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An Intelligent Decision Support Model for Optimal Selection of Machine Tool under Uncertainty: Recent Trends

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Abstract: Many scholars have been interested in the subject of machine tool selection as a result of the growing number of different machines and the continuous advancement of technology associated with these machines. The selection of an unsuitable machine tool may lead to a variety of issues, including limitations on production capacities and productivity indicators when taking into account both time and money from an industrial and practical perspective. The present strategy of selecting machine tools, known as multi-criteria decision-making (MCDM), relies on the subjective viewpoint the vast majority of the time. When selecting an appropriate machining tool, however, it is necessary to take both the subjective and objective points of view into consideration. This is due to the fact that the objective assessment accurately reflects the performance of the machine tools. As a result, the purpose of this work is to provide a strategy for selecting machine tools that are based on an innovative hybrid MCDM framework. The study was conducted under a neutrosophic environment and using triangular neutrosophic numbers (TNNs). In the beginning, the CRiteria Importance through Intercriteria Correlation (CRITIC) method is used to assess and prioritize the criteria set for the study. Then, the Additive Ratio Assessment (ARAS) method is applied to evaluate and rank four machine tools that were selected and used as alternatives in the study. The results indicate that the criteria of maximum spindle speed and linkage accuracy are the most important in determining the best machine tool. Also, the results indicate that the best alternative among the four tools used is FIDLA GTF-28. As a result, the requirements and priorities for research in the future are highlighted.

Keywords: Machine tool selection; Decision support model; Neutrosophic MCDM; CRITIC method; ARAS method.

1. Introduction

Manufacturing sectors are experiencing many problems such as globalization and quickly changing market demand, which result in greater manufacturing needs and more complex components. These issues have resulted in higher manufacturing requirements and more complicated products [1]. Because of this, it is essential for the continued profitability of businesses to choose suitable machining equipment for the various production activities they must do. In large-scale mechanical equipment, such as ships, construction machinery, railway vehicles, wind turbines, hydroelectric generators, nuclear power equipment, petrochemical equipment, and so on, machine tools are typically used because they are efficient, cost-effective, have a high value-added component, and have a complex structure [2]. This type of electromechanical equipment is known as a machine tool. Machine tools provide the key manufacturing capacity to turn raw materials into finished parts for final product assembly. When it comes to specialized machining jobs, manufacturing companies often have more than one machine tool that is capable of meeting the machining requirements. In order to pick the proper machine tools, manufacturing businesses need to examine the cost, productivity, and company profit. If you choose the appropriate machine tool, you may cut down on the amount of time it takes to supply produced goods, increase the flexibility and quality of your output, and boost your total productivity. Inappropriate judgments regarding the selection of machines lower the return on investments, raise the expenses associated with quality and maintenance, and finally have a negative influence on customer satisfaction. Because choosing machines is both an involved and time-consuming procedure, it is essential that those in charge of making the call possess the appropriate level of expertise and experience. Researchers have been motivated to construct models that may assist decision-makers as a result of testing the machine selection issue [3]. methods for rational decision support that are based on numerical models provide a methodical approach that makes use of the existing knowledge and, in addition, offers insights that may assist the decision-maker in analysing the choices that have been reached as a consequence of using the methods.

On the other hand, if the machine tool is not appropriately chosen, it might result in damage to the machine tool. There are around 300 businesses in the United States that are capable of remanufacturing machine tools. It has been shown that the cost of machine tool downtime and maintenance brought on by failure or incorrect usage is very close to 75 percent of the cost of brand-new machine tools. There are about 2000 businesses in China that are capable of providing services for the repair and remanufacturing of machine tools. According to the findings of the study, however, the primary cause for machine tool downtime and maintenance is still due to the failure of the machine tools themselves or incorrect usage of the machine tools. As a result, when confronted with particular processing tasks, how to choose the appropriate machine tool from among the many candidates of machine tools has always been a major difficulty for enterprise decision-makers. This is due to the fact that an incorrect selection of machine tools may have the potential to negatively affect the overall performance of the manufacturing system [4].

