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DEVELOPMENT OF A METHODOLOGY FOR AUTOMATED SELECTION OF CUTTING TOOLS FOR A WEB APPLICATION

In the study, the decision-making methodology for a web application for automated cutting tool and tooling selection is considered. It is proposed that the constraint satisfaction logic method be used to filter the sets of alternatives in the application database, and the multi-criteria decision-making (MCDM) can be used to rank the alternatives further. For evaluation and ranking based on the proposed criteria, it is suggested that MCDM methods, including the weighted sum method (WSM) and the similarity preference ordering technique (TOPSIS) are used. A calculation using the specified methods for five alternatives (sets of cutting tools for mechanical turning) in the MATLAB environment was carried out. Based on the calculation, it was established that for a small sample, the WSM and TOPSIS methods had a similar result, but due to the difference in calculation approaches when the sample (filtered set of alternatives) increases, the result may differ, which makes it advisable to use these methods in parallel.

Keywords: *multi-criteria decision-making (MCDM); web application; constraint logic; automated selection; cutting tool; machining; filtering; ranking.*

Fig.: 6. Tables: 16. References: 21.

Relevance of the research. The cutting tool industry is steadily growing due to the expansion of the automotive, construction, and manufacturing sectors. This, in turn, creates demand both for cutting tools and for simplifying the process of their selection, since the choice of the correct cutting tool significantly impacts both the qualitative and economic factors of machining. One of the major factors influencing the selection process is the human factor (the competencies of a technologist or machine operator). The war and the reduction in the number and quality of personnel lead to decreased competencies and, as a consequence, reduced efficiency in cutting tool selection, which results in economic losses in manufacturing.

Target setting. To reduce the influence of the human factor on tool selection, software for automated tool selection is being increasingly applied. This software makes it possible to decrease the dependence on personnel competencies and significantly simplify the selection process in accordance with machining operations and production needs. Although there are several solutions for automated tool selection available on the market, their significant disadvantages include limited access, the requirement for local installation of the application, and/or a focus only on specific cutting tool manufacturers, which does not allow covering a wider range of cutting tools and equipment.

Actual scientific researches and issues analysis. At present, based on accumulated experience and practices, there exists a set of techniques that form the methodology of cutting tool selection [1, 2]. The methods of tool selection can be divided into manual and automated approaches [1]. In the manual method, technologists or machine operators use manufacturers' catalogs and websites of local or global suppliers of cutting tools, relying on their empirical experience, education, and knowledge. All this, in turn, may reduce the efficiency of selection due to a lack of experience and increase the impact of the human factor, leading to a greater number of non-optimal solutions [1, 3, 4]. A significant advantage of using these systems is relying on existing experience and considering input data about the workpiece in the selection process. In contrast, the drawback is their focus on certain manufacturers only (Sandvik Coromant ToolGuide, Walter GPS, Kennametal NOVO, Iscar IOTA), which significantly narrows the variability and range of cutting tools during selection. In automated applications, various algorithms can be used for decision-making, such as methods based on multi-criteria decision-making (MDCM) [5-7] as well as methods based on artificial intelligence [8].

The multi-criteria decision-making method (MCDM) is widely applied in the foundations of algorithms for automated selection software. For example, Wang et al. used a combination of these MCDM methods as COPRAS-G (Complex Proportional Assessment of alternatives with grey relations), AHP (Analytic Hierarchy Process), and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) in a tool selection application [9].

Some applications are based on constraint logic [1; 10; 11], which does not always provide the possibility of obtaining flexible selection results. Using digital twins in combination with artificial intelligence methods is also possible [1].

Uninvestigated parts of general matters defining. A properly selected combination of the proposed methods can serve as a solid basis for implementing technical solutions in automated tool selection applications to address the identified issues. A relevant solution to the problem of tool selection is the development of a web application, which in turn makes it possible to resolve several technical challenges and reduce the influence of the human factor. This, in turn, creates the need to develop a decision-making methodology for the web application.

The purpose of the article to develop a methodology for decision-making, filtering, and criteria for the selection of cutting tools for a web-based automated tool selection application.

Methods. Considering existing solutions proposed in applications [5-7] and the general application scheme described in the study [1], it is suggested to use the MCDM method. To rationalize the selection process, AHP (Analytic Hierarchy Process) is applied, based on whose weights the alternatives are ranked using WSM (Weighted Sum Model) and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). This makes it possible to implement algorithms for selecting sets of cutting tools (tool–holder–adapter) based on a range of technical parameters and the experience of previous users. The proposed application scheme of the automated program is shown in Fig. 1.

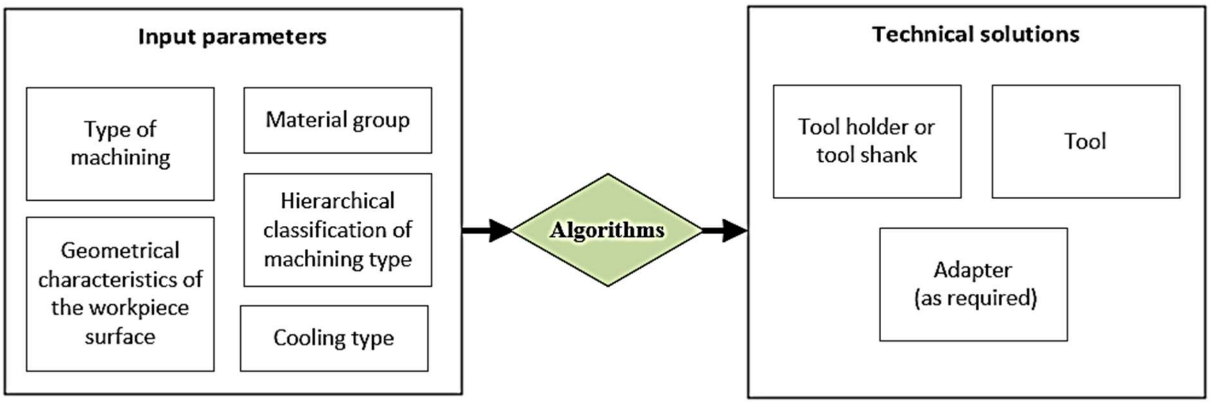

Fig. 1. Schematic diagram of the proposed application

To filter out technically unacceptable options from the electronic catalog (database), it is proposed to use the method of constraint satisfaction logic [12, 13]. (Constraint Satisfaction Problem, CSP). The constraint satisfaction logic method is a formal approach to selecting solutions that satisfy predefined conditions or constraints. This method is actively applied in planning, configuration, optimization, and design tasks.

