A Hybrid Method based on BWM and TOPSIS-LP Model to Assess Computer Numerical Control Machines

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Abstract. *The escalating global competitiveness within the industrial sector has necessitated a critical requirement to enhance facilities to meet market demands. In this context, the selection of computer numerical control (CNC) machines plays a vital role in enhancing productivity and manufacturing flexibility. This study presents a hybrid method combining the Best-Worst Method (BWM) with a novel TOPSIS linear programming (TOPSIS-LP) model for CNC machine selection. The BWM is employed to address information challenges and simplify data collection by assigning weights to specified criteria. These weights are then utilized in the TOPSIS-LP model to rank alternatives based on their closeness coefficients. A numerical illustration is conducted to validate the proposed model, with outcomes compared to established Multi-Attribute Decision-Making (MADM) methodologies. The Spearman correlation matrix reveals strong correlations between the proposed method and existing methods, such as MOORA (0.96) and WASPAS (0.88), highlighting the hybrid approach's reliability. This method provides a straightforward and reliable tool for organizations to make informed CNC machine selections, ultimately improving their productivity and manufacturing capabilities.*

Keywords:

Best-worst method, multi-attribute decision-making, TOPSIS, TOPSIS linear programming model, computer numerical control

1. Introduction

The introduction of Computer Numerical Control (CNC) equipment has profoundly impacted the manufacturing industry. These sophisticated machines have enhanced production processes by increasing precision, efficiency, and flexibility. Consequently, CNC machines have become indispensable across various sectors such as automotive, aerospace, electronics, and healthcare, particularly as the demand for high-quality and complex components grows. Evaluating CNC machines is critical to maximize their performance and productivity, involving the assessment of criteria like accuracy, speed, reliability, durability, and cost-effectiveness. Historically, decision-makers have relied on subjective judgments or single-criterion evaluations, which could lead to biased or suboptimal decisions. To address these challenges, the use of Multi-Attribute Decision Making (MADM) techniques has become increasingly common in the evaluation of machine tools.

Recent scholarly focus has been on applying MADM methodologies to the CNC machine tool selection problem, recognizing the complexity of this decision-making process and the need for systematic and unbiased methods to aid decision-makers. Key methodologies such as the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are prominent in this field. Bologa et al. [2] utilized AHP to assess the decision-making process for adopting continuous 5-axis CNC machine tools, analyzing both technical and economic aspects.

Recent academic research has increasingly concentrated on employing MADM methodologies for selecting CNC machine tools. This focus underscores the complexity of these decisions and highlights the necessity for systematic and impartial methods to support decision-makers. Prominent methodologies in this domain include the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). For instance, Bologa et al. [2] applied AHP to evaluate the decision-making process involved in adopting continuous 5-axis CNC machine tools, taking into account both technical and economic factors. Azizi [3] advocated for the use of AHP to improve equipment selection in the secondary wood industries, providing a systematic framework that considers performance, cost, and maintenance. Camci et al. [4] used AHP integrated with hesitant fuzzy sets to select CNC routers for SMEs in the woodworking sector, tailoring the approach to their specific needs and constraints. Çimren et al. [5] employed AHP to provide decision-makers with a comprehensive framework for evaluating and ranking machine tool alternatives, thus enhancing decision accuracy and operational efficiency across industries. Cioca et al. [6] introduced a hybrid AHP-TOPSIS method to select the safest CNC machining workshops, integrating diverse safety criteria. Similarly, Dawal et al. [7] developed a hybrid fuzzy AHP-TOPSIS methodology for CNC machine tool selection in Flexible Manufacturing Cells (FMC), addressing both subjective and objective factors and managing uncertainties. İç [8] implemented an experimental design using the TOPSIS method to select computer-integrated manufacturing (CIM) technologies, aiming to systematize the decision-making process. Tho et al. [9] introduced an intuitionistic fuzzy TOPSIS method for selecting CNC machines in flexible manufacturing systems, effectively managing uncertainty with this approach.

In MADM problems, assigning weights to criteria is a critical step, utilizing a variety of methodologies that fall into two categories: subjective and objective weighting methods. Subjective weighting techniques, such as SMART, AHP, and the Best-Worst Method (BWM), rely on the decision-makers' preferences to determine criteria weights. However, as the number of criteria increases, the precision of these preferences may decrease. In contrast, objective weighting methods like the Entropy method, Standard Deviation method, CRITIC, Data Envelopment Analysis (DEA), and Simultaneous Evaluation of Criteria and Alternatives (SECA) use data-driven approaches, bypassing direct consideration of decision-makers' preferences [10-19]. Each method has its own strengths and weaknesses, with the choice influenced by factors such as the number of criteria, data availability, and the preferred level of subjectivity. The hybrid approach that integrates the BWM and TOPSIS-LP model provides a balanced evaluation by incorporating both subjective preferences and objective data, thereby improving decision quality and minimizing biases.

