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Research article

CLASSIFYING VOLUNTEERS PARTICIPATED IN SEARCH AND RESCUE ACTIVITIES: A COMPARATIVE ANALYSIS OF TOPSIS-SORT AND ORESTE-SORT METHODS

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Abstract: Volunteers collaborate with professionals to provide institutional assistance in various areas; their management differs from that of professionals. To maximise volunteer productivity, categorising volunteers according to their knowledge and experience levels and distributing tasks increases volunteer retention and task efficiency. This study categorizes volunteers into four groups, fulfilling nine criteria identified through a literature review of search and rescue activities. TOPSIS-Sort and ORESTE-Sort (Optimist and Pessimist approaches) are employed in classification. Only one alternative is consistently assigned to the same class across all methods. While ORESTE-Sort offers greater flexibility and three distinct classification outcomes, it is more complex and sensitive to threshold values. TOPSIS-Sort, though simpler and producing a single classification, requires criterion weight. The Wilcoxon signed rank test is applied to evaluate the similarity between ORESTE-Sort and TOPSIS-Sort results; there are significant differences between the two methods. The study concludes by comparing the methods' applications, steps, and solution approaches, highlighting their respective advantages and disadvantages, and suggesting directions for future research.

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Keywords: Search and rescue, volunteer classification, TOPSIS-Sort, ORESTE-Sort.

MSCM: 90B50, 90C29, 90C90

1. INTRODUCTION

Due to its geological structure, Turkey is exposed to many disasters such as earthquakes, floods, fires, avalanches, and landslides. One of these disasters, especially earthquakes, causes serious loss of life and property in Turkey. According to the Turkish Strategy Development Presidency reports, more than 48 thousand people lost their lives, and more than half a million buildings were damaged in two major earthquakes of 7.7 and 7.6 magnitudes, respectively, in Kahramanmaras and Elbistan, Turkey, on February 6, 2023[1]. Disaster Management must be planned, executed, implemented, and developed effectively to prevent these heavy losses. Many people affected by the disaster during and after the disaster have many vital needs such as search and rescue, first aid, shelter, and nutrition. After a disaster, many professional and volunteer teams quickly get involved in fieldwork. After the February 6 earthquake, 35.250 search and rescue personnel, public officials, NGOs, international search and rescue personnel, and volunteers worked in the region[1]. Volunteers meet with significant manpower and meet your needs by working with a professional team, but their planning is different from that of professionals. Volunteers generally do not work for a salary, and their numbers vary; many volunteers may be willing to take on more tasks than an organization needs. Assigning a job to volunteers who do not suit their personal characteristics and abilities may result in the volunteer being unable to continue their job. It is important to select volunteers considering their personal characteristics and knowledge to prevent these. Especially during and after the disaster, it is possible to benefit from the volunteers in the most efficient way by selecting volunteers who have experience or knowledge in their field. Therefore, to facilitate volunteer assignments and reduce the time and complexity required in volunteer selection, it is necessary to divide the volunteer group in an organization into classes such as expert, experienced, and insufficient.

Despite the importance of the topic, studies on classification are limited [2], and further research and methodological advancement are needed. While some studies focus on volunteer classification and matching [3,4,5], they are limited by the number of criteria, specific geographic areas, and a lack of focus on disaster and emergency response. Study [6] attempts to address this gap by providing volunteer training and matching experienced with inexperienced volunteers in emergencies, but no MCDM-based method has been used to analyze volunteer classification. Existing studies have focused on MCDM and ranking alternatives within the framework of specific criteria. The Multiple Criteria Sorting Methods(MCSM), which are developed by adding different steps to some MCDM methods (such as TOPSIS, ELECTRE, ORESTE), have a limited scope of use [7]. These classification methods group alternatives using lower and upper bound values determined by the decision maker.

The MCSM has been applied to different research areas in the literature. The TOPSIS-Sort method, first developed by Sabotkar et al. [8], is used in risk assessment in occupational health and safety in [9], [10], and [11]. When evaluating tourism areas after

COVID-19 by Yamagishi and Ocampo [12], In volunteer selection, Ozdemir et al. [13] applied this method. On the other hand, the ORESTE-Sort method, first developed by Qin et al. [2], is used to rank the competitiveness of port areas in a particular region. Due to the novelty of this method, research on it is limited.

ORESTE-Sort method, which is one of these methods and has been newly introduced to the literature, differs from other classification methods in terms of several features. This classification method improves upon others by removing the need for criterion weighting via Besson's rule and enabling more objective classification through established relationships between alternatives. Furthermore, using the Attitudes-Driven Assignment Rule (ARDA), a flexible ranking rule combining optimistic and pessimistic views, provides adaptable results incorporating three perspectives [2].

This research undertakes a comparative analysis of a newly developed classification method of ORESTE-Sort against the established and broadly implemented TOPSIS-Sort methodology [10,11,12,13]. By detailing the advantages and disadvantages of each step, it evaluates the applicability, limitations, and potential drawbacks of both methods. To address this gap in the literature, this comparison summarizes the commonalities and differences in a table and suggests optimal usage scenarios for each method.

The contributions that are made to the literature in this study are as follows:

- Dividing the student group who voluntarily attend search and rescue activities into 4 groups (expert, experienced, sufficient, and insufficient) for their experience and knowledge; aims to prevent volunteers who do not have sufficient knowledge and experience from participating in search and rescue activities of the organisation.
- Expanding the coverage area of the methods by applying the ORESTE-Sort and TOPSIS-Sort, among the Multiple Criteria Sorting Method(MCSM) methods, to the volunteer or personnel classification problem.
- Comparing the results obtained from the ORESTE-Sort Optimistic-Pessimistic approaches and the TOPSIS-Sort method to determine their similarities and differences.
- Determining the pros and cons of these two methods and making suggestions for future studies.

