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Group Decision Methodology for Collaborative Multicriteria Assignment

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Abstract: In this paper we present a group decision methodology for multicriteria classification decisions focusing on small collaborative teams, where group members express their preferences on problem parameters in numeric and linguistic format. Individual preferences are aggregated by appropriate operators and a group parameter set is produced which is used as input for the classification algorithm. NeXClass multicriteria classification algorithm is applied for the classification, initially at a training set of alternatives and later at the entire set. Finally, group members evaluate results and consensus as well as satisfaction metrics are calculated. In case of low acceptance level, problem parameters are redefined by group members and aggregation phase is repeated. Finally, we present an illustrative example of the methodology, demonstrating its application to real world problems. The methodology has been applied to classification problems in business environment, with results depicting its validity for such problems.

Key words: Group decision making . multicriteria analysis . classification

INTRODUCTION

Group decisions are inherently more complex compared to single decision making, since a number of contradicting factors are involved, such as: *conflicting individual goals*, *not efficient knowledge*, *validity of information*, *individuals' motivation*, *personal opinions*, *goals and stakes*, resulting in a social procedure, where negotiation and strategy plays a critical role. However, group decision making has become an essential component for today's organizations and enterprises. Since complexity of business environment requires sufficient knowledge from a wide range of domains, contribution of a team of experts with key skills is the only way to achieve efficiency in decisions.

Besides other group support techniques, multicriteria analysis can be incorporated as a method to model preferences and facilitate decision making within a group of decision makers. Modeling under a multicriteria setting can be formulated under two major directions: In the first approach, individual multicriteria models are developed, which capture individuals' preferences. Each group member formulates a multicriteria problem defining the parameters according to his preferences and solves the problem getting an individual solution set. Next, the separate solutions are aggregated by aggregation operators providing thus the group solution. In the second approach, a multicriteria model is developed for the entire team. Each group member provides a set of parameters which are aggregated by appropriate operators, providing finally a group parameter set. Upon this set the muticriteria method is applied and the solution expresses group preference.

Multicriteria analysis has been utilized to assist group decision making in a variety of problems, resulting in numerous methodologies and group decision support systems. Matsatsinis and Samaras present an extensive review of such approaches [1], which clearly indicates that multicriteria analysis is a valid way to handle the inherent complexity of group decisions and structure such problems. It provides a structured way for problem formulation and guides members to understand all the requirements in an effective way and express their preferences reflecting their individual decision model. Multicriteria analysis focuses mainly on three types of decision problems: *choice, ranking* and *sorting*. Although groups also face sorting and classification decisions, there is relative lack in methodologies that support such problems. Analyzing existing approaches [2-11] we identified that: *the majority of the approaches provide support to sorting and selection decisions* and *the majority of the approaches utilize Analytic Hierarchy Process methodology and Utility theory*.

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Thus, the objective of our work is to propose a multicriteria methodology which supports group classification decisions. In brief, the objective of the methodology is the assignment of a set of alternatives to a number of predefined non-ordered categories, according to their performance on a set of evaluation criteria, by a group of decision makers. Initially a set of parameters defined by stakeholders is proposed by group facilitator to the group. Next, each group member evaluates the proposed parameter set and expresses his preferences in numeric and linguistic format. Individual preferences are aggregated by appropriate operators and a group parameter set is produced which is used as input for the classification algorithm. NeXClass multicriteria classification algorithm is used for the classification of alternatives, initially at a training set of alternatives and later at the entire set. Finally, group members evaluate results and consensus as well as satisfaction metrics are calculated. In case of low level of acceptance, problem parameters are redefined by group members and aggregation phase is repeated.

In this paper we present the methodology in details, as well as an illustrative example, which demonstrates its application to real world problems. The paper is structured as following. Introduction presents the problem domain and presents an overview of multicriteria analysis utilization in group decisions, as well as a brief overview of the proposed methodology. The proposed methodology is presented in details in Section 2 and in Section 3 we continue with an example group classification problem, which demonstrates methodology's applicability, as well as a discussion on empirical findings. Finally, we conclude summarizing key findings.

PROPOSED GROUP DECISION METHODOLOGY

Overview: The main objective of our work is to support a group of decision makers in classification problems. The classification problem refers to the assignment of a set of alternatives in a number of predefined non-ordered categories, according to their performance on a set of evaluation criteria.

