } j, \tag{5}$$

$$\sum_{j=1}^{n} w_j = 1, \tag{6}$$

$$w_j \geqslant 0, \quad \text{for all } j.$$

With the solving of the model, the value of the optimal weights is obtained that is the criterion that shows how consistent the evaluations are. If this value is close to zero, it means that a consistent evaluation has been made.

3.2.2. *Grey Relational Analysis (GRA)*

An essential approach of the grey system theory (GST) used in the decision-making process and measuring the changes of similarities and differences between its factors over time is called Grey Relational Analysis (GRA) (Feng and Wang, 2000; Aydemir *et al.*, 2013). This method is used in the elimination and analysis of ambiguous relationships between criteria and options, examination of integrated circuit marking process (Jiang *et al.*, 2002), restoration planning of power distribution systems (Chen *et al.*, 2005), recruitment decisions (Olson and Wu, 2006), damage assessment (He and Hwang, 2007), a causal decision-making model (Tseng, 2009), determination of critical path through a network (Zhongmin and Xizu, 2009), supplier selection (Yang and Chen, 2006; Özdemir and Deste, 2009; Zavadskas *et al.*, 2010; Hashemi *et al.*, 2015; Cakir and Akel, 2017), stock market forecasts and portfolio selection (Huang and Jane, 2009), optimization of turning parameters (Yilmaz and Gungor, 2010; Ramesh *et al.*, 2016; Prakash *et al.*, 2020; Lakshmanan *et al.*, 2021), evaluation of e-commerce system security (Liu, 2011), ergonomics (Akay, 2011), evaluation of the performance of enterprises (Tayyar *et al.*, 2014; Aydemir and Sahin, 2019), risk and quality analysis (Baynal *et al.*, 2018; Yazdani *et al.*, 2019), product analysis (Chan and Tong, 2007; Sahin and Aydemir, 2019), and social networks (Weng *et al.*, 2021).

In the method, when the decision-maker has no information, that is, when the information is black, the greyness of a process is done. In most decision problems with insufficient and/or incomplete information, the GRA method is used to select, rank, and evaluate (Chan and Tong, 2007; Yildirim, 2014; Aydemir, 2020). In the solution process, logical and numerical measurements between two decision series are called grey relational degrees, and values are assigned between 0–1. The method consists of three steps: normalization, grey relational coefficient calculation, and grey relational degree calculation. In the first step, the data of the alternatives are transformed into comparison sequences by the normalization process. In the GRA method, the normalization process is performed using Eqs. (7)–(9), respectively, according to benefit, cost, and optimality (Feng and Wang, 2000; Yildirim, 2014; Sahin and Aydemir, 2019):

$$x_i^* = \frac{x_i(j) - \min_j x_i(j)}{\max_j x_i(j) - \min_j x_i(j)}, \tag{7}$$

$$x_i^* = \frac{\max_j x_i(j) - x_i(j)}{\max_i x_i(j) - \min_i x_i(j)}, \tag{8}$$

$$x_i^* = \frac{x_i(j) - x_{ob}(j)}{\min_i x_i(j) - x_{ob}(j)}, \tag{9}$$

here:

$x_i(j)$: The value of criteria j for alternative i;

$\min_j x_i(j)$: the smallest value for criteria j;

$\max_j x_i(j)$: the greatest value for criteria j;

$x_{ob}(j)$: the reference series (ideal sequence) value for criteria j.

After the normalization process, all values take values between 0–1. A decision alternative (i) getting a value close to 1, and 1 for a criterion (j) means that the alternative is one of the best alternatives for that criteria. It is uncommon in practice that any decision alternative provides the best value for all criteria. Therefore, the closest alternative to a reference series should be determined (Kuo *et al.*, 2008). For this process, the absolute differences between the reference series values and the normalized benchmark value are calculated using Eq. (10) and thus the absolute difference matrix is created (Yildirim, 2014).

$$\Delta_{0i}(j) = \left|x_o^*(j) - x_i^*(j)\right|, \tag{10}$$

here:

$x_o^*(j)$: the normalized value of reference value for criteria j;

$x_i^*(j)$: the normalized value alternative i for criteria j.

In the following step, the relationship between the desired and actual experimental data is determined by calculating the grey relational coefficient from the absolute difference matrix. Grey coefficients ($\gamma_{01}(j)$) are calculated with the help of Eq. (11). $\Delta_{\min}$ and $\Delta_{\max}$ in the equation are the smallest and largest values in the absolute difference matrix, Δ_{0i} is the reference series value and expresses the absolute difference between the value of the alternative j. The discriminant coefficient (ζ) is the discriminant coefficient that can take values between 0 and 1 and generally takes 0.5 (Ho and Lin, 2003).

$$\gamma_{0i}(j) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(j) + \zeta\Delta_{\max}}. \tag{11}$$

In the last step, the grey relational degree is calculated by taking the average of the grey relational coefficients and the ranking is performed according to this value. Grey relational degrees (γ_i) are determined by Eq. (12) by dividing the sum of the grey relational coefficients calculated by Eq. (11) by the number of criteria (n), that is, for the case where the criteria are equally weighted (Lin *et al.*, 2002). Also, if the criteria have weights in terms of the decision-maker (w_j), grey relational degrees (γ_i) are determined by Eq. (13). The order of suitability and/or preference of the alternatives is obtained with the order of the calculated grey relational degrees in descending order.

$$\gamma_i = \frac{1}{n}\sum_{j=1}^{n}\gamma_{0i}(j), \tag{12}$$

$$\gamma_i = \sum_{j=1}^{n}\left[w_j * \gamma_{0i}(j)\right]. \tag{13}$$

3.2.3. *COPRAS Method*

The COPRAS method developed by Zavadskas *et al.* (1994) applies a stepwise ranking procedure to evaluate the performance of each alternative, taking into account the contradictory situations. It is a frequently preferred method especially for ranking processes in subjects such as evaluation of road design solutions (Zavadskas *et al.*, 2007), supplier selection (Keshavarz Ghorabaee *et al.*, 2014; Yildirim and Timor, 2019), investment project selection (Popović *et al.*, 2012), and analysis of the basic factors of sustainable architecture (Amoozad Mahdiraji *et al.*, 2018).