The rest of the paper is organised as follows: The Literature review is given in detail, and volunteer criteria and weights obtained from previous studies are announced in the methodology. The TOPSIS- Sort and ORESTE- Sort that are used in the study are briefly mentioned. For the implementation phase, the two methods are applied separately to a group of volunteers operating in the field of search and rescue. The results obtained are discussed and suggestions for future research are presented.

2. LITERATURE REVIEW

2.1. Classification of Volunteers

Volunteer classification enhances task suitability and distribution by efficiently organising volunteers. This is especially critical in disaster management, where numerous qualified volunteers are needed to distribute basic needs (water, food, etc.), support experts, aid victims, and provide essential resources. This topic has been explored in existing research, and its limitations are presented chronologically.

Endo and Sugita [3] suggested dividing the volunteers into 4 groups according to their practical knowledge: expert, experienced, inexperienced, and problematic volunteers, to prevent the chaos that occurs after the disaster and to increase the effectiveness of task distribution, and they excluded the problematic group from disaster rescue efforts. However, their studies were not evaluated in a real environment, and they chose disaster knowledge and computer use skills as criteria. Lassiter et al. [4] classified the volunteers and examined their training and task distribution under various demand scenarios. As a result of the study, it was suggested that expert volunteers be used in high-risk and emergencies and that inexperienced volunteers be paired with expert personnel to gain experience in stable situations. Urrera et al. [5] observed that two types of volunteers (Experienced (Exp) and Inexperienced (Inexp)) arrived at a warehouse at different times; They designed warehouse congestion policies (allowing and preventing congestion) in 32 different situations and four different conditions. The results showed that, on average, shuffled matching (Inexp-Exp) was better than unscrambled matching under constant conditions. Ozdemir et al. [6] studied the criterion weights for volunteers in search and rescue activities using the AHP method, but the number of criteria was limited, and no discussion of other Multi-Criteria Decision-Making (MCDM) methods was provided. Ozdemir et al.[13] calculated criterion weights using the Best-Worst Method (BWM) to classify volunteers by their knowledge of the search and rescue activities according to 9 different criteria. The results showed that search and rescue, and first aid knowledge were the two most valuable criteria. However, the study was a preliminary study for the classification of volunteers, and no grouping of any volunteer group into groups such as experienced, expert, and inexperienced has been done.

2.2. The Multiple Criteria Sorting Method (MCSM)

Classification involves assigning alternatives to classes or groups by categorising them based on their properties and how well they meet specific criteria. This approach is useful for describing a defined set of decision alternatives by organising them into undefined, homogeneous sets.[7]

The Multiple Criteria Sorting Method(MCSM) has been applied to different research areas in the literature. The TOPSIS-Sort method, first developed by Sabotkar et al. [8], is used in risk assessment in occupational health and safety in [9],[10], and [11]. The main purpose of these studies is to separate the risk factors in work areas into different classes and to recommend not using the areas in the high-risk class. advise against using high-risk areas. Yamagishi and Ocampo [12] studied assessing customer-perceived COVID-19 exposure in restaurants by applying an intuitive fuzzy set extension of TOPSIS-Sort using six attributes to classify restaurants into low, medium, and high exposure categories. Ozdemir et al. [13] used AHP to weight criteria for volunteer classification and then employed TOPSIS-Sort to categorise volunteers by information level. However, the study's scope and criteria were limited. These studies focus solely on TOPSIS-Sort without comparison to other classification methods.

ELECTRE-SORT has developed a new method for classification by Ishizaka and Nemery [14] to create effective maintenance schedules by assigning machines to maintenance tasks according to certain criteria. Liang et al. [15] employed a consensus-based group ELECTRE-SORT method for machine maintenance strategy assignment, accommodating incomparable classes. Suson et al. [16] analysed 16 educational user-generated content videos from platforms like Facebook, YouTube, and TikTok. Using ELECTRE-SORT, they assessed the videos' content, design, and technology quality based on a randomly generated dataset of normally distributed user ratings. The analysis revealed that most videos (14 out of 16) were of "medium quality," indicating a notable standard for educational content. These studies, employing classification methods across various fields, did not compare the method's strengths and weaknesses against other classification approaches.

The ORESTE-Sort method, first developed by Qin et al. [2], is used to rank the competitiveness of port areas in a particular region. Its effectiveness is evaluated through comparative analyses with the ELECTRE-SORT method. Ozdemir et al. [17] also utilized ORESTE-Sort to classify and identify optimal disaster assembly areas based on regional suitability.

3. METHODOLOGY

Volunteer classification enables efficient task allocation by matching volunteers' expertise to specific roles. In emergencies, prioritising experienced volunteers for critical tasks ensures organisational continuity and minimises risks to less experienced personnel. This study compares the TOPSIS-Sort and ORESTE-Sort methods, addressing a gap in the literature regarding their relative advantages and disadvantages in the classification of volunteers for the search and rescue activities. The study's workflow is summarised in Figure 1. Criteria selected from the literature will be used to classify search and rescue volunteers by knowledge level, and this data will be analysed using both TOPSIS-Sort and ORESTE-Sort in two stages. The study will conclude with a table comparing the strengths and weaknesses of each method.

