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Article

Assessing Machine Tool Selection Process in Sustainable Production to Address Climate Change Based on Hybrid MCDM Methods

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Abstract. In recent years, there has been an increasing focus on optimizing production processes with the concept of sustainability because of the awareness of climate change around the world. Meanwhile, the machine tool is a crucial component of the manufacturing process. Therefore, this research aims to evaluate the process of machine tool selection in production with a concentration on reducing carbon dioxide emissions. Through the integration of different Multi-Criteria Decision-Making (MCDM) methods, including the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Evaluation based on Distance from Average Solution (EDAS), a mathematical model is proposed to make the best choice for machine tools. According to the AHP method, the motor output of the main spindle holds the most significant weight in the evaluation criteria, making it the most important factor to consider. The selection of the ideal machine tool is determined through the TOPSIS and EDAS methods. After careful evaluation, the CKQ 6136 CNC lathe has been identified as the optimal choice, as it scored the highest assessment value in both TOPSIS and EDAS methods. This study contributes to environmentally responsible manufacturing practices by considering machine tool selection, sustainability, and climate change mitigation.

Keywords: Sustainable production, machine tool, MCDM, electricity, carbon dioxide.

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1. Introduction

The implementation of climate change guidelines has led to the widespread adoption of sustainability practices in industrial sectors [1]. Consumers and policymakers have become more aware of the importance of environmental protection and product recyclability [2]. Rehman et al. [3] illustrated that the objective of sustainable production consists of efficient utilization of working machines, suitable layouts of production machines, ideal reduction of waiting time, accurate management of inventory and ultimate satisfaction from consumers. To address climate change, this paper will consider the core elements of sustainability while performing the proper selection of machine tools. At the same time, the emergence of innovative science and technology has contributed to the development of various improved methods for achieving sustainable production. According to Abdullah et al. [4], Industry 4.0 technologies play an essential role in the intelligent transformation process of conventional manufacturing modes and the digitalization of manufacturing is the core element of this changing process. To assist in the digitalization of sustainable production processes, this paper aims to construct a mathematical decision model that can optimize the selection of machine tools for sustainable production.

The achievement of sustainability requires consideration of three key elements which are the environment, economy, and society [5]. However, previous research has mainly focused on attributes such as profits and safety while evaluating the criteria for selecting machine tools [6], thereby neglecting the environmental element necessary for implementing sustainable lean production. The use of machine tools in industrial production significantly contributes to environmental problems due to high electricity consumption. According to data from the World Nuclear Association, the burning of fossil fuels to generate electricity consistently releases significant amounts of carbon dioxide, making it a major contributor to the global climate crisis. Additionally, Boyd et al. [7] stated greenhouse gas emissions are the primary cause of climate change's loss and damage. Besides, Pariartha et al. [8] highlighted the correlation between climate change and flood damage caused by the appearance of sea level rise. To optimize sustainable production while considering environmental factors, electricity consumption will be considered as a determining factor for the best machine tool in this study.

MCDM methods are widely used in operation research studies and consist of various methods. According to Tian et al. [9], eleven classical MCDM methods have been frequently applied between 2010 and 2022, including AHP, the best-worst method (BWM), and TOPSIS. In recent years, researchers have been developing and enhancing MCDM methods. For instance, Wang et al. [10] proposed an enhanced version of the TOPSIS method by incorporating the Design of Experiment (DOE) and the Chebyshev orthogonal polynomial regression method. Moreover, Stevic et al. [11] put forward an original MCDM method named measurement alternatives and ranking according to compromise solution (MARCOS) to help choose the right supplier.

The AHP approach determines the weight of different criteria in decision-making for various production strategies, and the TOPSIS method identifies the best alternative for different manufacturing schemes [12]. In this paper, a mathematical model that combines AHP with TOPSIS is proposed to select the best alternative for machine tools. AHP computes the assessment criteria weights, while TOPSIS provides a comprehensive ranking of alternatives. Additionally, the EDAS method will be used to evaluate the distance from the average solution and select the best alternative. A comparison between the ranking results of TOPSIS and EDAS will demonstrate any discrepancies in the numerical analysis results from the two MCDM methods.