The primary purpose of applying this method is to eliminate invalid and incompatible options (sets) before evaluating alternatives according to criteria [12].

Before filtering, it is necessary to form a set of alternatives. In the proposed application scheme, the set of alternatives consists of the available combinations (sets) of cutting tools stored in the database, which may include a tool (insert, drill, etc.), a toolholder, and an adapter (if required). At the first selection stage, admissible options are filtered according to the input parameters defined by the user. Among these areas follows: workpiece material (group according to ISO 513 [14]), hierarchical classification of machining type, machining type (roughing, semi-finishing, finishing), geometric characteristics of the machined surface, type of cooling, and machine parameters. These parameters form the context of a specific manufacturing task.

Based on this context, the system generates a set of technically compatible alternatives through filtering (only those tool configurations that satisfy all the defined constraints are admitted). The filtered set of alternatives is then used for multi-criteria analysis. In this way, the formalization of the alternatives makes it possible to significantly reduce the number of options subject to evaluation, ensure compliance with technical requirements, and improve the relevance of the proposed solutions for a specific manufacturing situation. It also enables the identification of only technically and technologically suitable combinations from the total set of possible options, which is essential for further evaluation using AHP, WSM, and TOPSIS.

$$S = \{s_1, s_2, \dots, s_n\} \quad (1)$$

where S – the set combinations of tool equipment [7].

$$S = \{s_i = (T_i, H_i, A_i)\} \quad (2)$$

where T_i – cutting tool, H_i – holder or shank, A_i – adapter (if required).

For further filtering of the sets, the user specifies the required input parameters through the graphical user interface:

Table 1 – Input Parameters

Parameter	Description
M	Material group according to ISO 513
P	Type of machining (roughing, semi-finishing, finishing)
O	Hierarchical classification of machining type (routing in the graphical interface)
G	Geometric characteristics of the machined surface (e.g., radius at the tip for finishing operations, or groove width for grooving tools)
C	Type of cooling (with cooling / without cooling)

After this, the set for filtering using the CSP method [12] is formed:

$$F = \{s_i = (T_i, H_i, A_i) \in S \mid f_{constraints}(s_i; M.P, O, G, C) = 1\} \quad (3)$$

where F – is the admissible (filtered) set,

S – is the set of all possible combinations;

$f_{constraints}$ – is a boolean (1 or 0) function indicating whether the set meets the technical requirements.

If $F = 1$ the combination is admissible; if $F = 0$ it is excluded.

This strict filtering function allows obtaining all tool/holder/adapter combinations s_i that satisfy the task parameters defined by the user and discarding incompatible options. This prevents the comparison of incompatible or impractical solutions during the multi-criteria analysis.

After the admissible set of alternatives is formed, the system proceeds to the stage of constructing the multi-criteria decision-making (MCDM) matrix, which serves as the fundamental tool of the MCDM method. Quantitative values are determined according to the specified criteria for each admissible alternative that has passed the filtering stage. As a result, a matrix is formed where each row represents an alternative and each column represents an evaluation criterion.

Thus, each alternative is represented as a vector that numerically describes its characteristics. The decision matrix functions as a formalization of the input data in the proposed application, aimed at selecting optimal tool combinations (sets) for machining operations. Once the admissible set of alternatives – i.e., combinations of "cutting tool–holder–adapter" – is established, a set of values is assigned for each alternative according to price, user ratings, supplier availability, and previous usage experience. This structure allows the system to evaluate options across multiple dimensions simultaneously and provides the basis for subsequent selection stages [15].

Each alternative s_i is represented as a vector of values according to the criteria [16]:

$$d_i = (d_{i1}, d_{i2}, \dots d_{im}), \tag{4}$$

where $d_{ij} \in \mathbb{R}$ – is the value of alternative s_i for criterion C_j;

m – is the number of criteria.

A vector of indicators is formed for each alternative. Next, all vectors d_{ij} are combined into a decision matrix $D \in \mathbb{R}^{n\times m}$ [16]:

$$D = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1m} \\ d_{21} & d_{22} & \dots & d_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & d_{nm} \end{bmatrix}, \tag{5}$$

where $n -$ is the number of alternatives in the set F.

Each row of the matrix corresponds to one alternative, and each column corresponds to a criterion C_j. Each criterion C_j has its own optimization direction: minimization criteria, where lower values are better (e.g., price), and maximization criteria (e.g., rating).

The decision matrix is normalized to bring different criteria onto a common scale [0,1], enabling comparison. The resulting matrix is the normalized decision matrix [16]:

$$R = \left[r_{ij}\right] \in [0,1]^{n\times m} \tag{6}$$

For each criterion, if higher values are better:

$$r_{ij} = \frac{d_{ij} - \min d_{ij}}{\mathrm{ma} \quad {}_{ij} - \min d_{ij}}. \tag{7}$$

If lower values are better:

$$r_{ij} = \frac{\max d_{ij} - d_{ij}}{\max d_{ij} - \min d_{ij}}. \tag{8}$$

The AHP (Analytic Hierarchy Process) method is used to determine the weights of the criteria used in WSM and TOPSIS [17]. The method is based on constructing a matrix of pairwise criteria comparisons according to the principle of “how much more important is one criterion than another”. As a result of the comparisons, a quantitative vector of weights can be automatically calculated, reflecting the priority of each criterion in the overall model and checking the logical consistency of the provided ratings. The AHP method allows the administrator or web application developer to set a weight vector corresponding to each criterion's importance, per the user's strategy or expectation. For example, if the user needs the option “cheap, but with worse ratings”, the weight of the price coefficient can be increased, and the weight of the rating coefficient can be reduced. This, in turn, allows the system to be adapted in the future to specific options for both the user and the developer. Thomas Saaty developed the Analytic Hierarchy Process (AHP) method to formalize the process of making complex decisions.