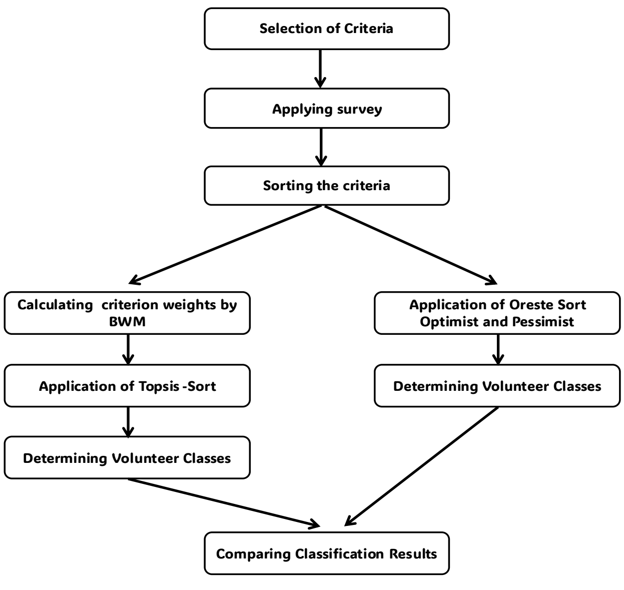

Figure 1: Voluntary Classification Steps of Study

This study begins with the selection of criteria for search and rescue activities based on a literature review. Ozdemir et al. [13] identified nine criteria for volunteer selection in search and rescue activities. These criteria are listed below.

i) Criterion (p_1): Knowledge of First Aid

First aid is the quick help given to injured or sick people until a professional comes. It also includes the processes of providing psychosocial support to people who witness a traumatic event other than illness or physical injury, or who experience emotional distress[18].

ii) Criterion (p2): Knowledge of Search and Rescue

Search and rescue activities are vital after manmade or natural disasters because the chances of survival of the injured are quite high in the first 24 hours of the disaster. According to the results obtained from [19], most of the injured people left in the rubble of the buildings that collapsed due to the earthquake in Kobe were rescued by volunteers nearby.

iii) Criterion (p3): Knowledge of Computer

Computers are used in creating search and rescue activity plans, distributing tasks, ensuring the flow of information among officers, and safely dispatching disaster victims. Endo and Sugita [3] aimed not to assign volunteers who do not have sufficient knowledge for task distribution in the disaster area. To determine volunteers' computer skills, they identified three interfaces to be used in volunteer classification: user interface, selectable user interface, and search user interface.

iv) Criterion (p4): Teamwork

Teamwork is when an individual acts in a group to accomplish his/her task quickly without disruption. O'Neil et al.[20] pointed out that teamwork skills are needed to function effectively in any organization. It has been determined that team skills enable better organization of tasks, better interaction with other team members, and better adaptation to changing environmental conditions.

v) Criterion (p5): Ability of Learning

Learning is associated with individuals establishing a more effective bond in society in the economic, cultural, and social fields. The primary area of interest is individual employability potential [21]. Khasanzyanova [22] defined volunteering as the most important factor in learning social skills. She argued that when students voluntarily participate in the learning process, the education process can be more fun , the student can be more active and their sense of responsibility can develop.

vi) Criterion (p6): Experience

Experience allows individuals to develop new ideas, shorten the adaptation process to the environment, and overcome the difficulties they encounter. Jannat et al. [23] examined the criteria required to select volunteers according to the tasks that will be required in a hospital. Among the 16 personal and social criteria determined, the two most important criteria in volunteer selection were determined to be practical and volunteer participation experience.

vii) Criterion (p7): Ability of Physics

Physical ability is needed for search and rescue activities that require long periods of time during or after a disaster. Heimburg et al. [24] compared the physical capacities of the fire brigade team that intervened to save the injured in the hospital and determined that those with higher physical abilities (strength, endurance, oxygen-carrying capacity) gave better performance in longer periods.

viii) Criterion (p8): Knowledge of Equipment and Devices

It is very important that the volunteers who work with the expert team during search and rescue activities have sufficient knowledge about the electronic devices and equipment they need. Cuber et al. [25] announced the ICARUS project to carry out search and rescue activities with robots. The project aims to provide first responders with detailed search and rescue tools, including an integrated drone and robot, in case of an emergency.

ix) Criterion (p9): Ability of Language Translation

In some cases, a translator is needed to ensure the flow of information to foreign organizations that voluntarily participate in search and rescue activities. O'Brien et al. [26] examined that since there are many different languages spoken in the global world, there is a demand for translators who can translate between languages. His work examines the feasibility, accessibility, and usability of translation between languages to evaluate the spread of knowledge.

After the criteria are determined, the questionnaire is applied to the group who want to volunteer to measure their knowledge level about search and rescue activities. The determined criteria are listed from the most important to the least important, and the classification results are compared and interpreted from a critical perspective by applying the TOPSIS-Sort and ORESTE-Sort methods summarized below.

3.1. TOPSIS-Sort

This method was obtained by extending the TOPSIS main method to rank its alternatives. The purpose of this method is to separate each class by ranking each alternative comparatively against the other. The TOPSIS-Sort technique includes the following steps for multi-criteria alternatives, developed by Sabodkar et al. [8] :

1. Create the decision matrix $X = (x_{ij})_{n\times m}$
   (xij) represents the performance of alternative i against criterion j, where there are m alternatives and n criteria considered by the decision-maker.
2. Decide a set of center profiles $P = \{(\underline{p_1}, \overline{p_1}), \ldots, (\underline{p_k}, \overline{p_k})\}$,here $\underline{p_k}$ is the lower limit, $\overline{p_k}$ is the upper limit of class K.
   Here, K = {1, …, k} represents the set of clusters corresponding to the classes defined by the decision maker.
3. Adding center profiles to the decision matrix $\xi = \{X, P\}$
4. Normalize the decision matrix ξ using the following equation:
   $$\Gamma_{ij} = \left\{\frac{\xi_{ij}}{\max x}\middle| J, 1 - \frac{\xi_{ij}}{\max x}\middle| J'\right\}$$
   here, J and J' indicate the criterion sets of benefit and cost, respectively.
5. Finding the weighted normalized decision matrix $V = (V_{ij})_{n\times m}$. The weighted normalized decision matrix is calculated by multiplying the normalized alternative and center profiles by their respective criterion weights.
   $$v_{ij} = w_J r_{ij}\ , i = 1.\cdots n; j = 1, \ldots, m$$
   Here, w_j is the relative weight of the j_{th} criterion, and $\sum_{j=1}^{m} wj = 1$.

