Developing an algorithm for decision support process*

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Abstract
The complexity of decision-making stems from the fact that conducting an exact analysis of a situation prior to making a decision is often impossible or extremely difficult. Given the large number of decisions that must be made, individuals frequently face a dilemma: to act on incomplete information or risk missing the appropriate time to decide. Decision-making situations arise both in everyday life and in managerial activities involving complex systems of interdependencies, such as organizations and information systems. Many researchers note that managerial decisions require consideration not only of the overall goal but also of the objectives of the participants involved in the process. The multiplicity of goals emphasizes the need to examine the decision-making process across multiple levels.Therefore, there is a need to develop a systematic approach to implementing decision-support processes. Decision-making situations of this type primarily involve multiple criteria and a variety of possible alternatives. Managerial problems are distinguished by the considerable flexibility of their parameters and by the highly variable relationships between criterion values and their resulting outcomes. Several characteristics of these decision-making problems explain why methods of mathematical optimization cannot be effectively applied to them. The first important aspect of such situations is the unpredictable influence of the external environment on the implementation process. This creates the crucial need to account for uncertainty in the decision-support process, highlighting the necessity of adaptability and flexibility in decision-making. Another significant difficulty in decision analysis lies in the presence of imprecise and sometimes purely verbal descriptions of many parameters. Under such conditions, adequate support requires the development of new approaches that apply computational methods based on the modelling of continuous and subjective phenomena. Information that is not explicitly expressed in the form of decision-making criteria often emerges from the context of the situation and is difficult to model or incorporate into multicriteria computational methods. Nevertheless, these contextual factors are taken into account when evaluating the outcomes, particularly during the implementation of the recommended scenario. This is because even a simple adaptation of the decision-making process to external social, political, or technical conditions, which are of significant importance, can significantly influence the quality of the multicriteria selection process. Therefore, there is a need to develop a formalized approach to constructing a decision-support algorithm for distributed environments. Such an approach should apply to complex decision-making situations, explicitly incorporating the environmental elements that influence the implicit specifics of each situation.

Keywords
decision-making process, support algorithm, preference relations, criterion aggregation, system user interface, knowledge base, data mining [1]

1. Introduction

The first task necessary for implementing the decision-support process is to create a description of the decision-making situation. The information provided by the decision-maker must supply this description, defining as precisely and reliably as possible the features of reality relevant to the decision problem. These features of reality represent the characteristics of the analyzed objects, events, or phenomena, as well as the decision-maker's expectations regarding the outcomes of the

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chosen alternative [1, 2]. The use of mathematical methods for decision support requires that the decision-making situation be described by treating each criterion as an independent dimension. A continuous description of a decision-making situation characterized by n criteria is represented as a set of information C, defined by the following formula:

$$C = C_1, C_2, \ldots, C_n \tag{1}$$

where $C_i, i=1,2,\ldots,n$ - a subset that defines the i-th criterion of the decision-making situation.

The decision-making problem is characterized by an a priori unknown set of alternative options. Therefore, when constructing a model under conditions where the set of possible decisions is unknown, the symbol $\widetilde{A}$ is used to denote a "hypothetical set of decision alternatives". Conversely, to describe mathematical operations performed on the quantities representing known decision alternatives, the notation *A* is used to denote the set of considered decision options [3, 4].

The information describing a criterion reflects the relationship between the value of a decision alternative for the attribute corresponding to that criterion and the degree of preference assigned to that alternative [5, 6]. This relationship can be either absolute (the strength of preference for an attribute depends only on its values) or relative (a relational model expressing mutual preferences between decision alternatives) [6, 8]. Thus, the informational resource for criterion C_i is defined as the set:

$$C_i = \{ g_i(\widetilde{A}), D_i(A) \} \tag{2}$$

where $g_i(\widetilde{A})$ - a preference-strength function, whose argument is the value of the attribute described by criterion *C* for a given decision alternative, and $D_i(A)$ - the domain of admissible values of decision alternatives for criterion *C*.