Determining criteria weight coefficients is a fundamental step in MADM, involving various methods categorized into objective, subjective, and hybrid approaches. The objective method calculates weights based on criteria values, exemplified by the entropy method [20], the CRITIC method [21], and standard deviation [22]. The subjective approach involves decision-makers' preferences and is represented by methods such as the AHP [23], the BWM [24], and SMART [25]. The BWM, highlighted by Rezaei [26], reduces the number of necessary pairwise comparisons, enhancing reliability and consistency. Unlike the AHP, the BWM uses reference comparisons to determine the superiority of the best criterion relative to all others, simplifying and refining the decision-making process. This method has been applied across various fields, demonstrating its versatility and effectiveness in decision-making scenarios [27-32].

TOPSIS is a highly effective decision-making methodology that measures the closeness of alternatives to both ideal and anti-ideal solutions, thereby promoting objective decision-making. First introduced by Hwang and Yoon in 1981 [33], the TOPSIS method has gained considerable popularity and has been applied in numerous fields [34-38]. In the field of engineering, noteworthy applications of TOPSIS and BWM include: Oke et al. [39], who conducted a multicriteria analysis of the electrohydraulic forming process for automotive panel production using 1100 aluminum alloy sheets, employing five multicriteria methods to determine optimal parameters and finding that both subjective and objective methods were effective in evaluating process parameters; Ighravwe and Oke [40], who developed a framework using fuzzy axiomatic design (FAD) principles and Fuzzy-TOPSIS to rank maintenance strategies for sustainable maintenance planning in manufacturing systems, demonstrating its effectiveness in promoting eco-friendly practices and providing a robust tool for aligning decisions with sustainability goals; Ighravwe and Oke [41], who presented a grey-TOPSIS and fuzzy-logic framework for determining the competitive advantages of products in the manufacturing sector, effectively prioritizing measures and resources to enhance competitive advantage; and Sawyerr et al. [42], who introduced a fuzzy TOPSIS method for selecting parameters in the wire electrical discharge machining (WEDM) process for Nitinol-60, demonstrating its ability to optimize outputs and assist process engineers in optimizing parametric resource allocations. These studies illustrate the versatility and effectiveness of TOPSIS and related methods in addressing complex decision-making scenarios within the engineering domain, showcasing their potential to improve process optimization, sustainability, and competitive advantage in various industrial applications.

In a recent investigation, To-on et al. [43] first offered a unique optimization approach for determining the optimal parameters of lightweight concrete blocks. The motivation for using the TOPSIS-LP model lies in its ability to provide a streamlined and accessible method for multi-criteria decision-making. The authors developed this model based on the Response Surface Methodology (RSM) as an alternative method for optimizing these parameters. The TOPSIS-LP model builds upon the Relative Closeness Coefficient model introduced by Wichapa et al. [44], retaining the core principles of the original TOPSIS approach but distinguished by its simplicity and user-friendliness. This model offers a more efficient and accessible alternative to the complex computational procedures typically associated with the original TOPSIS method. In order to address Multi Response Optimization, Sriburum et al. [45] proposed a variant of the TOPSIS-LP model that is combined with the Taguchi method. This was demonstrated through a case study of a Fish Scale Scraping Machine. Using the McKinsey 7s Framework in organizational management, Lawong et al. [46] introduced a TOPSIS-LP and BWM approach for assessing the performance of Health-Promoting Hospitals. Pawaree et al. [47] introduced a method for optimizing the production process of charcoal briquettes using a combination of TOPSIS-LP and genetic algorithms based on response surface methodology. This approach aimed to determine the optimal mixture ratio of materials such as coconut shell, bagasse ash, and corncob, resulting in improved heating value and burning time while reducing moisture content. The advantages of this method include enhanced product quality, cost-efficiency, and alignment with green economy principles. Additionally, Phuangpornpitak et al. [48] introduced a new routing model integrated with the TOPSIS-LP approach to optimize tourist routes in Nong Khai, Thailand. This method considers multiple criteria in the decision-making process to enhance tourist satisfaction and operational efficiency. The TOPSIS-LP approach consistently ranks optimal routes across various MADM methods, ensuring robust and efficient route optimization, supporting environmental conservation, and promoting local economic growth.

Based on the literature review, hybrid methodologies have been devised to tackle the complexity of MADM problems by incorporating various strategies. An effective hybrid approach merges the Best-Worst Method (BWM) with the TOPSIS-LP method. The TOPSIS-LP method is a user-friendly yet powerful tool for handling large datasets, as it helps minimize computational errors due to its fewer steps compared to the original TOPSIS. This integration allows for a more efficient and accurate decision-making process, enabling analysts to manage complex decision-making scenarios effectively. By integrating TOPSIS-LP and BWM, their respective strengths are leveraged while their individual limitations are mitigated, thus enhancing the efficacy of the decision-making process. This hybrid methodology allows decision-makers to incorporate the significance of criteria when evaluating options, considering their proximity to both ideal and negative ideal solutions, and providing a comprehensive solution for MADM challenges. The primary aim of this study is to present a comprehensive framework for evaluating CNC machines through the utilization of a hybrid approach that combines the BWM and TOPSIS-LP model, which is an analogous variant of TOPSIS. The objective of this study is to provide decision-makers with a reliable and unbiased approach for assessing the performance of CNC machines in a multi-criterion setting by incorporating two efficient MADM approaches. The primary purpose of this paper is to investigate the following fundamental questions:

1. How can the BWM be employed to evaluate the significance of criteria within the context of CNC machine assessment?

2. How can the TOPSIS-LP model be utilized to rank CNC machines based on their performance across multiple criteria?

3.The model introduced in this study offers a more robust and precise framework for MADM. It includes detailed Lingo code to demonstrate its practical application and effectiveness in solving MADM problems. Additionally, the model is designed with flexibility in mind, allowing it to be used with a variety of optimization solvers. The TOPSIS-LP method is a user-friendly yet powerful tool for handling large datasets, as it helps minimize computational errors due to its fewer steps compared to the original TOPSIS.

The paper is structured in the following manner. Section 2 of this paper introduces the proposed methodology, which integrates the BWM and the TOPSIS-LP model. Section 3 of the study centers on the assessment of the operational effectiveness of CNC devices. Finally, Section 4functions as the conclusion section of the study.

2. Method

This study presents two techniques for the purpose of ranking a CNC machine selection dilemma. First and foremost, the BWM is employed for the purpose of ascertaining the relative weights of various criteria. Subsequently, a comprehensive methodology that combines the BWM and TOPSIS is proposed as a versatile and practical hybrid technique for the purpose of evaluating and ranking alternative options. Fig. 1 illustrates the conceptual framework.

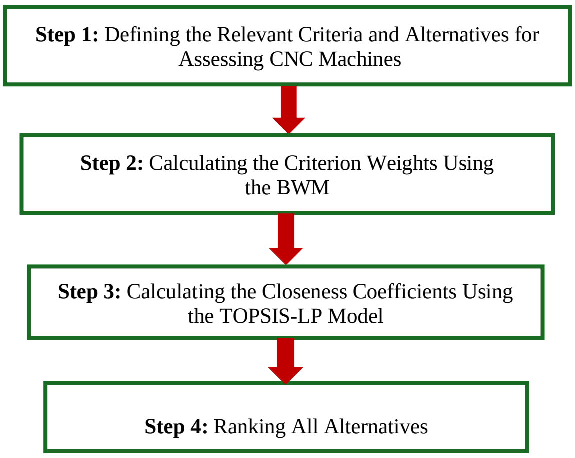


Fig. 1 The framework of this research

2.1 Defining the Relevant Criteria and Alternatives for Assessing CNC Machines

2.1.1 Identifying the criteria that are essential for evaluating CNC machines. This might include factors such as precision, speed, cost, reliability, and other pertinent parameters.

2.1.2 Compiling a comprehensive list of all available CNC machine alternatives that will be assessed.

2.2 Calculate the Criterion Weights Using the Best-Worst Method (BWM)

2.2.1 Establishing a comparison matrix

This paper provides a definition of criteria, denoted as C_1, C_2, ... ,C_n. Comparisons between CNC machine alternatives will be recorded within the matrix's cells.

2.2.2 Defining the best and worst criteria

For each criterion, it is necessary to select the option that exhibits the most favorable performance and the alternative that exhibits the least favorable performance.

2.2.3 Assessing and assigning scores to the best criterion

Experts assess and assign scores to the best criterion or each individual criterion, utilizing a Likert scale with a range of 1 to 9, representing the relative importance of the criteria.

$$a_{Bj} = \{a_{B1}, a_{B2}, ..., a_{Bj}\}$$

The comparison scores between the best criteria a_{Bj} and each *j-th* criterion are being examined.

2.2.4 Evaluating and assigning scores to the worst criterion

Evaluating and assigning scores to the worst criterion for each individual criterion, employing a Likert scale with a rating range of 1 to 9, indicating the relative importance of the criteria. $a_{jW} = \{a_{1W}, a_{2W}, ..., a_{jW}\}^T$. The objective is to compare the scores of the worst criterion, denoted as W, with each criterion indexed as a_{jW}.

2.2.5 Calculating the optimal weights

The optimal weights assigned to criteria are denoted as $w_j^*(j = 1, 2, 3, ..., n)$, whereas the index used to measure the consistency ratio is represented as ε^{L*}. The model that has been constructed is outlined as follows.

Objective function: $Min\, Z = \varepsilon^L$ (1)

Constraints:

$$\left| w_B - a_{Bj} w_j \right| \leq \varepsilon^L, \ \forall j \tag{2}$$

$$\left| w_j - a_{jW} w_W \right| \leq \varepsilon^L, \ \forall j \tag{3}$$

$$\sum_{j=1}^{n} w_j = 1 \tag{4}$$

$$w_j \geq 0, \ \forall j \tag{5}$$

In the mathematical framework of the BWM, the objective function is designed to minimize inconsistency in comparisons. Equation (2) ensures that the absolute difference between the weight of the best criterion and any given criterion *j* does not exceed a predefined consistency index. Similarly, Equation (3) maintains that the absolute difference between the weight of the worst criterion and each criterion *j* remains within this consistency index. Furthermore, Equation (4) stipulates that the total sum of the weights for all criteria must equal one, while Equation (5) dictates that the weight assigned to each criterion must be non-negative.