In summary, the purpose of this study is to evaluate and enhance the selection process of machine tools by applying hybrid MCDM methods with a specific focus on incorporating environmental sustainability factors. Hybrid MCDM methods are beneficial for sustainable machine tool selection because they encompass different evaluation criteria, handle trade-offs, enhance decision accuracy, and support sustainability objectives, ultimately leading to more well-informed and balanced decision-making. This study builds on prior research by addressing constraints in conventional machine tool selection methods, incorporating environmental sustainability criteria, and advancing hybrid MCDM approaches.

2. Literature Review

In this section, the literature review primarily covers three aspects. Firstly, it focuses on the way to assess and improve environmental sustainability in sustainable production. Secondly, it investigates the correlation between appropriate machine tool selection and the progression of sustainable production. In the end, it explores the development and application of MCDM techniques.

2.1. Environmental Sustainability in Production

Favi et al. [13] created an industrial metabolism model to assess the environmental sustainability of a factory plant. The model takes into consideration input parameters like materials, fossils, and electricity, and outputs like emissions and waste. Moreover, Favi et al. [14] introduced a sustainability evaluation framework based on energy material flow analysis (EMFA) and life cycle assessment (LCA). The framework uses key performance indicators (KPIs) to aid in the EMFA and LCA process. The KPIs are categorized into three types: resource consumption KPIs, environmental KPIs, and finance KPIs. Resource consumption KPIs include electricity, water, natural gas, and lubricant consumption. Environmental KPIs include climate change, ozone depletion, terrestrial acidification, freshwater eutrophication, and more. Economic KPIs refer to the daily production cost. In addition, Barak et al. [15] proposed a mathematical modelling algorithm to improve environmental sustainability by increasing energy use efficiency in production equipment utilization and vehicle scheduling. Furthermore, a systematic Green Lean Six Sigma (GLSS) framework was developed by Rathi et al. [16] to enhance the environmental sustainability of manufacturing industries. The execution of this framework consists of five key procedures: problem identification, environmental value stream mapping (EVSM) and LCA, discovering the root causes of problems, development of effective solutions, and reassessment of the entire production process through EVSM and LCA. Besides, Chen et al. [17] proposed a framework which combines measures of lean production with digitalization techniques to achieve environmental sustainability. The main digitalization operations include the Internet of Things (IoT), big data and cloud computing, and machine learning. Nupet and Yenradee [18] focused on addressing environmental sustainability in production by reducing carbon dioxide emissions through the supply chain. This includes emissions from the production of raw materials, the manufacturing processes, and the transportation of goods.

2.2. Machine Tool Selection for Sustainable Production

The generation of electricity led by consumption demand is an essential contributor to carbon dioxide emissions. Therefore, the reduction of energy consumption is extremely important in sustainable manufacturing to mitigate climate change [19]. As per the findings of Kong et al. [20], the primary factors that contribute to energy consumption during production are the machinery tools and transportation equipment used for workpiece circulation. Hence, it is crucial to select energy-efficient machine tools for machining and optimize processing routes and parameters to reduce energy consumption during production. Liow [21] conducted a study to compare the energy consumption of a conventional machine tool with a novel machine tool. The results of the experiment showed that the conventional machine tool consumed significantly more energy than the novel machine tool when they were machining the same test piece. The main reason for the high energy consumption of the conventional machine tool was the need to drive the spindle, even though most of the available torque was not required. In other words, the conventional machine tool was oversized for the machining task, and most of the energy used was wasted. Last but not least, the selection of machine tools for reducing energy consumption is not limited to new machines. Older machines owned by the manufacturer can also be selected for energy efficiency. According to Yusuf et al. [22], some manufacturers often face financial constraints and cannot replace their old machine tools with new energy-efficient ones. However, energy consumption can be reduced through effective production planning and scheduling strategies. One possible solution is to evaluate each machine tool during operation and determine whether it is the best option among all older machine tools for completing specific tasks at specific times. This critical assessment can help minimize energy consumption and carbon dioxide emissions at the intermediate level.