2. Analysis of recent research and publications

Today, decision-making methods must account for multiple criteria and significant information uncertainty [7]. Among the most widely used and actively studied approaches are fuzzy logic methods, the Analytic Hierarchy Process (AHP), the Analytic Network Process (ANP), as well as the ELECTRE, PROMETHEE, and TOPSIS methods, together with their numerous modifications designed for operation under conditions of fuzziness and risk.

In studies on fuzzy logic, particularly in the seminal work of Zadeh (1965) and subsequent research by his followers, the importance of applying fuzzy sets to model decision-making under uncertainty is emphasized. Fuzzy logic enables the incorporation of imprecise or incomplete information when criteria cannot be clearly measured or classified, and it integrates subjective expert judgments into the decision-making process.

The analytic hierarchy process (AHP), proposed by Saaty in the 1970s, is one of the most widely used decision-making approaches. It enables researchers to construct a hierarchical structure of the problem and assign weights to each criterion, reflecting their relative importance in the decision-making process.

Other approaches, such as the ELECTRE and PROMETHEE methods, were developed to address situations where criteria conflict and not all decision alternatives can be clearly classified as strictly the best or the worst [8, 9]. These methods compare each pair of alternatives, allowing researchers to more accurately evaluate the advantages of each option under conditions of uncertainty and subjective judgment.

A limitation of the PROMETHEE method is the absence of criterion compensation and the lack of clearly defined priorities in the decision-making problem. The method also does not guide in determining the weights of the criteria [10].

The ranking nature of the ELECTRE methods, in particular the majority rule that determines the preference of alternatives when a coalition supports an option and no strong opposition exists, makes these methods unsuitable for evaluating individual products. However, researchers do use ELECTRE methods to assess improvements in decision-making processes [11].

TOPSIS methods, which focus on selecting the alternative closest to the ideal solution, have also become widespread in decision-making research [12]. Various modifications of this method enable researchers to apply it to situations involving imprecise information, thereby allowing them to model real decision-making processes more accurately.

It is important to note that methods based on pairwise comparisons of alternatives are sensitive to the addition of new alternatives. Because the alternatives are interdependent, introducing a new option into the set can alter the evaluation of their relationships.

Studies that focus on selecting an appropriate method for a specific problem also play an important role. Researchers in this area emphasize that no universal approach to multicriteria decision-making exists [13] because applying different methods to the same problem typically produces different results.

3. Main part

3.1. Formal description of the decision-making process

The decision-making process includes a set of categories that encompass the values influencing the entire process [14, 15]. The following formula represents the set of decision-making process metadata defined in this way:

$$\Phi=\{W,P,Q,V,U,K\} \tag{3}$$

where the values of vectors $P=\{p_1,p_2,\dots,p_n\}$ and $Q=\{q_1,q_2,\dots,q_n\}$ define the conditions for supporting relations *P* and *Q*, respectively, and are referred to as the preference threshold *p* and the indifference threshold *q*. The set $W=\{W_1,W_2,\dots,W_n\}$ contains the values or subsets of values W_i, which define the absolute and relative importance of criterion C_i, respectively.

In the case of relative weights, the values of the subset $W_i=\{w_{i1},w_{i2},\dots,w_{¿}\}$ are determined using the Saaty scale, whereas for a single-element subset $W_i=\{w_i\}$ the value may be either crisp or fuzzy depending on the specification. The set $U=\{u_1,u_2,\dots,u_n\}$ represents the utility functions for the attributes corresponding to each criterion C_i. The set $V=\{v_1,v_2,\dots,v_n\}$ contains veto values, which define the rejection criterion for a decision alternative due to a significant difference in the value of a single criterion [16, 17]. Finally, K - denotes the description of the decision domain, which serves as the basis for selecting the appropriate method according to practical applications.

