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AN ANALYTICAL APPROACH FOR THE SELECTION OF CUTTING TOOL SUPPLIERS USING THE RSMVC METHOD. CASE STUDY

Flaviu CORB, Caius STANASEL, Iulian STANASEL

Abstract: *In the CNC (Computer Numerical Control) machining industry, cutting tools play a crucial role in ensuring quality and optimizing production costs. The large number of cutting tool suppliers and the often contradictory performance criteria make the process of selecting the optimal supplier a complex task. This article presents a multi-criteria analysis method for selecting cutting tool suppliers used in the machining of injection mold dies for plastics. The case study discussed in the article examines 16 suppliers and 19 criteria, utilizing the RSMVC method (Ranking the Solutions based on the Mean Value of Criteria). This method provides a thorough evaluation, taking into account the sensitivity and robustness of the decision. The proposed method offers a framework for making efficient decisions.*

Keywords: *Multicriteria decision, cutting tools, supplier selection, RSMVC method.*

1. INTRODUCTION

Injection molds for plastics play a significant role in the production of components used across a wide range of industries, such as automotive, electronics, packaging, and consumer goods. The machining of mold cavities through chip removal is a critical stage that directly impacts the precision, quality, and durability of the molds. In this context, the cutting tools used for machining these components must meet strict requirements, such as wear resistance, dimensional accuracy, and the ability to work with hard materials, among others.

The selection of cutting tool suppliers thus becomes a strategic decision, considering that the performance of these tools impacts not only the quality of the final product but also the efficiency of the machining process. Choosing the right supplier can contribute to reducing production costs, increasing productivity, and minimizing downtime caused by premature tool wear.

The large number of suppliers, along with the multitude of technical, economic, and logistical criteria, makes the selection process highly complex. For instance, one supplier may offer high-performance tools but at a high cost, while

another may provide competitive pricing but with lower tool durability. Additionally, factors such as delivery time, technical support, after-sales services, and the supplier's reputation add another layer of difficulty to the decision-making process. This complexity requires an analytical and systematic approach to identify the supplier that best meets the specific requirements of the machining process. In the specialized literature, there are studies addressing various aspects related to the selection of cutting tools.

Computer-Aided Process Planning (CAPP) relies heavily on the selection of cutting tools. Traditionally, this problem was addressed by process planners using their technical expertise and databases built over time. To optimize the process, the study [1] employed neural networks and other AI techniques. The study proposes a neural network model for selecting tools for milling and drilling operations. Examples of machining processes are presented, demonstrating the effectiveness of the model.

For metal machining, the materials for cutting tools are selected based on various criteria. This selection is typically made in accordance with the recommendations found in manufacturers' catalogs, specialized literature, or advice from

experts in the field of machining. For objective classification, study [2] suggests the RSMVC method, which is based on the mean value of the criteria. The proposed method has the advantage of simplifying the selection process and being reliable. The method has been successfully validated in solving problems across various cases of tool material selection.

To reduce machining costs and improve working precision, the correct selection of milling tools is a critical step in the preparation of the technological process. In this context, study [3] focuses on process and tool costs. A wide variety of tools were used to simulate the roughing operation. To rank the tools, a weighted cost analysis was performed, and the optimal order was influenced by the variation in weights. The study demonstrates that selecting cutting tools requires a thorough analysis of costs and technical constraints.

The turning of hardened OHNS steel (48 HRC) is a challenging task that requires optimal cutting parameters. Study [4] analyzes the cutting parameters—feed rate, speed, and depth of cut—using VP-coated carbide inserts and a Central Composite Design (CCD) experimental approach. To optimize the Metal Removal Rate (MRR) and surface finish (Ra), experimental design techniques and the TOPSIS method are employed. The results highlight the optimized cutting parameter values, which are validated through testing.

