

# Multi-Criteria Decision-Making with Linguistic Labels

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**Abstract**—This paper proposes an approach that is suitable for solving multi-criteria decision-making problems characterized by fuzzy (subjective) criteria. A finite set (universe) of alternatives will be expressed as a decision table that represents a fuzzy information system in which every fuzzy criterion is connected with a set of its linguistic values. We apply subjective preference degrees for linguistic values that should be provided by a decision-maker. To simplify the process of decision-making in big data environments, an additional stage will be introduced that can produce a smaller set of alternatives represented by fuzzy linguistic labels of similarity classes. We select a small set of similarity classes for the final ranking. A measure of compatibility will be defined that should express the accordance of a selected alternative with preferences given for the linguistic values of a particular fuzzy criterion.

## I. INTRODUCTION

**M**ULTI-CRITERIA decision-making is a very important task that has to be performed in various areas of human activity, especially in technique, industry, economy, business, and in everyday life. Depending on the number of considered criteria and the size of the solution space (number of alternatives), the process of determining the best alternative can be problematic, therefore, only small-sized and relative simple decision-making tasks can be effectively solved by humans. Moreover, as a general rule, there is no accordance in monotonicity between particular criteria, i.e., one obtains different rankings of alternatives for each criterion, hence a compromise solution should be determined. In recent decades, several approaches were proposed for solving multi-criteria decision-making problems, e.g., AHP, TOPSIS, VIKOR, PROMETHE, and ELECTRE [1]. In the case of very large solution spaces, for example when dealing with the combinatorial optimization problems, metaheuristic approaches such as simulated annealing, swarm optimization, and genetic algorithms can be applied.

Another issue, often encountered in practical optimization tasks, is uncertainty and vagueness in the characteristic of evaluated alternatives. Standard optimization methods only base on classic knowledge representation by utilizing deterministic objective functions and constraints, crisp set theory, and bi-valued logic. In order to take vagueness and subjectivity into account, many decision-making and optimization algorithms have been extended or combined with various soft computing methods in the form of hybrid approaches.

The fuzzy set theory has proved to be one of the most successful paradigms for dealing with problems that are vague in nature and require the use of linguistic terms or subjective evaluation. This makes it possible to use notions such as “quite large” or “very young”. Linguistic values expressed as fuzzy sets were widely applied and adopted by many researchers, who introduced several generalization, e.g., intuitionistic, type-2, hesitant fuzzy sets, and hybrid fuzzy-rough set models [2], [3].

Because in many decision-making algorithms a fuzzy representation of knowledge could be successfully implemented [4], [5], popular multi-criteria optimization algorithms have also been extended to deal with fuzzy terms instead of crisp numbers [6], [7].

In our previous work [8], we introduced the concept of fuzzy linguistic label that can be utilized in the framework of fuzzy or fuzzy-rough decision systems. The principle of the label-based approach consists in a simplified way of comparing and classifying the elements of a universe that are described with fuzzy attributes. Such an approach can be helpful in analysis of complex information systems that have large number of attributes and fuzzy linguistic values. The obtained results strongly depend on the used fuzzy operators and they may be not easy to interpret. This is why the label-based approach does not use standard fuzzy relation for determining classes of similar elements (alternatives) of the universe. Instead, by finding positive (dominant) linguistic values of attributes (criteria), a common description of similar objects can be easily obtained in the form of fuzzy linguistic labels.

In the current work, we propose a label-based approach to multi-criteria decision-making. We introduce several new ideas. First, we extend the requirements imposed on the membership degree of elements in linguistic values of attributes in the information system. This can be helpful in the process of preparing a consistent high-quality decision table by an expert. As only two neighbouring linguistic values of criteria can be activated, the decision table can be given in a compact form. Secondly, we propose a method of finding the best alternatives in the case of subjective fuzzy criteria. We define compatibility measure that can be used to evaluate the accordance of alternatives with the subjective preferences for linguistic values that are required by a decision-maker. Furthermore, the approach consists of two stages. This can be useful when the process of decision-making is performed

in a big-data environment. We avoid detailed evaluation of each alternative in a huge solution space. Instead, the best linguistic labels can be easily discovered at the first stage. The final solution can then be obtained by examining only a small number of the promising similarity classes of alternatives connected with the selected linguistic labels.