6. Deciding the positive and negative ideal solutions.

$$A^{+} = \{v_1^{+}, \ldots, v_m^{+}\} = \{\max_j v_{ij} | j\varepsilon J, \min_j V_{ij} | j\varepsilon J'\}$$

$$A^{-} = \{v_1^{-}, \ldots, \quad v_m^{-}\} = \{\min_j v_{ij} | j\varepsilon J, \max_j V_{ij} | j\varepsilon J'\}$$

Here, J and J' are the criteria sets of benefit and cost, respectively

7. Calculating the distance to the positive and negative ideal solution for each alternative in Euclidean terms

$$D_i^{+} = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^{+}\right)^2}, i = 1, \cdots, n$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{m} \left(v_{ij} - v_j^{-}\right)^2}, \quad i = 1, \cdots, n$$

8. Calculating for each alternative its relative closeness to the ideal solution. A_i to A^{+} is defined the alternative of relative closeness.

$$cl_i = \frac{D_i^{-}}{D_i^{+} + D_i^{-}}, i = 1, \ldots, n.$$

9. Ranking alternatives from the relative closeness to the ideal solution: the bigger the cl_i the better the alternative A_i. The one with the highest relative closeness to the ideal solution is determined as the best alternative.

3.2. ORESTE-Sort

ORESTE-SORT, a new ranking method introduced to the literature, was developed by Qin et al. [2]. The flowchart illustrating the method steps is shown in Figure 2. This method ranks and categorizes alternatives by comparing them to central profiles to establish preference relationships: Preference (P), Indifference (I), and Incomparability (R). ORESTE-Sort distinguishes itself from other classification methods by classifying data without requiring weighting information and by employing the Besson mean rank method, which relies on preference order rather than strict numerical values for ranking.

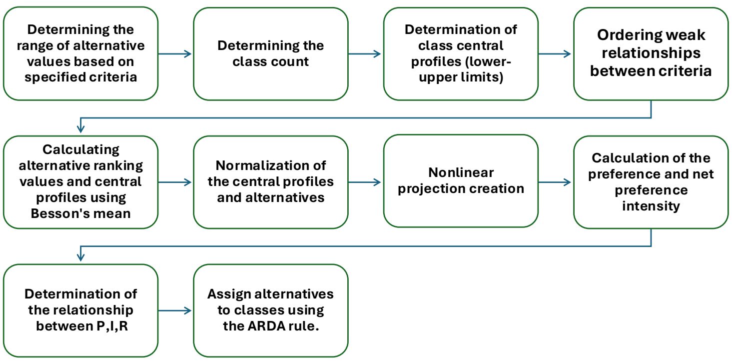

Figure 2: Steps to implement the ORESTE-Sort

The Besson mean rank combines rankings, accommodating modifications via deviation measures (as in the ORESTE method) or by using the arithmetic mean as the ideal solution (*equation 1*). It can also be calculated using the projection formula. This ranking method offers the advantage of ranking alternatives and calculating distance scores instead of evaluating all alternatives and determining criterion weights.

After ranking and normalizing the alternative and center profiles, a flexible nonlinear projection determines the net preference intensity. The attitude-based assignment rule (ARDA) then classifies alternatives based on preference relationships within their center profiles. ARDA, a general classification method, incorporates the decision maker's risk attitudes when an alternative is assigned to multiple classes, using optimistic, pessimistic, or compromise rules. These attitudes generate classification results from different perspectives, enabling the decision maker to evaluate the classification flexibly from three viewpoints rather than relying on a single outcome. Optimistically, alternatives incomparable to a center profile are assigned to the upper class; pessimistically, they are assigned to a lower class. The compromise class identifies suitable center profiles for the alternative. Table 1 provides the method's notations. The steps of the method are as follows.

Table 1: Notation of the Oreste-Sort

$\boldsymbol{A = \{a_1, a_2, \dots, a_m\}}$	Alternative set
$\boldsymbol{C = \{c_1, c_2, \dots, c_n\}}$	Criteria set
$\boldsymbol{y_{vj}\ \{v = 1, 2, \cdots, m\}}$	The performance of alternatives under the criterion $c_j\{j = 1,2,\dots,n\}$
$\mathbf{k}\ \boldsymbol{\{k = 1, 2, \cdots, K\}}$	Classes k under the L level $\{l = 1, 2, \cdots, L\}$
$\boldsymbol{cpk\ \{k = 1, 2, \cdots, K\}}$	$(\dot{c}\,\dot{p}_{kj})$ shows the performance of (cp_k) under criterion c_j
$\mathbf{B = \{b_1, b_2, \dots, b_{m+K}\}}$	Classes k performance set
$\boldsymbol{S}$	Criteria sequence $c_{(1)}\aleph c_{(2)}\aleph\cdots c_{(j)}\aleph\cdots\aleph c_{(n)}$ $\aleph$ takes *"P" or "I."*
$\boldsymbol{\zeta_j}$	Random element
$\boldsymbol{r(SE\zeta_j)}$	Sequence of criterion $SE: \zeta_1 \aleph \zeta_2 \aleph\cdots \zeta_j \aleph\cdots\aleph \zeta_\pi$
$\boldsymbol{r(S_{c_j})}$	Bessian's mean ranking of the criterion c_j
$\mathbf{r(S^j_{b_i})}$	Bessian's mean ranking of cp_k under criterion c_j
$\boldsymbol{D^j(b_j)}$	Flexible notation $\{i = 1,2,\dots,(m+K);\ j = 1,2,\dots,n\}$
$\boldsymbol{S_D}:\{\mathbf{b_{(1)}\aleph b_{(2)}\aleph\cdots b_{((m+K)n)}}\}$	Sequence of alternatives and classes based on the criteria
$\boldsymbol{\beta}$	Threshold value of indifferences
$\boldsymbol{\gamma}$	Threshold value of incomparability
$\boldsymbol{C^*}$	The relationships of distinguishing indifference and incomparability

1. Determine a set of alternatives $A = \{a_1, a_2, \dots, a_m\}$, criteria sets $C = \{c_1, c_2, \dots, c_n\}$ and the performance of a_v, $v = 1, 2, \cdots, m$ under criterion $c_j, j = 1,2,\dots n$ denoted as y_{vj}, $v = 1,2,\dots,m; j = 1,2,\dots,n$.
2. Specify *K classes k, k = 1, 2, ⋯ , K under the L level l = 1, 2, ⋯ , L*
   K represents the number of classes, and *L* represents the hierarchical degree between them, where level *l*+1 is superior to level *l*.
3. Determine the central profiles *(cps)* of all classes.