It is typical for engineers and managers to find the process of selecting machine tools to be a challenging one [5]. This is due to the fact that there is a great deal of qualitative and quantitative aspects that need to be taken into consideration when choosing the proper machine tool. A significant amount of work and effort has been put into selecting the appropriate machine tools. The most important components of the present methodologies are the multi-criteria decision-making (MCDM) model and the optimization-based model. The best mathematical model is one that is able to deal with objective facts well, but it often misses the qualitative and subjective aspects. Because there are many different criteria for selecting machine tools, some of which are in direct opposition to one another, the quantification of unknown qualitative attribute information may be an incredibly difficult task. For instance, the amount of time spent on auxiliary tasks, clamping tasks, machining tasks, and changeover tasks might vary depending on the capabilities of the machine tool. As a result, for a successful selection of machine tools, it is necessary to find a middle ground between competing physical and intangible variables; MCDM has been shown to be helpful in finding solutions to these problems. The evaluation of qualitative characteristics by experts, on the other hand, is inherently subjective and, as a result, imprecise because of the ambiguity involved. The neutrosophic linguistic approach has been proven to be an appropriate strategy for dealing with the issue of expert assessment. This is due to the fact that the evaluation information, such as criterion weights and alternative ratings, are often stated in terms of language.

The primary contribution of this study is the development of a machine tool selection approach that incorporates expert knowledge and the actual performance of alternatives. This is achieved through the application of a proposed neutrosophic CRiteria Importance through Intercriteria Correlation (CRITIC) [6] - Additive Ratio Assessment (ARAS) [7] framework. By integrating these factors, the decision-making process yields results that closely align with real-world conditions, thereby enhancing the reliability and practicality of the evaluation outcomes.

This work makes a number of important contributions, one of the most important of which is the development of a system for selecting machine tools that makes use of both expert knowledge and actual operation information in order to deliver the most suitable machine tool for a given manufacturing job. Another contribution that was made was the development of a hybrid MCDM framework known as neutrosophic CRITIC-ARAS. This framework permits the examination of alternatives from both subjective and objective points of view and gives the decision-makers with the best possible choice.

The purpose of this work is to present a decision-making approach for the purpose of resolving the issue of alternative selection in machine tools. This method is one that can avoid the subjectivity of standard decision-making methods that are based on experience.

2. Problem Elements

In this section, the criteria used in the study are presented to select the most appropriate machine tool. The criteria used are maximum spindle speed (C_1), failure rate (C_2), utilization (C_3), linkage accuracy (C_4), maximum spindle torque (C_5), and cost (C_6). The alternatives determined namely: APEC GL-27 (A_1), FIDLA Y2K-411 (A_2), FRFQ-250-VR/A8 (A_3), and FIDLA GTF-28 (A_4). Three professionals were hired to participate in the study, and their information appears in Table 1. Also, Figure 1 presents the main objective of the study, evaluation criteria, and four machine tools used in the study.

Table 1. Particulars about professionals.

Professionals	Experience	Title	Graduation degree
Professional_1	24	Senior engineer	Ph.D. in Mechanical Engineering
Professional_3	12	Process engineer	B.S. in Process Engineering
Professional_4	17	Operation manger	MSc. in Industrial Engineering