2.3. Development and Application of MCDM

The application of hybrid MCDM methods in actual industrial production has become a significant research trend in recent years. Mathew et al. [23] successfully integrated AHP with TOPSIS to make an accurate flexible manufacturing system (FMS) choice. Previously, Nouri et al. [24] developed an innovative technology selection model with the combination of analytic network process (ANP) and TOPSIS in a local production enterprise. Plenty of hybrid MCDM methods are widely used in various research fields, not limited to the manufacturing industry. For instance, Kumari et al. [25] identified potential failure modes in a water treatment plant using a hybrid MCDM method that includes AHP and TOPSIS. Furthermore, Lin et al. [26] constructed a model to evaluate the safety degree of an excavation system through a TOSIS-based MCDM.

The MCDM methods are constantly used in conjunction with other methods. A review of previous journal publications reveals that fuzzy theory is one of the most commonly applied tools in conjunction with MCDM methods. The fuzzy set theory is adopted to solve ambiguous questions while using MCDM methods in an uncertain environment [27]. Chai et al. [28] used a fuzzy MCDM approach to select appropriate suppliers of shared bikes while considering the 3R principles of reduce, reuse, and recycle. Rudnik and Kacprzak [29] integrated the fuzzy TOPSIS method with ordered fuzzy numbers (OFN) to optimize the flow control in five concurrent and independent production lines. Apart from the fuzzy theory, there are other ancillary analysis methods used with MCDM techniques. For example, Dohale et al. [30] proposed an original methodology framework that combines the Delphi method and Bayesian network (BN) with the AHP method to make informed decisions for manufacturing systems. In addition, Yasmin et al. [31] demonstrated that MCDM methods have a close relationship with big data analytics, and the accuracy of analysis results can be guaranteed with abundant data. Lo et al. [32] performed a failure modes and effects analysis (FMEA) of a computer numerical control (CNC) machine tool based on MCDM principles, which optimized the traditional FMEA method by building risk assessment models. Besides, Hosouli et al. [33] designed and employed an innovative

MCDM methodology based on graph theory and matrix approach to address the issue of heat storage material selection. A two-part model was built by Phumchusri and Tangsiriwattana [34] for supplier selection of automotive parts, combining AHP and integer programming to optimize supplier matches.

3. Methodology

This paper utilizes three MCDM methods, all of which are introduced in this section. The AHP method is utilized to calculate the criteria weights, while the TOPSIS and EDAS methods are used to calculate the ranking of alternatives.

3.1. AHP

According to Longaray et al. [35] and Suban and Bajec [36], there is a series of steps to implement the AHP method. The first step is to identify and define the evaluation criteria that are specific to the needs of decision-makers. Simultaneously, the relative importance of assessment attributes should be determined in alignment with the decision-making purpose. Next, create a pairwise comparison matrix using the relative importance scale shown in Table 1, as described in Eq. (1).

Table 1. The relative importance scale of assessment attributes.

Scale	Relative importance (x_{ij})
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate values
1/3, 1/5, 1/7, 1/9	Values for inverse comparison

$$X = [x_{ij}]_{n\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & & x_{2n} \\ \vdots & & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nn} \end{bmatrix} \tag{1}$$

In Eq. (1), x_{ij} represents the relative importance ratio of the ith evaluation criterion to the jth evaluation criterion, and it has the characteristics described in Eq. (2) and Eq. (3).

$$x_{ij} = \frac{1}{x_{ji}} \ (i \neq j) \tag{2}$$

$$x_{ij} = 1 \ (i = j) \tag{3}$$

The third step involves standardizing the pairwise comparison matrix that has been constructed. This process begins by calculating the sum of each column in the matrix. Then, each element in the same column is divided by the sum of all the elements in that column. These manipulations will result in a new standardized matrix $\bar{X}$, as shown in Eq. (4).

$$\bar{X} = [\overline{x_{ij}}]_{n\times n} \tag{4}$$

The fourth procedure is to calculate the weights of each evaluation criterion. This can be done by adding up all the elements in each row of the standardized matrix $\bar{X}$ and dividing the sum by the number of elements in that row. These division results represent the weights of each assessment attribute. For instance, the final division result for the first row of the standardized matrix $\bar{X}$ corresponds to the weight of the first evaluation criterion.

