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Managing Group Decision Making criteria values using Fuzzy Ontologies

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Abstract

Most of the available Multi-criteria Group Decision Making methods that deal with a high number of elements usually focus on managing scenarios that have high number of alternatives and/or experts. Nevertheless, there are also cases in which the number of criteria values is difficult for the experts to tackle. In this paper, a novel Group Decision Making method that employs Fuzzy Ontologies in order to deal with a high number of criteria values is presented. Our method allows the criteria values to be combined in order to generate a reduced set of criteria values that the experts can comfortably deal with.

Keywords: Fuzzy Ontologies, Multi-criteria Group Decision Making, linguistic modelling, clustering

1. Introduction

Multi-criteria Group Decision Making is a field that is quite present in the recent literature. They are valuable methods that can be applied to different fields such as architecture [1, 2], manufactoring [3, 4], marketing [5] and artificial intelligence [6, 7].
Traditional Multi-criteria Group Decision Making methods were designed in order to assist a set of experts that have to discuss about how to rank a set of alternatives taking into account an specific set of criteria. They assumed that the experts can manually handle and discuss all the elements of the decisions. These traditional methods focused on organizing the decision process in different steps, retrieving information from the experts, measuring consensus and calculating the ranking.
With the spread of Internet and the appearance of Web 2.0 technologies [8], experts have access to a high amount of information. Therefore, it cannot be assumed that the experts can handle the decision information by themselves. Therefore, there is a need of Group Decision Making methods that are capable of dealing with a high amount of

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data in an organized way. In order to achieve this goal, the large-scale Group Decision Making area appeared. Methods that cover this field mainly cover cases where there are a high number of experts [9, 10] and/or a high number of alternatives [11, 12]. Nevertheless, there are also scenarios where the experts must deal with a high number of criteria. That is, alternatives can be analyzed from a high number of different perspectives. In recent literature, it is not possible to find Group Decision Making methods that deal with this type of environments. However, given the large amount of information available on the Internet on any given item, this is one of the most common cases. Therefore, a novel Group Decision Making method that deals with this type of environments is needed.

One common way of dealing with a high number of elements is by classifying them into Fuzzy Ontologies. A Fuzzy Ontology is an hierarchical description that allow the representation of a set of individuals described by a set of concepts. In previous research, fuzzy ontologies have proven to be a very useful tool in representing and handling the imprecise information that is typical of Group Decision Making methods [13, 14]. By the use of queries, it is possible to retrieve information that fulfill certain characteristics. Thanks to fuzzy ontologies, it is possible to sort high amounts of information and allow the experts to comfortably deal with the stored information. Therefore, this is an interesting tool to use for large-scale scenarios.

In this paper, Fuzzy Ontologies are used in order to design a novel Multi-criteria Group Decision Making method that is capable of dealing with decision scenarios that have a high amount of criteria values. The proposed method creates a reduced set of criteria by combining all the available possibilities. The way that criteria should be combined is made by employing clustering methods over the experts' suggestions. Similar specific criteria values are combined in order to generate general criteria. Thanks to these grouping process, experts can carry out the decision process in a comfortable way by using the generic criteria in order to provide their preferences to the system.

The rest of the paper is organized as follows. In section 2, basis needed to comprehend the proposed methods are exposed. In section 3, the proposed method is detailed. Section 4 provides an use case example shown for a better understanding of the process. Finally, some conclusions are pointed out.

2. Preliminaries

2.1. Basis of Multi-criteria Group Decision Making

A multi-criteria group decision making problem can be define as follows [15, 16]:

Definition 1: Let $E = \{e_1, \ldots, e_n\}$ be a set of experts. Let $X = \{x_1, \ldots, x_m\}$ be a set the set of alternatives. Experts must rank the set of alternatives according to the way that they think that they fulfil a set of criteria $C = \{c_1, \ldots, c_l$ that are available for all the experts.