Solving Equations (1) through (5) allows for the determination of optimal criterion weights and the consistency ratio using Lingo software.The ξ^{L*} shows to what extent the results are reliable, the closer the ε^{L*} to zero better. In addition, the optimal criterion weights will then be incorporated into the TOPSIS -LP model.

2.3 Calculating the closeness coefficients using TOPSIS-LP method

The first step of the TOPSIS-LP model, as initially proposed by To-on et al. [43], is to establish the decision matrix that will be used in the decision-making process. This involves creating a decision matrix that includes the different alternatives to be evaluated, along with their respective performances on each of the specified criteria. The decision matrix (X) is represented by Equation (6).

$$X = \begin{array}{cc} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{6}$$

In the given framework, A_i (where i=1,2,…,m) denotes the various alternatives being considered. Similarly, C_j (where j=1,2,…,n) represents the criteria used to evaluate the performance of these alternatives. The notation x_{ij} is used to indicate the inputs or outputs of alternative *i* concerning criterion *j*. Subsequently, the decision matrix is normalized to ensure that each criterion contributes equally to the decision-making process. The normalized decision matrix, represented as *Y*, is mathematically defined by Equation (7).

$$X = \begin{array}{cc} & \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \end{array} \tag{7}$$

In this context, y_{ij} denotes the normalized performance of alternative iii with respect to criterion *j*. Equations (8) and (9) are utilized to calculate the normalized performance of alternative *i* for beneficial criterion *j* and cost criterion *j*, respectively.

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij}^2}}, \ \text{for beneficial criteria} \tag{8}$$

$$y_{ij} = 1 - \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij}^{2}}}, \text{, for cost criteria} \tag{9}$$

The variables λ_i^{min} and λ_i^{max} are used to denote the optimal weights assigned to the sum of distances from the negative ideal solution to alternative *i* and the sum of distances from the positive ideal solution to alternative *i*, respectively. The negative and positive ideal values of each criterion *j* are denoted as $y_j^{\min}$ and $y_j^{\max}$, respectively. The relative closeness coefficient value (CC_i) based on the TOPSIS-LP model is defined by Equation (10).

Objective Function:

$$\mathrm{CC}_i = \max \lambda_i^{\min}\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_{ij})^2-(y_j^{\min})^2\right)}\right),$$

Subject to:

$$\begin{aligned}
&\lambda_i^{\min}\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_{ij})^2-(y_j^{\min})^2\right)}\right)+\\
&\lambda_i^{\max}\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_j^{\max})^2-(y_{ij})^2\right)}\right)=1,\ i=1,2,\dots,m,\\
&\lambda_i^{\min}\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_{ij})^2-(y_j^{\min})^2\right)}\right)\le\\
&\lambda_i^{\min}\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_{ij})^2-(y_j^{\min})^2\right)}\right)+\\
&\lambda_i^{\max}\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_j^{\max})^2-(y_{ij})^2\right)}\right),\ i=1,2,\dots,m,\\
&\lambda_i^{\min}=\lambda^{\max}_i,\ \lambda_i^{\min},\lambda_i^{\max}\ge 0,\ i=1,2,3,\dots,m,\\
&w_j\ge 0,\ \ j=1,2,\dots,n.
\end{aligned} \tag{10}$$

where $y_j^{\min} = \min\{y_{ij},\ j=1,2,..,n\}$ and $y_j^{\max} = \max\{y_{ij},\ j=1,2,..,n\}$. The primary objective of the suggested model is to optimize the objective function in order to get maximum results; the CC_i, $\lambda_i^{\min}$ and $\lambda_i^{\max}$ can be achieved using model (5). The ranking of the alternative increases proportionally with the CC_i value.

2.4 Ranking All Alternatives

In the final step, all alternatives (CNC machines) are ranked according to their closeness coefficients, which were calculated in the previous step. The alternative with the highest closeness coefficient is deemed the best choice, followed by those with progressively lower coefficients. This ranking aids in identifying the most suitable CNC machine based on the specified criteria and their corresponding weights. This method ensures a structured and objective evaluation of CNC machines, assisting decision-makers in selecting the most appropriate machine for their needs.

3. Result and Discussion

The comparison decision matrix survey is carried out by six experts or six decision-makers, who assess seven attributes extracted from literature and the CNC machines' catalogue. Table 1 presents the decision matrix of CNC machines used in this case study. In addition, Table 2 presents the definition of relevant criteria. The comparison decision matrix survey is carried out by six experts or six decision-makers, who assess seven attributes extracted from literature and the CNC machines' catalogue. Table 1 presents the decision matrix of CNC machines used in this case study. In addition, Table 2 presents the definition of relevant criteria.