Sculptured-dies roughing (SDR) is more challenging than machining prismatic shapes, as it requires trade-offs between conflicting objectives. Study [5] analyzes the selection of depth of cut and cutting tools using multi-objective optimization to minimize machining time. Multi-objective optimization methods employ algorithms such as MODP and MOGA. The results validate the theoretical approaches presented in the study.

The cutting tool plays an important role in the production process, influencing material removal, surface finishing, dimensional accuracy, productivity, and costs. Selecting a suitable cutting tool is a complex task, given the numerous alternatives available from different manufacturers, each with unique characteristics. The study [6] proposes an MCDM model for selecting the most suitable cutting insert for

medium machining of unalloyed structural steel. The model includes 14 alternative inserts from 8 manufacturers and 7 criteria, based on information from manufacturers' catalogs and machining estimates. Although six MCDM methods were initially used for evaluation and ranking, the resulting inconsistencies led to the adoption of a robust decision-making method to solve the problem.

Study [7] proposes a methodology for tool selection and optimization of cutting parameters, based on mathematical formulations of optimization criteria. Finite element modeling of the machining process is utilized, and a standardized database is developed, including factors such as the coefficient of friction and the impact of the cutting edge radius, to enable more precise selections.

Study [8] proposes a methodology for optimizing the selection of milling tools in the machining of triangular pockets, with the objective of minimizing machining time. An analytical model was developed for optimization, utilizing sequential quadratic programming to evaluate tool path lengths and trajectories. The research concludes that the proposed strategy reduces tool path length, thereby minimizing machining time.

Study [9] focuses on the selection of abrasive tools and cutting regimes, based on experiments aimed at improving surface quality. The article compares grinding and honing of gear teeth, analyzing their advantages, disadvantages, and areas of application. It also addresses aspects related to tool correction and restoration, along with recommendations for cooling fluids. The precision and quality of gears are closely linked to the correct selection of finishing tools. The study provides a concise comparative analysis of the impact of machining methods on the surface quality of gear teeth.

The paper presents a case study using the RSMVC method as a solution for selecting cutting tool suppliers. Additionally, a sensitivity analysis is conducted to evaluate the impact of weight variation of the criteria on the final decision. This approach provides insight into how the proposed method can be utilized to support decision-making in an industrial environment.

2. METHODOLOGY

The RSMVC method is a novel Multi-Criteria Decision-Making (MCDM) approach [2] that relies on calculating the mean value of criteria for each solution, eliminating the need for data normalization, which simplifies the decision-making process.

In this method, each solution (alternative) is evaluated based on multiple criteria. These criteria can have either unique values or value ranges. RSMVC addresses this by using the mean values of the criteria.

The first step involves creating a matrix where each row represents a solution, and each column represents an evaluation criterion. As mentioned, the criteria values can be either ranges or unique values.

The matrix takes the following form:

$$A = \begin{bmatrix} a_{11} \div b_{11} & L & a_{1n} \div b_{1n} \\ a_{21} \div b_{21} & L & a_{2n} \div b_{2n} \\ & M & O & M \\ a_{m1} \div b_{m1} & L & a_{mn} \div b_{mn} \end{bmatrix}. \quad (1)$$

For each criterion j of solution i , the mean value is calculated using the formula:

$$\bar{x}_{ij} = \frac{a_{ij} + b_{ij}}{2}. \quad (2)$$

If the criterion value is unique, the formula remains valid because $a_{ij} = b_{ij}$.

For "larger is better" criteria, the solution with the highest mean value is ranked 1st, while the one with the lowest mean value is ranked last.

For "smaller is better" criteria, the solution with the lowest mean value is ranked 1st, while the one with the highest mean value is ranked last.

The total score for each solution is calculated using the formula

$$S_i = \sum_{j=1}^n r_{ij} \cdot w_j. \quad (3)$$

where:

r_{ij} is the rank of solution i for criterion j ,
 w_j is the weight of criterion j .

The solution with the lowest score S_i is considered the best, while the one with the highest score is considered the weakest. After conducting the study and establishing the ranking, a sensitivity analysis of the method is performed. The purpose of the sensitivity analysis is to study how changes in the importance (weight) of a criterion affect the final score and the ranking of the solutions (alternatives). This analysis was applied by varying the weights of the criteria [10].