First, it is necessary to construct a matrix of pairwise comparisons. For example, if we have n criteria $C_1, C_2, \dots, C_n$ we construct a square matrix $A \in \mathbb{R}^{n\times m}$, where each element a_{jk} means how much criterion j critical than criterion k [7]:

$$A = \left[a_{jk}\right], \tag{9}$$

where a_{jk} – relative preference of criterion j over k.

If $a_{jk} > 1$ – criterion j is more important than criterion k; $a_{jk} < 1$ – criterion j less important than k; $a_{jk} = 1$ – criterion is compared with itself; $a_{kj} = \frac{1}{a_{jk}}$ – reciprocal rule.

Table 2 – Saaty Scale for Criteria [18]

Value	Description
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Absolute importance

For example, if the rating criterion is five times more important than price:

$$a_{rating.price} = 5,\ a_{price,rating} = \frac{1}{5}.$$

The next step is to perform column normalization, which is to scale the elements to a scale that will allow row comparisons. We normalize each component of the matrix a_{jk} by column k [7]:

$$\widetilde{a_{jk}} = \frac{a_{jk}}{\sum_{i=1}^{n} a_{jk}}. \qquad (10)$$

This means that each element is divided by the sum of the corresponding column, i.e., all columns will have a sum = 1. We obtain the normalized matrix $\tilde{A}$.

Now we take the arithmetic mean of each row of the normalized matrix [7]:

$$w_j = \frac{1}{n}\sum_{k=1}^{n} \widetilde{a_{jk}}, \text{ that is } w = (w_1, \dots, w_n). \qquad (11)$$

The weight vector $w = (w_1, \dots, w_n)$ describes the relative importance of each criterion, derived from the expert assessments**.**

We perform a consistency check to ensure that the expert assessments are logical and not contradictory. The matrix product by the weight vector is calculated using the formula [7]:

$$(Aw)_j = \sum_{k=1}^{n} a_{jk} \cdot w_k. \qquad (12)$$

The maximum eigenvalue λ_{max} is calculated [18]:

$$\lambda_{max} = \frac{1}{n}\sum_{j=1}^{n} \frac{(Aw)_j}{w_j}. \qquad (13)$$

The consistency index (CI) is computed as [18]:

$$CI = \frac{\lambda_{max} - n}{n-1}. \qquad (14)$$

The consistency ratio (CR) is defined as [18]:

$$CR = \frac{CI}{RI}, \qquad (15)$$

where RI – random index.

The RI index is chosen according to the Saaty scale [18] and corresponds to the number of criteria *n*.

If $CR < 0.1$ – the matrix is consistent and weights can be used.

After determining the weights, the system evaluates alternatives using the WSM and/or TOPSIS methods. These methods allow ranking to the top of the set table those options that suit the user the most. This will allow the price, rating, availability, and use experience to be considered simultaneously.

Integral evaluation (WSM), Weighted Sum Model, is a weighted sum model, one of the most common decision-making methods by several criteria [19, 20]. In WSM, each alternative is evaluated according to a certain set of criteria, which are assigned weights according to their importance. As a result, a total score is calculated for each option, reflecting the degree of compliance with the specified requirements. As a result, you can get an ordered list of options, where the best one will have the highest overall score. The WSM method is a simple and widely used multi-criteria evaluation method that allows you to calculate the integral score of each alternative based on the normalized values of the criteria and weights obtained by the AHP method.

To calculate this method, we need to have the decision matrix $R = [r_{ij}] \in [0,1]^{n\times m}$ and the weight vector $w = (w_1, \dots, w_n)$ determined by the AHP method. The integral score of each alternative s_i is calculated by the formula [20]:

$$U_i = \sum_{j=1}^{m} w_j \cdot r_{ij}. \tag{16}$$

Or in vector form [20]:

$$U_i = \vec{r_i} \cdot \vec{w}^{\mathrm{T}}, \tag{17}$$

where $\vec{r_i} = (r_{i1}, r_{i2}, \dots, r_{im})$ – normalized vector of alternative s_i;

$\vec{w}$ – vector of criteria weights;

$U_i \in [0,1]$ – integral alternative score.

The obtained value of the integral score U_i always belongs to the interval [0,1], since both the normalized values and the weights lie within [0,1] and the sum of the weights is 1. The value of U_i reflects the overall utility or compliance of the alternative with all criteria, considering their weight. The larger the value of U_i the better the alternative is from the point of view of the given priority structure. This means that this alternative fulfills the requirements for essential criteria well. Options with high U_i, values are considered to be the most consistent with the expectations of the user or system and should be located at the top positions in the final ranking.

After calculating the values of U_i ranking is performed [20]:

$$U_{\pi(1)} \geq U_{\pi(2)} \geq \cdots U_{\pi(n)}, \tag{18}$$

where π – permutation of indices of alternatives;

$U_{\pi(1)}$ – best alternative.

The TOPSIS method (Technique for Order Preference by Similarity to Ideal Solution) is that the optimal solution should be closest to the conditionally best alternative and as far away from the worst possible Each alternative is evaluated based on the distance to these two reference points in the multidimensional space of criteria. The TOPSIS method can be used in cases where the requirements have opposite directions (for example, it is desirable to maximize “quality” and minimize “cost”), which will ensure balanced decision-making. To calculate this method similarly to WSM, we need to have a decision matrix $R = [r_{ij}] \in [0,1]^{n\times m}$ and a weight vector $w = (w_1, \dots, w_n)$ determined by the AHP method.