## II. FUZZY DECISION SYSTEMS

To formalize the process of multi-criteria decision-making in a fuzzy environment, we should use the notion of fuzzy information system [9] that is expressed as a 4-tuple

$$\text{FDS} = \langle U, A, \mathbb{V}, f \rangle, \quad (1)$$

where:

$U$  – is a nonempty set (universe) of elements (alternatives),

$A$  – is a finite set of fuzzy attributes (criteria),

$\mathbb{V}$  – is a set of linguistic values of criteria,  $\mathbb{V} = \bigcup_{a \in A} \mathbb{V}_a$ ,  
 $\mathbb{V}_a$  is the set of linguistic values of a criterion  $a \in A$ ,

$f$  – is an information function,  $f : U \times \mathbb{V} \rightarrow [0, 1]$ ,  
 $f(x, V) \in [0, 1]$ , for all  $x \in U$ , and  $V \in \mathbb{V}$ .

Any fuzzy criterion  $a_i \in A$ , where  $i = 1, 2, \dots, n$ , can take value from the family of its linguistic values denoted by  $\mathbb{A}_i = \{A_{i1}, A_{i2}, \dots, A_{in_i}\}$ . For all elements  $x \in U$ , the membership degree in the linguistic values of all fuzzy criteria will be assigned by experts. We require the following conditions to be satisfied, when the membership is assigned:

$$\begin{aligned} \exists A_{ik} \in \mathbb{A}_i \quad & (\mu_{A_{ik}}(x) \geq 0.5, \\ & \mu_{A_{ik-1}}(x) = 1 - \mu_{A_{ik}}(x) \vee \\ & \mu_{A_{ik+1}}(x) = 1 - \mu_{A_{ik}}(x)), \end{aligned} \quad (2)$$

$$\text{power}(\mathbb{A}_i(x)) = \sum_{k=1}^{n_i} \mu_{A_{ik}}(x) = 1. \quad (3)$$

The requirements (2), and (3) constitute a generalization of the properties that can be observed in crisp information systems. They are necessary for creating well-defined and consistent information systems.

Every information system can be represented by a decision table in which the rows correspond to the elements of the universe  $U$ , and the columns to the linguistic values of criteria. Due to the requirement (2), we would obtain a large sparse decision matrix, when the number of criteria and the number of their linguistic values is large. Therefore, it is more convenient to introduce a compact form of a decision table that only contains the information about the dominant linguistic values, which satisfy the requirement (2), for every element of the universe  $U$ .

Membership degree of any element  $x \in U$ , in the dominant  $k$ -th linguistic value of a selected fuzzy criterion  $a_i \in A$ , will be expressed in the following form

$$\mu_{A_{ik}}(x)(\text{neighbour})/A_{ik} \quad (4)$$

where:

$\text{neighbour} = L$  indicates a nonzero membership degree in the neighbouring left linguistic value, with  $\mu_{A_{ik-1}}(x) = 1 - \mu_{A_{ik}}(x)$ ,

$\text{neighbour} = R$  indicates a nonzero membership degree in the neighbouring right linguistic value, with  $\mu_{A_{ik+1}}(x) = 1 - \mu_{A_{ik}}(x)$ ,

$\text{neighbour} = C$  indicates no membership in the right and left neighbouring linguistic values.

The introduced concepts are used in an illustrative example in Section V.

## III. LINGUISTIC LABELS

The elements of a given universe of discourse can be compared to each other by using a binary relation for determining the degree of their similarity. In the standard rough set theory [10], a crisp indiscernibility relation is utilized that generates a partition of the universe into classes of elements that cannot be discerned, because they have the same value of (selected) attributes. Comparison of elements in a fuzzy model can be done in different ways, because various fuzzy operators can be used to determine the similarity of elements [2]. Another difficulty arises in analysis of big information systems that have not only large number of elements, but also many fuzzy attributes and linguistic values. In consequence, one can obtain a vast number of similarity classes, which complicates the calculations and, above all, makes it difficult to interpret the results. This issue was an inspiration for proposing a straightforward method of classifying the elements of fuzzy decision systems [8].

The principle of this approach consists in finding classes of characteristic elements of the universe that have the same description given in the form of tuple of dominant linguistic values of attributes. According to the requirement (2), for every element of the universe  $U$ , and every attribute  $a \in A$ , a distinct linguistic value can be found for which the membership degree has the greatest value. Hence, we do not apply a standard fuzzy similarity relation, but only identify dominant linguistic values in all rows of the decision table. This way we can easily discover the groups of (characteristic) elements that have the same dominant linguistic values of all attributes.