The team solves a structured classification problem contributing their preferences. Although the methodology can be extended to large decision teams, our approach is based on collaborative teams, which target towards maximizing consensus. Non-collaborative teams require a negotiation-based approach, which is out of scope of the present methodology. In addition, the entire group decision process is coordinated by a facilitator. Usually, in group decision making a negotiation phase takes place at the preliminary steps of the decision problem formation. During this negotiation, which can be structured or not, basic parameters are defined. Since our methodology is not focusing on group formation procedure and initial negotiations, we consider that a preliminary negotiation step has already been executed, possibly by utilizing brainstorming technique, between stakeholders and the outcome of this process is an initial proposal of parameters. This set is expressed from facilitator as the initial proposal upon which group members will express their preferences. Facilitator guides the entire process in order to produce efficient and timely results.

The methodology is divided in the following four major phases (Fig. 1):

- *Problem initiation*. Facilitator defines the basic parameters of the problem. The parameters are related to the specific multicriteria methodology and refer to criteria, alternatives and categories.
- *Aggregation of individual parameters*. Members evaluate the proposed parameter set and express their preferences in numeric and linguistic format. Next, individual preferences are aggregated and a group parameter set is produced which is used as input for the classification algorithm.

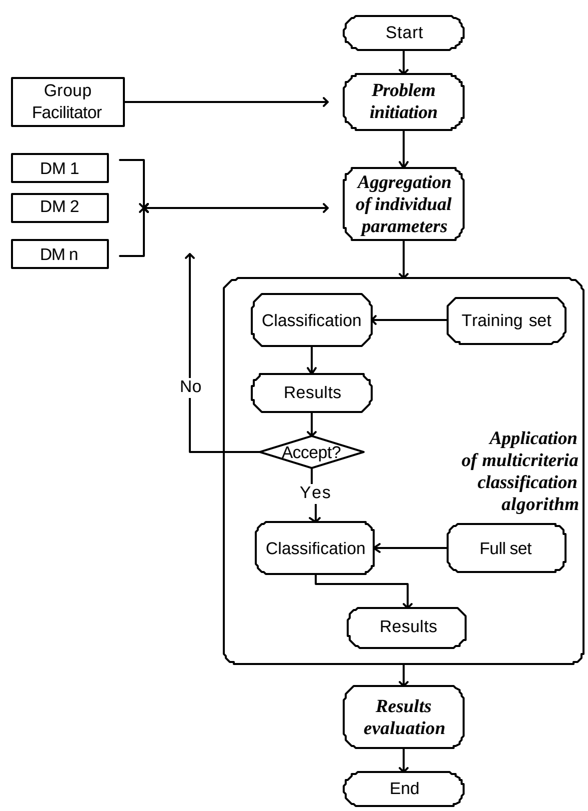

Fig. 1 : Group decision methodology

- *Application of multicriteria classification algorithm*. Using the group parameter set, the multicriteria algorithm is initially applied to a training set of alternatives. Group members evaluate results and if accepted, the same parameter set is used for the classification of the entire set of alternatives.
- *Results evaluation*. Group members evaluate the classification results of the entire set expressing their opinion.

Phases of methodology

Problem initiation: In this phase facilitator initiates the decision problem and defines all the necessary parameters:

- *Basic problem parameters*. Basic parameters of the problem are the number of group members, the number of categories, the number of criteria and consensus, satisfaction and acceptance levels. These levels define minimum required levels for the group decision. In case they are not satisfied, a second round is executed with modification of individual preferences.
- *Members*. Facilitator defines group members $M = \{m_1, m_2, ... m_n\}$ assigning all necessary details for each one.
- *Categories*. Facilitator proposes the set of categories $C = \{C^1, C^2, ..., C^h\}$ for the classification of alternatives.
- *Evaluation criteria*. Facilitator proposes the set of evaluation criteria $G = \{g_1, g_2, ..., g_n\}$ according to problem requirements.
- *Criteria weights*. Facilitator defines the criteria weights.
- *Alternatives*. Facilitator defines the set of alternatives $A = \{a_1, a_2, \ldots, a_m\}$ for classification and defines their performance on the evaluation criteria $\forall a, g(a) = (g_1(a), g_2(a), ..., g_n(a))$.
- *Entrance thresholds*. Facilitator proposes appropriate entrance thresholds $B^h = \{b_1^h, b_2^h, ..., b_k^h\}$ for each category $C = \{C^1, C^2, ..., C^h\}$. For each threshold facilitator defines preference, indifference and veto thresholds similar to ELECTRE TRI method. Each threshold can be considered as a virtual alternative which defines the category limit.
- *Training set*. Facilitator proposes a subset of alternatives as training set, in order to evaluate parameters' accuracy.