The final step is to determine the consistency of the pairwise comparison matrix X. Each value of the same column in matrix X is multiplied with its corresponding criteria weight value to generate a new matrix. Then, the weighted sum value is calculated by adding up the values in each row of this new matrix. Next, ratios of these weighted sum values to their corresponding criteria weights are computed. The value of λ_{max} is obtained by averaging all these ratio values, and the consistency index $C.I.$ is calculated using Eq. (5) where n represents the number of compared alternatives.

$$C.I. = \frac{\lambda_{max} - n}{n-1} \tag{5}$$

Finally, the consistency ratio $C.R.$ is computed as Eq. (6). Here, the value of Random Index $R.I.$ can be found in Table 2.

Table 2. The number of compared alternatives n and its Random Index $R.I.$

n	1	2	3	4	5	6	7
$R.I.$	0.00	0.00	0.58	0.90	1.12	1.24	1.32

$$C.R. = \frac{C.I.}{R.I.} \tag{6}$$

If the calculated consistency ratio $C.R.$ is less than 0.1, it indicates that the pairwise comparison matrix X is reasonably consistent, which demonstrates the accuracy and effectiveness of criteria weights calculated by AHP.

3.2. TOPSIS

According to Behzadian et al. [37] and Wang et al. [10], the TOPSIS method involves seven sequential steps. Similar to other MCDM approaches, the first step in TOPSIS is to create a $m \times n$ decision matrix, denoted by Eq. (7). Here, m represents the number of alternatives, and n indicates the number of assessment attributes.

$$X = [x_{ij}]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & & x_{2n} \\ \vdots & & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (7)$$

The next step is to obtain the normalized matrix $\bar{X}$, as shown in Eq. (8) and Eq. (9).

$$\bar{X} = [\overline{x_{ij}}]_{m\times n} \quad (8)$$

$$\overline{x_{ij}} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (9)$$

The third step involves creating the weighted and normalized matrix $\tilde{X}$, as shown in Eq. (10) and Eq. (11). This is done by multiplying all the elements in each column of the matrix $\bar{X}$ with the corresponding criteria weight w_j to generate the new matrix $\tilde{X}$. For example, the first column of matrix $\bar{X}$ has a corresponding criteria weight of w_1, so all elements in this column are multiplied by the value of w_1. In addition, it's important to note that the sum of w_j must equal 1, as shown in Eq. (12).

$$\tilde{X} = [\tilde{x}_{ij}]_{m\times n} \quad (10)$$

$$\tilde{x}_{ij} = \overline{x_{ij}} \times w_j \quad (11)$$

$$\sum_{j=1}^{n} w_j = 1 \quad (12)$$

In the fourth step, both the ideal best value V_j^+ and the ideal worst value V_j^- for each column of the matrix $\tilde{X}$ are calculated and summarized. If a column in the matrix $\tilde{X}$ corresponds to a beneficial assessment criterion, the highest value in that column will be the ideal best value V_j^+, while the lowest value will be the ideal worst value V_j^-.

In the TOPSIS method, the fifth step is to calculate the Euclidean distance S_i^+ and S_i^- respectively. These calculations are based on Eq. (13) and Eq. (14).

$$S_i^+ = \left[\sum_{j=1}^{n}\left(\tilde{x}_{ij} - V_j^+\right)^2\right]^{0.5} \quad (13)$$

$$S_i^- = \left[\sum_{j=1}^{n}\left(\tilde{x}_{ij} - V_j^-\right)^2\right]^{0.5} \quad (14)$$

The last procedure is to compute the performance indicator P_i for each alternative using Eq. (15) and then rank them. The alternative with the highest value of P_i will be chosen as the best option.