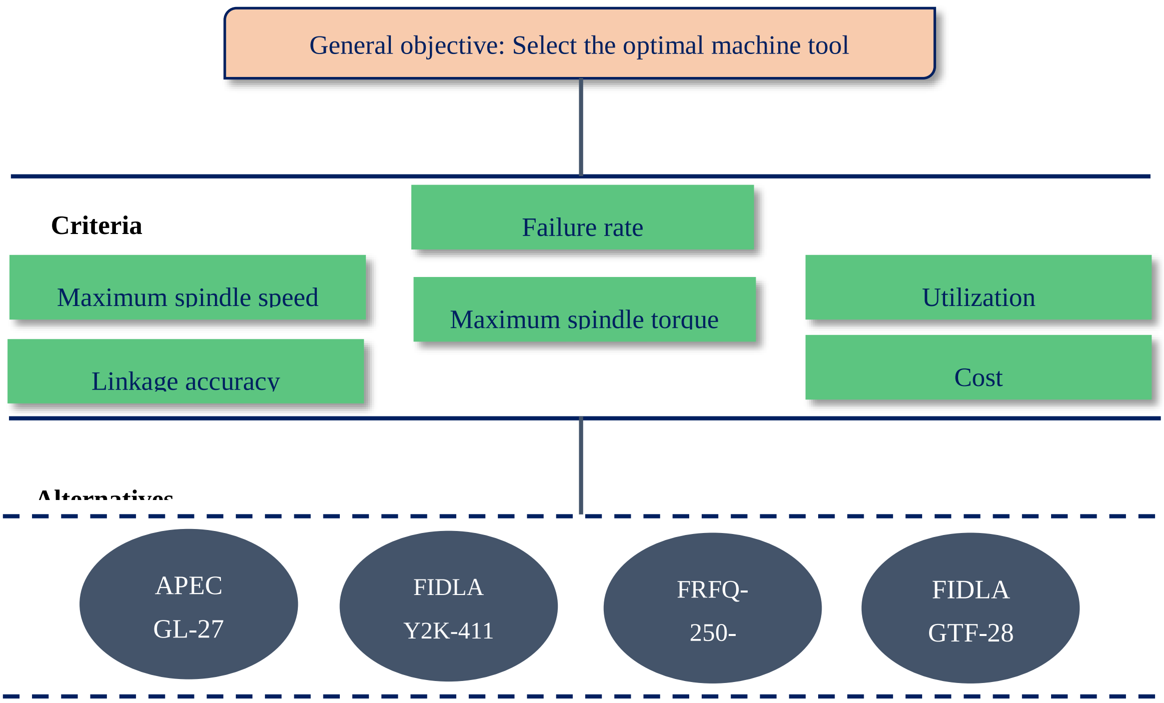

Figure 1: Objective, criteria, and alternatives of the problem.

3. Research Framework

In this section, the proposed CRITIC-ARAS methodology is presented to solve the machine tools selection problem. The proposed methodology is performed under a neutrosophic environment using TFNs. Figure 2 provides details of the proposed methodology.

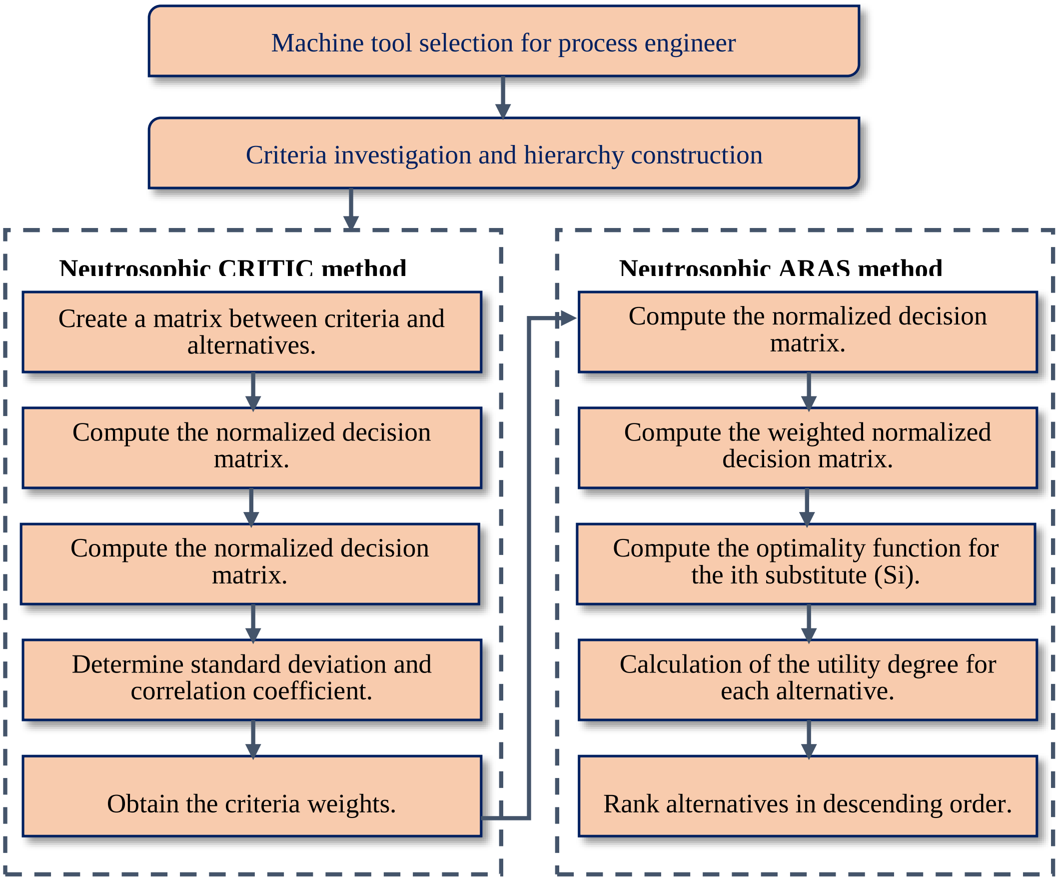

Figure 2: The main structure of the research methodology for this problem.