Aggregation of individual parameters: In this phase group members express their preferences on the proposed parameter set. Member preferences are expressed in numeric values and linguistic preferences.

1. *Linguistic*: Members express their opinion on categories, alternatives and criteria in terms of a five point linguistic scale representing their acceptance level on the proposal. In case of low acceptance level, the parameter is marked for reconsideration or rejection from the problem. For the aggregation of non-numeric values we apply the following aggregation procedure based on Ordered Weighted Averaging Operator.
   The Ordered Weighted Averaging operator (OWA) was proposed by Yager [17] and provides a family of aggregation operators which have the "end" operator at the one limit and the "or" operator at the other limit. OWA operators fill the gap between the operators Min and Max and can be verified that are commutative, increasing monotonous and idempotent, but in general not associative.
   Following this aggregation approach, if p_i is the non-numeric value of a parameter as defined by ith decision maker, then the aggregated group value of the parameter is defined as

$$\phi_w(p_1, \ldots, p_n) = \sum_{i=1}^{n} w_i \cdot p_{\sigma(i)}$$

where, $\sigma : \{1,...,n\} \to \{1,...,n\}$ is a permutation such that, $p_{\sigma(i)} \geq p_{\sigma(i+1)}$ $\forall i = 1,...n-1$, $p_{\sigma(i)}$ is the i-th highest value of $\{p_1, \ldots, p_n\}$ set and $W = (w_1, \ldots w_n)$ with

$$w_i \in [0,1], \sum_{i=1}^{n} w_i = 1$$

a set of associated weights.

An issue arises with the calculation of the weighting vector $W = (w_1, \ldots w_n)$. Yager has proposed two ways to obtain it [17]. The first approach is to use some kind of learning mechanism using some sample data and the second approach is to try to give some semantics or meaning to the weights. In our approach we follow the idea of quantifier guided aggregations. This is based on the idea to calculate weights for the aggregation operations using linguistic quantifiers that represent the concept of fuzzy majority. For the case of a non-decreasing proportional quantifier Q, weights $W = (w_1, \ldots w_n)$ with $w_i \in [0,1], \sum_{i=1}^{n} w_i = 1$ are given by the following expression

$$w_i = Q(i/n) - Q((i-1)/n), i = 1,...,n.$$

In order to represent the concept of fuzzy majority, we utilize a fuzzy quantifier [4], with membership function given by the following expression

$$Q(r) = \begin{cases} 0, & \text{if } r < a \\ \dfrac{(r-a)}{b-a}, & \text{if } a \le r \le b \qquad a,b,r \in [0,1] \\ 1, & \text{if } r > b \end{cases}$$

and (a, b) = 0.3, 0.8.

Application of fuzzy majority concept in group decision making can be found in several research works [13].

2. *Numeric*. Members express their preferred values on categories thresholds, alternatives performance and criteria weights. For the aggregation of the values we utilize the Social Judgment Scheme. Social Judgment Scheme (SJS) theory was proposed by Davis following studies on aggregation of individual preferences in a group decision setting [14]. This model assumes a dominant role of members whose opinions are relative central in the group. Thus, each decision maker is given a weight depending on the centrality of his/her position relative to the other members of the group and the group decision is a weighted sum of the members' preferences. This model has been tested empirically with sufficient results [15].
   Thus, if w_{ij} is the numeric value of ith parameter as defined by jth decision maker, then the aggregated group value c_i of ith parameter is defined as

$$c_i = \sum_{j=1}^{n} v_{ij} w_{ij}$$

where v_{ij} is the consensus weight of jth decision maker relative to ith parameter. Consensus weight is calculated according to the following expression

$$v_{ij} = \frac{\sum_{l=1, l \neq j}^{n} \exp(-|w_{ij} - w_{il}|)}{\sum_{j=1}^{k} \sum_{l=1, l \neq j}^{n} \exp(-|w_{ij} - w_{il}|)}$$

Application of multicriteria classification algorithm: After the aggregation of individual members' parameters, a group parameter set is created and NeXClass algorithm for multicriteria classification is applied on this set. NeXClass algorithm classifies an alternative to a specific category with respect to alternative's performance to the evaluation criteria, considering a set of alternatives, a set of predefined non-ordered categories and a set of evaluation criteria.