The sensitivity analysis aimed to determine the independent effect of each criterion on the MCDM results. In this regard, the weight of each studied criterion was modified within a 20% range, while the other criteria remained unchanged. Each time, the calculations for the decision matrix were redone, observing changes in the final ranking of the studied alternatives. In applying the method, it was assumed that all criteria have equal importance, meaning they were assigned equal weights.

3. CASE STUDY

For the selection of cutting tools used in machining injection molds for plastics, there are 16 suppliers from six countries to be ranked using 19 criteria. The criteria considered for evaluating the suppliers are presented in Table 1. The matrix showing the suppliers and selection criteria is presented in Table 2.

As mentioned, the method allows the evaluation of criteria expressed as value ranges (e.g., C1) by considering the average of the range, while for qualitative criteria (C4, C6, C7, C8, C10, C17, C18, C19), numerical substitution is proposed, e.g., Yes = 1, No = 0. For criterion C16, which represents the country where the cutting tool brand is headquartered, the consulted specialists proposed the following coding: CHINA (1), ROMANIA (2), POLAND (3), SPAIN (4), SWEDEN (5), GERMANY (6).

The engineering team recommended that the "brand's country of origin" be included in the analysis because their experience revealed that suppliers from various nations differed in terms of quality, dependability, support, and supply chain risks. Operational realities are reflected in the industry's preference for or avoidance of

particular brands based on risk considerations. This criterion is not used as the only factor in the decision-making process; rather, it is used in combination with other evaluation criteria.

In the case of qualitative criteria, a binary scale was employed because, for all the analyzed suppliers, these services were either present or absent, without any intermediate values. Consequently, the 0/1 coding accurately reflects the available data and did not result in any loss of information.

Table 3 presents the matrix where the average was calculated for criterion C1, and substitutions were made for the qualitative criteria.

Using relation (3), the calculation of criteria is presented for criterion C1, evaluated under the consideration that "larger is better," and for criterion C2, considering that "smaller is better." The values of criterion C1 are evaluated according to the rule "larger is better." For the values in Table 4, under the "Criterion" column, the scores in the "Score" column are obtained.

With a score of 2, there are 4 positions. Using relation (3), an average is calculated, and as a result, all alternatives with a score of 2 occupying positions 2-5 will receive a rank of 3.5. Alternatives with a score of 6 occupying positions 6-11 will receive a rank of 8.5, while

positions 12-14 with a score of 12 will receive a rank of 13. The remaining two positions will have ranks of 15 and 16, corresponding to their scores.

Table 1

Criteria for evaluating cutting tool suppliers.		
Crit.	Name	Evaluation
C1	Machining hardness	Max.
C2	Execution tolerance	Min.
C3	Tool durability	Max.
C4	Quality certificate	Max.
C5	Delivery time	Min.
C6	Reusability	Max.
C7	Return possibility	Max.
C8	Machining capability	Max.
C9	Purchase price	Min.
C10	Technical support	Max.
C11	Number of cutting edges	Max.
C12	Flute length	Max.
C13	Total length	Max.
C14	Radial runout	Min.
C15	Negotiation availability	Max.
C16	Brand	Max.
C17	New geometries	Max.
C18	Tests before aquisition	Max.
C19	Promotional prices	Max.