The set of criteria values allows the experts to focus on the important aspects of the alternatives avoiding the debate to move to unimportant or irrelevant aspects of the alternatives. A Multi-criteria Group Decision Making process can be solved following the next steps:

- **Providing preferences to the system**: Experts provide their preferences to the system. For this purpose, they can employ preference relations. That is, for each pair of alternatives, x_i and x_j they can provide a p_{ij} value indicating how much they prefer x_i over x_j. This preference value can be provided by taking into account all the criteria or, on the contrary, it is possible to provide a separate p_{ij}^k where expert indicates his/her preference for each c_k only [13].
- **Calculating the collective preference value**: The preferences of the experts are aggregated into a single collective preference matrix that contains the overall opinion of all the experts.
- **Measuring consensus** [17, 18]: When carrying out a decision process, it is important to allow experts to dialogue and help them to bring their opinions closer in order to reach a common solution. Consensus measures have an important role in this scheme. After the experts have provided their preferences, it is possible to calculate how close are their opinions. If they all think similarly, then it is possible to calculate the final ranking of alternatives. On the contrary, if there are disagreement among them, it is possible to allow them to debate and provide their preferences again.
- **Determining the final ranking of alternatives**: Once that the experts' consensus is high enough or if too many time has passed and experts have not brought their opinions closer, the final ranking of alternatives is

calculated. By applying a selection process [19, 20], the final ranking of alternatives is calculated by using the collective preference matrix.

2.2. Basis of Fuzzy Ontologies

Fuzzy Ontologies [21] are an interesting tool that is capable of organizing high amount of information in an organized way. It has queries that users can employ in order to retrieve information that fulfil certain characteristics. Formally, a fuzzy ontology can defined as a quintuple $< I, C, R, F, A >$ [14, 22] where:

- I: **Set of individuals**. The elements that wants to be stored and described by the Fuzzy Ontology.
- C. **Set of concepts**. They refer to descriptions and characteristics of the individuals store in the Fuzzy Ontology.
- R: **Relations**. They relate two individuals or an individual and a concept. They indicate if an individual fulfil a certain concept or not. R are crisp relations assigning a $\{0, 1\}$ value depending whether the individual fulfil the relation or not.
- F: **Fuzzy relations**. They are similar to R relations. Its main difference is that they allow an individual to be related to another individual or concept by a certain degree. Thanks to F relations, it is possible to represent imprecise information on the Fuzzy Ontologies. Therefore, i_j can be related with c_k in a certain degree indicated by the interval [0,1].
- A: **Axioms**. They are rules that the defined Fuzzy Ontology must fulfil.

Once that the information has been represented on the Fuzzy Ontology, it is possible to retrieve information as follows [23]:

- **Establishing the query**: The users specify which are the desired characteristics of the individuals that they want to retrieve from the Fuzzy Ontology. In other words, they indicate which concepts should be fulfilled by the individuals. By using this information, it is possible to build a query indicating both the importance if each concepts and how each individual should fulfil it. The query can have the following form:

$$Q = \{(w_1, c_1), \ldots, (w_l, c_l)\}$$

  where l is the number of concepts that the fuzzy ontology has. It is also possible to build queries that only include a subset of concepts.
- **Ranking individuals using the similarity value**: For each individual, its similarity value with the query is calculated. For this purpose, the similarity value for i_j can be calculated using the following expression:

$$s_j = w_1 \cdot r_{j1} + \ldots + w_l \cdot r_{jl} \tag{1}$$

  where r_{j1} indicates the relation between i_j and c_1. The higher the similarity value, the better the individual fulfil the experts' requirements.
- **Presenting final results**: Once that the similarity values have been calculated for all the individuals, they are ranked using the obtained results.

3. A Group Decision Making method for dealing with a high number of criteria

In this section, the proposed Multi-criteria Group Decision Making method for environments that have a high number of criteria values is described in detail. In the following subsections, the four steps needed to carry out the process are presented and described.

3.1. Representing decision information in fuzzy ontologies

First of all, the information that the experts have to discuss about must be represented on a Fuzzy Ontology. The following representation is used:

- **Alternatives**: Each alternative is an individual of the fuzzy ontology. Concepts will be used in order to determine how they fulfil the criteria.