The COPRAS method assumes a direct and proportional dependence of the degree of importance and utility of decision options on a system of criteria that adequately defines the alternatives and the values and weights of the criteria. Determining the importance, priority order, and degree of use of alternatives is carried out in five stages (Kaklauskas *et al.*, 2005, 2006):

Step 1: The weighted normalized decision matrix (D) is created. The aim is to take non-dimensional weighted values from comparative indices. For this, the following equation is used:

$$d_{ij} = \frac{x_{ij} q_i}{\sum_{j=1}^{n} x_{ij}}, \quad i = \overline{1, m}; \; j = \overline{1, n}. \tag{14}$$

The sum of the dimensionless weighted index values is equal to "q_{ij}", which is the weight value of each criteria

$$q_i = \sum_{j=1}^{n} d_{ij}, \quad i = \overline{1, m}; \; j = \overline{1, n}. \tag{15}$$

Step 2: The sum of the weighted normalized indices defining the alternative j is calculated. The index of the criteria trying to be minimized is shown as "S_{-j}" and the index of the criteria trying to be maximized is shown as "S_{+j}". The lower the value of indices such as total cost and implementation time (S_{-j}) is, the larger the value of indices calculated for criteria such as utility and strategy fit (S_{+j}), the better the goals are achieved. Based on this, the total value of the indices is calculated with the following equation:

$$\begin{aligned} S_{+} &= \sum_{j=1}^{n} S_{+j} = \sum_{i=1}^{m} \sum_{j=1}^{n} d_{+ij}, \\ S_{-} &= \sum_{j=1}^{n} S_{-j} = \sum_{i=1}^{m} \sum_{j=1}^{n} d_{-ij}. \end{aligned} \tag{16}$$

Step 3: The degree of importance of comparative alternatives (Q_j) is determined by the following equation:

$$Q_j = S_{+j} + \frac{S_{-\min} \sum_{j=1}^{n} S_{-j}}{S_{-j} \sum_{j=1}^{n} (S_{-\min}/S_{-j})}, \quad j = \overline{1, n}. \tag{17}$$

The larger the value of Q_j, the higher the priority of the alternative. The alternative with the highest Q_j value will be the one that meets the demands and targets the most.

Step 4: The utility degree of the alternative j (N_j) is calculated using equation (18):

$$N_j = \left(\frac{Q_j}{Q_{\max}} \right) * 100(\%). \tag{18}$$

Step 5: The order of the alternatives is determined according to the degree of use (N_j). The alternative with this value of 100 is the best.

3.2.4. *MULTIMOORA Method*

The Multi-Objective Optimization Based on Ratio Analysis (MOORA) method proposed by Brauers and Zavadskas (2006) was later developed as MULTIMOORA by Brauers and Zavadskas (2010) with the addition of the "Full Multiplicative Form of Multiple Objectives" method. MOORA plus the full Multiplicative form, which consists of three subordinate methods: full multiplicative, reference point, and full multiplicative.

MULTIMOORA is mostly used as a multi-criteria decision-making technique in fields such as industry, economy, environment, health services, and information technologies as practical applications. In this section, we first explain the MULTIMOORA method in terms of the subordinate ranking methods. The first step also involves generating a decision matrix and weight vector, as seen below, with x_{ij} ratings for m alternatives and n criteria.

$$\mathbf{X} = \begin{array}{c} \begin{array}{ccccc} c_1 & \cdots & c_j & \cdots & c_n \end{array} \\ \left[\begin{array}{ccccc} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & & \vdots & & \vdots \\ x_{i1} & \cdots & x_{ij} & \cdots & x_{in} \\ \vdots & & \vdots & & \vdots \\ x_{m1} & \cdots & x_{mj} & \cdots & x_{mn} \end{array}\right] \end{array} \begin{array}{c} \\ A_1 \\ \vdots \\ A_i \\ \vdots \\ A_m \end{array}, \tag{19}$$

$$\mathbf{W} = \begin{bmatrix} w_1 & \cdots & w_j & \cdots & w_n \end{bmatrix}.$$

Also, on the MCDM problems, the ratings of alternatives may have different dimensions generally, so, the normalized ratings should be required and for this, Van Delft and Nijkamp normalization approach is used in MULTIMOORA application considering the most robust choice and proving by Brauers *et al.* (2008) for the denominator in the ratio system:

$$x_{ij}^* = x_{ij} \Big/ \sqrt{\sum_{i=1}^{m} (x_{ij})^2}. \tag{20}$$

In certain cases, the triple subordinate methods are also known as the ratio, complete multiplicative, and reference point forms, and they are used to solve the exits problem. The ratio method should be used as a completely compensatory model if the problem has any independent criteria. The ratio system is computed by Eq. (21), where g is the number of useful criteria and y_i is the utility value. The best alternative solution by using the ratio system is applied to select the maximum utility y_i in descending order with Eq. (22)

(Hafezalkotob *et al.*, 2019):

$$y_i = \sum_{j=1}^{g} w_j x_{ij}^* - \sum_{j=g+1}^{n} w_j x_{ij}^*, \tag{21}$$

$$R_{RS} = \left\{A_{i|\max_i y_i} \succ \cdots \succ A_{i|\min_i y_i}\right\}. \tag{22}$$

The reference point approach, on the other hand, is a conservative method for measuring and comparing the ratio system and complete multiplicative form with Eqs. (23)–(25). Initially, the maximal objective reference point (MORP) vector is defined as Eq. (23), where r_j represents the utility value (Hafezalkotob *et al.*, 2019):

$$r_j = \left\{\max_i x_{ij}^*,\ j \leqslant g,\ \min_i x_{ij}^*,\ j > g\right\}. \tag{23}$$

Eq. (24) defines the distance between the weighted value of the vector members and the weighted alternative rating, and the efficiency of the Reference Point Approach is obtained by maximizing the distance introduced in Eq. (25):

$$d_{ij} = \left|w_j r_j - w_j x_{ij}^*\right|, \tag{24}$$

$$z_i = \max_J d_{ij}. \tag{25}$$

The best alternative found by the Reference Point Approach has the least benefit (z_i), and the approach's order is provided by Eq. (26):

$$R_{RPA} = \{A_{i|\min_i z_i} \succ \cdots \succ A_{i|\max_i z_i}\}. \tag{26}$$

Although Brauers and Zavadskas (2012) demonstrated that using weights as multipliers in the full multiplicative form is meaningless, it is mentioned that the weights determined in the developed MULTIMOORA method proposed by Hafezalkotob and Hafezalkotob (2016) can be calculated as shown in Eq. (27):

$$u_i = \prod_{j=1}^{g} \left(x_{ij}^*\right)^{w_j} \Big/ \prod_{j=g+1}^{n} \left(x_{ij}^*\right)^{w_j}. \tag{27}$$