Table 2

Suppliers and selection criteria.																			
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19
A01	30-60	-0.0041	4	Yes	1	Yes	Yes	Yes	115	Yes	4	25	120	0.002	1	SWEDEN	Yes	Yes	Yes
A02	30-60	-0.0039	3	Yes	1	Yes	Yes	Yes	104	Yes	4	30	100	0.002	1	GERMANY	Yes	Yes	Yes
A03	30-62	-0.0040	3	Yes	2	Yes	Yes	Yes	125	Yes	4	30	100	0.003	1	GERMANY	Yes	Yes	Yes
A04	30-60	-0.0042	4	Yes	1	Yes	Yes	Yes	117	Yes	4	30	100	0.002	1	SPAIN	Yes	Yes	Yes
A05	30-62	-0.0046	4	No	2	Yes	Yes	Yes	65	Yes	4	25	110	0.004	1	CHINA	Yes	Yes	Yes
A06	30-58	-0.0050	2	Yes	3	Yes	No	Yes	84	Yes	4	25	120	0.003	1	SWEDEN	Yes	No	Yes
A07	30-58	-0.0071	2	No	5	Yes	No	Yes	92	No	4	30	100	0.002	1	CHINA	Yes	Yes	Yes
A08	30-68	-0.0038	3	Yes	2	Yes	Yes	Yes	132	Yes	4	30	100	0.002	1	GERMANY	Yes	Yes	No
A09	30-62	-0.0044	3	Yes	3	Yes	Yes	Yes	106	Yes	4	25	100	0.002	1	POLAND	Yes	Yes	Yes
A10	30-60	-0.0032	4	Yes	3	Yes	No	Yes	131	Yes	4	25	100	0.002	1	GERMANY	Yes	Yes	No
A11	30-58	-0.0065	3	Yes	2	Yes	Yes	Yes	88	Yes	4	25	80	0.003	1	ROMANIA	Yes	Yes	Yes
A12	30-55	-0.0068	2	No	4	Yes	No	Yes	75	No	4	30	100	0.002	1	CHINA	Yes	Yes	No
A13	30-60	-0.0042	3	Yes	3	Yes	Yes	Yes	93	Yes	4	25	100	0.002	1	GERMANY	Yes	Yes	Yes
A14	30-56	-0.0055	2	No	3	Yes	No	Yes	68	Yes	4	30	100	0.002	1	CHINA	Yes	Yes	Yes
A15	30-62	-0.0065	2	No	5	Yes	Yes	Yes	97	No	4	25	100	0.003	1	CHINA	Yes	Yes	Yes
A16	30-60	-0.0058	3	Yes	5	Yes	No	Yes	88	Yes	4	25	100	0.003	1	GERMANY	Yes	No	No

Table 3

Suppliers and selection criteria, numerical data.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19
A01	45	-0.0041	4	1	1	1	1	1	115	1	4	25	120	0.002	1	5	1	1	1
A02	45	-0.0039	3	1	1	1	1	1	104	1	4	30	100	0.002	1	6	1	1	1
A03	46	-0.0040	3	1	2	1	1	1	125	1	4	30	100	0.003	1	6	1	1	1
A04	45	-0.0042	4	1	1	1	1	1	117	1	4	30	100	0.002	1	4	1	1	1
A05	46	-0.0046	4	0	2	1	1	1	65	1	4	25	110	0.004	1	1	1	1	1
A06	44	-0.0050	2	1	3	1	0	1	84	1	4	25	120	0.003	1	5	1	0	1
A07	44	-0.0071	2	0	5	1	0	1	92	0	4	30	100	0.002	1	1	1	1	1
A08	49	-0.0038	3	1	2	1	1	1	132	1	4	30	100	0.002	1	6	1	1	0
A09	46	-0.0044	3	1	3	1	1	1	106	1	4	25	100	0.002	1	3	1	1	1
A10	45	-0.0032	4	1	3	1	0	1	131	1	4	25	100	0.002	1	6	1	1	0
A11	44	-0.0065	3	1	2	1	1	1	88	1	4	25	80	0.003	1	2	1	1	1
A12	42.5	-0.0068	2	0	4	1	0	1	75	0	4	30	100	0.002	1	1	1	1	0
A13	45	-0.0042	3	1	3	1	1	1	93	1	4	25	100	0.002	1	6	1	1	1
A14	43	-0.0055	2	0	3	1	0	1	68	1	4	30	100	0.002	1	1	1	1	1
A15	46	-0.0065	2	0	5	1	1	1	97	0	4	25	100	0.003	1	1	1	1	1
A16	45	-0.0058	3	1	5	1	0	1	88	1	4	25	100	0.003	1	6	1	0	0

Table 4

Determination of the rank for criterion C1.