- **Criteria**: Each criteria value is represented by g concepts on the Fuzzy Ontology. A linguistic label set $S^g = \{s_1, \ldots, s_g\}$ is defined in order to establish several levels of fulfilment. For each one, a concept is created.
- **Fuzzy Ontology connections**: All individuals are fuzzily related to all the concepts. A value on the interval [0,1] is established in each relation in order to determine how the individual fulfill each of the defined concepts.

An example of how the initial information of the decision process is represented is shown on Table 1.

Table 1. Example for a Fuzzy Ontology definition with $g = 3$ for criteria values c_1 and c_2 and 5 alternatives.

X	c_1^1	c_1^2	c_1^3	c_2^1	c_2^2	c_2^3
x_1	0	0.1	0.3	1	0.3	0
x_2	0	0	0.3	0.7	1	0.7
x_3	0	0	0	0	0.7	1
x_4	0	0.1	0.3	1	0.3	0
x_5	0.3	1	0.7	0	0	0

Once that the initial Multi-Criteria Group Decision Making information is stored on the Fuzzy Ontology, it is possible to start the criteria reduction process.

3.2. Creating criteria clusters

The main goal of this task is to create groups of criteria that are similar among them. Thanks to this, it is possible to reduce the initial number of criteria values by creating generic categories. It should be noticed that it is important to take everybody's advice in order to build the groups. Therefore, the proposed method takes all the opinions into account in order to create the final groups. In order to create these group of clusters, the following procedure is followed:

- **Grouping similar criteria**: Each expert specifies several groups of criteria according to their similarity. Each expert can propose the number of groups and reunite the criteria as they prefer.
- **Building the co-occurrence matrix from experts' groups**: By taking into account all the experts' provided information, a co-ocurrence matrix that aggregates all the experts groups is created. A co-occurrence matrix is an squared matrix that compare each possible pair of criteria values. In co_{ij}, the number of times that c_i has been classified by the experts with c_j is stored. Since $co_{ij} = co_{ji}$ and co_{ii} is a value that does not make any sense only values under the matrix diagonal must be specified. An CO matrix for 6 criteria values can be seen on Table 2.

Table 2. Co-occurrence matrix for 6 criteria values example.

	c_1	c_2	c_3	c_4	c_5	c_6
c_1	-	-	-	-	-	-
c_2	1	-	-	-	-	-
c_3	3	2	-	-	-	-
c_4	1	2	2	-	-	-
c_5	0	0	2	1	-	-
c_6	1	0	0	2	3	-

- **Creating collective groups**: Once that the co-occurrence matrix has been built, it is possible to create the final criteria clusters. For this purpose, an hierarchical clustering method can be used in order to create several group configurations. Thanks to these, it is possible for experts to specify the number of final criteria values that they want to take into account and use them in order to debate. The new criteria value set, RC is defined such as:

$$RC = \{rc_1, \ldots, rc_x\} \tag{2}$$

where each rc_i value is conformed by a set of initial criteria values. For instance, imagine that an initial set of 11 criteria values, $C = \{c_1, \ldots, c_11\}$. After performing the grouping tasks the new generated RC is as:

$$RC = \{rc_1, \ldots, rc_4\}$$

where

$$rc_1 = \{c_1, c_4, c_5, c_6\}$$
$$rc_2 = \{c_2, c_3\}$$
$$rc_3 = \{c_7, c_9, c_{10}\}$$
$$rc_4 = \{c_8, c_{11}\}$$

Once that the final number of criteria values is calculated, it is possible to aggregate the information related to each of the initial criteria values in order to generate a new Fuzzy Ontology containing information related to the new selected criteria.