First, the normalized decision matrix is constructed [21]:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}. \tag{19}$$

Next, the weighted normalized matrix is formed [21]:

$$v_{ij} = w_j \cdot r_{ij}. \tag{20}$$

The ideal and anti-ideal points are then determined [21]:

$$\mathrm{A}^+ = \left\{\max_i v_{ij}\right\}. \qquad A^- = \left\{\min_i v_{ij}\right\}. \tag{21}$$

Subsequently, the distances to the ideal and anti-ideal solutions are calculated [21]:

$$D_i^+ = \sqrt{\sum_{j=1}^{4} (v_{ij} - A_j^+)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^{4} (v_{i=j} - A_j^-)^2}. \tag{22}$$

The index of proximity to ideals is calculated [21]:

$$C_i = \frac{D_i^-}{D_i^- + D_i^+}, \quad C_i \in [0,1]. \tag{23}$$

Results. To verify the proposed methodology, we will calculate the ranking of sets (alternatives) for the transition of turning the external cylindrical surface of a part made of AISI 420 material. The calculation is performed using MATLAB 24 software, and Minitab 17 software is used to visualize the data. The block diagram of the sequence of the selection algorithm described in the methodology is shown in Fig. 2.

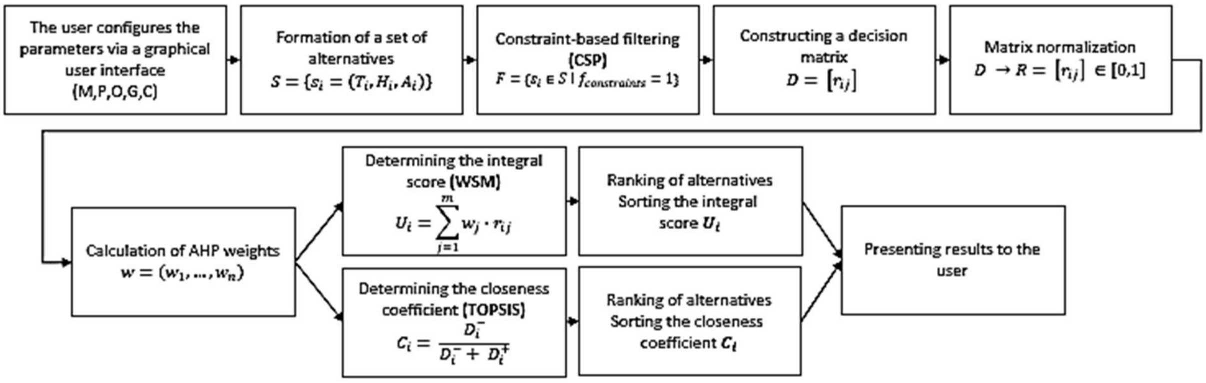

Fig. 2. Proposed methodology for selection algorithms

The input set of alternatives is presented in Table 3. The calculations will be performed for sets of turning tools, including the tool and holder. The tool inserts names in the table according to the international standard ISO 1832. For example, CNMG120408: C – insert shape (80°), N – relief angle of the insert (0°), M – insert tolerance class, G – insert clamping method, 12 – cutting edge length, 04 – insert thickness, 08 – nose radius (0,8 mm).

The holder coding follows ISO 5608. For example, MCLNL2525M12: M – insert clamping method, C – insert shape (80°), L – tool angle (95°), N – insert relief angle (0°), L – cutting direction (left), 2525 – tool height and width (25 × 25 mm), M – tool length (150 mm), 12 – cutting edge length.

Table 3 – Input Set of Alternatives

№	T (Tool)	H (Holder)
A_1	CNMG120408 LF6018 (Cemented carbide insert)	MCLNL2525M12 (left-hand turning tool)
A_2	CNMG120408 LF9018 (Cemented carbide insert)	DCLNL2525M12 (left-hand turning tool)
A_3	CNMG120408 P9125 (Cemented carbide insert)	MCLNL2020K12 (left-hand turning tool)
A_4	CNMG120408 YBC251 (Cemented carbide insert)	MCLNL2525M12 (left-hand turning tool)
A_5	CNMG120408 P8080 (Cemented carbide insert)	DCLNL2525M12 (left-hand turning tool)
A_6	DNMG110404-TM P9125 (Cemented carbide insert)	S20R-MDWNL11 (left-hand **boring** tool)
A_7	16 ER 1.5 ISO (Cemented carbide **threading** insert)	SER2020K16 (right-hand **threading** tool)
A_8	MGMN300 (Cemented carbide **grooving**/cutting insert)	MGHH320R 48/66 T25 (right-hand **grooving**/cutting tool)

The CSP method is applied for further filtering according to the user-defined input parameters. A schematic visualization of the filtering process is shown in Figure 3. The filtering parameters (M, P, O, G, C) are presented in Table 1.