The algorithm is based on the concept of *Excluding degree* which is defined to express the degree of validation of the statement

'Alternative a ÎA is preferred or roughly preferred over the entrance threshold', or the equivalent *'Alternative aÎA is not excluded or is not roughly excluded'.*

When the excluding degree is maximized, alternative is less preferred over the entrance threshold and excluded, while when it is maximized alternative is more preferred over the entrance threshold and included.

In order to estimate the degree of validation of the above statement we utilize outranking relations, following a similar approach to ELECTRE TRI method. In details, alternative is preferred over the entrance threshold if

$$aPb_i^h \Leftrightarrow aSb_i^h \wedge \neg b_i^h Sa\,.$$

Degrees of validation of aSb_i^h and $b_i^h Sa$ are given by the credibility indexes $g_i(a,b_i^h)$ and $g_i(b_i^h,a)$. So, maximization of preference of alternative *a ÎA* over the entrance threshold b_i^h occurs when

$$\gamma_i(a,b_i^h) \longrightarrow 1 \quad \text{and} \quad \gamma_i(b_i^h,a) \longrightarrow 0$$

On the other hand, minimization of preference of alternative *a ÎA* over the entrance threshold b_i^h occurs when

$$\gamma_i(a,b_i^h) \longrightarrow 0 \quad \text{and} \quad \gamma_i(b_i^h,a) \longrightarrow 1$$

In order to estimate the degree of preference of alternative *a ÎA* over the entrance threshold b_i^h we define the 'excluding degree' as

$$\gamma_i^{tot} = \frac{\gamma_i(b_i^h,a)}{1+\gamma_i(a,b_i^h)} \in [0,1]$$

where $g_i(a,b_i^h)$ and $g_i(b_i^h,a)$ are the degrees of validation of aSb_i^h and $b_i^h Sa$ statements. When

$\gamma_i^{tot} \longrightarrow 0$ 'excluding degree' of alternative *a ÎA* over the entrance threshold b_i^h is maximized, while when $\gamma_i^{tot} \longrightarrow 1$ 'excluding degree' of alternative *a ÎA* over the entrance threshold b_i^h is minimized.

Following the above definitions, the algorithm works as follows:

1. For each category $C = \{C^1, C^2, ..., C^h\}$, decision maker defines an entrance threshold $B^h = \{b_1^h, b_2^h, ..., b_k^h\}$ using available information. This threshold represents the minimum requirements for an alternative in terms of performance on the evaluation criteria in order to be included in this category. This threshold can be considered as a virtual alternative.
2. Decision maker defines alternatives' performance $\forall a, g(a) = (g_1(a), g_2(a), ..., g_n(a))$ on the evaluation criteria $F = \{g_1, g_2 \ldots, g_n\}$.
3. For each alternative an excluding degree $\gamma_i^{tot} = \dfrac{\gamma_i(b_i^h, a)}{1 + \gamma_i(a, b_i^h)}$ is calculated for every category threshold, based on outranking relations, following a similar approach to ELECTRE TRI method. Expressions $g_i(a, b_i^h)$ and $g_i(b_i^h, a)$ are the degrees of validation of the statements aSb_i^h and b_i^hSa respectively and are calculated by the concordance and discordance indexes from the following expressions

$$\gamma_i(a, b_i^h) = \begin{cases} C(a, b_i^h) & \text{if} \quad d_i(a, b_i^h) < C(a, b_i^h) \\ C(a, b_i^h) \prod \dfrac{1 - d_i(a, b_i^h)}{1 - C(a, b_i^h)} & \text{otherwise} \end{cases}$$

$$\gamma_i(b_i^h, a) = \begin{cases} C(b_i^h, a) & \text{if} \quad d_i(b_i^h, a) < C(b_i^h, a) \\ C(b_i^h, a) \prod \dfrac{1 - d_i(b_i^h, a)}{1 - C(b_i^h, a)} & \text{otherwise} \end{cases}$$

respectively. Concordance $[C(a, b_i^h), C(b_i^h, a)]$ and discordance $[d(a, b_i^h), d(b_i^h, a)]$ indexes are calculated in a way similar to ELECTRE III method.
4. Next, the fuzzy excluding degree $\gamma(a, C^h) = P(a, b^h) = \gamma^{tot}$ of an alternative *a ÎA* over a category $C^h \in C$ is calculated.