4. Determine the order of weakly ranked relationships of the criteria $c_j, j = 1,2, \ldots n$ using "*P*" and "*I*" denoted as the order S: $c_{(1)} \aleph c_{(2)} \aleph \cdots c_{(j)} \aleph \cdots \aleph c_{(n)}$, where (j) is the criteria sequence and $\aleph$ takes *"P" or "I."*
5. Using Besson's mean ranking (***equation 1***) to get the rank of the random element ζ_j in its order SE : $\zeta_1 \aleph \zeta_2 \aleph \cdots \zeta_j \aleph \cdots \aleph \zeta_\pi$ indicated as r(SEζ_j), where $\aleph$ takes "*P*" or "*I*":

$$\mathrm{r}(\mathrm{SE}\zeta_j) = \begin{cases} Position(\zeta_j), if\ the\ left\ and\ right\ preferences\ of\ \zeta\ j\ are\ both\ P; \\ \dfrac{\mathrm{Position}(\zeta\,\mathrm{j}) - I_{\zeta_j}^{bf} + \cdots + \mathrm{Position}(\zeta_j) + \cdots + \mathrm{Position}(\zeta_j) + I_{\zeta}^{af}}{I_{\zeta_j}^{bf} + I_{\zeta_j}^{af} + 1}, others; \end{cases} \tag{1}$$

here $I_{\zeta_j}^{bf}$ shows the number of successive "I" on the left of ζ_j, $I_{\zeta_j}^{af}$ denotes the number of successive "I" on the right of ζ_j , and at least one "I" appears next to ζ_j . Position (ζ_j) demonstrates the number of positions of ζ_j in the order SE.
6. Normalization of alternatives Y = $(y_{vj})_{m\times n}$ and the central profiles(cps) $\dot{c}\,\dot{p}_{kj}$, $k = 1, 2, \cdots, K; j = 1, 2, \cdots, n$ by Equation (2) and (3), respectively.

$$x_{vj} = \begin{cases} \dfrac{y_{vj} - \min\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\}}{\max\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\} - \min\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\}}, If\ c_j\ is\ a\ benefit\ criterion \\ \dfrac{max\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\} - y_{vj}}{max\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\} - min\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\}}, If\ c_j\ is\ a\ cost\ criterion \end{cases} \tag{2}$$

$$\overline{cp}_{kj} = \begin{cases} \dfrac{\dot{c}\dot{p}_{kj} - \min\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\}}{\max\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\} - \min\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\}}, If\ c_j\ is\ a\ benefit\ criterion \\ \dfrac{max\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\} - \dot{c}\dot{p}_{kj}}{max\{\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\} - min\{y_{vj}|v=1,2,\ldots,n\} \cup \{\dot{c}\,\dot{p}_{kj}|k=1,2,\ldots,K\}\}}, If\ c_j\ is\ a\ cost\ criterion \end{cases} \tag{3}$$

7. Creating the nonlinear projection using a flexible notation:

$$D^j(b_j) = \left[\emptyset\left(\mathrm{r}(S_{c_j})\right)^{\overline{\omega}} + (1-\emptyset)\left(\mathrm{r}(S_{b_i}^j)\right)^{\overline{\omega}}\right]^{\frac{1}{\overline{\omega}}} \tag{4}$$

Here $\mathrm{r}(S_{c_j})$ and $\mathrm{r}\left(S_{b_i}^j\right)$ are computed by steps 5 and 6, and $\overline{\omega}$ is a mean ranking parameter ($\overline{\omega} = 1$ means the weighted arithmetic mean, $\overline{\omega} = -1$ means the harmonic mean, $\overline{\omega} = 2$ means the quadratic mean.)
8. Comparison of the values $D^j(b_i)$ $i = 1,2, \ldots, (m+K); j = 1,2, \ldots, n$ and to get the order S_D : $b_{(1)} \aleph b_{(2)} \aleph \cdots b_{((m+K)n)}$, where $\aleph$ takes "P" or "I".
9. Calculate the normalized preference intensity for the alternative a_v, over cp_k by equation 5:

$$C(a_v, cp_k) = \frac{1}{(m+K-1)n^2} \sum_{j=1}^{n} f(vkj)\left(r\left(S_{cp_{kj}}^D\right) - r\left(S_{a_{vj}}^D\right)\right) \tag{5}$$

here $f(vkj) = \begin{cases} 1, & r\left(S_{cp_{kj}}^D\right) > r\left(S_{a_{vj}}^D\right); \\ 0, & others; \end{cases}$ is an indicator function $r\left(S_{cp_{kj}}^D\right)$ and $r\left(S_{a_{vj}}^D\right)$ are get in step 8.
10. Calculate the net preference intensity between the alternatives a_v and cp_k using.

$$NC(a_v, cp_k) = C(a_v, cp_k) - C(cp_k, a_v) \tag{6}$$

11. Ensure that the indifference threshold β, incomparability threshold γ, and terminology threshold C^* that distinguish indifference and incomparability satisfy the relationships , $\beta < \frac{1}{(\mathrm{m}+\mathrm{K}-1)\mathrm{n}}$, $\gamma > \frac{n-2}{4}$, and $C^* < \frac{d}{2(\mathrm{m}+\mathrm{K}-1)}$, respectively [27].