The maximum utility alternative is the best alternative based on the Full Multiplicative Form, and the sequence of this technique is obtained by equation (28) in descending order:

$$R_{FMF} = \{A_{i|\max_i u_i} \succ \cdots \succ A_{i|\min_i u_i}\}. \tag{28}$$

Using these subordinate ranks, we also should decide the final ranking of the alternatives in the final phase. The aggregating multiple subordinate rankings are presented by Brauers and Zavadskas (2012) to obtain a final ranking list that is more robust than each ranking list of the subordinate methods. Dominance-based principles, mathematical operators, MCDM methods, and programming approaches are examples of these approaches. Using the principle of dominance, the original MULTIMOORA incorporates MOORA with the exact multiplicative form. At this point, it is obvious that Dominance Theory (Brauers and Zavadskas, 2011) is the most widely applied method; but, in recent years, other tools with potential success have been used instead of this theory (Brauers and Zavadskas, 2006; Hafezalkotob *et al.*, 2019). As a result, the dominance theory is used in this analysis to produce a unified final ranking list.

4. Results

One of the most important decisions in the design and construction of a competitive manufacturing environment is the selection of the appropriate machine tools. This chapter contains the application of the proposed method to solve the machine tool selection problem. The basic framework of the methods proposed within the scope of the study and detailed in Section 3.2 is shown in Fig. 1. The method starts with determining the criteria to be used. After the literature review and the determination of the criteria by taking the expert opinion, the criteria weights were determined with the BWM, details of which are specified in Section 3.2.1. The determined weighted criteria are used as inputs to the GRA, COPRAS, and MULTIMOORA methods used in the ranking of machine alternatives. Final rankings were obtained as a result of the calculations made separately with these methods.

4.1. *Determination of Criteria and Weighting*

According to the consumer specifications, the appropriate machine should be selected from the existing database. At the beginning of the research, 4 main and 13 sub-criteria were determined to be used in the solution of the problem, taking into account the literature research and expert opinions. Dimensions (C_1), Flexibility (C_2), Productivity (C_3), and Cost (C_4) criteria, whose sub-criteria are shown in Table 2, were determined as the main criteria.

The determined weights can be used with equal weight or they can be weighted differently according to the needs of the company. The importance of the criteria was determined by using the Best-Worst method, details of which are given in Section 3.2.1, as a result of the interviews with six experts. BWM is a method based on testing the importance level of criteria. Also, BWM emerges as a method that is being used frequently in scientific and industrial situations. The criterion weights determined as a result of the calculations made with the BO and OW vectors created as a result of expert opinions are shown in Tables 3, 4 and 5, respectively.

The weights of all the main and sub-criteria are shown in Table 6, and the values taken by the alternatives for these criteria (decision matrix) are shown in Table 7. The weight calculations of the sub-criteria are presented in Appendix A.

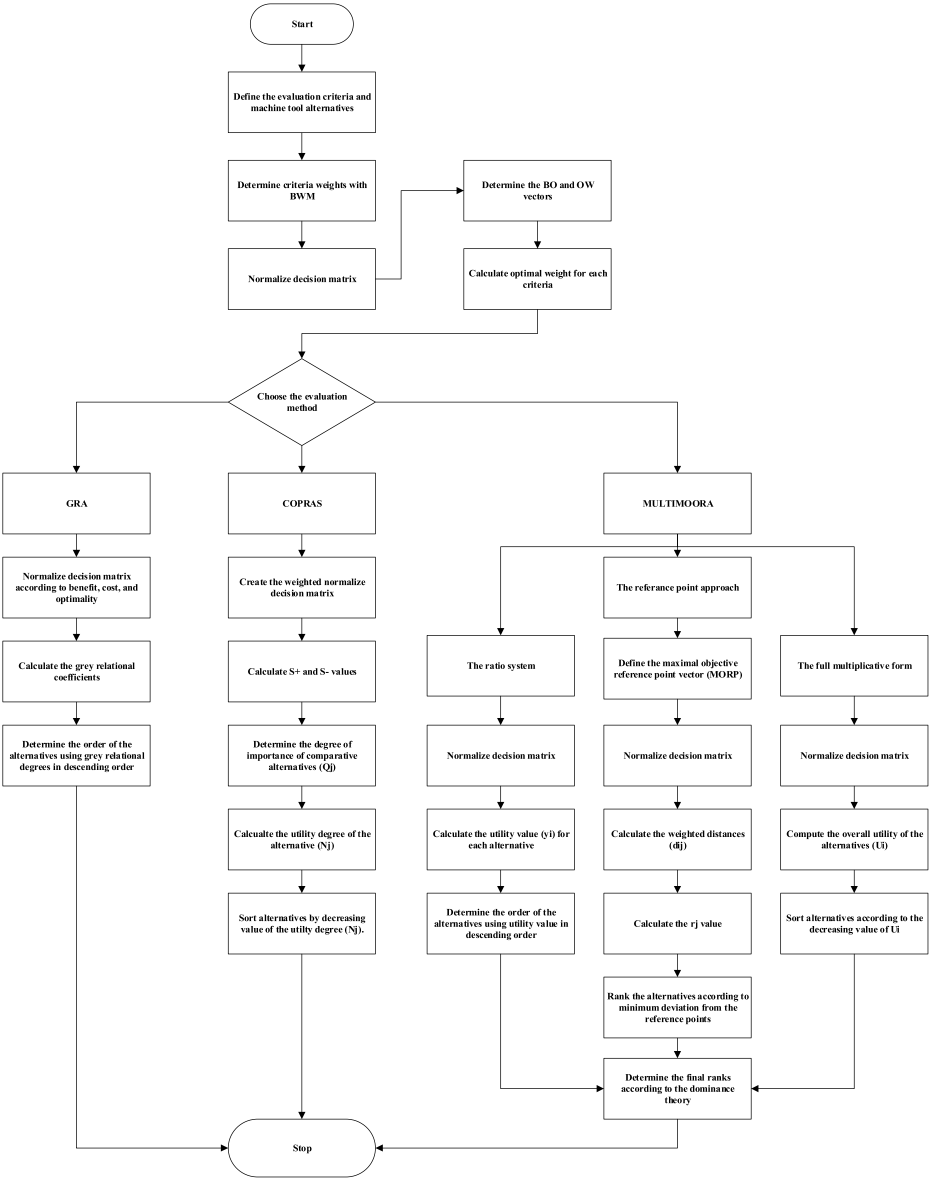

Fig. 1. The basic framework of the proposed method.