In view of the above, the decision-making problem can be represented as an ordered quadratic equation [18, 19]:

$$(C,\Phi,\widetilde{A},\Psi) \tag{4}$$

where C is the set of criteria; Φ is the set of process metadata (context); $\widetilde{A}$ is the set of potential decision alternatives; and Ψ is the set of methods used to solve the problem.

The objective is to select the alternative that best corresponds to the established preferences according to the given set of criteria [20]. Therefore, the resolution of the decision-making situation is considered as a problem of maximizing the result of the transformation *F*, which determines the degree of satisfaction of the specified criteria:

$$G(a_p)=max\,F(C(A),\Phi) \tag{5}$$

where a_p is the most desirable decision alternative selected from the set of options A; $G(a_p)$ represents the effectiveness of alternative a_p (as an assessment of the satisfaction of the group of criteria C); and the set Φ denotes the collection of characteristics - the metadata of the decision-making situation [21].

3.2. Formulation of the selection problem based on the description of the decision-making situation

The interaction stage with the decision-maker is critically important for ensuring the high quality of recommendations obtained as a result of the decision-support process.

The iterative process of gathering expectations, illustrated in Figure 1, is used as a set of guidelines for designing the user interface of the decision-support system.

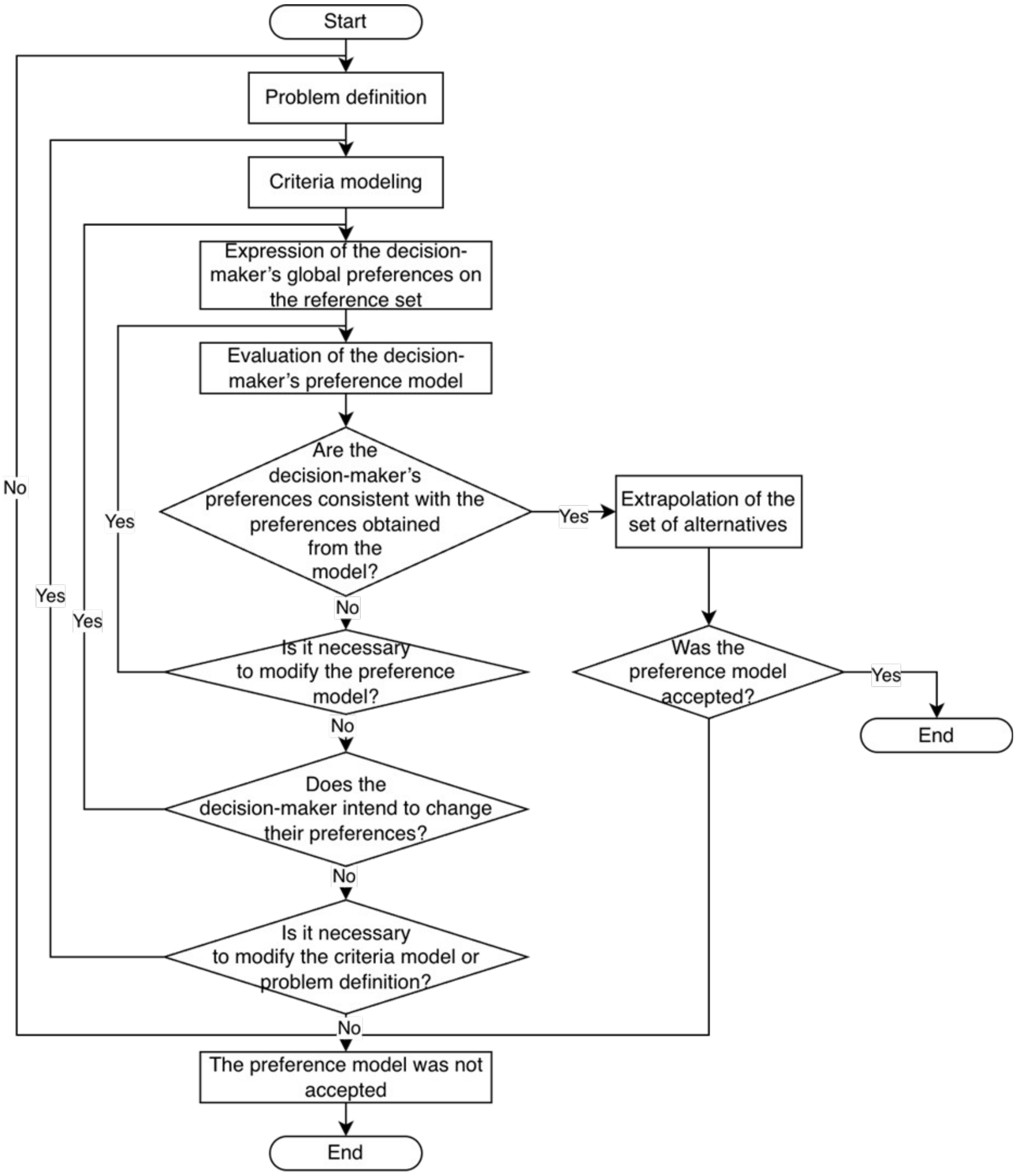

Figure 1. Diagram of the decision-making process based on disaggregation.

The following algorithmic steps were adopted to support decision-making through an expert-based approach:

- Expert evaluation: experts select linguistic assessments, define the corresponding fuzzy sets, and evaluate the alternatives.
- Synthesis of individual expert evaluations: expert assessments for each alternative are aggregated.
- Decision-making: the final choice is made based on the synthesized expert evaluations of all alternatives.

The above stages of the decision-making process depend on the outcomes of the preceding steps. Based on these dependencies, the execution flow of the algorithm was defined, as illustrated in Figure 2.