At this stage, P, I and, R are distinguished with the help of the β, γ, C^* values and net preference intensity obtained from the steps given in Figure 3.

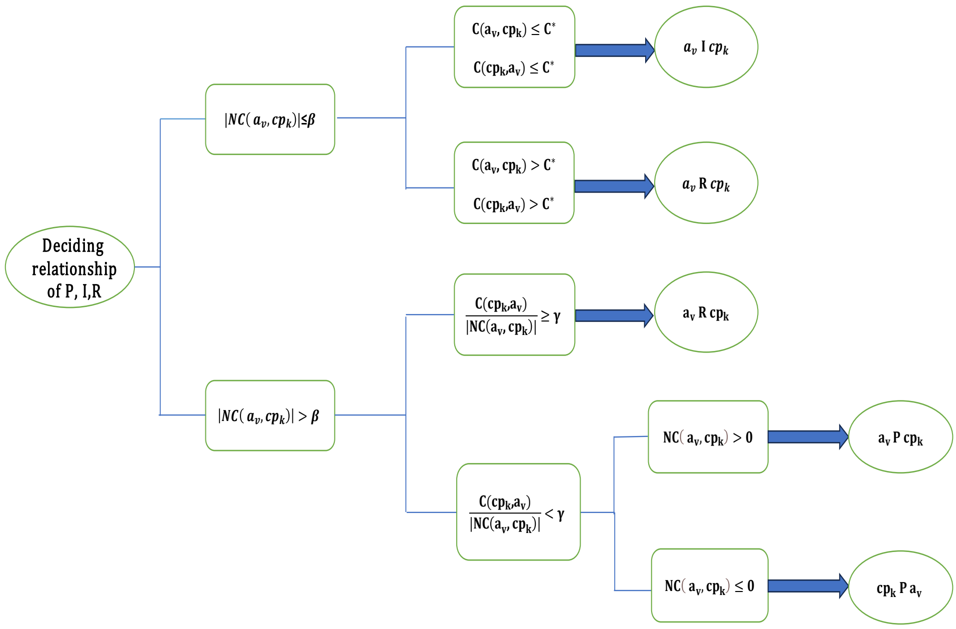

Figure 3: Stages of deciding the relationship between P, I and, R with the help of β, γ and C^*

12. Assigning alternatives to the specified class.

This method uses the ARDA rule to classify each alternative by comparing it to class ranges, unlike other classification methods. Alternatives are categorized based on optimistic, pessimistic, and compromise rules, leading to potential variations in their class assignments.

4. APPLICATION

A questionnaire is conducted to measure the knowledge and experience of students who applied to the Munzur University Disaster and Emergency Management Club for volunteer classification. 67 of the 81 students in the club participated in the online survey. Responses to survey questions, according to 9 criteria in search and rescue activities, are scored for each volunteer's level of knowledge, ranging from 1 (poor) to 9 (excellent). The required class ranges for both methods are determined as C1 (expert), C2 (experienced), C3 (sufficient), and C4 (insufficient), and the scores volunteers received based on their responses to each criterion are shown in Table 2 (see Appendix).

The data underwent a comprehensive analysis using two different Multiple Criteria Sorting Method techniques: the TOPSIS-Sort method and the ORESTE-Sort method. A detailed explanation of how each method was applied is provided, including an in-depth description of the procedures involved in its execution. Additionally, the key steps of both methods are summarised in tables, ensuring a clear and concise understanding of their respective processes.

4.1. The Implementation of TOPSIS-Sort

The TOPSIS-Sort method relies on criterion weights to classify alternatives, prioritising those that strongly meet the more important criteria into higher classes. For the criterion weights, the data were derived from a published study by Ozdemir et al. [13]. The study used the Best-Worst (BWM) method to calculate the criterion weights for nine criteria in search and rescue operations, and the results are presented in Table 3.

Table 3: The result of the criteria weights by the Best-Worst Method

Weights	*Knowledge of First Aid*	*Knowledge of Search and Rescue*	*Knowledge of Computer*	*Teamwork*	*Ability of Learning*	*Experience*	*Ability in Physics*	*Knowledge of Equipment and device*	*Ability of Language Translation*
	0,2160	**0,2777**	**0,0395**	**0,0758**	**0,0482**	**0,0705**	**0,0977**	**0,0655**	**0,0495**

After the criteria weights are calculated, the 1st, 2nd, and 3rd steps of the TOPSIS-Sort are shown in Table 2 by adding the range of each class to the survey results obtained from volunteers' knowledge of search and rescue activities. Then, the data in Table 2 is normalised (step 4), and the weighted normalised decision matrix (step 5) is calculated by multiplying the normalised decision matrix by the criterion weights obtained from the BWM method in Table 3. The resulting weighted normalised decision matrix and ideal and anti-ideal solutions in step 6 are shown in Table 4 (see Appendix) .

By calculating the Euclidean distance of each alternative to the positive and negative ideal solution, respectively (step 7), the relative closeness of the alternatives to the ideal solution is determined (step 8). For the final step of the method, each alternative is evaluated according to the ideal solution, and class assignments are made from the C1 expert group to the C4 insufficient group (Table 5). The classification data obtained is summarized in Table 6.

According to Table 6, 5 students in the C1 group, who voluntarily participate in search and rescue activities, are the priority group when distributing tasks. The second volunteer group, which will be evaluated from now on, is much more crowded than the first group, and the number of students is close to C3, which is 6 times the number of volunteers in C1. In terms of knowledge level, it is expected that the 4 volunteer students in the last group will be excluded from the task distribution, and their knowledge and experience regarding search and rescue activities will be increased.

4.2. The Implementation of ORESTE Sort

To obtain a consistent comparison; the data set and central profiles used in the TOPSIS-Sort method is taken. (The steps of the method 1,2 and 3).