Table 1 Decision matrix for CNC machines

Alter-natives	C_1	C_2	C_3	C_4	C_5	C_6	C_7
CNC#1	36,900	3000	16	165	600	750	1860
CNC#2	30,400	4000	12	180	465	266	700
CNC#3	88,900	3500	8	250	760	165	2440
CNC#4	20,000	1600	6	330	1500	300	500
CNC#5	10,000	1600	8	240	1050	400	850
CNC#6	89,200	6000	12	215	605	340	554
CNC#7	120,000	5000	12	215	605	340	535
CNC#8	86,150	4000	12	140	305	250	264
CNC#9	129,200	4000	12	215	1155	340	1055
CNC#10	50,400	2500	4	160	550	145	750
CNC#11	39,800	4000	6	165	600	275	600
CNC#12	50,400	2500	8	250	760	400	900

Table 2 Definition of main criteria

Criteria	Definition	Type
C_1	CC: Capital cost	Cost
C_2	SS: Spindle speed	Beneficial
C_3	TC: Tool capacity	Beneficial
C_4	TX: Traverse rate of the X-axis	Beneficial
C_5	TZ: Traverse rate of the Z-axis	Beneficial
C_6	MD: Maximum turning diameter	Beneficial
C_7	ML: Maximum turning length	Beneficial

3.1 The results of the criterion weights obtained through the BWM

The first phase in the process entails the determination of the weights assigned to the choice criterion. In the present investigation, the assigned weights are as follows: The initial phase of the BWM involves the identification of the most favorable and unfavorable selection criteria. In the context of this particular situation, the criterion of "tool capacity (C_3)" is deemed to be the most favorable, but the criterion of "maximum machine turning length (C_7)" is regarded as the least desirable. During the second stage, the determination of the preferences of the best criterion in comparison to the other criteria is accomplished by computing the average score derived from the input provided by six decision makers, as illustrated in Table 3.

Table 3 The BO vector

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Best criterion: C_3	1.67	1.17	1.00	1.50	1.67	1.17	1.50

In the third step, the preferences of the criteria relative to the least important factor are determined by calculating the average score based on the input of six decision makers, as shown in Table 4.

Table 4 The OW vector

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Worst criterion: C_3	1.00	1.50	1.67	1.00	1.00	1.33	1.17

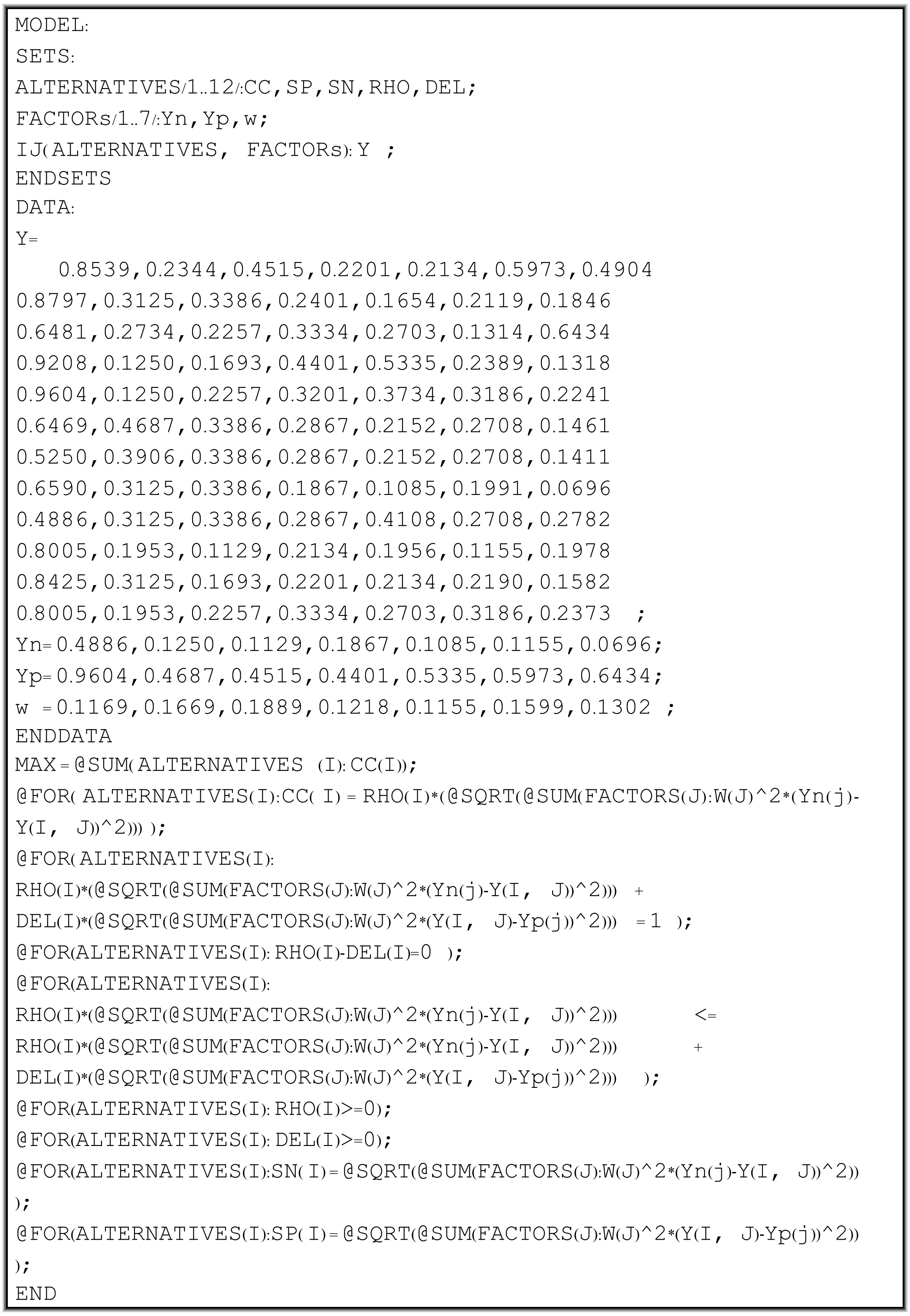
By analyzing the data presented in Table 3 and Table 4 and applying the BWM equations (1) to (5), the corresponding weights are obtained as follows: $w_1^* = 0.1169$, $w_2^* = 0.1669$, $w_3^* = 0.1889$, $w_4^* = 0.1218$, $w_5^* = 0.1155$, $w_6^* = 0.1599$, and $w_7^* = 0.1302$. Furthermore, the consistency ratio (ε^{L^*}) is calculated to be 0.061, indicating a high level of reliability. The results of this numerical case demonstrate the ease and consistency of the BWM method.