A tuple of dominant linguistic values of attributes is called a linguistic label. We can say that the characteristic elements of a linguistic label belong to the same similarity class. The degrees of membership in the dominant linguistic values are in a general case different numbers from the interval  $[0.5, 1]$  for every element of the similarity class. However, we can also introduce an ideal element with the membership degree equal to 1 for all dominant linguistic values. Such ideal elements can be seen as an abstract representation of the linguistic labels.

By using linguistic labels, one is able to imitate the process of classifying objects that can be observed in human experts. Instead of performing an exhaustive comparison for every pair of elements of the universe, they rather try to discover a limited subset of ideal elements having a common characteristic.

Now, let us recall the basic notions of the label-based approach. The characteristic elements of the universe will be determined directly from the decision table, by respecting their membership in the linguistic values of all fuzzy attributes. Since the dominance of a linguistic value is a matter of the membership degree, we need to use a threshold of similarity, denoted by  $\beta$ , which satisfies the inequality

$$0.5 < \beta \leq 1. \quad (5)$$

A suitable value of the parameter  $\beta$  should be chosen as the threshold of similarity for classifying linguistic values of attributes.

Given a fuzzy information system FDS, we define [8] for any element  $x \in U$ , and any fuzzy attribute  $a \in A$ : the set  $\widehat{\mathbb{V}}_a(x) \subseteq \mathbb{V}_a$  of positive linguistic values

$$\widehat{\mathbb{V}}_a(x) = \{V \in \mathbb{V}_a : f(x, V) \geq \beta\}, \quad (6)$$

the set  $\overline{\mathbb{V}}_a(x) \subseteq \mathbb{V}_a$  of boundary linguistic values

$$\overline{\mathbb{V}}_a(x) = \{V \in \mathbb{V}_a : 0.5 \leq f(x, V) < \beta\}, \quad (7)$$

and the set  $\check{\mathbb{V}}_a(x) \subseteq \mathbb{V}_a$  of negative linguistic values

$$\check{\mathbb{V}}_a(x) = \{V \in \mathbb{V}_a : 0 \leq f(x, V) < 0.5\}. \quad (8)$$

Due to the constraints (2) and (3), the sets  $\widehat{\mathbb{V}}_a(x)$ ,  $\overline{\mathbb{V}}_a(x)$ , and  $\check{\mathbb{V}}_a(x)$  have the following properties [8]:

- (P1)  $\text{card}(\widehat{\mathbb{V}}_a(x)) \leq 1$ ,
- (P2)  $\text{card}(\overline{\mathbb{V}}_a(x)) \leq 2$ ,
- (P3)  $\text{card}(\check{\mathbb{V}}_a(x)) < |\mathbb{V}_a|$ .

Every element  $x \in U$  can be described with a combination of those linguistic values that are positive for that particular element. In this way, we determine the linguistic labels for all elements of the universe.

Formally, the set of linguistic labels  $\widehat{\mathbb{L}}(x)$  is equal to the Cartesian product of the sets of positive linguistic values  $\widehat{\mathbb{V}}_a(x)$ , for all  $a \in A$ :

$$\widehat{\mathbb{L}}(x) = \prod_{a \in A} \widehat{\mathbb{V}}_a(x). \quad (9)$$

When inspecting the decision table, we can also discover elements  $x \in U$  which have a common linguistic label  $L(x)$ .

By  $X_L$ , we denote the subset of the elements  $x \in U$  that correspond to a linguistic label  $L \in \mathbb{L}$ , for all fuzzy attributes  $a \in A$ :

$$X_L = \{x \in U : L(x) = L\}. \quad (10)$$

The subset  $X_L$  is called the set of characteristic elements of the linguistic label  $L$ .

A linguistic label  $L \in \mathbb{L}$  can be represented by an ordered tuple of positive linguistic values, for all attributes  $a \in A$ :

$$L = \left( \widehat{V}_{a_1}^L, \widehat{V}_{a_2}^L, \dots, \widehat{V}_{a_n}^L \right). \quad (11)$$

In the present paper, the notion of an attribute denotes a criterion, and an element of the universe is called an alternative.

#### IV. LABEL-BASED EVALUATION OF ALTERNATIVES

We divide the process of searching for the best alternatives into two stages. First, all rows of the decision table have to be inspected for determining the linguistic labels which are present in the information system.