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \quad (15)$$

3.3. EDAS

As outlined by Torkayesh et al. [38], the EDAS approach can be effectively executed through a series of steps. The initial step involves constructing a $m \times n$ decision matrix, as shown in Eq. (16). In this matrix, m denotes the quantity of alternatives while n signifies the amount of evaluation criteria.

$$X = [x_{ij}]_{m\times n} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & & x_{2n} \\ \vdots & & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (16)$$

Furthermore, the second step is to calculate the average of each column in the decision matrix using Eq. (17).

$$\mu_j = \frac{\sum_{i=1}^{m} x_{ij}}{m} \quad (17)$$

To evaluate various options based on advantageous and disadvantageous criteria, the third procedure involves calculating the Positive Distance from Average (PDA) and the Negative Distance from Average (NDA) respectively. If the criteria are beneficial, PDA and NDA are computed using Eq. (18) and Eq. (19). On the contrary, PDA and NDA are calculated using Eq. (20) and Eq. (21) if the criteria are non-beneficial.

$$PDA_{ij} = \frac{max\,(0, x_{ij} - \mu_j)}{\mu_j} \quad (18)$$

$$NDA_{ij} = \frac{max\,(0, \mu_j - x_{ij})}{\mu_j} \quad (19)$$

$$PDA_{ij} = \frac{max\,(0, \mu_j - x_{ij})}{\mu_j} \quad (20)$$

$$NDA_{ij} = \frac{max\,(0, x_{ij} - \mu_j)}{\mu_j} \quad (21)$$

The next step is to calculate the weighted sum of PDA (SP_i) and NDA (SN_i) separately based on Eq. (22) and Eq. (23).

$$SP_i = \sum_{j=1}^{n} w_j PDA_{ij} \quad (22)$$

$$SN_i = \sum_{j=1}^{n} w_j PDA_{ij} \quad (23)$$

To complete the process, the values of SP_i and SN_i need to be normalized according to Eq. (24). The resulting normalized values will be denoted as AS_i.

$$AS_i = \frac{1}{2}\left[\frac{SP_i}{max_i(SP_i)} + \left(1 - \frac{SN_i}{max_i(SN_i)}\right)\right] \quad (24)$$

The alternative which owns the highest value of AS_i will be chosen as the best one under the disciplines of the EDAS method.

4. Results and Analysis

4.1. Determination of Evaluation Criteria

When evaluating machine tool selection for production, it is important to consider the high-efficiency and low-carbon machine tools. The more electricity consumed by the machine tools, the more electricity has to be produced, which then leads to more carbon dioxide emissions. Therefore, reducing electricity use is very essential to achieving low carbon goals. The spindle motor consumes more electricity power than other auxiliary parts in a computer numerical control (CNC) machine tool, according to Triebe et al. [39]. As a result, the motor output of the main spindle is one of the criteria used to select the best CNC machine tool alternative. Additionally, there are three other crucial assessment attributes for machine tools: the maximum spindle speed, the maximum machining diameter, and the maximum machining length. These characteristics play a vital role in determining the machining efficiency of production processes and thus are selected as the ultimate evaluation criteria. To summarize, a total of four evaluation criteria are selected to determine the optimal machine tool alternative. Among these four assessment attributes, the motor output of the main spindle is deemed unbeneficial, while the other three are considered advantageous. Figure 1 is a block illustration that shows the criteria for selecting a machine tool based on sustainability assessment. The illustration helps in determining the machine tool that is most suitable for a given application.