4.2 The results of the closeness coefficients obtained through TOPSIS -LP model

In Table 1, criterion C_1 (cost criterion) was normalized using Equation (8), whereas the remaining criteria were normalized using Equation (9). This process resulted in the creation of a normalized decision matrix, referred to as the *Y* matrix. The specific details of the *Y* matrix can be found in Table 5. After obtaining the normalized decision matrix and appropriate weights, they were integrated into the TOPSIS-LP model using model (10). Model (10) was subsequently converted into Lingo code, with the specifics depicted in Fig 2.

Table 5 Normalized decision matrix for the CNC machines

CNCs	C_1	C_2	C_3	C_4	C_5	C_6	C_7	**CC**
1	0.8539	0.2344	0.4515	0.2201	0.2134	0.5973	0.4904	0.6575
2	0.8797	0.3125	0.3386	0.2401	0.1654	0.2119	0.1846	0.4129
3	0.6481	0.2734	0.2257	0.3334	0.2703	0.1314	0.6434	0.4567
4	0.9208	0.1250	0.1693	0.4401	0.5335	0.2389	0.1318	0.4061
5	0.9604	0.1250	0.2257	0.3201	0.3734	0.3186	0.2241	0.4322
6	0.6469	0.4687	0.3386	0.2867	0.2152	0.2708	0.1461	0.4408
7	0.5250	0.3906	0.3386	0.2867	0.2152	0.2708	0.1411	0.3884
8	0.6590	0.3125	0.3386	0.1867	0.1085	0.1991	0.0696	0.3191
9	0.4886	0.3125	0.3386	0.2867	0.4108	0.2708	0.2782	0.4298
10	0.8005	0.1953	0.1129	0.2134	0.1956	0.1155	0.1978	0.2426
11	0.8425	0.3125	0.1693	0.2201	0.2134	0.2190	0.1582	0.3338
12	0.8005	0.1953	0.2257	0.3334	0.2703	0.3186	0.2373	0.3895
y^+	**0.9604**	**0.4687**	**0.4515**	**0.4401**	**0.5335**	**0.5973**	**0.6434**	
y^-	**0.4886**	**0.1250**	**0.1129**	**0.1867**	**0.1085**	**0.1155**	**0.0696**	



```
MODEL:
SETS:
ALTERNATIVES/1..12/:CC,SP,SN,RHO,DEL;
FACTORs/1..7/:Yn,Yp,w;
IJ(ALTERNATIVES, FACTORs):Y ;
ENDSETS
DATA:
Y=
   0.8539,0.2344,0.4515,0.2201,0.2134,0.5973,0.4904
0.8797,0.3125,0.3386,0.2401,0.1654,0.2119,0.1846
0.6481,0.2734,0.2257,0.3334,0.2703,0.1314,0.6434
0.9208,0.1250,0.1693,0.4401,0.5335,0.2389,0.1318
0.9604,0.1250,0.2257,0.3201,0.3734,0.3186,0.2241
0.6469,0.4687,0.3386,0.2867,0.2152,0.2708,0.1461
0.5250,0.3906,0.3386,0.2867,0.2152,0.2708,0.1411
0.6590,0.3125,0.3386,0.1867,0.1085,0.1991,0.0696
0.4886,0.3125,0.3386,0.2867,0.4108,0.2708,0.2782
0.8005,0.1953,0.1129,0.2134,0.1956,0.1155,0.1978
0.8425,0.3125,0.1693,0.2201,0.2134,0.2190,0.1582
0.8005,0.1953,0.2257,0.3334,0.2703,0.3186,0.2373  ;
Yn=0.4886,0.1250,0.1129,0.1867,0.1085,0.1155,0.0696;
Yp=0.9604,0.4687,0.4515,0.4401,0.5335,0.5973,0.6434;
w =0.1169,0.1669,0.1889,0.1218,0.1155,0.1599,0.1302 ;
ENDDATA
MAX=@SUM(ALTERNATIVES (I):CC(I));
@FOR( ALTERNATIVES(I):CC( I) = RHO(I)*(@SQRT(@SUM(FACTORS(J):W(J)^2*(Yn(j)-
Y(I, J))^2))) );
@FOR( ALTERNATIVES(I):
RHO(I)*(@SQRT(@SUM(FACTORS(J):W(J)^2*(Yn(j)-Y(I, J))^2))) +
DEL(I)*(@SQRT(@SUM(FACTORS(J):W(J)^2*(Y(I, J)-Yp(j))^2))) =1 );
@FOR(ALTERNATIVES(I): RHO(I)-DEL(I)=0 );
@FOR(ALTERNATIVES(I):
RHO(I)*(@SQRT(@SUM(FACTORS(J):W(J)^2*(Yn(j)-Y(I, J))^2)))       <=
RHO(I)*(@SQRT(@SUM(FACTORS(J):W(J)^2*(Yn(j)-Y(I, J))^2)))       +
DEL(I)*(@SQRT(@SUM(FACTORS(J):W(J)^2*(Y(I, J)-Yp(j))^2)))  );
@FOR(ALTERNATIVES(I): RHO(I)>=0);
@FOR(ALTERNATIVES(I): DEL(I)>=0);
@FOR(ALTERNATIVES(I):SN( I)=@SQRT(@SUM(FACTORS(J):W(J)^2*(Yn(j)-Y(I, J))^2))
);
@FOR(ALTERNATIVES(I):SP( I)=@SQRT(@SUM(FACTORS(J):W(J)^2*(Y(I, J)-Yp(j))^2))
);
END
```