Alternative	Criterion 1	Score	Rank
A08	49.0	1	1
A03	46.0	2	3.5
A05	46.0	2	3.5
A09	46.0	2	3.5
A15	46.0	2	3.5
A01	45.0	6	8.5
A02	45.0	6	8.5
A04	45.0	6	8.5
A10	45.0	6	8.5
A13	45.0	6	8.5
A16	45.0	6	8.5
A06	44.0	12	13
A07	44.0	12	13
A11	44.0	12	13
A14	43.0	15	15
A12	42.5	16	16

Table 5

Determination of the rank for criterion C2.

Alternative	Criterion 2	Score	Rank
A01	-0.0041	12	12
A02	-0.0039	14	14
A03	-0.0040	13	13
A04	-0.0042	10	10.5
A05	-0.0046	8	8
A06	-0.0050	7	7
A07	-0.0071	1	1
A08	-0.0038	15	15
A09	-0.0044	9	9
A10	-0.0032	16	16
A11	-0.0065	3	3.5
A12	-0.0068	2	2
A13	-0.0042	10	10.5
A14	-0.0055	6	6
A15	-0.0065	3	3.5
A16	-0.0058	5	5

For criteria evaluated under the consideration that "smaller is better," the score is assigned to the smallest value, and the rank is determined similarly using equation (3). The values are presented in Table 5. After calculating the rank for each criterion, the data is centralized into a table. To complete the decision matrix, the score

is calculated by summing the ranks of the criteria for each row. A value is obtained for each alternative (Table 6). In the RSMVC method, the optimal solution is considered to be the alternative with the smallest score. The final ranking is presented in Table 7 and graphically in Fig. 1

Table 6

Decision matrix for RSMVC method.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	Sum
A01	8.5	12	2.5	6	2	8.5	5.5	8.5	12	7	8.5	12	1.5	5.5	8.5	7.5	8.5	7.5	6.5	138.5
A02	8.5	14	8	6	2	8.5	5.5	8.5	10	7	8.5	4	9.5	5.5	8.5	3.5	8.5	7.5	6.5	140.0
A03	3.5	13	8	6	5.5	8.5	5.5	8.5	14	7	8.5	4	9.5	13	8.5	3.5	8.5	7.5	6.5	149.0
A04	8.5	10.5	2.5	6	2	8.5	5.5	8.5	13	7	8.5	4	9.5	5.5	8.5	9	8.5	7.5	6.5	139.5
A05	3.5	8	2.5	14	5.5	8.5	5.5	8.5	1	7	8.5	12	3	16	8.5	14	8.5	7.5	6.5	148.5
A06	13	7	14	6	10	8.5	13.5	8.5	4	7	8.5	12	1.5	13	8.5	7.5	8.5	15.5	6.5	173.0
A07	13	1	14	14	15	8.5	13.5	8.5	7	15	8.5	4	9.5	5.5	8.5	14	8.5	7.5	6.5	182.0
A08	1	15	8	6	5.5	8.5	5.5	8.5	16	7	8.5	4	9.5	5.5	8.5	3.5	8.5	7.5	14.5	151.0
A09	3.5	9	8	6	10	8.5	5.5	8.5	11	7	8.5	12	9.5	5.5	8.5	10	8.5	7.5	6.5	153.5
A10	8.5	16	2.5	6	10	8.5	13.5	8.5	15	7	8.5	12	9.5	5.5	8.5	3.5	8.5	7.5	14.5	173.5
A11	13	3.5	8	6	5.5	8.5	5.5	8.5	5.5	7	8.5	12	16	13	8.5	11	8.5	7.5	6.5	162.5
A12	16	2	14	14	13	8.5	13.5	8.5	3	15	8.5	4	9.5	5.5	8.5	14	8.5	7.5	14.5	188.0
A13	8.5	10.5	8	6	10	8.5	5.5	8.5	8	7	8.5	12	9.5	5.5	8.5	3.5	8.5	7.5	6.5	150.5
A14	15	6	14	14	10	8.5	13.5	8.5	2	7	8.5	4	9.5	5.5	8.5	14	8.5	7.5	6.5	171.0
A15	3.5	3.5	14	14	15	8.5	5.5	8.5	9	15	8.5	12	9.5	13	8.5	14	8.5	7.5	6.5	184.5
A16	8.5	5	8	6	15	8.5	13.5	8.5	5.5	7	8.5	12	9.5	13	8.5	3.5	8.5	15.5	14.5	179.0