Step 1: The problem is studied in detail and its main aspects are identified, which consist of the main objective, criteria, and substitutes used. A set of alternatives are identified to be used in the evaluation process. The set machine tools = $(A_1, A_2, \dots, A_m)$ having i = 1, 2... m substitutes, is measured by n decision criteria of $C_j = (C_1, C_2, \dots, C_n)$, with j = 1, 2...n. Let $w = (w_1, w_2, \dots, w_n)$ be the vector set utilized for defining the criteria weights, $w_j > 0$ and $\sum_{j=1}^{n} w_j = 1$.

Step 2: A set of terms and their corresponding TFNs is defined in Table 2, to be used by the authors and professionals involved in evaluating the criteria and alternatives used.

Table 2. Linguistic variables and their equivalent TNNs for evaluating criteria and alternatives.

Linguistic variables	Abbreviations	TNNs
Absolute Low Worth	ALW	$\langle(0.1, 0.2, 0.3); 0.4, 0.1, 0.3\rangle$
Very Low Worth	VLW	$\langle(0.2, 0.3, 0.4); 0.5, 0.1, 0.3\rangle$
Low Worth	LOW	$\langle(0.3, 0.4, 0.5); 0.6, 0.2, 0.1\rangle$
Modest Low Worth	MLW	$\langle(0.4, 0.5, 0.6); 0.7, 0.3, 0.2\rangle$
Nearly Worth	NWO	$\langle(0.5, 0.6, 0.7); 0.8, 0.3, 0.3\rangle$
Modestly High Worth	MHW	$\langle(0.6, 0.7, 0.8); 0.9, 0.4, 0.4\rangle$

High Worth	HGW	⟨(0.7, 0.8, 0.9); 1.0, 0.3, 0.5⟩
Very High Worth	VHW	⟨(0.8, 0.9, 1.0); 1.0, 0.2, 0.3⟩
Absolute High Worth	AHW	⟨(0.9, 1.0, 1.0); 1.0, 0.2, 0.2⟩

Step 3: Create a pairwise comparison matrix amongst the alternatives and the selected criteria by all professionals to simplify their preferences for these criteria.

Step 4: Transform the TNNs to crisp values by applying the score function according to Eq. (1).

$$S(\tilde{x}_{ij}) = \frac{1}{8}(l + m + u) \times (2 + \alpha_{\tilde{x}} - \theta_{\tilde{x}} - \beta_{\tilde{x}}) \quad (1)$$

Step 5: Calculate the normalized decision matrix for criteria according to Eq. (2).

$$x_{ij}^{*} = \frac{x_{ij} - min(x_{ij})}{max(x_{ij}) - min(x_{ij})} \quad i = 1, 2 \ldots m \text{ and } j = 1, 2 \ldots n. \quad (2)$$

Step 6: Compute the standard deviation and correlation coefficient.

Step 7: Compute the quantity of information of criteria according to Eq. (3). D_j is an abbreviation that stands for "the amount or volume of information provided in the jth criteria".

$$D_j = \sigma_j \, . \, \sum_{k=1}^{m}(1 - r_{jk}) \quad (3)$$

Step 8: Obtain the criteria weights according to Eq. (4).

$$w_j = \frac{D_j}{\sum_{k=1}^{m} D_k} \quad (4)$$

Step 9: Create the assessment decision matrix by all professionals between the determined criteria and the available alternatives to evaluate a machine tools by using the linguistic variables, provided in Table 2.

Step 10: Compute the normalized decision matrix for the advantageous criteria according to Eq. (5), and for non-advantageous factors according Eq. (6).

$$y_{ij} = \frac{y_{ij}}{\sum_{i=0}^{m} y_{ij}} \quad (5)$$

$$y_{ij} = \frac{1}{y_{ij}^{*}} \; ; \quad y_{ij} = \frac{y_{ij}}{\sum_{i=0}^{m} y_{ij}} \quad (6)$$

Step 11: Compute the weighted assessment decision matrix by multiplying the value of the normalized decision matrix by the corresponding weights according to Eq. (7).

$$y_{ij} = w_j \times y_{ij} \quad (7)$$

Step 12: Define the values of optimality function for the ith substitute according to Eq. (8).

$$S_i = \sum_{j=1}^{n} y_{ij}, \; i = 1, 2 \ldots m. \quad (8)$$

Step 13: Compute the utility degree for each substitute according to Eq. (9). Then, rank the substitutes in descending order according to the value ofk_i.

$$k_i = \frac{S_i}{S_0} \quad , i = 1, 2 \ldots m. \quad (9)$$

4. Application

4.1 Implementation of the recommended methodology

In this part, the proposed CRITIC-ARAS methodology is applied to evaluate and rank four machine tools.