After determining the decision alternatives and criteria weights, the ranking process was started with the GRA, COPRAS, and MULTIMOORA methods. The following section explains the details of the sorting process with the aforementioned methods.

Table 2
The main and sub-criteria.

Main criteria	Sub-criteria	Objective	Unit
Dimensions (C_1)	Table load (C_{11})	Max	kg s
	Main travel (C_{12})	Max	mm
	Table size (C_{13})	Max	m^2
	Machine weight (C_{14})	Min	kg s
Flexibility (C_2)	Spindle rate (C_{21})	Max	rpm
	Spindle power (C_{22})	Max	kw
	Max. tool weight (C_{23})	Max	kg s
Productivity (C_3)	Feed rate (axis x, y and z) (C_{31})	Max	mm/min s
	Tool magazine capacity (C_{32})	Max	set
	Cutting feed rate (C_{33})	Max	mm/min s
Cost (C_4)	Procurement price (C_{41})	Min	$
	Operation cost (C_{42})	Min	$
	Maintenance cost (C_{43})	Min	$

Table 3
BO vectors for main criteria.

Experts no.	Best	Dimensions (C_1)	Flexibility (C_2)	Productivity (C_3)	Cost (C_4)
Experts 1	Cost (C_4)	6	4	2	1
Experts 2	Cost (C_4)	5	3	2	1
Experts 3	Cost (C_4)	7	4	2	1
Experts 4	Cost (C_4)	6	5	3	1
Experts 5	Cost (C_4)	6	2	4	1
Experts 6	Cost (C_4)	6	2	4	1

Table 4
OW vectors for main criteria.

Experts No.	Worst	Dimensions (C_1)	Flexibility (C_2)	Productivity (C_3)	Cost (C_4)
Experts 1	Dimensions (C_1)	1	2	4	6
Experts 2	Dimensions (C_1)	1	2	3	5
Experts 3	Dimensions (C_1)	1	2	3	7
Experts 4	Dimensions (C_1)	1	2	2	6
Experts 5	Dimensions (C_1)	1	3	2	6
Experts 6	Dimensions (C_1)	1	4	2	6

Table 5
The weights of the main criteria.

Criteria	Weights of criteria						Mean
	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	
Dimensions (C_1)	0.0784	0.0923	0.0784	0.0879	0.0811	0.0709	0.0815
Flexibility (C_2)	0.1373	0.1692	0.1373	0.1255	0.2703	0.2196	0.1765
Productivity (C_3)	0.2745	0.2538	0.2549	0.2092	0.1351	0.1318	0.2099
Cost (C_4)	0.5098	0.4846	0.5294	0.5774	0.5135	0.5777	0.5321
Ksi	0.0392	0.0231	0.0196	0.0502	0.0270	0.0811	0.0400

Table 6
The final weights of criteria.

Main criteria	The weight of main criteria	Sub-criteria	The weight of sub-criteria	Final weights
Dimensions (C_1)	0.0815	Table load (C_{11})	0.197	0.016
		Main travel (C_{12})	0.558	0.046
		Table size (C_{13})	0.153	0.012
		Machine weight (C_{14})	0.092	0.007
Flexibility (C_2)	0.1765	Spindle rate (C_{21})	0.222	0.039
		Spindle power (C_{22})	0.591	0.104
		Max. tool weight (C_{23})	0.187	0.033
Productivity (C_3)	0.2099	Feed rate (C_{31})	0.159	0.033
		Tool magazine capacity (C_{32})	0.581	0.122
		Cutting feed rate (C_{33})	0.261	0.055
Cost (C_4)	0.5321	Procurement price (C_{41})	0.719	0.382
		Operation cost (C_{42})	0.169	0.090
		Maintanance cost (C_{43})	0.113	0.060

Table 7
The data of the alternatives (decision matrix).

	C_1				C_2			C_3			C_4		
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
Units	kg s	mm	m^2	kg s	rpm	kw	kg s	mm/min s	set	mm/min s	$	$	$
Goal	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Min	Min	Min
Weights / Alt.	0.016	0.046	0.012	0.007	0.039	0.104	0.033	0.033	0.122	0.055	0.382	0.090	0.060
A_1	400	687	0.465	5800	8000	7.5	7	28.0	24	10.0	206250	25800	5150
A_2	400	720	0.500	6000	8000	5.5	6	26.7	24	12.0	262500	32000	5800
A_3	800	710	0.720	8000	15000	7.5	10	27.9	32	1.2	318750	39800	7000
A_4	300	600	0.550	3300	10000	10.1	3	52.0	21	30.0	335750	41000	8000
A_5	1600	953	0.975	11000	8000	11	6	18.3	24	5.0	412500	51500	10300
A_6	250	567	0.336	3800	12000	5.5	6	48.0	25	15.0	262500	31250	5470
A_7	3000	980	1.000	12500	8000	11	15	19.3	20	10.0	487500	58000	11000
Min	250	566.67	0.336	3300	8000	5.5	3	18.333	20	1.2	206250	25800	5150
Max	3000	980	1.000	12500	15000	11	15	52	32	30	487500	58000	11000

4.2. *Sorting the Alternatives Using GRA*

The method consists of three basic steps: normalization, grey relational coefficient calculation, and grey relational degree calculation. In the first step, the data of the alternatives are transformed into comparison sequences by normalizing the criteria according to the benefits, cost, and optimality of the criteria. Normalized versions of the data presented in Table 7 are shown in Table 8.

After the normalization process, the absolute value table is created by using the equation shown in equation (10). The values in the absolute value table correspond to the absolute value of the difference between the reference series and the criteria value. The absolute values calculated are shown in Table 9.

Table 8
The normalized decision matrix.

Alt. \ Ref. serie	C_1				C_2			C_3			C_4		
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
Ref. serie	1.000	1.000	1.000	0.000	1.000	1.000	1.000	1.000	1.000	1.000	0.000	0.000	0.000
A_1	0.055	0.290	0.194	0.728	0.000	0.364	0.333	0.287	0.333	0.306	1.000	1.000	1.000
A_2	0.055	0.371	0.247	0.707	0.000	0.000	0.250	0.248	0.333	0.375	0.800	0.807	0.889
A_3	0.200	0.347	0.578	0.489	1.000	0.364	0.583	0.284	1.000	0.000	0.600	0.565	0.684
A_4	0.018	0.081	0.322	1.000	0.286	0.836	0.000	1.000	0.083	1.000	0.540	0.528	0.513
A_5	0.491	0.935	0.962	0.163	0.000	1.000	0.250	0.000	0.333	0.132	0.267	0.202	0.120
A_6	0.000	0.000	0.000	0.946	0.571	0.000	0.250	0.881	0.417	0.479	0.800	0.831	0.945
A_7	1.000	1.000	1.000	0.000	0.000	1.000	1.000	0.030	0.000	0.306	0.000	0.000	0.000

Table 9
The absolute value table.