We define the fuzzy excluding degree, of an alternative *a ÎA* over a category $C^h \in \Omega$ as $\gamma(a, C^h) = P(a, b^h) = \gamma^{tot}$ for the case of one entrance threshold for the category.

In the case of more than on entrance thresholds, expression

$$\gamma_i^{tot} = \frac{\gamma(b_i^h, a)}{1 + \gamma(a, b_i^h)}$$

is calculated for every threshold for the category b_i^h and the fuzzy excluding degree is defined as

$$\begin{aligned} \gamma(a, C^h) &= \min\{P(a, b_1^h), P(a, b_2^h), ..., P(a, b_k^h)\} \\ &= \min\{\gamma_1^{tot}, \gamma_2^{tot}, ..., \gamma_k^{tot}\} \end{aligned}.$$

Fuzzy excluding degree in the case of one threshold expresses the degree of preference of alternative *a ÎA* over the entrance threshold b^h, while in the case of more thresholds, it expresses the degree of preference of alternative *a ÎA* over the threshold b_i^h for which the excluding degree is the minimum.

Assignment to a category is based on the rule

$$a \in C^h \Leftrightarrow \gamma(a, C^h) = \min\{\gamma(a, C^i) / i \in \{1, ..., k\}\}$$

which states that alternative *a ÎA* is assigned to the category $C^h \in C$ for which the excluding degree over the entrance threshold is minimum.

Application of NeXClass classification algorithm is executed through the following steps

1. *Training set classification.* Classification algorithm is initially applied to the training set initially.
2. *Evaluation of results.* Each member expresses linguistic preferences on the results in a five point linguistic scale. For the aggregation of the values we follow again the aggregation procedure based on Ordered Weighted Averaging Operator. In case of low acceptance level, facilitator executes a second round of parameter definition from members in order to calibrate the model. When training set classification is acceptable, facilitator proceeds with the classification of the entire set of alternatives.
3. *Entire set classification.* Classification algorithm is finally applied to the entire set of alternatives.

Results assessment: Group members assess the results expressing their preference in a five point linguistic scale. In case of low acceptance level, facilitator reruns the model, requesting modifications from members. For the aggregation of the values we follow again the aggregation procedure based on Ordered Weighted Averaging Operator.

APPLICATION OF THE METHODOLOGY

Illustrative example: In the following we demonstrate the application of methodology providing sample data, focusing on the aggregation of group preferences. We consider the following classification problem with the following initial parameters:

- A group of seven members $M = \{m_j\}, j = 1,...,7$ as decision makers,
- A set of categories $C = \{C^i\}, i = 1,...,4$ for the classification of alternatives,
- A set of evaluation criteria $G = \{g_i\}, i = 1,...,8$ according to problem requirements,
- A set of alternatives $A = \{a_i\}, i = 1,...,6$ for classification,

The objective is to classify the alternatives $A = \{a_i\}, i = 1,...,6$ in appropriate categories $C = \{C^i\}, i = 1,...,4$.

Initially, each group member m_j expresses his opinion indicating acceptance level in a linguistic scale {*Extremely High*, *High*, *Medium*, *Low*, *Extremely Low*}, on the set of criteria

$$\left[g_{ij}\right] = \begin{bmatrix} EH & EH & H & EH & H & H & H \\ H & L & M & EL & L & EL & L \\ EH & EH & M & H & EH & M & H \\ M & EH & M & H & EH & H & EH \\ L & H & M & H & EH & EH & H \\ H & H & EH & H & EH & EH & EH \\ EH & H & EH & EH & EH & EH & EH \\ EL & M & L & M & EL & L & L \end{bmatrix}, i = 1,\ldots,8,\ j = 1,\ldots,7$$

and the set of categories.

$$\left[C_{ij}^{i}\right] = \begin{bmatrix} M & EH & EH & EH & H & M & H \\ EL & M & L & M & EL & L & L \\ EH & EH & EH & EH & EH & H & EH \\ H & EH & EH & EH & H & H & H \end{bmatrix}, i = 1,\ldots,4, j = 1,\ldots,7$$

These values are converted to numeric ones from 5 to 1 as below.