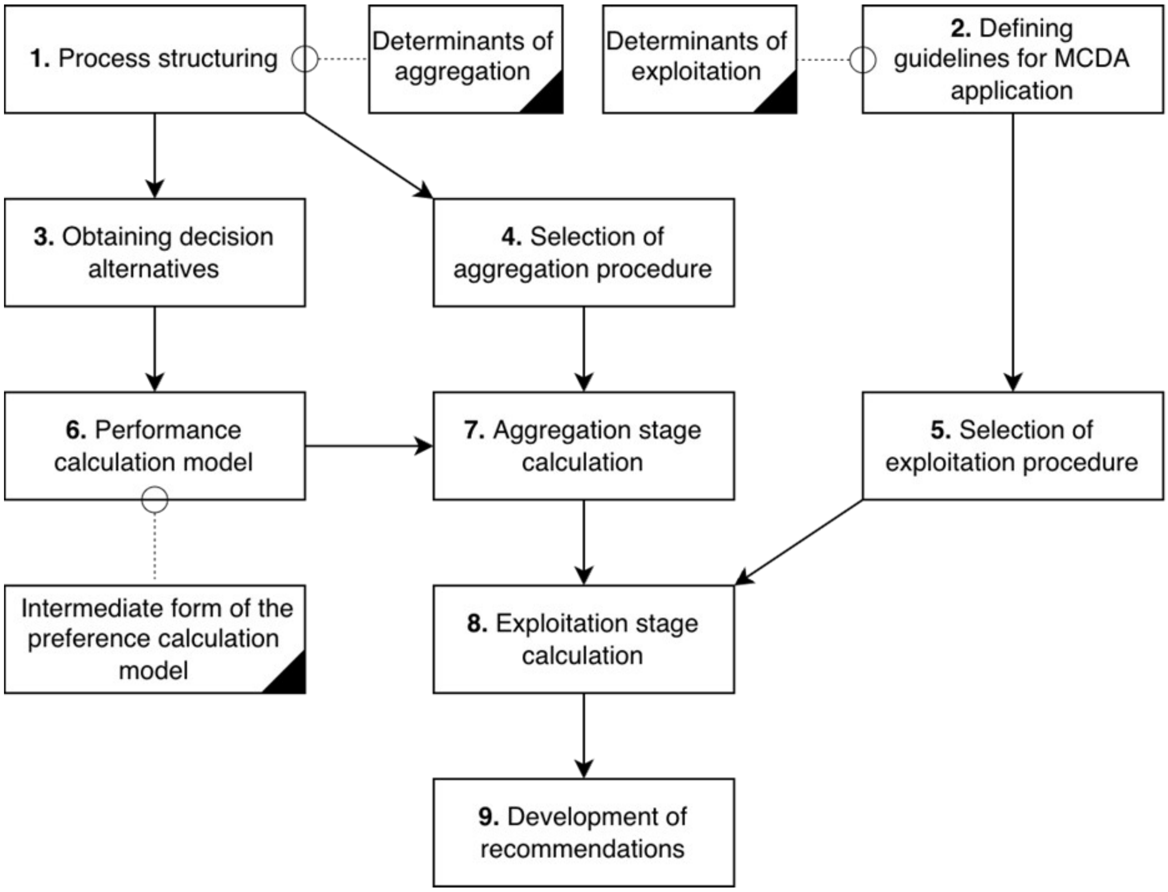

Figure 2. Structure of the developed decision-support algorithm.

The selection process algorithm shown in Figure 2 performs the following transformations:

1. construction of the set C,
2. construction of the set Φ,
3. creation of the set A,
4. selection of the aggregating component of the transformation F,
5. selection of the operational component of the transformation F,
6. determination of the effectiveness value G (decision matrix),
7. computation of the aggregate component max F,
8. execution of calculations for the operational component of the transformation max F,
9. assignment of the resulting decision a_p.

The result of the first stage is the structure of the decision-making problem, represented by formula (1), where each element of the set C is defined according to formula (2). In the second stage, these values are analysed to determine inter-criteria relationships. Based on the obtained data, the set Φ is constructed. The third stage involves obtaining descriptions of decision alternatives, based on which the set of considered alternatives A is defined [21]. In the fourth stage of the algorithm, the characteristics of the problem description are compared with the knowledge base of method selection, and, based on this comparison, a multicriteria aggregation procedure is chosen from the implemented set (a decision is made regarding the aggregating component of the transformation *F*). The next stage is similar to the fourth and involves selecting the procedure for operating the global preference system obtained during the aggregation stage. The sixth stage includes calculating the effectiveness value $g_i(a_i)$ for each criterion and each considered decision alternative, based on which the effectiveness table G is constructed. The following stage applies the aggregation F-transformation to the effectiveness table G obtained in the previous step and constructs a global preference relation system, which is then transformed to determine the final ranking. The last (final) stage is the selection of the optimal alternative.

4. Data analysis methods for the selection process

The next stage in developing the knowledge base involves identifying the rules that determine the application of a chosen method to specific classes of decision-making situations. Due to the nominal nature of the parameters that describe the selection criteria for solving the given problem, the most appropriate analytical approaches are data mining methods [21].

To analyse data related to the application of multicriteria methods, SAS Enterprise Miner was chosen because of its extensive data analysis capabilities and its scripting language, which enables the automation of tasks associated with detecting and verifying relationships for various configurations of input data.

Decision tree induction was performed using the χ^2 test method, the entropy minimization method, and the reduction method. The SAS Enterprise Miner software includes an integrated decision tree induction algorithm that enables tree construction based on various parameters, such as the significance level, the number of child nodes per branch, and the splitting criteria.

Decision tree induction using the χ^2 statistical criterion involves performing statistical tests for successive splits. For a given significance level, it is necessary to find such a partition where the rejection of the null hypothesis receives the strongest support [22, 23].

The expected outcome of the expert knowledge analysis is to determine the influence of individual factors on the suitability of a multicriteria method for a given decision-making situation within the context of the examined reality. The process of building the knowledge base is illustrated in Figure 3.