Alt. \ Goal	C_1				C_2			C_3			C_4		
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
Goal	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Min	Min	Min
A_1	0.945	0.710	0.806	0.728	1.000	0.636	0.667	0.713	0.667	0.694	1.000	1.000	1.000
A_2	0.945	0.629	0.753	0.707	1.000	1.000	0.750	0.752	0.667	0.625	0.800	0.807	0.889
A_3	0.800	0.653	0.422	0.489	0.000	0.636	0.417	0.716	0.000	1.000	0.600	0.565	0.684
A_4	0.982	0.919	0.678	1.000	0.714	0.164	1.000	0.000	0.917	0.000	0.540	0.528	0.513
A_5	0.509	0.065	0.038	0.163	1.000	0.000	0.750	1.000	0.667	0.868	0.267	0.202	0.120
A_6	1.000	1.000	1.000	0.946	0.429	1.000	0.750	0.119	0.583	0.521	0.800	0.831	0.945
A_7	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.970	1.000	0.694	0.000	0.000	0.000

$\Delta_{min} = 0$ / $\Delta_{max} = 1$ / The discriminant coefficient $(\zeta) = 0.500$.

Grey coefficients ($\gamma_{01}(j)$) are calculated with the help of equation (11). Then, the grey relational degrees (γ_i) to be used in the ranking are determined by dividing the total weighted grey coefficients value by the number of criteria as shown in Table 10. As a result of the sorting made with the grey relational analysis method, the order of preference of the alternatives was determined as $A_7 \succ A_5 \succ A_3 \succ A_4 \succ A_6 \succ A_2 \succ A_1$.

4.3. *Sorting the Alternatives Using COPRAS*

The second method used to sort the alternatives is the COPRAS method. This method starts with the formation of the weighted decision matrix with the help of Eq. (14). The matrix obtained with this equation is shown in Table 11.

After calculating the normalized decision matrix, the sum of the criteria values to be minimized for each alternative (S_{-j}) and the sum of the criteria values to be maximized (S_{+j}) is calculated. Depending on the S_{-j} and S_{+j}values, the importance degrees of the alternatives (Q_j) are calculated using Eq. (17). Then, the utility degree of the alternatives (N_j) are calculated by writing the obtained "Q_j" values into Eq. (18). In the last step, the order of alternatives is obtained in descending order of the utility degree of

Table 10
The absolute value table.

	C_1				C_2			C_3			C_4			γ_i	Weighted rank
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}		
Goal	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Min	Min	Min		
Weights	0.016	0.046	0.012	0.007	0.039	0.104	0.033	0.033	0.122	0.055	0.382	0.090	0.060		
A_1	0.346	0.413	0.383	0.407	0.333	0.440	0.429	0.412	0.429	0.419	0.333	0.333	0.333	0.0286	7
A_2	0.346	0.443	0.399	0.414	0.333	0.333	0.400	0.399	0.429	0.444	0.385	0.382	0.360	0.0298	6
A_3	0.385	0.434	0.542	0.505	1.000	0.440	0.545	0.411	1.000	0.333	0.455	0.469	0.422	0.0411	3
A_4	0.337	0.352	0.425	0.333	0.412	0.753	0.333	1.000	0.353	1.000	0.481	0.486	0.494	0.0402	4
A_5	0.495	0.886	0.930	0.754	0.333	1.000	0.400	0.333	0.429	0.365	0.652	0.712	0.807	0.0493	2
A_6	0.333	0.333	0.333	0.346	0.538	0.333	0.400	0.808	0.462	0.490	0.385	0.376	0.346	0.0314	5
A_7	1.000	1.000	1.000	1.000	0.333	1.000	1.000	0.340	0.333	0.419	1.000	1.000	1.000	0.0645	1

Table 11
The weighted normalized decision matrix for the COPRAS method.

	C_1				C_2			C_3			C_4		
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
Goal / Alt.	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Min	Min	Min
A_1	0.0010	0.0060	0.0013	0.0009	0.0046	0.0135	0.0044	0.0042	0.0172	0.0066	0.0345	0.0083	0.0059
A_2	0.0010	0.0063	0.0014	0.0009	0.0046	0.0099	0.0037	0.0040	0.0172	0.0079	0.0439	0.0103	0.0066
A_3	0.0019	0.0062	0.0020	0.0012	0.0085	0.0135	0.0062	0.0042	0.0229	0.0008	0.0533	0.0128	0.0080
A_4	0.0007	0.0052	0.0015	0.0005	0.0057	0.0181	0.0019	0.0079	0.0151	0.0197	0.0562	0.0132	0.0091
A_5	0.0038	0.0083	0.0027	0.0016	0.0046	0.0197	0.0037	0.0028	0.0172	0.0033	0.0690	0.0165	0.0117
A_6	0.0006	0.0049	0.0009	0.0006	0.0068	0.0099	0.0037	0.0073	0.0179	0.0099	0.0439	0.0100	0.0062
A_7	0.0071	0.0086	0.0027	0.0019	0.0046	0.0197	0.0094	0.0029	0.0143	0.0066	0.0816	0.0186	0.0125

Table 12
Calculations of the COPRAS method.

Alternatives	S_{+j}	S_{-j}	$S_{\min}$	$\sum_{j=1}^{n} S_{-j}$	$S_{-\min}/S_{-j}$	$\sum S_{-\min}/S_{-j}$	Q_j	N_j	Order of alternatives
A_1	1.059	0.395	0.395	4.000	1.000	5.258	1.8195	86	4
A_2	1.038	0.458			0.862		1.6936	80	7
A_3	1.278	0.573			0.689		1.8020	85	5
A_4	1.376	0.511			0.774		1.9647	93	2
A_5	1.337	0.778			0.508		1.7236	82	6
A_6	1.147	0.406			0.974		1.8877	90	3
A_7	1.766	0.878			0.451		2.1089	100	1

the alternatives (N_j). The alternative with a N_j value of 100 is the best alternative. The S_{-j}, S_{+j}, "Q_j" and N_j values calculated for the alternatives and the priority order of the alternatives are shown in Table 12. The order obtained with the COPRAS method is $A_7 \succ A_4 \succ A_6 \succ A_1 \succ A_3 \succ A_5 \succ A_2$.