$$\left[g_{ij}\right] = \begin{bmatrix} 5 & 5 & 4 & 5 & 4 & 4 & 4 \\ 4 & 2 & 3 & 1 & 2 & 1 & 2 \\ 5 & 5 & 3 & 4 & 5 & 3 & 4 \\ 3 & 5 & 3 & 4 & 5 & 4 & 5 \\ 2 & 4 & 3 & 4 & 5 & 5 & 4 \\ 4 & 4 & 5 & 4 & 5 & 5 & 5 \\ 5 & 4 & 5 & 5 & 5 & 5 & 5 \\ 1 & 3 & 2 & 3 & 1 & 2 & 2 \end{bmatrix},$$

$$\left[C_{ij}^{i}\right] = \begin{bmatrix} 3 & 5 & 5 & 5 & 4 & 3 & 4 \\ 1 & 3 & 2 & 3 & 1 & 2 & 2 \\ 5 & 5 & 5 & 5 & 5 & 4 & 5 \\ 4 & 5 & 5 & 5 & 4 & 4 & 4 \end{bmatrix}$$

Aggregation of the values for every criterion and every category provides the group values in terms of acceptance. For the aggregation, we consider the fuzzy majority concept and use the values (a,b) = (0.3, 0.8) representing the 'most' value for the quantifier

$$Q(r) = \begin{cases} 0, & \text{if } r < a \\ \dfrac{(r-a)}{b-a}, & \text{if } a \le r \le b \\ 1, & \text{if } r > b \end{cases}$$

and evaluate the weights of the OWA operator with the expression

$$w_i = Q(i/n) - Q((i-1)/n), i = 1,..., n.$$

For the criteria g_i and categories C^i the aggregated values are depicted below.

$$\left[g_i\right] = \begin{bmatrix} 4.257 \\ 1.828 \\ 4.085 \\ 4.085 \\ 3.828 \\ 4.542 \\ 5.0 \\ 1.828 \end{bmatrix}, \quad \left[C^i\right] = \begin{bmatrix} 4.085 \\ 1.828 \\ 5.0 \\ 4.257 \end{bmatrix}$$

As it can be seen acceptance of two criteria (g_2, g_8) and one category (C^2) is very low and thus they are excluded from the problem, since they fall below the 'most' value. So, the following parameters are considered now as accepted from the group for the problem:

- A set of categories $C=\{C^i\}, i=1,...,3$ for the classification of alternatives,
- Aa set of evaluation criteria $G=\{g_i\}, i=1,...,6$ according to problem requirements,

Next, each member m_j expresses his preference on criteria weights w_i in numeric values for each criterion g_i as depicted in the following table

$$\left[w_{ij}\right]=\begin{bmatrix} 18 & 15 & 14 & 15 & 16 & 19 & 20 \\ 28 & 33 & 26 & 30 & 25 & 23 & 21 \\ 7 & 5 & 9 & 8 & 10 & 9 & 11 \\ 15 & 12 & 13 & 12 & 16 & 16 & 12 \\ 11 & 9 & 14 & 8 & 5 & 9 & 6 \\ 21 & 26 & 24 & 27 & 28 & 6 & 30 \end{bmatrix}, i=1,...,6, j=1,...,7$$

Aggregation of the values for every criterion based on SJS provides the following group values for criteria weights

$$\left[w_i\right]=\begin{bmatrix} 16.4 \\ 26.2 \\ 9.6 \\ 13.3 \\ 8.5 \\ 25.8 \end{bmatrix}$$

Next, for each category C^m each member m_j expresses his preference on entrance threshold b_{ij}^m for every criterion g_i. Below we depict individual thresholds for each one of the three categories.

$$b_{ij}^1=\begin{bmatrix} 36 & 45 & 47 & 49 & 44 & 39 & 40 \\ 36 & 41 & 43 & 40 & 42 & 43 & 35 \\ 24 & 25 & 35 & 33 & 30 & 29 & 31 \\ 14 & 13 & 15 & 18 & 19 & 15 & 17 \\ 21 & 23 & 24 & 18 & 22 & 27 & 26 \\ 23 & 26 & 20 & 17 & 18 & 24 & 20 \end{bmatrix},$$

$$b_{ij}^2=\begin{bmatrix} 2 & 3 & 4 & 2 & 4 & 1 & 2 \\ 16 & 11 & 13 & 10 & 12 & 18 & 17 \\ 42 & 45 & 43 & 44 & 42 & 46 & 44 \\ 47 & 43 & 45 & 48 & 49 & 53 & 51 \\ 21 & 23 & 24 & 18 & 22 & 27 & 26 \\ 13 & 16 & 10 & 17 & 18 & 14 & 13 \end{bmatrix}$$