Table 7

Rank of alternative for cutting tools suppliers.

Rank	Alternative	Score
1	A01	138.5
2	A04	139.5
3	A02	140.0
4	A05	148.5
5	A03	149.0
6	A13	150.5
7	A08	151.0
8	A09	153.5
9	A11	162.5
10	A14	171.0
11	A06	173.0
12	A10	173.5
13	A16	179.0
14	A07	182.0
15	A15	184.5
16	A12	188.0

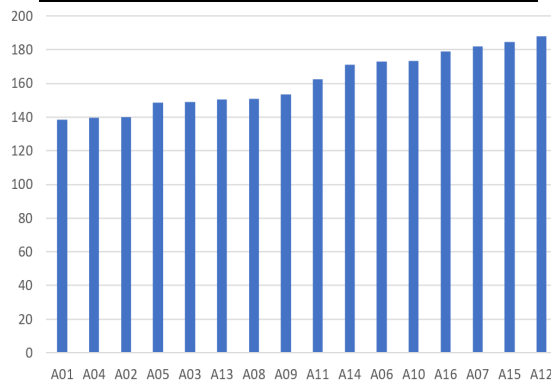


Fig. 1. Ranking the alternatives for cutting tools suppliers

4. SENSITIVITY ANALYSIS

The RSMVC method is based on ranking solutions according to the mean value of the criteria. Each criterion was assigned a weight reflecting its relative importance; in the presented case study, all criteria have equal weights, with their sum equal to 1.

Sensitivity analysis aims to evaluate how changes in the weights of the criteria affect the ranking of the solutions (alternatives). The sensitivity study is applied after completing the calculations and determining the final ranking of the alternatives. For the presented case study, it was proposed that the evaluation be conducted by modifying, in turn, each criterion's weight by $\pm 10\%$ of its initial value. The weight of the first criterion is increased by $+10\%$ of its initial value, and then the weights of the other criteria are adjusted proportionally to ensure that the sum of all weights remains equal to 1.

All necessary calculations are redone, and a new decision matrix is obtained, corresponding to the modified values of the first criterion. The solutions (alternatives) are reordered, and the influence of the modification on the ranking of the alternatives is observed. These steps are repeated for all criteria for each modification. The methodology is labor-intensive and involves a large number of calculations. Following the modifications of both $+10\%$ and $-$

10%, after performing the calculations to determine the scores, it was found that the ranking of each criterion remains unchanged compared to the initial, unmodified version.

Table 8

Values and scores for C2 in the initial and 10% modified versions.

Alternative	Initial		Modified with -10%	
	values	score	values	score
A01	-0.0041	12	-0.00369	12
A02	-0.0039	14	-0.00351	14
A03	-0.0040	13	-0.0036	13
A04	-0.0042	10	-0.00378	10
A05	-0.0046	8	-0.00414	8
A06	-0.0050	7	-0.0045	7
A07	-0.0071	1	-0.00639	1
A08	-0.0038	15	-0.00342	15
A09	-0.0044	9	-0.00396	9
A10	-0.0032	16	-0.00288	16
A11	-0.0065	3	-0.00585	3
A12	-0.0068	2	-0.00612	2
A13	-0.0042	10	-0.00378	10
A14	-0.0055	6	-0.00495	6
A15	-0.0065	3	-0.00585	3
A16	-0.0058	5	-0.00522	5

Table 8 illustrates the score and rank values for criterion C2 in the initial version and modified by -10%. It can be concluded that, within the considered variation range, the method is stable, maintaining the order of the alternatives.