4.1. Defining criteria in the decision-making problem

The decision-making problem is defined as a task of maximizing the specified efficiency functions in accordance with the selected transformation *F*:

$$maxF\left(g_1, g_2, \ldots, g_n\right) \tag{6}$$

The construction of criterion functions leads to determining the effectiveness of a given decision weight in relation to a specified attribute, based on the criterion assigned to that attribute. The function g accounts for the preference of attribute values and the differences in their respective scales, so that the decision table contains the effectiveness values *g*, rather than the direct attribute values of the decision alternatives. The general form of the function g is represented by the following equation:

$$g_i(a_j) = \sum_{\gamma=1}^{k} \alpha_\gamma a_{ji}^{\gamma} + \beta,$$

$$g_i(a_j) = \alpha a_{ji}^{\gamma} + \beta \tag{7}$$
$$g_i(a_j) = \log_{\gamma} \alpha a_{ji} + \beta$$

where $g_i(a_j)$ is the effectiveness value of criterion g for decision alternative a_j, and a_{ji} is the attribute value of alternative a_i. Thus, it is assumed that $g_i(a_j)$ is equivalent to $g_i(a_{ji})$. The form of the function is chosen from the presented set of forms, while the support factors are selected based on specific constraints regarding the magnitude and direction of preference.

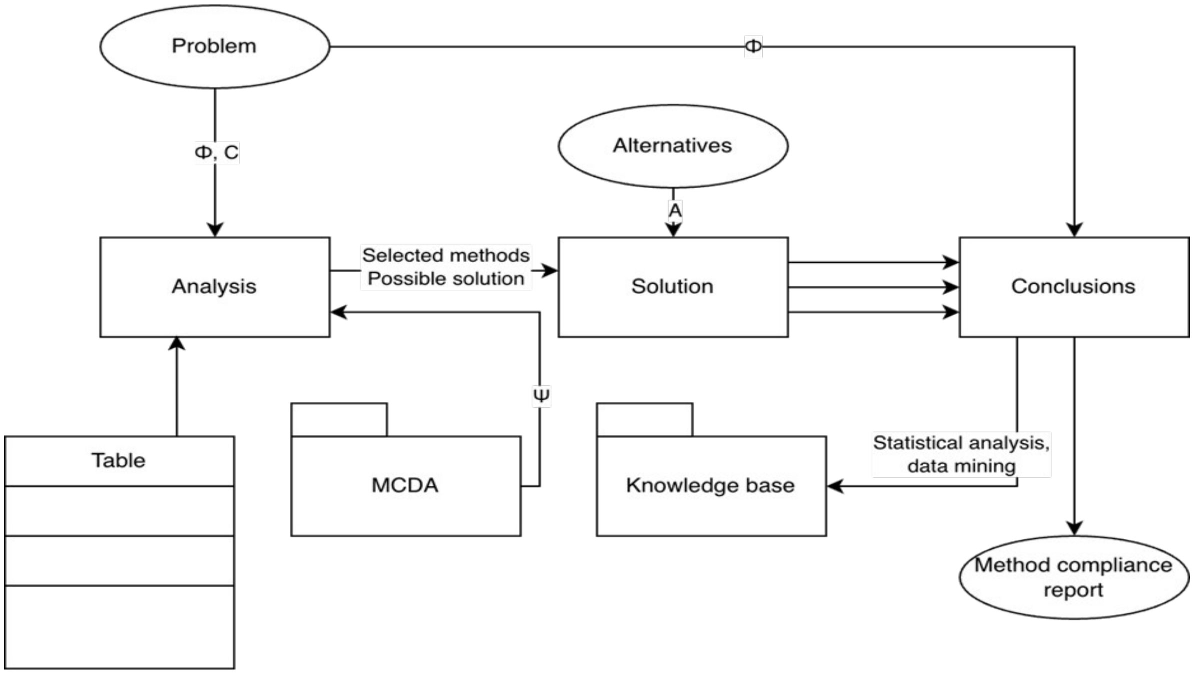

Figure 3. Diagram of the knowledge base construction process.