Fig 2. The Lingo code of TOPSIS-LP model for this case.

As a result, the values of CC were calculated, and the corresponding outcomes are presented in Table 6. Furthermore, we conducted a comparison between the weight determination achieved using the AHP technique by a panel of experts and the weight derived from the evaluation conducted by experts using the BWM. The weights of the criterion were calculated and are displayed in Table 7.

Table 6 Ranking for the CNC machines

Alternatives	Details	CC	Rank
CNC#1	CNC Lathe L 33 Optimum	0.6575	1
CNC#2	CNC Lathe L 28 Optimum	0.4129	6
CNC#3	CNC Lathe L 44 Optimum	0.4567	2
CNC#4	CNC Lathe CK6150 with CE	0.4061	7

Alternatives	Details	CC	Rank
CNC#5	CNC Lathe CK6140	0.4322	4
CNC#6	CNC Lathe 100MSY	0.4408	3
CNC#7	CNC Lathe 200MSY	0.3884	9
CNC#8	CNC Lathe QTP-150 SG	0.3191	11
CNC#9	CNC Lathe QT- 300M	0.4298	5
CNC#10	CNC Lathe CK6132	0.2426	12
CNC#11	CNC Lathe L 770A Optimum	0.3338	10
CNC#12	CNC Lathe L 771 Optimum	0.3895	8

Table 7 The criteria weights obtained from AHP and BWM

	AHP	Rank	BWM	Rank
C_1	0.116	6	0.1169	6
C_2	0.180	2	0.1669	2
C_3	0.201	1	0.1889	1
C_4	0.116	5	0.1218	5
C_5	0.090	7	0.1155	7
C_6	0.153	3	0.1599	3
C_7	0.144	4	0.1302	4

Table 7 displays the weights assigned to the criteria (C1 to C6) obtained using the AHP and the BWM. The rankings of the criteria are identical across both techniques. Although both AHP and BWM produce identical rankings, the BWM approach is characterized by its simplicity, convenience, and efficiency in terms of operational procedures. BWM's efficiency arises from its streamlined procedure, in contrast to AHP, which necessitates pairwise comparisons of numerous parameters, resulting in increased complexity and time consumption. Therefore, although the ranks remain consistent, BWM provides a more efficient method because it has a lower level of complexity when dealing with repeated comparisons.

Using the weights calculated from BWM, Table 8 presents a comprehensive comparison between the proposed method and other MADM methodologies, including WASPAS [49], COPRAS [50], and MOORA [51].