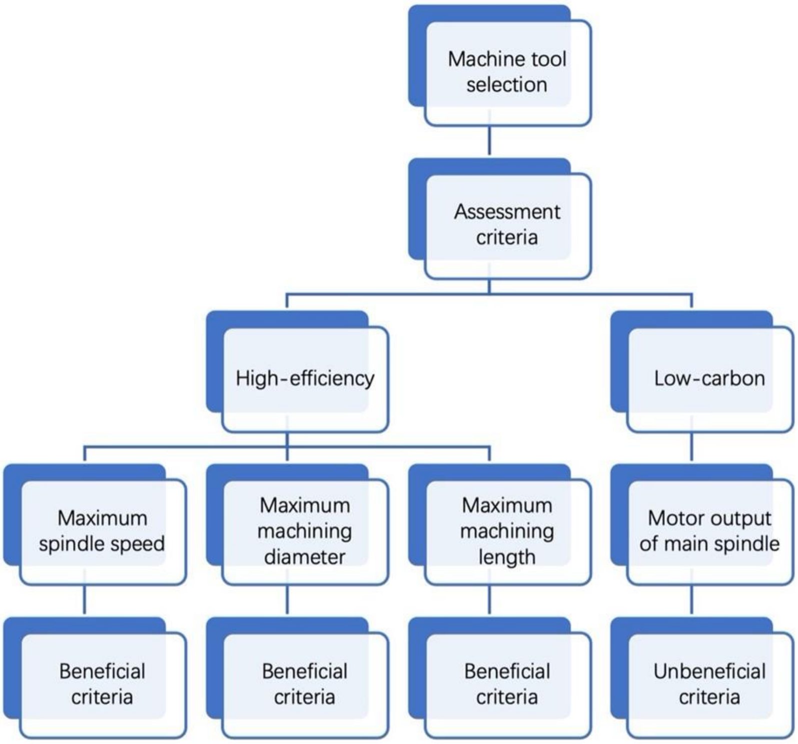

Fig. 1. Block illustration of assessment criteria for machine tool selection.

Table 3. The relative importance value of the four chosen evaluation criteria.

Relative importance (x_{ij})	Motor output of main spindle	Maximum spindle speed	Maximum machining diameter	Maximum machining length
Motor output of main spindle	1	2	3	4
Maximum spindle speed	1/2	1	2	3
Maximum machining diameter	1/3	1/2	1	2
Maximum machining length	1/4	1/3	1/2	1

The main spindle with a higher motor output consumes more electricity, resulting in a higher demand for electricity production. According to Ozdemir et al. [40], the majority of electricity is generated by burning fossil fuels, leading to a significant rise in carbon dioxide emissions. Hence, a higher motor output of the primary spindle can negatively impact both the environment and electricity costs. Meanwhile, it has been observed that there exists a direct relationship between the spindle speed and machining speed when working on workpieces of identical size. The faster the spindle rotates, the faster the machining process will be. The machine tool with a higher machining speed enables manufacturers to complete more workpieces, leading to increased profits. At the same time, the maximum machining diameter and the maximum machining length determine the size range of workpieces that can be processed. The machine tool with a larger processing size range expands the number of processing tasks that can be accomplished, which in turn dictates the machine tool enhances the contribution to more profits made by manufacturers.

4.2. Computation of Weights of Evaluation Criteria by AHP

To start with, the relative importance values of the four selected evaluation criteria are determined and all the related data are shown in Table 3.

Next, a matrix for pairwise comparison X is constructed based on data from Table 3, as shown in Eq. (25).

$$X = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1/2 & 1 & 2 & 3 \\ 1/3 & 1/2 & 1 & 2 \\ 1/4 & 1/3 & 1/2 & 1 \end{bmatrix} \tag{25}$$

After a series of calculations by AHP, the weights of evaluation criteria are summarized in Table 4. Related parameter values of criteria weights are shown in Table 5.

Table 4. The weights of evaluation criteria of machine tools.

Evaluation criteria	Weights
Motor output of main spindle	46.6%
Maximum spindle speed	27.7%
Maximum machining diameter	16.1%
Maximum machining length	9.6%

Table 5. Related parameter values of criteria weights.

Related parameter	Value
λ_{max}	4.031
$C.I.$	0.010
$R.I.$	0.9
$C.R.$	0.011

The calculated consistency ratio $C.R.$ is 0.011 which is less than 0.1, demonstrating that the pairwise comparison matrix X is reasonably consistent, and criteria weights calculated by AHP are accurate and effective.