5. CONCLUSION

Cutting tools play an important role in machining molds for injecting plastic products, having a direct impact on the precision and quality of the final products. The correct selection of tool suppliers is a strategic decision that influences the efficiency of the machining process.

The complexity of the selection process is determined by the large number of suppliers and the multitude of technical, economic, and logistical criteria. This requires an analytical and systematic approach to identify the optimal solution.

The RSMVC method is a multi-criteria decision-making (MCDM) method that simplifies the selection process by using the mean values of the criteria, eliminating the need

for data normalization as required in other methods.

The ranking of solutions is based on the scores calculated for each criterion, and the solution with the lowest score is considered optimal.

In the case study, the RSMVC method was used to evaluate 16 suppliers from 6 countries, using 19 criteria. The final ranking identified supplier A01 as the top performer, followed by A04 and A02.

Although it has limitations in handling qualitative criteria, the method demonstrated its ability to manage both quantitative and qualitative criteria by using mean values and numerical codifications for qualitative criteria.

The sensitivity analysis showed that the method is robust, maintaining the ranking of solutions even when the criterion weights were modified by $\pm 10\%$.

For further validation, the same dataset was analyzed using the VIKOR and PROMETHEE II methods, maintaining equal weights. The resulting rankings exhibit a Spearman correlation exceeding 0.9 with RSMVC (RSMVC – VIKOR: $\rho = 0.93$ and RSMVC – PROMETHEE: $\rho = 0.94$), with the top six positions being virtually identical and minor discrepancies observed in the mid-range. This convergence confirms that the proposed method yields results consistent with established MCDM techniques, but with a more streamlined and expedited calculation process.

The supplier ranking generated by the proposed method was benchmarked against the internal ranking of the company's specialists, revealing a strong correspondence, with the top six positions being identical and only minor variations (at most one position) observed for the remaining suppliers. This alignment corroborates the relevance of the selected criteria and the practical applicability of the model.

The stability of the RSMVC method makes it suitable for industrial applications, where decisions need to be robust and resistant to variations in evaluation conditions.

RSMVC's limitations include the requirement for numerical evaluation of criteria and the inherent subjectivity in expert-derived

weights. Future development aims to extend its applicability to other industrial sectors and potentially integrate it with artificial intelligence tools.

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O abordare analitică pentru selectarea furnizorilor de scule aşchietoare folosind metoda RSMVC. Studiu de caz

În industria prelucrării pe maşini-unelte cu comandă numerică (CNC), sculele aşchietoare joacă un rol esenţial în asigurarea calităţii şi optimizarea costurilor de producţie. Numărul mare de furnizori de scule aşchietoare şi criterii de performanţă, face ca procesul de selecţie a furnizorului optim să devină o sarcină complexă. În articol se prezintă o metodă de analiză multicriterială pentru alegerea furnizorilor de scule aşchietoare. Studiul de caz prezentat în articol examinează 16 furnizori şi 19 criterii, folosind metoda RSMVC (Ranking the Solutions based on the Mean Value of Criteria). Această metodă oferă o evaluare amănunţită, luând în considerare sensibilitatea şi robusteţea deciziei.

Flaviu CORB, PhD student, Doctoral School of Engineering Sciences, University of Oradea, Romania, corbflaviu@gmail.com

Caius STĂNĂŞEL, PhD student, Doctoral School of Engineering Sciences, University of Oradea, Romania, caius.stanasel@gmail.com

Iulian STĂNĂŞEL, PhD, Professor, Department of Industrial Engineering, University of Oradea, Romania, stanasel@uoradea.ro