Table 8 The ranking comparison for the CNC machine selection

CNC	WASPAS	Rank	COPRAS	Rank	MOORA	Rank	Proposed	Rank
CNC#1	0.6403	1	1.0000	1	0.3181	1	0.6575	1
CNC#2	0.4709	7	0.7005	7	0.2083	7	0.4129	6
CNC#3	0.4784	5	0.7644	4	0.2237	2	0.4567	2
CNC#4	0.4668	8	0.7555	5	0.2142	6	0.4061	7
CNC#5	0.5340	2	0.9220	2	0.2211	4	0.4322	4
CNC#6	0.5025	4	0.7433	6	0.2230	3	0.4408	3
CNC#7	0.4711	6	0.6978	8	0.1951	9	0.3884	9
CNC#8	0.3665	11	0.5497	11	0.1524	11	0.3191	11
CNC#9	0.5183	3	0.7758	3	0.2182	5	0.4298	5
CNC#10	0.3041	12	0.4596	12	0.1234	12	0.2426	12
CNC#11	0.3984	10	0.5936	10	0.1728	10	0.3338	10
CNC#12	0.4583	9	0.6809	9	0.2056	8	0.3895	8

Table 8 presents a comparison of the rankings of twelve CNC machines using four multi-criteria decision-making methods: WASPAS [], COPRAS [], MOORA [], and a Proposed approach. Every approach assigns a numerical value to the machines, and their positions in the ranking are listed appropriately. CNC#1 consistently achieves the highest rankings across all evaluation methods, obtaining the top position in WASPAS, COPRAS, and the Proposed approach, and the second position in MOORA. CNC#3 and CNC#5 consistently demonstrate strong performance, consistently ranking among the top five across all methods. In contrast, CNC#10 and CNC#11 consistently have lower rankings. The table illustrates a consensus among the methodologies about the performance of the CNC machines, indicating the strength and reliability of these evaluation procedures.

Fig. 3 displays the Spearman correlation matrix for the CNC rankings, revealing strong positive relationships between the ranking methods: WASPAS, COPRAS, MOORA, and the Proposed method, indicating high consistency in their outcomes. Specifically, WASPAS and COPRAS show a very strong agreement with a correlation of 0.872, while WASPAS and MOORA have a strong positive relationship at 0.820. WASPAS and the Proposed method demonstrate a very high level of consistency with a correlation of 0.881. COPRAS and MOORA, although slightly lower at 0.742, still indicate substantial alignment, and COPRAS and the Proposed method have a strong correlation of 0.842. The highest correlation is between MOORA and the Proposed method at 0.961, indicating near-perfect agreement in their ranking results. These correlations underscore the robustness and reliability of the Proposed method, showing its effectiveness alongside other multi-criteria decision-making methods in evaluating and ranking CNC machines.

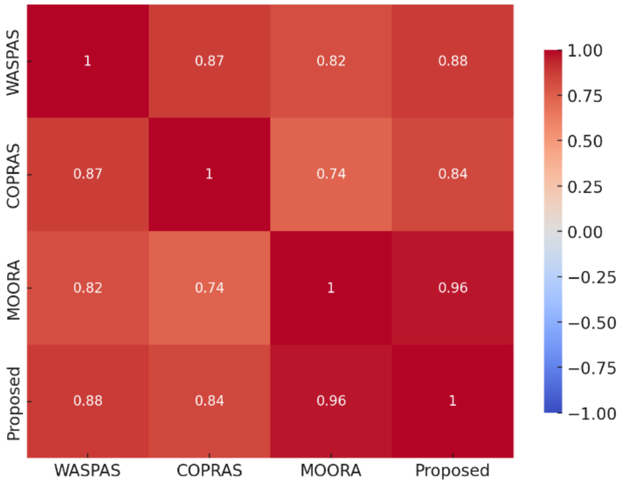


Fig 3. The Spearman correlation matrix for the CNC rankings.

4. Conclusions

This study presented a novel method for assessing Computer Numerical Control (CNC) devices by utilizing the BWM-TOPSIS-LP model. The combination of the Best-Worst Method (BWM) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) created a structured evaluation framework that considers several factors. The study's findings showed that the BWM-TOPSIS-LP model consistently and successfully rates CNC machines, providing decision-makers with a reliable tool for making informed decisions. The examination of the Spearman correlation matrix for CNC rankings validated robust positive associations among the utilized ranking techniques, including WASPAS, COPRAS, MOORA, and the proposed BWM-TOPSIS-LP method, underscoring its dependability. The correlations varied from 0.742 between COPRAS and MOORA to 0.961 between MOORA and the suggested approach, demonstrating a high level of agreement. The alignment highlights the efficacy of the BWM-TOPSIS-LP model in delivering consistent and dependable evaluations, closely correlating with other known decision-making methodologies.

Although the results show promise, this study recognizes certain limitations. The conclusions are derived from a particular sample of CNC machines and criteria, which could restrict the model's applicability. To maximize the relevance of the study, it would be beneficial to increase the sample size and incorporate a wider range of machine kinds and criteria. Furthermore, the inherent subjectivity of criteria weighting, albeit being systematically addressed by BWM, still poses a possible bias. Subsequent investigations could investigate methods to reduce subjectivity and enhance objectivity in this procedure. Validation is essential in various industrial contexts to verify the wider applicability of the model. Finally, the incorporation of BWM with TOPSIS-LP brings in computational intricacy, which could be streamlined for more user-friendly implementations. By addressing these constraints, the model's resilience and applicability in varied scenarios will be improved, hence leading to more informed decision-making in CNC machine selection.

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