Step 1: The problem was studied and its basic details were determined. In this regard, the main goal has been identified, which is to determine the best machine tool. Also, six criteria have been identified that have a direct impact on solving the problem. The six criteria used are maximum spindle speed (C_1), failure rate (C_2), utilization (C_3), linkage accuracy (C_4), maximum spindle torque (C_5), and cost (C_6). Finally, the alternatives used were identified namely: APEC GL-27 (A_1), FIDLA Y2K-411 (A_2), FRFQ-250-VR/A8 (A_3), and FIDLA GTF-28 (A_4).

Step 2: A pairwise comparison matrix amongst the alternatives and the selected criteria was created by all professionals to simplify their preferences for these criteria using linguistic terms in Table 2, as presented in Table 3, then using TNNs as exhibited in Table 4. Also, the TNNs were transformed to crisp values by applying the score function according to Eq. (1).

Step 3: The normalized decision matrix was computed for criteria according to Eq. (2), as presented in Table 5. Then, the standard deviation was computed, as presented in Table 5.

Step 4: The quantity of information of criteria was computed according to Eq. (3), as presented in Table 6. Finally**,** the criteria weights were obtained according to Eq. (4), as presented in Table 6 and shown in Figure 3.

Table 3. Evaluation matrix based on the selected criteria for all professionals using linguistic variables.

Criteria/	Professional$_s$					
Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
A_1	MLW	MLW	MHW	VLW	HGW	MHW
A_2	AHW	ALW	MLW	HGW	MLW	ALW
A_3	MLW	LOW	HGW	ALW	MLW	MHW
A_4	MHW	MHW	MHW	NOW	VLW	MLW

Table 4. Evaluation matrix based on the selected criteria for all professionals using TNNs.

Criteria/	Professional$_s$		
Alternatives	C_1	C_2	C_3
A_1	$\langle(0.4, 0.5, 0.6); 0.7, 0.3, 0.2\rangle$	$\langle(0.4, 0.5, 0.6); 0.7, 0.3, 0.2\rangle$	$\langle(0.6, 0.7, 0.8); 0.9, 0.4, 0.4\rangle$
A_2	$\langle(0.9, 1.0, 1.0); 1.0, 0.2, 0.2\rangle$	$\langle(0.1, 0.2, 0.3); 0.4, 0.1, 0.3\rangle$	$\langle(0.4, 0.5, 0.6); 0.7, 0.3, 0.2\rangle$
A_3	$\langle(0.4, 0.5, 0.6); 0.7, 0.3, 0.2\rangle$	$\langle(0.3, 0.4, 0.5); 0.6, 0.2, 0.1\rangle$	$\langle(0.7, 0.8, 0.9); 1.0, 0.3, 0.5\rangle$
A_4	$\langle(0.6, 0.7, 0.8); 0.9, 0.4, 0.4\rangle$	$\langle(0.6, 0.7, 0.8); 0.9, 0.4, 0.4\rangle$	$\langle(0.6, 0.7, 0.8); 0.9, 0.4, 0.4\rangle$
Criteria	Professional$_s$		
	C_4	C_5	C_6
A_1	$\langle(0.2, 0.3, 0.4); 0.5, 0.1, 0.3\rangle$	$\langle(0.7, 0.8, 0.9); 1.0, 0.3, 0.5\rangle$	$\langle(0.6, 0.7, 0.8); 0.9, 0.4, 0.4\rangle$
A_2	$\langle(0.7, 0.8, 0.9); 1.0, 0.3, 0.5\rangle$	$\langle(0.4, 0.5, 0.6); 0.7, 0.3, 0.2\rangle$	$\langle(0.1, 0.2, 0.3); 0.4, 0.1, 0.3\rangle$
A_3	$\langle(0.1, 0.2, 0.3); 0.4, 0.1, 0.3\rangle$	$\langle(0.4, 0.5, 0.6); 0.7, 0.3, 0.2\rangle$	$\langle(0.6, 0.7, 0.8); 0.9, 0.4, 0.4\rangle$
A_4	$\langle(0.5, 0.6, 0.7); 0.8, 0.3, 0.3\rangle$	$\langle(0.2, 0.3, 0.4); 0.5, 0.1, 0.3\rangle$	$\langle(0.4, 0.5, 0.6); 0.7, 0.3, 0.2\rangle$

Table 5. Normalized decision matrix based on criteria by all professionals.