$$b_{ij}^3=\begin{bmatrix} 7 & 6 & 5 & 12 & 9 & 10 & 7 \\ 5 & 5 & 6 & 2 & 3 & 1 & 3 \\ 1 & 4 & 4 & 2 & 2 & 3 & 2 \\ 32 & 33 & 35 & 38 & 39 & 29 & 28 \\ 46 & 43 & 42 & 49 & 48 & 41 & 49 \\ 39 & 42 & 46 & 43 & 44 & 41 & 45 \end{bmatrix}, i=1,...,6, j=1,...,7$$

Aggregation of the values for every criterion based on SJS provides the following group values for category thresholds.

$$b_i^1=\begin{bmatrix} 43.14 \\ 41.38 \\ 29.29 \\ 15.52 \\ 23.40 \\ 20.45 \end{bmatrix}, b_i^2=\begin{bmatrix} 2.49 \\ 13.62 \\ 43.50 \\ 48.00 \\ 23.40 \\ 14.42 \end{bmatrix}, b_i^3=\begin{bmatrix} 7.27 \\ 3.69 \\ 2.49 \\ 33.26 \\ 46.51 \\ 43.25 \end{bmatrix}$$

Finally, we depict the alternatives' (a_i) performance on evaluation criteria (g_j), where we have followed the above aggregation procedure to individual preferences.

$$\left[a_{ij}\right]=\begin{bmatrix} 47 & 46 & 33 & 22 & 29 & 23 \\ 7 & 19 & 45 & 50 & 26 & 19 \\ 10 & 11 & 5 & 35 & 49 & 50 \\ 53 & 55 & 38 & 28 & 35 & 33 \\ 14 & 33 & 48 & 50 & 12 & 5 \\ 4 & 6 & 9 & 43 & 50 & 50 \end{bmatrix}, i=1,...,6, j=1,...,6$$

Aggregated alternatives' performance $[a_{ij}]$, criteria weights $[w_i]$ and categories' thresholds $[b_{ij}^m]$, is the input for the multicriteria classification algorithm. Executing NeXClass classification on the above parameter set we derive the following results.

Category	Alternative
C1	{a1, a4}
C2	{a2, a5}
C3	{a3, a6}

DISCUSSION

The methodology has been applied to real world problems with sufficient results. An indicative problem that has been resolved refers to classification of locations for potential ATM installation into appropriate categories at the environment of a Greek bank. In brief, the bank wanted to classify locations for potential ATM installation in order to decrease failed installation costs as well as relocations. The bank's objective was to create a pool of potential viable sites for further consideration, excluding less viable ones. Thus, we formulated a decision problem for the classification of locations to appropriate non-ordered categories. Following a brainstorming technique, stakeholders from bank's divisions defined an initial set of parameters and assigned the supervision and operation of the entire decision procedure as well as the group coordination to a group facilitator. Group members were selected from several bank's divisions, resulting to a group of nine decision makers. Next, applying the methodology following all the steps, we received result sets with very high degree of accuracy compared to training sets, as well as high acceptance degree from group members.

Application of methodology in business environment and empirical findings provide evidence that the methodology is a valid approach for similar decision problems. In addition, we believe that the methodology can be easily applied to support group decisions in a variety of environments. However, since the methodology requires a relative substantial number of parameters, it is possible that group members who are not familiar enough with the methodology will be confused. Thus, the number of criteria and parameters should be kept to a number, which will minimize complexity without however loosing critical problem parameters. In addition, the number of members should be kept within the limits of a small collaborating team, since for quite a few members anonymity is not so well established and preferences can be easily identified and for large number of members complexity will increase and extra facilitation will be necessary.

CONCLUSION

In this paper we presented a group multicriteria decision methodology for classification decisions where aggregation of members' preferences is executed at the parameter level. We presented in details the methodology as well as an illustrative application for a classification problem demonstrating its usage for similar problems. The methodology has been tested and evaluated within business environment supporting mainly financial decisions.

Empirical findings provide evidence that the methodology proposes a valid approach for similar decision problems in business environment. In addition, we believe that this methodology can be easily deployed to support group decisions in similar environments.

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