Table 13
Normalized decision matrix.

Alternatives	C_1				C_2			C_3			C_4		
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
Goal	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Min	Min	Min
Weights	0.0160	0.0455	0.0125	0.0075	0.0393	0.1042	0.0330	0.0333	0.1219	0.0547	0.3825	0.0897	0.0599
A_1	0.1120	0.3410	0.2540	0.2780	0.2970	0.3300	0.3160	0.3130	0.3700	0.2590	0.2300	0.2360	0.2480
A_2	0.1120	0.3580	0.2730	0.2870	0.2970	0.2420	0.2710	0.2980	0.3700	0.3100	0.2930	0.2930	0.2800
A_3	0.2250	0.3530	0.3930	0.3830	0.5570	0.3300	0.4510	0.3120	0.4930	0.0310	0.3560	0.3640	0.3380
A_4	0.0840	0.2980	0.3000	0.1580	0.3710	0.4440	0.1350	0.5820	0.3230	0.7760	0.3750	0.3750	0.3860
A_5	0.4490	0.4740	0.5330	0.5270	0.2970	0.4840	0.2710	0.2050	0.3700	0.1290	0.4600	0.4710	0.4970
A_6	0.0700	0.2820	0.1840	0.1820	0.4460	0.2420	0.2710	0.5370	0.3850	0.3880	0.2930	0.2860	0.2640
A_7	0.8430	0.4870	0.5460	0.5980	0.2970	0.4840	0.6770	0.2160	0.3080	0.2590	0.5440	0.5310	0.5300

Table 14
Calculations of the ratio system.

	C_1				C_2			C_3			C_4			y_i	Order
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}		
Alt. \ Goal	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Min	Min	Min		
A_1	0.002	0.016	0.003	0.002	0.012	0.034	0.010	0.010	0.045	0.014	0.088	0.021	0.015	0.020	1
A_2	0.002	0.016	0.003	0.002	0.012	0.025	0.009	0.010	0.045	0.017	0.112	0.026	0.017	−0.018	4
A_3	0.004	0.016	0.005	0.003	0.022	0.034	0.015	0.010	0.060	0.002	0.136	0.033	0.020	−0.024	5
A_4	0.001	0.014	0.004	0.001	0.015	0.046	0.004	0.019	0.039	0.042	0.143	0.034	0.023	−0.016	3
A_5	0.007	0.022	0.007	0.004	0.012	0.050	0.009	0.007	0.045	0.007	0.176	0.042	0.030	−0.087	6
A_6	0.001	0.013	0.002	0.001	0.017	0.025	0.009	0.018	0.047	0.021	0.112	0.026	0.016	−0.001	
A_7	0.014	0.022	0.007	0.004	0.012	0.050	0.022	0.007	0.038	0.014	0.208	0.048	0.032	−0.106	

4.4. *Sorting the Alternatives Using MULTIMOORA*

The first step of the MULTIMOORA method also includes creating a decision matrix and weight vector with x_{ij}ratings for m alternatives and n criteria, as seen below. As in the other methods, in the first step of this method, the normalization process is carried out by using Eq. (20). The normalized decision matrix obtained by Eq. (20) is shown in Table 13.

After the normalized decision matrix is created, the alternative ranking is determined according to the decreasing order of the calculated y_i value. Alternative ranking obtained with the Ratio System (RS) is "$A_1 \succ A_6 \succ A_4 \succ A_2 \succ A_3 \succ A_5 \succ A_7$" as shown in Table 14.

In the Reference Point Approach (RPA), which is a conservative method, first of all, the absolute difference (distance) between the r_j values obtained by Eq. (23) and the normalized value (x_{ij}^*) is determined. The decreasing order of "z" values obtained using Eq. (25) determines the order of the alternatives. The calculations of the Reference Point Approach are shown in Table 15 and alternative ranking obtained with the Reference Point Approach is "$A_7 \succ A_5 \succ A_4 \succ A_3 \succ A_2 = A_6 \succ A_1$".

Table 15
Calculations of the reference point approach.

	C_1				C_2			C_3			C_4				
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}	z_i	Order
Alt. \ Goal	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Min	Min	Min		
A_1	0.012	0.007	0.004	0.002	0.010	0.016	0.012	0.009	0.015	0.028	0.120	0.026	0.017	0.1201	7
A_2	0.012	0.006	0.003	0.002	0.010	0.025	0.013	0.009	0.015	0.025	0.096	0.021	0.015	0.0961	5-6
A_3	0.010	0.006	0.002	0.002	0.000	0.016	0.007	0.009	0.000	0.041	0.072	0.015	0.012	0.0720	4
A_4	0.012	0.009	0.003	0.003	0.007	0.004	0.018	0.000	0.021	0.000	0.065	0.014	0.009	0.0648	3
A_5	0.006	0.001	0.000	0.001	0.010	0.000	0.013	0.013	0.015	0.035	0.032	0.005	0.002	0.0353	2
A_6	0.012	0.009	0.005	0.003	0.004	0.025	0.013	0.001	0.013	0.021	0.096	0.022	0.016	0.0961	5-6
A_7	0.000	0.000	0.000	0.000	0.010	0.000	0.000	0.012	0.023	0.028	0.000	0.000	0.000	0.0283	1
r_j	0.014	0.022	0.007	0.004	0.022	0.050	0.022	0.019	0.060	0.042	0.208	0.048	0.032		

Table 16
Calculations of the full multiplicative form.

	C_1				C_2			C_3			C_4				
	C_{11}	C_{12}	C_{13}	C_{14}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}	u_i	Order
Alt. \ Goal	Max	Max	Max	Min	Max	Max	Max	Max	Max	Max	Min	Min	Min		
A_1	0.966	0.952	0.983	0.990	0.953	0.891	0.963	0.962	0.886	0.929	0.570	0.879	0.920	1.28132	1
A_2	0.966	0.954	0.984	0.991	0.953	0.862	0.958	0.961	0.886	0.938	0.625	0.896	0.927	1.10843	3
A_3	0.976	0.954	0.988	0.993	0.977	0.891	0.974	0.962	0.917	0.827	0.674	0.913	0.937	0.99529	5
A_4	0.961	0.946	0.985	0.986	0.962	0.919	0.936	0.982	0.871	0.986	0.687	0.916	0.945	1.06753	4
A_5	0.987	0.967	0.992	0.995	0.953	0.927	0.958	0.949	0.886	0.894	0.743	0.935	0.959	0.90819	6
A_6	0.958	0.944	0.979	0.987	0.969	0.862	0.958	0.979	0.890	0.950	0.625	0.894	0.923	1.15174	2
A_7	0.997	0.968	0.992	0.996	0.953	0.927	0.987	0.950	0.866	0.929	0.792	0.945	0.963	0.89015	7

In the Full Multiplicative Form (FMF), the multiplication values of the criteria in the normalized decision matrix, which are in the direction of maximization, are divided by the multiplication value of the criteria to be minimized, and "u_i" values for each alternative are calculated. The order made according to the decreasing value of the "u_i" values of the alternatives will give the final ranking. The calculations of the FMF Approach are shown in Table 16. The order obtained with the full multiplicative form is "$A_1 \succ A_6 \succ A_2 \succ A_4 \succ A_3 \succ A_5 \succ A_7$".