##### A. Stage I

At the first stage, every linguistic label will be evaluated by determining its accordance with the preferences for linguistic values provided by a decision-maker. We also take into account the weights of criteria. The decision-maker should give the vector of weights  $W = [w_1, w_2, \dots, w_n]$ , which usually satisfy the requirement:  $\sum_{i=1}^n w_i = 1$ .

Let us denote by  $pref(V)$  the preference for the linguistic value  $V \in \mathbb{V}$ . The compatibility of a linguistic label with the preferences for linguistic values of criteria can be presented in a detailed manner as a fuzzy set  $C_L$  on the domain of positive linguistic values of the label  $L$

$$C_L = \{pref(\widehat{V}_{a_1}^L)/\widehat{V}_{a_1}^L, pref(\widehat{V}_{a_2}^L)/\widehat{V}_{a_2}^L, \dots, pref(\widehat{V}_{a_n}^L)/\widehat{V}_{a_n}^L\}. \quad (12)$$

Now, we define the measure of weighted compatibility of the linguistic label  $L$  with the preferences of the decision-maker as follows

$$compat(L) = \sum_{i=1}^n w_i \cdot pref(\widehat{V}_{a_i}^L). \quad (13)$$

where  $\widehat{V}_{a_i}^L$  denotes the positive linguistic value of the criterion  $a_i$  in the linguistic label  $L$ , as given in the formula (11).

By applying the measure (13), a ranking of all linguistic labels can be determined. Basing on the ranking of the linguistic labels, we can select a group of the best linguistic labels and their characteristic elements as the promising candidates for generating the set of the best alternatives.

##### B. Stage II

At the second stage, evaluation of alternatives from the classes of characteristic elements of the selected linguistic labels is performed. The analyzed alternatives are represented in the form (4).

We define the measure of the weighted compatibility of an alternative  $x \in U$  with the preferences for the linguistic values of attributes as follows

$$compat(x) = \sum_{i=1}^n w_i \cdot pref(V(x, i)) \cdot \mu_{V(x, i)}(x) + \sum_{i=1}^n w_i \cdot pref(N(x, i)) \cdot \mu_{N(x, i)}(x), \quad (14)$$

where:

$V(x, i)$  – is the positive linguistic value of the criterion  $a_i$  in the linguistic label  $L(x)$ ,  $V(x, i) = \widehat{V}_{a_i}^L(x)$ ,

$N(x, i)$  – is the neighbouring linguistic value of  $a_i$  in the linguistic label  $L(x)$ ,  $\mu_{N(x, i)}(x) = 1 - \mu_{V(x, i)}(x)$ .

The measure (14) will be used to generate a set of the best alternatives.

## V. EXAMPLE

Let us consider a fuzzy information system that includes alternatives:  $x_1, x_2, \dots, x_{15}$ . There are three fuzzy criteria:  $c_1, c_2$ , and  $c_3$ . The criteria  $c_1$  and  $c_3$  can take three linguistic values, whereas the criterion  $c_2$  five linguistic values.

We assume that the decision regarding the degree of membership of every alternative in the linguistic values of all fuzzy criteria was made taking into account the requirements (2) and (3). The fuzzy information system was prepared in a compact form (Table I), according to the formula (4).

TABLE I  
COMPACT DECISION TABLE

	$a_1$	$a_2$	$a_3$
$x_1$	0.8(L)/ $A_{12}$	0.7(L)/ $A_{23}$	0.7(L)/ $A_{33}$
$x_2$	0.8(L)/ $A_{12}$	0.7(L)/ $A_{24}$	0.8(L)/ $A_{32}$
$x_3$	0.8(R)/ $A_{12}$	0.7(R)/ $A_{22}$	0.8(L)/ $A_{32}$
$x_4$	0.8(R)/ $A_{12}$	0.7(R)/ $A_{23}$	0.7(L)/ $A_{33}$
$x_5$	0.8(R)/ $A_{12}$	0.7(R)/ $A_{24}$	0.8(R)/ $A_{32}$
$x_6$	0.8(L)/ $A_{12}$	0.7(L)/ $A_{22}$	0.8(R)/ $A_{32}$
$x_7$	0.8(L)/ $A_{12}$	0.7(R)/ $A_{23}$	0.7(L)/ $A_{33}$
$x_8$	0.7(R)/ $A_{11}$	0.7(L)/ $A_{23}$	0.6(L)/ $A_{33}$
$x_9$	0.7(L)/ $A_{13}$	0.8(L)/ $A_{23}$	0.7(L)/ $A_{33}$
$x_{10}$	0.7(L)/ $A_{13}$	0.8(R)/ $A_{23}$	0.7(L)/ $A_{33}$
$x_{11}$	0.8(L)/ $A_{13}$	0.8(L)/ $A_{25}$	0.7(L)/ $A_{32}$
$x_{12}$	0.8(R)/ $A_{12}$	0.7(L)/ $A_{23}$	0.7(L)/ $A_{33}$
$x_{13}$	0.8(L)/ $A_{13}$	0.8(L)/ $A_{25}$	0.7(R)/ $A_{32}$
$x_{14}$	0.8(R)/ $A_{11}$	0.7(R)/ $A_{23}$	0.8(L)/ $A_{33}$
$x_{15}$	0.8(R)/ $A_{11}$	0.7(R)/ $A_{21}$	1.0(C)/ $A_{33}$