3.3. Creating a Fuzzy Ontology with a reduced number of criteria

Once that the new set of criteria values, RC is calculated, it is necessary to create a Fuzzy Ontology that represents the alternatives' characteristics by using the new generated criteria set. In order to carry out this task, relation values must be aggregated. Imagine that rc_i, that includes c_1, c_2 and c_3 relation values must be generated. For this purpose, the following expression can be used:

$$rc_i^1 = \phi(c_1^1, c_2^1, c_3^1)$$
$$rc_i^2 = \phi(c_1^2, c_2^2, c_3^2)$$
$$rc_i^3 = \phi(c_1^3, c_2^3, c_3^3)$$

ϕ refers to the mean operator and this operation must be performed for each alternative that is available on the Fuzzy Ontology.

3.4. Carrying out a decision process over criteria

Once that the Fuzzy Ontology that has the reduced set of criteria values is created, experts can debate and provide information taking into account the reduced set of criteria generated. In order to carry out the Group Decision Making process, we propose an approach that is independent of the number of alternatives that are available on the Fuzzy Ontology. Since what really matters on the decision is the criteria values and how important each of them are, experts can directly debate among the criteria values and use the Fuzzy Ontology to obtain the alternatives that better fulfil them. In order to carry out this process, the following steps can be followed:

- **Carrying out a Group Decision Making process over the criteria**: Experts carry out a Group Decision Making process using the criteria values as alternatives. The process described in subsection 2.1 can be followed. Thanks to these, it is possible to generate a ranking where the most important criteria are pinpointed.
- **Establishing the query**: Once that the criteria values are ranked, it is possible to establish the query that will be used in order to obtain the ranking of alternatives. First of all, it is necessary to associate weights to the criteria. For this purpose, the following expression can be used:

$$W_j = \frac{j}{\sum_{i=1}^{n} i}, j \in \{1, n\} \tag{3}$$

  Once that each criteria values has an associate weight, the query resolving process defined in subsection 2.2, can be used in order to retrieve the alternatives' ranking.

4. Example

In order to enhance the comprehension of the proposed method, a brief example is presented. Let $E = \{e_1, e_2, e_3, e_4\}$ be the set of experts and $X = \{x_1, \ldots, x_6\}$ the set of alternatives. There are also 11 criteria, $C = \{c_1, \ldots, c_{11}\}$.
The first step is to generate the new set of criteria that the experts will discuss about. For this purpose, each expert

Table 3. Co-occurrence matrix for the 11 criteria.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9	c_{10}	c_{11}
c_1	-	-	-	-	-	-	-	-	-	-	-
c_2	1	-	-	-	-	-	-	-	-	-	-
c_3	1	4	-	-	-	-	-	-	-	-	-
c_4	1	4	4	-	-	-	-	-	-	-	-
c_5	0	1	1	1	-	-	-	-	-	-	-
c_6	0	1	1	1	4	-	-	-	-	-	-
c_7	0	1	1	1	2	2	-	-	-	-	-
c_8	0	0	0	0	0	0	0	-	-	-	-
c_9	0	0	0	0	0	0	0	4	-	-	-
c_{10}	0	0	0	0	0	0	0	4	4	-	-
c_{11}	0	1	1	1	1	1	0	3	3	3	-

Table 4. Reduced criterion values.

Group name	**Criterion values**
rc_1	$\{c_1\}$
rc_2	$\{c_2, c_3, c_4\}$
rc_3	$\{c_5, c_6, c_7\}$
rc_4	$\{c_8, c_9, c_{10}, c_{11}\}$

groups the available criteria in different sets. The number of times that each pair of criteria have been classified together is counted in order to build the co-ocurrence matrix. On Table 3, the co-ocurrence matrix is shown.

The *hclust* implementation provided by R is used in order to generate the final criteria grouping. On Table **??**, the final groups of criteria are depicted.