4.3. Ranking of Alternatives by TOPSIS & EDAS

This section employs both TOPSIS and EDAS to rank alternative machine tools and compare the ranking results of both methods. As part of this research, five CNC lathes are selected as comparison alternatives: CK 6136, CK 6140V, CAK 6140, CKQ 6136, and CAK 6166. In the previous section, four evaluation criteria have been chosen to assess the alternatives, and the weights of these criteria have also been confirmed. Table 6 displays attribute data for the evaluation criteria of compared alternatives, sourced from the machine tool supplier.

Table 6. The attribute data for the evaluation criteria of comparison alternatives.

Optional machine tool model	Motor output of main spindle (kW)	Maximum spindle speed (RPM)	Maximum machining diameter (mm)	Maximum machining length (mm)
CK 6136	5.5	1800	360	2000
CK 6140V	7.5	1800	500	3000
CAK 6140	7.5	1500	400	3000
CKQ 6136	4	2000	360	700
CAK 6166	11	1500	660	3000

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Based on the above information provided, a decision matrix has been formulated with four columns and five rows. The first column outlines the motor output of the main spindle, while the second column specifies the maximum spindle speed. The third column denotes the maximum diameter that can be machined, and the fourth column defines the maximum machining length. Relevant data on five alternatives have been arranged in separate rows within this matrix, which is presented in Eq. (26).

$$X = \begin{bmatrix} 5.5 & 1800 & 360 & 2000 \\ 7.5 & 1800 & 500 & 3000 \\ 7.5 & 1500 & 400 & 3000 \\ 4 & 2000 & 360 & 700 \\ 11 & 1500 & 660 & 3000 \end{bmatrix} \quad (26)$$

According to the calculations performed by TOPSIS, Table 7 summarizes both the ideal best value V_j^+ and the ideal worst value V_j^-. Furthermore, both the Euclidean distance S_i^+ and S_i^- are calculated and summarized in Table 8. Finally, Table 9 outlines the results and rankings of performance indicator P_i for each alternative.

Based on the calculations conducted by EDAS, Table 10 presents a summary of the weighted sum of PDA (SP_i) and NDA (SN_i). Furthermore, Table 11 displays the results and rankings of performance indicator AS_i for each option.

Table 7. The ideal best value V_j^+ and the ideal worst value V_j^-.

Parameter	Motor output of main spindle	Maximum spindle speed	Maximum machining diameter	Maximum machining length
V_j^+	0.11144507	0.1431376	0.101095	0.05132
V_j^-	0.30647394	0.1073532	0.055143	0.01198

Table 8. The Euclidean distance S_i^+ and S_i^-.

Model	S_i^+	S_i^-
CK 6136	0.06600	0.15632
CK 6140V	0.10156	0.10944
CAK 6140	0.11125	0.10533
CKQ 6136	0.06050	0.19828
CAK 6166	0.19828	0.06050

Table 9. The results and rankings of P_i for each alternative.

Model	P_i	Ranking
CK 6136	0.70314	2
CK 6140V	0.51868	3
CAK 6140	0.48635	4
CKQ 6136	0.76623	1
CAK 6166	0.23377	5

Table 10. The weighted sum of PDA (SP_i) and NDA (SN_i).

Model	SP_i	SN_i
CK 6136	0.117897805	0.047843455
CK 6140V	0.055495732	0.026253521
CAK 6140	0.027076923	0.081455684
CKQ 6136	0.248557812	0.101176788
CAK 6166	0.099103239	0.291402064

Table 11. The results and rankings of AS_i for every alternative.