Table 5: The classification results of volunteers by the TOPSIS-Sort method

Volunteer	D_i^+	D_i^-	cl_i	Class	Volunteer	D_i^+	D_i^-	cl_i	Class
a_1	0,053	0,022	0,296	C_3	a_{35}	0,060	0,015	0,196	C_4
a_2	0,035	0,037	0,514	C_2	a_{36}	0,005	0,070	0,932	C_1
a_3	0,047	0,027	0,363	C_3	a_{37}	0,063	0,014	0,183	C_4
a_4	0,022	0,051	0,697	C_2	a_{38}	0,048	0,032	0,401	C_3
a_5	0,021	0,053	0,719	C_2	a_{39}	0,026	0,050	0,653	C_2
a_6	0,047	0,026	0,360	C_3	a_{40}	0,028	0,049	0,635	C_2
a_7	0,043	0,030	0,406	C_3	a_{41}	0,047	0,026	0,358	C_3
a_8	0,029	0,045	0,605	C_2	a_{42}	0,042	0,032	0,435	C_3
a_9	0,035	0,036	0,504	C_2	a_{43}	0,060	0,022	0,266	C_3
a_{10}	0,030	0,045	0,602	C_2	a_{44}	0,057	0,027	0,320	C_3
a_{11}	0,035	0,037	0,514	C_2	a_{45}	0,044	0,031	0,412	C_3
a_{12}	0,038	0,034	0,477	C_3	a_{46}	0,065	0,013	0,166	C_4
a_{13}	0,022	0,051	0,700	C_2	a_{47}	0,068	0,012	0,151	C_4
a_{14}	0,019	0,054	0,737	C_2	a_{48}	0,051	0,021	0,290	C_3
a_{15}	0,036	0,036	0,503	C_2	a_{49}	0,034	0,038	0,529	C_2
a_{16}	0,018	0,055	0,756	C_1	a_{50}	0,034	0,038	0,528	C_2
a_{17}	0,016	0,067	0,809	C_1	a_{51}	0,024	0,060	0,715	C_2
a_{18}	0,049	0,024	0,333	C_3	a_{52}	0,049	0,025	0,334	C_3
a_{19}	0,030	0,048	0,614	C_2	a_{53}	0,049	0,026	0,347	C_3
a_{20}	0,034	0,040	0,545	C_2	a_{54}	0,034	0,040	0,541	C_2
a_{21}	0,036	0,036	0,505	C_2	a_{55}	0,038	0,034	0,477	C_3
a_{22}	0,038	0,034	0,475	C_3	a_{56}	0,037	0,036	0,489	C_3
a_{23}	0,047	0,026	0,354	C_3	a_{57}	0,033	0,042	0,563	C_2
a_{24}	0,033	0,039	0,539	C_2	a_{58}	0,047	0,025	0,350	C_3
a_{25}	0,020	0,052	0,720	C_2	a_{59}	0,040	0,034	0,456	C_3
a_{26}	0,046	0,027	0,366	C_3	a_{60}	0,043	0,030	0,411	C_3
a_{27}	0,023	0,058	0,720	C_2	a_{61}	0,047	0,027	0,366	C_3
a_{28}	0,023	0,059	0,717	C_2	a_{62}	0,052	0,020	0,278	C_3
a_{29}	0,048	0,025	0,341	C_3	a_{63}	0,029	0,046	0,615	C_2
a_{30}	0,034	0,041	0,551	C_2	a_{64}	0,051	0,023	0,309	C_3
a_{31}	0,044	0,030	0,407	C_3	a_{65}	0,045	0,031	0,406	C_3
a_{32}	0,034	0,040	0,537	C_2	a_{66}	0,038	0,035	0,481	C_3
a_{33}	0,018	0,057	0,764	C_1	a_{67}	0,044	0,029	0,398	C_3
a_{34}	0,015	0,060	0,797	C_1					

Table 6: Center profile values and number of assigned volunteers

Center Profiles	D_i^+	D_i^-	cl_i	Volunteer numbers
C1	0,018	0,053	0,750	5
C2	0,035	0,035	0,500	27
C3	0,053	0,018	0,250	30
C4	0,062	0,009	0,125	4

In the 4th step, weakly ranked relationships according to the criteria were determined by considering the criterion weights calculated with the Best Worst method to obtain more consistent results instead of the decision maker ($p_2\ P\ p_1\ P\ p_7\ P\ p_4\ P\ p_6\ I\ p_8\ P\ p_9\ I\ p_5\ P\ p_3$). With the Bessian mean ranking method, the criterion weights are listed as follows (Step 5)

$r(p_1) = 2\,; r(p_2) = 1; r(p_3) = 9; r(p_4) = 4; r(p_5) = 7.5; r(p_6) = 5.5; r(p_7) = 3;$
$r(p_8) = 5.5; r(p_9) = 7.5$

The values of the alternatives and central profiles are normalised in step 6 and shown in Table 7 (see Appendix). To create a non-linear projection using a flexible representation, the weighted arithmetic mean is taken as $\varpi = 1$ and the following Table 8 (see Appendix) is obtained by applying the Bessian mean ranking to all the alternatives and center profile values according to the calculated data. (Steps 7-8)

After the Bessian ranking matrix is obtained, the net preference intensity (Table 9) is reached by calculating the normalized preference intensity for the alternatives over the central profiles to determine the relationships between the preferences relation of "P", "I", *and* "R". (Steps 9-10)