Criteria/Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.0000	0.6542	0.5600	0.1691	1.0000	0.9969

A_2	1.0000	0.0000	0.0000	1.0000	0.4100	0.0000
A_3	0.0000	0.4860	1.0000	0.0000	0.4159	1.0000
A_4	0.2653	1.0000	0.5600	0.6765	0.0000	0.6480
Standard Deviation	0.4726	0.4160	0.4097	0.4600	0.4113	0.4708

Table 6. Correlation coefficient of the relationship among the criteria and final weights.

Criteria	C_1	C_2	C_3	C_4	C_5	C_6	D_j	w_j
C_1	1.0000	-0.6981	-0.8986	0.9134	-0.2873	-0.9959	3.2926	0.214
C_2	-0.6981	1.0000	0.5438	-0.3491	-0.2350	0.6316	2.1242	0.138
C_3	-0.8986	0.5438	1.0000	-0.8926	0.0162	0.8975	2.1853	0.142
C_4	0.9134	-0.3491	-0.8926	1.0000	-0.4640	-0.9443	3.0985	0.201
C_5	-0.2873	-0.2350	0.0162	-0.4640	1.0000	0.3537	2.3102	0.150
C_6	-0.9959	0.6316	0.8975	-0.9443	0.3537	1.0000	2.3808	0.155

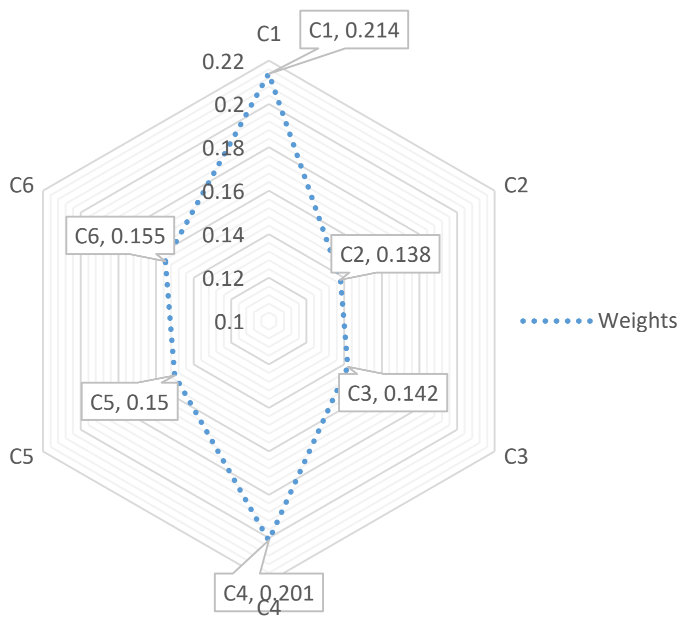

Figure 3. Final weights of the selected criteria.

Step 5: The assessment decision matrix was created by all professionals between the determined criteria and the four machine tools by using the linguistic variables, provided in Table 2.

Step 6: The normalized decision matrix was computed for the advantageous criteria according to Eq. (5), and for non-advantageous factors according Eq. (6), as presented in Table 7.

Step 7: The weighted assessment decision matrix was computed by multiplying the value of the normalized decision matrix by the corresponding weights according to Eq. (7), as presented in Table 8.

Step 8: The values of optimality function for the ith substitute was defined according to Eq. (8), as presented in Table 9.

Step 9: The utility degree for each substitute was computed according to Eq. (9), as presented in Table 9. Then, the four machine tools were ranked in descending order according to the value of k_i, as presented in Table 9 and shown in Figure 4.

Table 7. Normalized evaluation matrix of four machine tools regarding criteria.