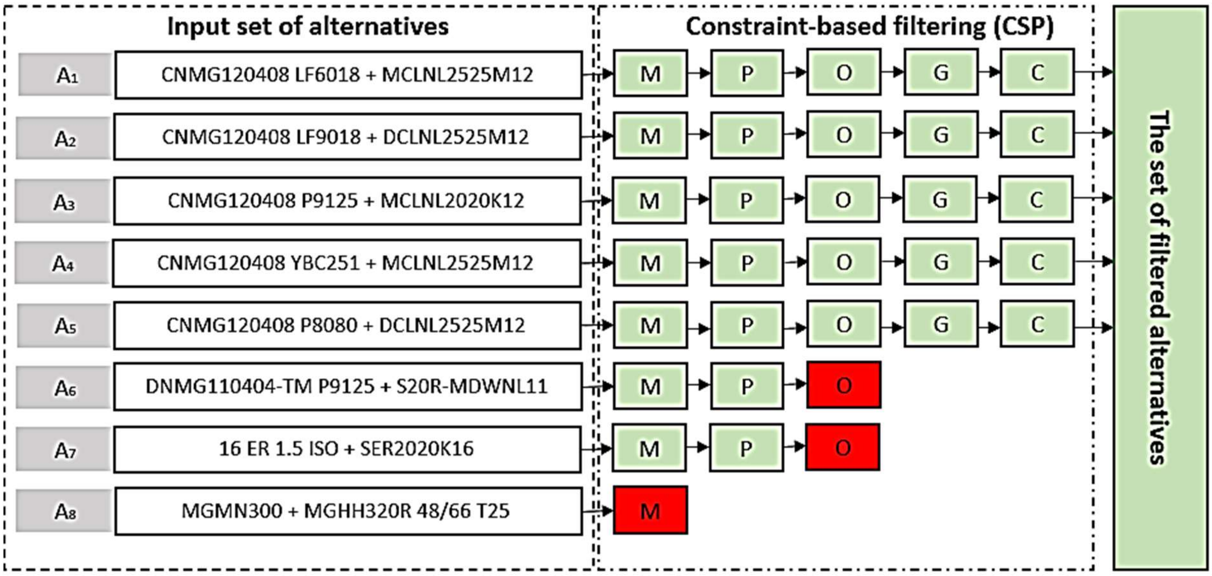

Fig. 3. CSP Filtering Scheme

Five out of eight sets passed the preliminary filtering. Sets A_6-A_8 did not pass the filtering because they do not match the operation type. The holder of set A_6 is unsuitable for external turning operations, nor is set A_7 (threading) or set A_8 for grooving/cutting operations. Additionally, set A_8 is incompatible with the material for which the insert can be applied. The filtered set of alternatives is summarized in Table 4.

Table 4 – Filtered set of alternatives

№	T (Tool)	H (Holder)	Price (T+H), UAH	Availability (1 – yes, 0 – no)	Rating (1-5)	Previous User Experience (1-5)
A_1	CNMG120408 LF6018	MCLNL2525M12	115+650	1	4,8	5
A_2	CNMG120408 LF9018	DCLNL2525M12	95+690	1	4,9	4
A_3	CNMG120408 P9125	MCLNL2020K12	135+480	1	4,5	4
A_4	CNMG120408 YBC251	MCLNL2525M12	190+650	0	3,9	3
A_5	CNMG120408 P8080	DCLNL2525M12	215+690	1	4,3	4

The name and current prices at the time of calculation are taken from the website of the Ukrainian supplier of the tool; the availability, rating, and previous experience are set in random order according to the rating scale in the application (from 1 to 5). The availability is set to 1 or 0 (1 means the item is available, 0 means it is unavailable).

Now it is necessary to determine the evaluation criteria, which criteria need to be maximized, and which, on the contrary, should be minimized. These criteria can be set or changed by the application developer/administrator. Four criteria are proposed: price, availability of the set from the supplier, rating given by all users who have already ordered this set, and previous experience (rating) of the user. We determine the price as the criterion that needs to be minimized, and the availability, rating, and previous experience as the criteria that need to be maximized. This will guarantee the user the best experience with lower prices. We enter the criteria data in Table 5.

Table 5 – Normalization Criteria

№	Criterion	Notation	Type of Criterion
1	Price	C_1	Minimize
2	Availability	C_2	Maximize
3	Rating	C_3	Maximize
4	Previous Experience	C_4	Maximize

The decision matrix $D = [d_{ij}]$ is constructed according to formula 5:

$$D = \begin{bmatrix} 765 & 1 & 4.8 & 5 \\ 785 & 1 & 4.9 & 4 \\ 615 & 1 & 4.5 & 4 \\ 840 & 0 & 3.9 & 3 \\ 905 & 1 & 4.3 & 4 \end{bmatrix}.$$

Rows represent the alternatives (sets) $A_1, A_2 A_3, A_4 A_5$, columns represent the criteria C_1 – price, C_2 – availability, C_3 – rating, C_4 – previous experience.

The next step is to normalize the decision matrix $D \rightarrow R$, The formulas and factors are summarized in Table 6.

Table 6 – Criteria and Normalization Formulas

Criterion	Notation	Type	Normalization Formula
Price	C_1	Cost	$r_{ij} = \dfrac{\max d_{ij} - d_{ij}}{\max d_{ij} - \min d_{ij}}$
Availability	C_2	Benefit	$r_{ij} = \dfrac{d_{ij} - \min d_{ij}}{\max d_{ij} - \min d_{ij}}$
Rating	C_3	Benefit	$r_{ij} = \dfrac{d_{ij} - \min d_{ij}}{\max d_{ij} - \min d_{ij}}$
Experience	C_4	Benefit	$r_{ij} = \dfrac{d_{ij} - \min d_{ij}}{\max d_{ij} - \min d_{ij}}$

To perform normalization, it is necessary to specify the normalization threshold values for each criterion; for this, we take data from the table of alternatives (Table 7). Where min is the minimum value of the criterion, and max is the maximum value.

Table 7 – Normalization Criteria Values

Factor	min	max
Price	615	905
Availability	0	1
Rating	3,9	4,9
Experience	3	5

Next step calculates the results of the normalization $R = [r_{ij}]$ and enter them in Table 8, as a result we obtain the matrix normalized matrix R.

Table 8 – Normalization Calculation

Alternative	C_1	C_2	C_3	C_4
A_1	$\dfrac{905-765}{290} = 0{,}4828$	1	$\dfrac{4{,}8-3{,}9}{1{,}0} = 0{,}9$	$\dfrac{5-3}{2} = 1.0$
A_2	$\dfrac{905-785}{290} = 0{,}4138$	1	$\dfrac{4{,}9-3{,}9}{1{,}0} = 1.0$	$\dfrac{4-3}{2} = 0.5$
A_3	$\dfrac{905-615}{290} = 1$	1	$\dfrac{4{,}5-3{,}9}{1{,}0} = 0{,}6$	$\dfrac{4-3}{2} = 0.5$
A_4	$\dfrac{905-840}{290} = 0{,}2241$	0	$\dfrac{3{,}9-3{,}9}{1{,}0} = 0{,}0$	$\dfrac{3-3}{2} = 0.0$
A_5	$\dfrac{905-905}{290} = 0{,}0000$	1	$\dfrac{4{,}3-3{,}9}{1{,}0} = 0{,}4$	$\dfrac{4-3}{2} = 0.5$

After that, we build a matrix of pairwise comparisons $A = [a_{jk}]$, and manually set the criteria according to the Saaty scale (Table 9). The importance of each criterion can be changed depending on the need, and it provides flexibility in selection.