We also present the full decision table (Table II) with emphasized values of membership degree for the linguistic values which are dominant.

To assess mainly the influence of preferences of linguistic values, we can take the same weight for every criterion by using the following vector of weights:  $W = [0.33, 0.33, 0.34]$ . The preferences for the linguistic values of all criteria are given in Table III.

By inspecting the decision table, we obtain the following linguistic labels with their characteristic elements:

$$\begin{aligned}
 L_1 &= (A_{12}A_{23}A_{33}) : X_{L_1} = \{x_1, x_4, x_7, x_{12}\}, \\
 L_2 &= (A_{11}A_{23}A_{33}) : X_{L_2} = \{x_8, x_{14}\}, \\
 L_3 &= (A_{12}A_{24}A_{32}) : X_{L_3} = \{x_2, x_5\}, \\
 L_4 &= (A_{12}A_{22}A_{32}) : X_{L_4} = \{x_3, x_6\}, \\
 L_5 &= (A_{13}A_{23}A_{33}) : X_{L_5} = \{x_9, x_{10}\}, \\
 L_6 &= (A_{13}A_{25}A_{32}) : X_{L_6} = \{x_{11}, x_{13}\}, \\
 L_7 &= (A_{11}A_{21}A_{33}) : X_{L_7} = \{x_{15}\}.
 \end{aligned}$$

### A. Stage I

For all obtained linguistic labels, we determine the sets representing the compatibility with the preferences of the

decision-maker, according to the formula (12)

$$\begin{aligned}
 C_{L_1} &= \{0.50/A_{12}, 1.00/A_{23}, 1.00/A_{33}\}, \\
 C_{L_2} &= \{1.00/A_{11}, 1.00/A_{23}, 1.00/A_{33}\}, \\
 C_{L_3} &= \{0.50/A_{12}, 0.75/A_{24}, 0.50/A_{32}\}, \\
 C_{L_4} &= \{0.50/A_{12}, 0.50/A_{22}, 0.50/A_{32}\}, \\
 C_{L_5} &= \{0.25/A_{13}, 1.00/A_{23}, 1.00/A_{33}\}, \\
 C_{L_6} &= \{0.25/A_{13}, 0.25/A_{25}, 0.50/A_{32}\}, \\
 C_{L_7} &= \{1.00/A_{11}, 0.00/A_{21}, 1.00/A_{33}\}.
 \end{aligned}$$

Next, we determine the weighted compatibility of all linguistic labels according to the formula (13). The obtained ranking of the linguistic labels is included in Table IV.

### B. Stage II

Those similarity classes of the linguistic labels that have the greatest compatibility with the preferences for linguistic values of criteria will be selected for a detailed analysis of their alternatives. In a real-world application with a huge number of alternatives, the worst similarity classes would be discarded from further consideration. In our small example, all linguistic labels are taken into account for determining the ranking of all alternatives.

We demonstrate the evaluation of the alternative  $x_8$  that is a characteristic element of the linguistic label  $L_2$ . From Table I, we take the entry 0.7(R)/ $A_{11}$  expressing the fuzzy value of  $x_8$  for the criterion  $a_1$ . The alternative has a membership degree in the positive linguistic value  $A_{11}$  equal to 0.7, hence we have  $V(x_8, 1)(x_8) = A_{11}$ , and  $\mu_{V(x_8, 1)}(x_8) = 0.7$ . There is also a nonzero membership in the right neighbouring linguistic value  $A_{12}$ , that is,  $N(x_8, 1)(x_8) = A_{12}$ , and  $\mu_{N(x_8, 1)}(x_8) = 1 - 0.7 = 0.3$ .