Model	AS_i	Ranking
CK 6136	0.65507	2
CK 6140V	0.56659	3
CAK 6140	0.41470	4
CKQ 6136	0.82640	1
CAK 6166	0.19936	5

5. Discussion

The selection of MCDM methods plays an important role in operation research because it directly decides the accuracy and confidence of final ranking results. In this research, the CNC machine tool model CKQ 6136 lathe achieves the highest performance score by both the TOPSIS and EDAS methods, demonstrating it as the best option in a strong way. Moreover, it is assumed that all five CNC machine tools for comparison in this research can effectively complete common manufacturing tasks. However, it is worth noting that if future manufacturing tasks demand higher torque to process workpieces, the machine tool model identified as the best option in this research may need to be substituted with another option having a higher motor output of the main spindle to meet the specific manufacturing requirement. In this paper, the motor output power of the machine tool main spindle is considered the most important evaluation factor. Based on the primary objective of selecting machine tools for environmental sustainability in this paper, the relative importance of the evaluation criteria in the AHP method is also determined based on this point.

This research proposes a novel approach to machine tool selection by including the motor output of the main spindle as a significant evaluation criterion. Triebe et al. [39] have demonstrated that the main spindle consumes significantly more electricity than other auxiliary parts in a machine tool. Therefore, the motor output of the main spindle has a greater impact on the overall electricity consumption of a machine tool, compared to the motor output of other auxiliary components. Ozdemir [40] pointed out that electricity generation is mainly realized by burning fossil fuels despite the appearance of cleaner energy in modern electric power plants. Hence, using more electricity by a machine tool leads to increased carbon dioxide emissions from electric power plants, which are caused by burning fossil fuels. It is a fact that the volume of carbon dioxide emissions is a crucial factor in determining the environmental aspect of sustainability in a process. Therefore, when selecting a machine tool, it is important to consider the motor output of the main spindle as a key criterion, as it provides a straightforward way to assess the environmental sustainability of the machine tool selection process.

The selection of machine tools for sustainable production can sometimes be limited due to a lack of options available on the market. In certain situations, even the best machine tool identified through operation research cannot fully meet the requirements for sustainable production. However, future research on sustainable product development (SPD) of machine tools can help address this issue by considering sustainability aspects early in the product development process. In a study conducted by Wang et al. [41], they proposed a Low-Carbon Product Design Scheme (LCPDS) performing a multi-functional analysis of mechatronics equipment at the early design stage with MCDM methods. This scheme aims to optimize the design of mechatronics equipment for lower carbon dioxide emissions resulting from production. Future research on machine tools could be carried out using a similar approach to LCPDS to provide more options for machine tools that can fulfill the sustainability requirements of manufacturing sectors.

6. Conclusion

Machine tools are fundamental to manufacturing processes, influencing product quality, production efficiency, and environmental sustainability. Traditional selection methods of machine tools often prioritize cost and machining performance criteria, neglecting the ecological aspect of sustainability. The manufacturing industry consumes a lot of electricity energy and causes a large volume of greenhouse gas emissions. The machine tools, being a core manufacturing equipment to manufacturing processes, significantly influence the overall sustainability performance of a company. Manufacturers can make more responsible and future-oriented choices toward environmental sustainability by addressing the interconnectedness of machine tool selection, sustainability, and climate change mitigation.

Hybrid MCDM methods that integrate various decision-making techniques intend to improve the accuracy and reliability of sustainability assessments. Manufacturers can make well-informed decisions that help mitigate climate change while maintaining competitiveness and ensuring long-term sustainability through hybrid MCDM methods. The TOPSIS and EDAS methods are used to choose the best manufacturing option from several schemes, whereas the AHP approach involves assigning weights to decision-making criteria for multiple production strategies. This study incorporates the AHP and TOPSIS in a mathematical model to determine the optimal machine tool option. During the selection of machine tool models, the AHP method calculates the weights of the selected assessment criteria, while the TOPSIS approach provides a comprehensive ranking of all available options. To validate the data accuracy, the rankings from the TOPSIS and EDAS are compared in this research. Ultimately, both the TOPSIS and EDAS identify the same best alternative. Overall, the findings in this paper highlight the importance of adopting hybrid MCDM methods in improving the sustainability of production processes and advancing climate mitigation efforts in the manufacturing sector. At the same time, the paper provides valuable insights for industry practitioners, policymakers, and researchers to improve sustainability initiatives within production systems.

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