Table 9 – Pairwise Comparison Matrix

	Price C_1	Availability C_2	Rating C_3	Experience C_4
Price	1	1/3	1/7	1/5
Availability	3	1	1/5	1/3
Rating	7	5	1	3
Experience	5	3	1/5	1

The pairwise comparison matrix a_{jk}, is then normalized, with results summarized in Table 10:

$$\widetilde{a_{jk}} = \frac{a_{jk}}{\sum_{i=1}^{n} a_{jk}}.$$

Table 10 – Normalized Pairwise Comparison Matrix

Criterion	Price C_1	Availability C_2	Rating C_3	Experience C_4	Average w_j
Price	0,0625	0,0357	0,0853	0,0441	0,0569
Availability	0,1875	0,1071	0,1190	0,0730	0,1217
Rating	0,4375	0,5357	0,5968	0,6620	0,5580
Experience	0,3125	0,3214	0,1990	0,2208	0,2634

Let's define the final normalized weight vector of criteria:

$$\vec{w} = (w_{price}, w_{availability}, w_{rating}, w_{experience}) = (0{,}057, 0{,}122, 0{,}558, 0{,}263).$$

Then check for consistency and record the results:

$$(Aw)_1 = 0{,}231\ (Aw)_2 = 0{,}493, (Aw)_3 = 2{,}356, (Aw)_4 = 1{,}100.$$

The next step is to calculate $\frac{(Aw)_j}{w_j}$, the data are summarized in Table 11:

Table 11 – Consistency Check

J	$(Aw)_j$	w_j	$\frac{(Aw)_j}{w_j}$
1	0.231	0.057	4.053
2	0.493	0.122	4.041
3	2.356	0.558	4.221
4	1.100	0.263	4.184

Next, the maximum eigenvalue λ_{max}: is calculated as:

$$\lambda_{max} = \frac{1}{n}\sum_{j=1}^{n}\frac{(Aw)_j}{w_j} = \frac{1}{4}(4{,}063 + 4{,}041 + 4{,}221 + 4{,}184) \approx \frac{16{,}499}{4}.$$

The Consistency Index (CI) is then computed as:

$$CI = \frac{\lambda_{max} - n}{n - 1} = \frac{4{,}125 - 4}{3} \approx 0{,}0417.$$

The Consistency Ratio (CR) is calculated using RI = 0.90, for n = 4, [18]:

$$CR = \frac{CI}{RI} = \frac{0{,}0417}{0{,}90} \approx 0{,}046 < 0{,}1 \Longrightarrow \text{Consistency is acceptable.}$$

Having obtained the necessary data, calculate the Integral Score of each alternative using the WSM (Weighted Sum Model) method. Normalized matrix from previous calculations $R = [r_{ij}]$:

Table 12 – Normalized Decision Matrix

Tool + Holder	Price	Availability	Rating	Experience
CNMG120408 LF6018 + MCLNL2525M12	0,4828	1	0,9	1
CNMG120408 LF9018 + DCLNL2525M12	0,4138	1	1,000	0,5
CNMG120408 P9125 + MCLNL2020K12	1	1	0,6	0,5
CNMG120408 YBC251 + MCLNL2525M12	0,2241	0	0,0	0,0
CNMG120408 P8080 + DCLNL2525M12	0	1	0,4	0,5

Calculate the integral estimate of each set using formula 16:

Table 13 – Integral Scores of Alternatives Using the WSM Method

№	Set	Integral Score U_i
A_1	**CNMG120408 LF6018 + MCLNL2525M12**	**0,9147**
A_2	CNMG120408 LF9018 + DCLNL2525M12	0,8351
A_3	CNMG120408 P9125 + MCLNL2020K12	0,6453
A_5	CNMG120408 P8080 + DCLNL2525M12	0,4767
A_4	CNMG120408 YBC251 + MCLNL2525M12	0,0128

According to the WSM method, the best alternative is set **A_1 (LF6018 + MCLNL2525M12)** with a score of **0.9147**. This set will be displayed first in the application. The ranking of all sets is visualized in the chart (Fig. 4).

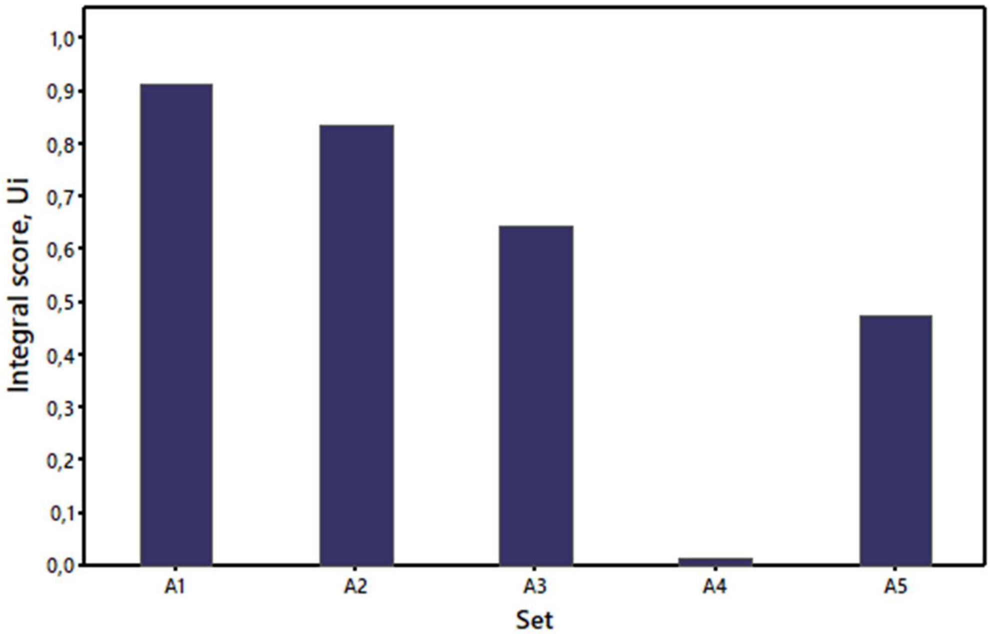

Fig. 4. Integral Scores of WSM Method

Next we'll perform the calculation using the TOPSIS method. This method can be used both alternatively and in parallel with the WSM method. As input data, similarly to the WSM method, we'll use the normalized matrix $R = [r_{ij}]$ and the weight vector:

$$\vec{w} = (0{,}057, 0{,}122, 0{,}558, 0{,}263).$$

Construct the weighted normalized matrix:

$$v_{ij} = w_j \cdot r_{ij}.$$

Table 14 – Weighted Normalized Matrix

№	v_1 Price	v_2 Availability	v_3 Rating	v_4 Experience
A_1	0,0275	0,1220	0,5022	0,2630
A_2	0,0236	0,1220	0,5580	0,1315
A_3	0,0570	0,1220	0,3348	0,1315
A_4	0,0128	0,000	0,0000	0,0000
A_5	0,0000	0,1220	0,2232	0,1315

Let's determine the positive and negative ideal solutions, positive ideal:

$$A^+ = (\max v_1, \max v_2, \max v_3, \max v_{4)} = (0.0570, 0.1220, 0.5580, 0.2630) .$$

Negative ideal:

$$A^- = (min\, v_1, \min v_2, \min v_3, \min v_{4)} = (0.0000, 0.0000, 0.0000, 0.0000) .$$

Let's calculate the distances to the ideals:

$$D_1^+ = \sqrt{(0.0275 - 0.057)^2 + (0.122 - 0.122)^2 + (0.5022 - 0.558)^2 + (0.263 - 0.263)^2} \approx 0.0631$$

$$D_1^- = \sqrt{(0.0275)^2 + (0.122)^2 + (0.5022)^2 + (0.263)^2} \approx 0.5805.$$

The closeness coefficient is computed as:

$$C_1 = \frac{D_1^-}{D_1^- + D_1^+} = \frac{0,5805}{0,0631 + 0,5805} = 0,9019 .$$

Table 15 – Closeness Coefficient

№	Tool + Holder	D_i^+	D_i^-	C_i	Rank
A_1	**CNMG120408 LF6018 + MCLNL2525M12**	**0,0631**	**0,5805**	**0,9019**	**1**
A_2	CNMG120408 LF9018 + DCLNL2525M12	0,1357	0,5866	0,8122	2
A_3	CNMG120408 P9125 + MCLNL2020K12	0,2591	0,3841	0,5972	3
A_5	CNMG120408 P8080 + DCLNL2525M12	0,3642	0,2863	0,4402	4
A_4	CNMG120408 YBC251 + MCLNL2525M12	0,6304	0,0128	0,1999	5

Similar to WSM, the best alternative according to the TOPSIS method is **A_1 (CNMG120408 LF6018 + MCLNL2525M12)** with score **0.9147**. The closeness coefficient for all alternatives is visualized in the graph (Fig. 5).

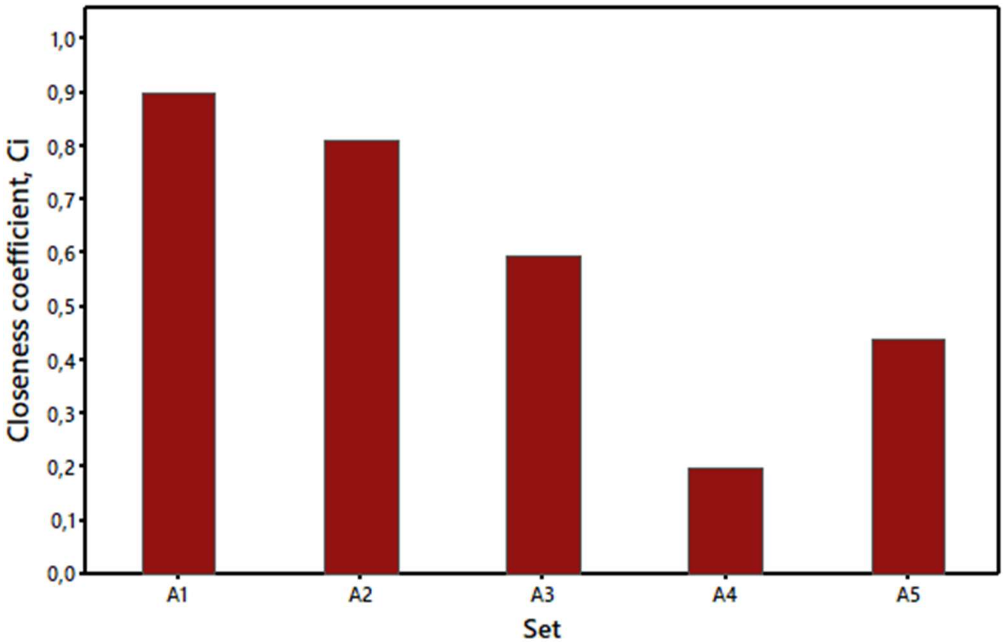

Fig. 5. TOPSIS Closeness Coefficient

Using the calculation results from the WSM and TOPSIS methods, we construct a comparative table of results (Table 16).

Table 16 – Integral Score and Closeness Coefficient

№	Tool + Holder	WSM Integral Score U_i	TOPSIS Closeness Coefficient C_i
A_1	**CNMG120408 LF6018 + MCLNL2525M12**	**0,9147**	**0,9019**
A_2	CNMG120408 LF9018 + DCLNL2525M12	0,8351	0,8122
A_3	CNMG120408 P9125 + MCLNL2020K12	0,6453	0,5972
A_5	CNMG120408 P8080 + DCLNL2525M12	0,4767	0,4402
A_4	CNMG120408 YBC251 + MCLNL2525M12	0,0128	0,1999

It can be seen that both methods ranked the proposed sets equally; the best option for both methods was set A_1, while the worst result was set A_4. A comparison of the scores of both methods is shown in Figure 6.