By the same way, the terms for the attributes  $a_2$  and  $a_3$  can be obtained. Therefore, according to the formula (14), the value  $compat(x_8)$  is equal to:

$$\begin{aligned}
 &w_1 \cdot (pref(A_{11}) \cdot \mu_{A_{11}}(x_8) + pref(A_{12}) \cdot \mu_{A_{12}}(x_8)) + \\
 &w_2 \cdot (pref(A_{23}) \cdot \mu_{A_{23}}(x_8) + pref(A_{22}) \cdot \mu_{A_{22}}(x_8)) + \\
 &w_3 \cdot (pref(A_{33}) \cdot \mu_{A_{33}}(x_8) + pref(A_{32}) \cdot \mu_{A_{32}}(x_8)) = 0.833
 \end{aligned}$$

The results obtained for all alternatives are presented in Table IV. We get the following ordering of alternatives:  $x_{14}, x_8, x_7, x_1, x_4, x_{12}, x_{10}, x_9, x_2, x_5, x_6, x_3, x_{13}, x_{11}$ . As we can see, the alternatives which are characteristic elements of the best linguistic labels have a high degree of compatibility with the preferences of the decision-maker.

## VI. CONCLUSIONS

Linguistic labels can be effectively used in analysis of fuzzy information systems, including multi-criteria optimization tasks. The concept of fuzzy linguistic label was inspired by observation of the decision-making activity performed by human experts. The label-based approach presented in this paper takes into account subjective preferences for linguistic values of fuzzy criteria given by a decision-maker. The proposed method can be applied especially in big-data environments, because it avoids a detailed evaluation of every alternative in a huge solution space. At the first stage, we

TABLE II  
FULL DECISION TABLE (FRAGMENT)

	$a_1$			$a_2$					$a_3$		
	$A_{11}$	$A_{12}$	$A_{13}$	$A_{21}$	$A_{22}$	$A_{23}$	$A_{24}$	$A_{25}$	$A_{31}$	$A_{32}$	$A_{33}$
$x_1$	0.2	<b>0.8</b>	0.0	0.0	0.3	<b>0.7</b>	0.0	0.0	0.0	0.3	<b>0.7</b>
$x_2$	0.2	<b>0.8</b>	0.0	0.0	0.0	0.3	<b>0.7</b>	0.0	0.2	<b>0.8</b>	0.0
...	...	...	...	...	...	...	...	...	...	...	...
$x_{15}$	<b>0.8</b>	0.2	0.0	<b>0.7</b>	0.3	0.0	0.0	0.0	0.0	0.0	<b>1.0</b>

TABLE III  
DEGREES OF PREFERENCE FOR THE LINGUISTIC VALUES OF CRITERIA

$A_{11}$	$a_1$		$a_2$					$a_3$		
	$A_{12}$	$A_{13}$	$A_{21}$	$A_{22}$	$A_{23}$	$A_{24}$	$A_{25}$	$A_{31}$	$A_{32}$	$A_{33}$
1.00	0.50	0.25	0.00	0.50	1.00	0.75	0.25	0.00	0.50	1.00

TABLE IV  
WEIGHTED COMPATIBILITIES OF LINGUISTIC LABELS AND ALTERNATIVES

Position of label	Label	Weighted compatibility of label	Alternative	Weighted compatibility of alternative	Order of alternatives
1	$L_2$	1.00	$x_8$ $x_{14}$	0.833 0.908	$x_{14}, x_8$
2	$L_1$	0.83	$x_1$ $x_4$ $x_7$ $x_{12}$	0.767 0.742 0.792 0.717	$x_7, x_1, x_4, x_{12}$
3	$L_5$	0.75	$x_9$ $x_{10}$	0.692 0.708	$x_{10}, x_9$
4	$L_7$	0.67	$x_{15}$	0.683	$x_{15}$
5	$L_3$	0.58	$x_2$ $x_5$	0.558 0.550	$x_2, x_5$
6	$L_4$	0.50	$x_3$ $x_6$	0.500 0.517	$x_6, x_3$
7	$L_6$	0.33	$x_{11}$ $x_{13}$	0.333 0.433	$x_{13}, x_{11}$

evaluate only the linguistic labels, which represent classes of similar alternatives. Only a small number of the promising similarity classes of alternatives are selected for a detailed evaluation of alternatives at the second stage. Implementation of the presented method is simple, and obtained results can be easily interpreted. In future work, we plan extend the proposed method to apply both subjective linguistic and objective numerical criteria.

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