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
Optimal value	0.2894	0.2743	0.2332	0.2998	0.2775	0.2492
A_1	0.1259	0.2052	0.1943	0.1073	0.2775	0.2486
A_2	0.2894	0.0746	0.1449	0.2998	0.1724	0.0678
A_3	0.1259	0.1716	0.2332	0.0681	0.1734	0.2492
A_4	0.1693	0.2743	0.1943	0.2249	0.0993	0.1853

Table 8. Weighted normalized evaluation matrix of four machine tools regarding criteria.

Alternatives	C_1	C_2	C_3	C_4	C_5	C_6
Optimal value	0.0619	0.0378	0.0331	0.0603	0.0416	0.0386
A_1	0.0269	0.0283	0.0276	0.0216	0.0416	0.0385
A_2	0.0619	0.0103	0.0206	0.0603	0.0259	0.0105
A_3	0.0269	0.0237	0.0331	0.0137	0.0260	0.0386
A_4	0.0362	0.0378	0.0276	0.0452	0.0149	0.0287

Table 9. Final ranking of four machine tools regarding all criteria.

Alternatives	S_i	K_i	Rank
S_0	0.2734	1.0000	
A_1	0.1846	0.6751	3
A_2	0.1894	0.6929	2
A_3	0.1621	0.5928	4
A_4	0.1905	0.6967	1

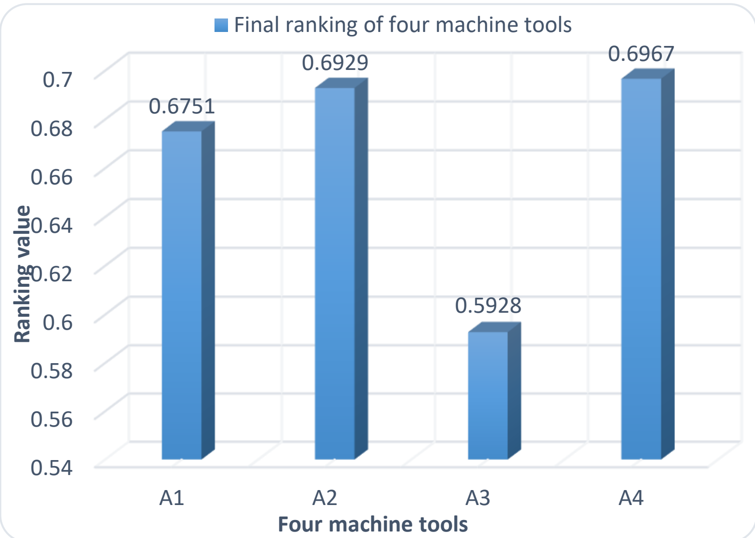

Figure 4. Final ranking of four machine tools using ARAS technique.

4.2 Discussion

In this part, the results obtained from the application of the proposed methodology CRITIC-ARAS under the neutrosophic environment are discussed.

Initially, the six criteria were evaluated using the CRITIC method. The results in Table 5 indicate that the maximum spindle speed criterion is the most influential criterion with a weight of 0.214, followed by the linkage accuracy criterion, while the failure rate criterion is the least influential with a weight of 0.138.

Also, four machine tools were evaluated and ranked as shown in Table 7. The results indicate that the FIDLA GTF-28 machine tool is the best to be used in the industry.

5. Conclusion

One of the most important decisions that must be made, which may have significant repercussions for the performance of a company, is which new machine will be introduced to the production system. In recent years, a rising number of scholars have been interested in the topic of machine selection. This is mostly due to the fact that the number of different machine tools is growing, as is the rate at which manufacturing technology is advancing. It was said that applying the MCDM approaches to the issue of machine selection is a project that requires appropriate preparation in order to be successful. This is because the judgments that go into machine selection are primarily impacted by technical and economic factors, both of which have clear evaluations easily accessible in the majority of situations. As a result, this is something that can be linked to the fact that this is the case. Comparing two machines' capacities, dimensions, levels of power consumption, and speeds, for instance, is as simple as comparing apples and oranges. Both the purchase price and the running expenses are able to be obtained in a similar fashion and included in the comparisons. The majority of the publications that were examined indicated that it was simple to use such criteria when making comparisons. In situations when some technical criteria do not have crisp values or when other non-crisp criteria are chosen, such as those relating to sustainability, maintainability, productivity, and other things of a similar kind, fuzzy representations are often used. Researchers are the most common users of fuzzy representations.

Data availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflict of interest

The authors declare that there is no conflict of interest in the research.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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