At the last stage, the rankings found as a result of the calculations above have been converted into a single line with the theory of dominance. The final ranks were determined by taking the average of the rankings. The final rankings determined by applying the theory of dominance in the MULTIMOORA method are given in Table 17. The order obtained in the last step is "$A_1 \succ A_6 \succ A_4 \succ A_2 \succ A_3 \succ A_5 \succ A_7$".

As a result, the different sequences shown in Table 18 and Fig. 2 were determined. The sequences obtained with the COPRAS and MULTIMOORA methods are similar. The rankings obtained by grey relational analysis differ from the other two methods. Due to the dominant ranking, decision-makers may consider Alternative 1 as the best option.

Table 17
Calculations of the full multiplicative form.

Alternatives	RS	RPA	FMF	Mean	Final order
A_1	1	7	1	3.00	1
A_2	4	6	3	4.33	4
A_3	5	4	5	4.67	5
A_4	3	3	4	3.33	3
A_5	6	2	6	4.67	6
A_6	2	5	2	3.00	2
A_7	7	1	7	5.00	7

Table 18
Rankings obtained by different methods.

Alternatives	GRA	COPRAS	MULTIMOORA
A_1	7	1	1
A_2	6	4	4
A_3	3	5	5
A_4	4	3	3
A_5	2	7	6
A_6	5	2	2
A_7	1	6	7

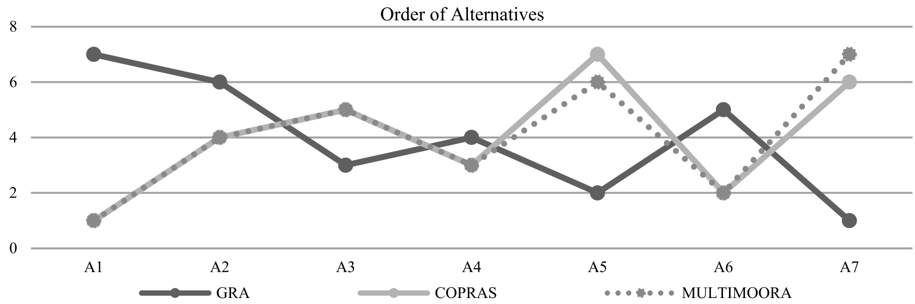

Fig. 2. The final rankings obtained by different methods.

5. Discussion and Conclusions

The abundance of machine alternatives, the difficulty in accessing reliable information, and the lack of experts in evaluating machine features make machine tool selection a difficult and important problem. In addition, it is known that an unsuitable machine selection adversely affects the efficiency, sensitivity, and flexibility of the entire production system. When all these situations are taken into consideration, it is seen that the right information should be made by the right people and using the appropriate methods for the selection of a proper machine tool. When the studies in the literature are examined, many different methods provide different solutions. In this context, many studies have been conducted in which the uncertainty situation, as well as deterministic methods, are taken into account.

The important thing here is to make the right decision by evaluating the opinions of more than one expert working in the production environment with different methods, rather than a single method and a single expert's opinion.

In this paper, a new framework is proposed to examine the performance of different methods using the same criteria weights for a suitable machine tool (CNC machine) selection problem. Weights of the criteria determined by BWM were used for weighting decision matrices for the sorting methods in this new framework. Using seven alternatives, four main, and thirteen sub-criteria in the problem, machine alternatives were evaluated with GRA, COPRAS, and MULTIMOORA methods. To create a reliable final ranking in the MULTIMOORA method, the theory of dominance was used and the final rankings were determined by averaging the different rank values. As a result, it is aimed to increase the reliability of the final solution with this new approach including BWM as the criteria weighting method. In the evaluations made for the main criteria, it has been seen that the cost of the machine tool is the most important criterion, as in the studies of similar criteria in the literature (Arslan *et al.*, 2004; Önüt *et al.*, 2008), followed by the productivity, flexibility and dimensions criteria, respectively. In the ranking made using the criterion weights obtained, it is seen that COPRAS and MULTIMOORA methods give similar rankings, but the gray relational analysis method offers a different ranking.

The proposed solution procedure is well-designed for the research problem. The CNC machine selection problem is also studied in many pieces of research. In this way, the selected seven alternatives, four main, and thirteen sub-criteria can also be accepted as the main research limitation. On the other hand, the obtained results are shown effective and robust decisions for the problem using comprehensive methods as the main advantage. In future studies, it may be considered that fuzzy logic-based methods can be used for the solution in cases where decision-makers express the importance levels of the criteria with linguistic variables. The evaluation of the expert opinions can be considered by intuitionistic approaches on MCDM methodologies.

A. Appendix. The Weights of Sub-Criteria

The weight calculation of sub-criteria of dimensions (C_1) main criteria.

	Experts No.	Best	Table load (C_{11})	Main travel (C_{12})	Table size (C_{13})	Machine weight (C_{14})
BO vectors for sub-criteria	Experts 1	Main travel (C_{12})	4	1	2	6
	Experts 2	Main travel (C_{12})	3	1	4	7
	Experts 3	Main travel (C_{12})	4	1	5	8
	Experts 4	Main travel (C_{12})	3	1	5	7
	Experts 5	Main travel (C_{12})	2	1	6	4
	Experts 6	Main travel (C_{12})	3	1	5	8

	Experts No.	Worst	Table load (C_{11})	Main travel (C_{12})	Table size (C_{13})	Machine weight (C_{14})
OW vectors for sub-criteria	Experts 1	Machine weight (C_{14})	2	6	3	1
	Experts 2	Machine weight (C_{14})	2	3	2	1
	Experts 3	Machine weight (C_{14})	2	8	2	1
	Experts 4	Machine weight (C_{14})	3	1	5	7
	Experts 5	Table size (C_{13})	2	6	1	2
	Experts 6	Machine weight (C_{14})	3	8	2	1

	Sub-criteria	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Mean
The weights of sub-criteria	Table load (C_{11})	0.135	0.231	0.163	0.208	0.238	0.206	0.197
	Main travel (C_{12})	0.514	0.496	0.630	0.589	0.524	0.598	0.558
	Table size (C_{13})	0.270	0.174	0.130	0.125	0.095	0.124	0.153
	Machine weight (C_{14})	0.081	0.099	0.076	0.079	0.143	0.072	0.092
	Ksi	0.027	0.198	0.022	0.034	0.048	0.021	0.058

The weight calculation of sub-criteria of flexibility (C_2) main criteria.