As it can be seen, the initial 11 criteria values are reduced to 4. We are assuming on this example that the linguistic label set $S^3 = \{s_1, s_2, s_3\}$ is being used for creating the associated concepts. In order to aggregate the information and create the new Fuzzy Ontology, it is possible to use expression 3. For rc_2 and x_1, the obtained results are shown below:

$$rc_2^1 = \phi(0.9, 0.2, 0.8) = 0.633$$
$$rc_2^2 = \phi(0.1, 0.8, 0.2) = 0.366$$
$$rc_2^3 = \phi(0, 0, 0) = 0$$

Once that the criteria set is obtained, experts need to rank the criteria values in order to build the Fuzzy Ontology query. For this purpose, they provide their preferences matrices, P to the system. All the matrices are aggregated into a collective preference matrix. C is calculated using the indexes of the labels from P. The obtained values are shown below:

$$P_1 = \begin{pmatrix} - & s_1 & s_2 & s_1 \\ s_2 & - & s_2 & s_1 \\ s_1 & s_2 & - & s_1 \\ s_5 & s_4 & s_5 & - \end{pmatrix} P_2 = \begin{pmatrix} - & s_1 & s_3 & s_1 \\ s_2 & - & s_2 & s_1 \\ s_1 & s_2 & - & s_1 \\ s_4 & s_5 & s_5 & - \end{pmatrix} P_3 = \begin{pmatrix} - & s_1 & s_2 & s_2 \\ s_2 & - & s_2 & s_2 \\ s_2 & s_2 & - & s_1 \\ s_5 & s_5 & s_5 & - \end{pmatrix}$$

$$P_4 = \begin{pmatrix} - & s_2 & s_1 & s_1 \\ s_1 & - & s_2 & s_1 \\ s_2 & s_1 & - & s_1 \\ s_4 & s_4 & s_5 & - \end{pmatrix} C = \begin{pmatrix} - & 1.25 & 2 & 1.25 \\ 1.75 & - & 2 & 1.25 \\ 1.5 & 1.75 & - & 1 \\ 4.5 & 4.5 & 5 & - \end{pmatrix}$$

In order to generate the final ranking of alternatives, it is possible to use the guided dominance degree operator [11]. Results are shown below:

$$GDD = \{0.21875, 0.25, 0.203125, 0.8125\}$$

Therefore, the actual ranking of alternatives is as $R = \{rc_4, rc_1, rc_2, rc_3\}$.
In order to build the Fuzzy Ontology query, weights are assigned to the criteria values using expression (3). Results are shown below:

$$W = \left\{\frac{4}{10}, \frac{3}{10}, \frac{2}{10}, \frac{1}{10}\right\} = \{0.4, 0.3, 0.2, 0.1\}$$

Therefore, the query is as follows:

$$Q = \{0.4 \cdot rc_4, 0.3 \cdot rc_1, 0.2 \cdot rc_2, 0.1 \cdot rc_3\}$$

Once that the query is specified, similarity values are calculated and alternatives are ranked. This process can be seen on Table 5. The final rank of alternatives is shown below:

$$R = \{, x_6, x_2, x_3, x_1, x_4, x_5\}$$

Results show that x_6 is the most promising alternative according to the selected criteria.

Table 5. Calculating similarity values for the 12 alternatives.

Alternative	**HS**	**HH**	**LP**	**HOS**	**Similarity value**
x_1	0.25	0	0.7	0	0.24
x_2	0.15	0.8333	0.7	0.8333	0.5333
x_3	0	0.5333	0.3	0.5333	0.27332
x_4	0	0.7333	0	0	0.21999
x_5	0.1	0	0	0.7333	0.11333
x_6	0.8	0.6333	0.7	0	0.64999

5. Conclusions

In this paper, a novel Multi-criteria Group Decision Making methods that work over environments that have a high number of criteria is presented. Fuzzy Ontologies are used in order to represent the information in an organized way. Also, hierarchical clustering methods are used in order to create groups of criteria that are similar among them according to the expert criteria.
Thanks to the presented method, it is possible for the experts to comfortably made decisions over environments that have a high number of criteria values. Without tools that allow experts to effectively manage the high amounts of information that they have to deal with in real world situations, it is not possible for them to made right decisions. Therefore, there is a need of methods, like the proposed one, that help the experts to deal with this kind of environments.
As future work, we will apply the developed method to real world situations with a high number of alternatives and criteria. Also, it would be interesting to establish procedures that allow the criteria values to aggregate in a more automatic way.

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