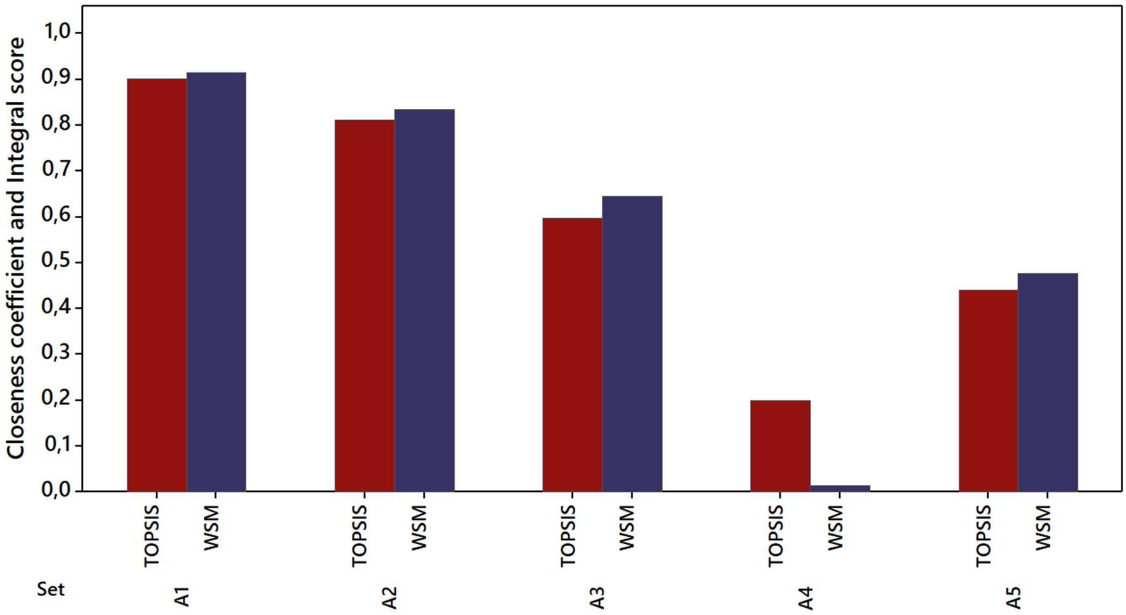

Fig. 6. Comparative chart of Integral Score and Closeness Coefficient

Conclusions. The study revealed that the human factor influences the selection process, and, as a result, incorrect selection of a cutting tool can negatively affect the economic and quality characteristics of the machining process of parts. One of the methods for solving this problem is to automate the selection of the cutting tool. To solve this problem, it is proposed that the methods of multi-criteria decision-making be supplemented to form a methodological basis for creating a web application for automated selection of cutting tools and technological equipment. A calculation was performed to verify the proposed calculation and ranking methodology.

1. To perform the actual selection of a cutting tool and its ranking in the application, it is advisable to use the preliminary method of CSP hard filtering, which will allow forming an actual set of sets of technical solutions for machining in mechanical operations.
2. It is proposed that further ranking of technical solutions using MCDM methods, namely AHP, WSM, and TOPSIS, be performed.
3. The WSM and TOPSIS methods can be used as independent parts of the decision-making algorithm, or in parallel, to obtain a more rational tool (experience-price) in the selection process.

4. The calculation showed that both methods give the same ranking result for a certain sample of sets, but this may change with a significant increase in alternatives. Therefore, it is advisable to use both methods in parallel for a better-quality result.

The current issue is the further implementation of the proposed methods into the technical algorithm of the web application.

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РОЗРОБКА МЕТОДОЛОГІЇ АВТОМАТИЗОВАНОГО ПІДБОРУ РІЖУЧОГО ІНСТРУМЕНТУ ДЛЯ ВЕБЗАСТОСУНКУ

У дослідженні розглянуто методологію ухвалення рішень для вебзастосунку автоматизованого підбору ріжучого інструменту та оснащення. Автоматизований підбір має низку переваг перед ручним підбором ріжучого інструменту технічним персоналом, в тому числі дозволяє знизити вплив людського фактору на процес підбору, що позитивно впливає на технічні та економічні показники процесу механічної обробки. Запропоновано використовувати метод жорсткої логіки обмежень (CSP) для фільтрації множин альтернатив бази даних застосунку, а для подальшого ранжування альтернатив використовувати метод багатокритеріального прийняття рішень (MCDM) та методику побудови ваг AHP. Для оцінки та ранжування інструменту або оснащення на основі визначених критеріїв запропоновано використовувати такі методики MCDM, як метод зваженої суми (WSM) для визначення інтегральної суми та техніку впорядкування переваг за схожістю (TOPSIS) для визначення коефіцієнтів близькості. Описано схему використання запропонованих методів у застосунку. Проведено розрахунок на основі зазначених методів для п'яти альтернатив (сетів ріжучого інструменту для процесу механічної токарної обробки) в середовищі MATLAB. Результатами розрахунку визначено, що для невеликої вибірки методи WSM та TOPSIS мали схожий результат, але через відмінність підходів обчислення при збільшенні вибірки (фільтрованої множини альтернатив) результат може відрізнятися, що робить доцільним застосування цих методів паралельно. Актуальним питанням є подальше впровадження запропонованої методології при розробці вебзастосунку для автоматизованого підбору ріжучого інструменту та оснащення.

Ключові слова: *метод багатокритеріального прийняття рішень; вебзастосунок; логіка обмежень; автоматизований підбір; ріжучий інструмент; обробка різанням; фільтрація; ранжування.*
Рис.: 6. Табл.: 16. Бібл.: 21.

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