	Experts No.	Best	Spindle rate (C_{21})	Spindle power (C_{22})	Max. tool weight (C_{23})
BO vectors for sub-criteria	Experts 1	Spindle power (C_{22})	2	1	4
	Experts 2	Spindle power (C_{22})	3	1	5
	Experts 3	Spindle power (C_{22})	3	1	2
	Experts 4	Spindle power (C_{22})	4	1	2
	Experts 5	Spindle power (C_{22})	3	1	2
	Experts 6	Spindle power (C_{22})	3	1	6

	Experts No.	Worst	Spindle rate (C_{21})	Spindle power (C_{22})	Max. Tool Weight (C_{23})
OW vectors for sub-criteria	Experts 1	Max. tool weight (C_{23})	2	4	1
	Experts 2	Max. tool weight (C_{23})	2	5	1
	Experts 3	Spindle rate (C_{21})	1	3	2
	Experts 4	Spindle rate (C_{21})	1	4	2
	Experts 5	Spindle rate (C_{21})	1	3	2
	Experts 6	Max. tool weight (C_{23})	2	6	1

	Sub-criteria	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Mean
The weights of sub-criteria	Spindle rate (C_{21})	0.286	0.225	0.167	0.143	0.292	0.222	0.222
	Spindle power (C_{22})	0.571	0.650	0.542	0.571	0.542	0.667	0.591
	Max. tool weight (C_{23})	0.143	0.125	0.292	0.286	0.167	0.111	0.187
	Ksi	0.000	0.025	0.042	0.000	0.042	0.000	0.0181

The weight calculation of sub-criteria of productivity ($\mathbf{C_3}$) main criteria.

BO vectors for sub-criteria

Experts No.	Best	Feed rate (C_{31})	Tool magazine capacity (C_{23})	Cutting feed rate (C_{33})
Experts 1	Tool magazine capacity (C_{23})	5	1	3
Experts 2	Tool magazine capacity (C_{23})	4	1	2
Experts 3	Tool magazine capacity (C_{23})	2	1	3
Experts 4	Tool magazine capacity (C_{23})	2	1	2
Experts 5	Tool magazine capacity (C_{23})	5	1	3
Experts 6	Tool magazine capacity (C_{23})	4	1	2

OW vectors for sub-criteria

Experts No.	Worst	Feed rate (C_{31})	Tool magazine capacity (C_{23})	Cutting feed rate (C_{33})
Experts 1	Feed rate (C_{31})	1	5	2
Experts 2	Feed rate (C_{31})	1	4	2
Experts 3	Cutting feed rate (C_{33})	2	3	1
Experts 4	Feed (C_{31})	1	2	1
Experts 5	Feed rate (C_{31})	1	5	2
Experts 6	Feed rate (C_{31})	1	4	2

The weights of sub-criteria

Sub-criteria	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Mean
Feed rate (C_{31})	0.125	0.143	0.167	0.250	0.125	0.143	0.159
Tool magazine capacity (C_{32})	0.650	0.571	0.542	0.500	0.650	0.571	0.581
Cutting feed rate (C_{33})	0.225	0.286	0.292	0.250	0.225	0.286	0.261
Ksi	0.025	0.000	0.042	0.000	0.025	0.000	0.015

The weight calculation of sub-criteria of cost ($\mathbf{C_4}$) main criteria.

BO vectors for sub-criteria

Experts No.	Best	Procurement price (C_{41})	Operation cost (C_{42})	Maintenance cost (C_{43})
Experts 1	Procurement price (C_{41})	1	5	8
Experts 2	Procurement price (C_{41})	1	4	7
Experts 3	Procurement price (C_{41})	1	6	4
Experts 4	Procurement price (C_{41})	1	3	5
Experts 5	Procurement price (C_{41})	1	4	9
Experts 6	Procurement price (C_{41})	1	5	8

OW vectors for sub-criteria

Experts No.	Worst	Procurement price (C_{41})	Operation cost (C_{42})	Maintenance cost (C_{43})
Experts 1	Maintenance cost (C_{43})	8	2	1
Experts 2	Maintenance cost (C_{43})	7	2	1
Experts 3	Operation cost (C_{42})	6	1	2
Experts 4	Maintenance cost (C_{43})	5	2	1
Experts 5	Maintenance cost (C_{43})	9	2	1
Experts 6	Maintenance cost (C_{43})	8	2	1

The weights of sub-criteria

Sub-criteria	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Mean
Procurement price (C_{41})	0.753	0.717	0.704	0.650	0.736	0.753	0.719
Operation cost (C_{42})	0.156	0.183	0.111	0.225	0.181	0.156	0.169
Maintanance cost (C_{43})	0.091	0.100	0.185	0.125	0.083	0.091	0.113
Ksi	0.026	0.017	0.037	0.025	0.014	0.026	0.024

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Y. Şahin received BSc and MSc degrees in industrial engineering from Yıldız Technical University and Pamukkale University, in 2005 and 2009, respectively. He received PhD degree in business administration from Suleyman Demirel University, in 2014. He has been an associate professor of business administration at Burdur Mehmet Akif Ersoy University since 2020. His field of study includes operation research, logistics, warehouse management, vehicle routing, meta-heuristics, multicriteria decision making, and quantitative models.

E. Aydemir received BSc and MSc degrees in industrial engineering from Selcuk University and Suleyman Demirel University, in 2005 and 2009, respectively. He received PhD degree in mechanical engineering from Suleyman Demirel University, in 2013. He has been an associate professor of Department of Industrial Engineering at Suleyman Demirel University since 2020. His field of study includes meta-heuristics optimization on industrial problems, operation research, logistics, vehicle/inventory routing, grey system theory, and decision models.