The main objective of the algorithm is to consider only acceptable decision alternatives, meaning those whose attribute values fall within the range defined for the corresponding criteria. Only alternatives that satisfy these requirements are included in the set of considered options A. This approach results in an increased effectiveness value:

$$a_j \in A \Rightarrow \forall_{g \in G} a_{ji} \in D \tag{8}$$

The application of preference constraints aims to determine normalization criteria a priori based on predefined boundary values and the decision-maker's preferences regarding the direction of value changes. An unrestricted domain of attribute values makes normalization impossible and thus complicates the use of methods based on utility function calculations.

During the analysis of how preference constraints affect the decision-support process, it was found that existing models fail to reflect the natural human tendency to adjust constraints when parameters take on very favorable values. This limitation was addressed by introducing into the model the concept of low-preference constraints for both profit and cost criteria. A 10% threshold of "outstanding" preferences is adopted, representing values that increase toward $+\infty$ (for the profit criterion) or decrease toward $-\infty$ (for the cost criterion).

The use of a limited preference domain makes it possible to ensure a constrained search space (for methods based on preference relations) and a bounded domain for defining the ideal solution (for methods based on aggregating criteria into a single distance criterion). As a result, specifying a limited preference domain for methods based on pairwise comparisons (the European school) leads to a restriction of the comparison domain.

The descriptions of decision alternatives obtained from the distributed search space are processed according to a predefined scheme. Calculations using the proposed algorithm are performed for m decision alternatives $a_1, a_2, \dots, a_m \in \widetilde{A}$ found within the search space $\widetilde{A}$. Obtaining descriptions that make it possible to determine the attribute values defined for all criteria from the set C leads to the construction of a complete set of decision alternatives, which serves as the input data for the decision-making process.

The resulting set A is then used to construct the decision matrix:

Table 1
Decision Matrix

A, G	g_1	g_2	$\cdots$	g_n
a_1	$g_1(a_1)$	$g_2(a_1)$	$\cdots$	$g_n(a_1)$
a_2	$g_1(a_2)$	$g_2(a_2)$	$\cdots$	$g_n(a_2)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
a_m	$g_1(a_m)$	$g_2(a_m)$	$\cdots$	$g_n(a_m)$

The effectiveness matrix G serves as the argument of the transformation F, which indicates the optimal decision alternative. As a result of obtaining the sets C and A, the contents of the set G are computed. Subsequently, descriptions representing the values of the set Φ are derived, enabling the determination of the best decision in the form of equation (5).

5. Results and discussion

Based on the developed method, the authors examined the problem of selecting a printing machine for a printing enterprise. This case involves choosing real equipment based on its technical characteristics. A set of subjective and linguistic criteria describes the decision-making situation. It represents a specific case in which a known object is selected from a set of alternatives, while its future behaviour in the technological process remains uncertain.

A distinctive feature of this decision-making situation is the limited precision of the available information, both in the selection of criteria and in the values assigned to them.

As shown in Figure 1, the study applied the fuzzy TOPSIS method, which is recommended for solving object selection problems.

In this case, a relatively small amount of data was used to construct the rule base shown in Figure 3, enabling the capture and formalization of the specific knowledge required for the selection process.

6. Conclusions

The task of the multicriteria method is to determine, based on the matrix presented above, a relationship that makes it possible to establish a preferential situation among decision alternatives.

These relationships extend the traditional approach to decision support by incorporating the notions of strong preference and incomparability. The existence of such relations is characteristic of certain types of decision-making situations.

The decision-making process is equivalent to the situations described in the literature. Therefore, this approach can be extended to other multicriteria methods and real-world domains to encompass decision-making situations that are not directly addressed by the proposed algorithm. It should be noted that certain categories of decision-making situations may already be well represented in the literature or in existing data sets. In such cases, it is advisable to consider the independent construction of a knowledge base with the involvement of domain experts.

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Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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