Table 9: Net preference intensity for the alternatives

Volunteer	$NC(a_v, cp_1)$	$NC(a_v, cp_2)$	$NC(a_v, cp_3)$	$NC(a_v, cp_4)$	Volunteer	$NC(a_v, cp_1)$	$NC(a_v, cp_2)$	$NC(a_v, cp_3)$	$NC(a_v, cp_4)$
a_1	-0,397	-0,138	0,150	0,274	a_{35}	-0,587	-0,328	-0,040	0,084
a_2	-0,229	0,030	0,318	0,442	a_{36}	0,126	0,385	0,673	0,797
a_3	-0,366	-0,107	0,182	0,306	a_{37}	-0,579	-0,320	-0,031	0,093
a_4	-0,143	0,116	0,405	0,529	a_{38}	-0,512	-0,253	0,036	0,160
a_5	-0,071	0,188	0,476	0,600	a_{39}	-0,252	0,007	0,296	0,419
a_6	-0,396	-0,136	0,152	0,276	a_{40}	-0,292	-0,032	0,256	0,380
a_7	-0,472	-0,213	0,076	0,200	a_{41}	-0,364	-0,104	0,184	0,308
a_8	-0,085	0,174	0,463	0,587	a_{42}	-0,334	-0,074	0,214	0,338
a_9	-0,218	0,041	0,330	0,454	a_{43}	-0,348	-0,088	0,200	0,324
a_{10}	-0,251	0,008	0,297	0,421	a_{44}	-0,309	-0,050	0,239	0,363
a_{11}	-0,217	0,042	0,331	0,454	a_{45}	-0,179	0,080	0,369	0,493
a_{12}	-0,407	-0,148	0,140	0,264	a_{46}	-0,591	-0,331	-0,043	0,081
a_{13}	-0,074	0,185	0,474	0,598	a_{47}	-0,541	-0,282	0,006	0,130
a_{14}	0,013	0,272	0,560	0,684	a_{48}	-0,376	-0,117	0,172	0,296
a_{15}	-0,264	-0,005	0,283	0,407	a_{49}	-0,144	0,115	0,403	0,527
a_{16}	0,015	0,274	0,562	0,686	a_{50}	-0,183	0,076	0,365	0,489
a_{17}	-0,099	0,161	0,449	0,573	a_{51}	-0,171	0,089	0,377	0,501
a_{18}	-0,530	-0,271	0,017	0,141	a_{52}	-0,472	-0,212	0,076	0,200
a_{19}	-0,127	0,133	0,421	0,545	a_{53}	-0,416	-0,156	0,132	0,256
a_{20}	-0,312	-0,053	0,236	0,360	a_{54}	-0,298	-0,039	0,249	0,373
a_{21}	-0,280	-0,020	0,268	0,392	a_{55}	-0,360	-0,101	0,187	0,311
a_{22}	-0,320	-0,061	0,227	0,351	a_{56}	-0,221	0,038	0,326	0,450
a_{23}	-0,444	-0,184	0,104	0,228	a_{57}	-0,102	0,157	0,446	0,570
a_{24}	-0,127	0,132	0,421	0,545	a_{58}	-0,423	-0,163	0,125	0,249
a_{25}	-0,119	0,141	0,429	0,553	a_{59}	-0,264	-0,005	0,283	0,407
a_{26}	-0,333	-0,074	0,215	0,339	a_{60}	-0,398	-0,139	0,150	0,274
a_{27}	-0,062	0,197	0,485	0,609	a_{61}	-0,350	-0,090	0,198	0,322
a_{28}	-0,083	0,177	0,465	0,589	a_{62}	-0,466	-0,206	0,082	0,206
a_{29}	-0,525	-0,266	0,023	0,147	a_{63}	-0,110	0,149	0,438	0,562
a_{30}	-0,248	0,012	0,300	0,424	a_{64}	-0,269	-0,009	0,279	0,403
a_{31}	-0,449	-0,189	0,099	0,223	a_{65}	-0,240	0,019	0,308	0,432
a_{32}	-0,146	0,113	0,401	0,525	a_{66}	-0,308	-0,048	0,240	0,364
a_{33}	-0,075	0,184	0,472	0,596	a_{67}	-0,466	-0,207	0,082	0,206
a_{34}	0,032	0,291	0,579	0,703					

Indifference threshold β, incomparability threshold γ and terminology threshold C* are calculated according to the numbers m=67, d=34 and K=4, n=9.

$$\beta < \frac{1}{(\mathrm{m+K-1})\mathrm{n}} = \frac{1}{(67+4-1)9} = 0{,}001587,\ \gamma > \frac{n-2}{4} = \frac{9-2}{4} = 1{,}75, \text{ and}$$

$$C^* < \frac{d}{2(\mathrm{m+K-1})} = \frac{34}{2(67+4-1)} = 0{,}242857$$

With the obtained $\beta = 0{,}0015$, $\gamma = 1{,}8$, C^*=0,242 and net preference density; P, I and R are distinguished by following the steps shown in Figure 3

It is shown in Table 10 that in the final stage of the method, each alternative will be classified according to three approaches (optimistic, pessimistic, and compromise). According to the obtained data, quite different results are obtained depending on the optimistic and pessimistic approaches preferred in this method. In the optimistic approach, only the C_1 and C_2 groups are distributed to the entire group who want to voluntarily participate in search and rescue activities, and approximately twice the number of volunteers into C_1 compared with C_2; whereas no volunteer distribution is made for the other two classes. On the contrary, to classify the volunteers with a pessimistic approach, there is only one volunteer in the C_1 group, and the volunteers are mostly selected for the C_3 group (37 volunteers). In addition, 7 volunteers in the C_4 group were excluded from the task distribution in the initial situations due to their lack of knowledge and experience regarding search and rescue activities.

Table 10: The results of volunteer classification by three approaches of ORESTE-Sort

Volunteer	C_1	C_2	C_3	C_4	**Optimistic**	**Pessimistic**	**Compromise**	**Volunteer**	C_1	C_2	C_3	C_4	**Optimistic**	**Pessimistic**	**Compromise**
a_1	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{35}	P<	P<	R	P>	C2	C4	C2/C3/C4
a_2	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{36}	P>	P>	P>	P>	C1	C1	C1
a_3	P<	P<	P>	P>	C2	C3	C2/C3	a_{37}	P<	P<	R	P>	C2	C4	C2/C3/C4
a_4	P<	P>	P>	P>	C1	C2	C1/C2	a_{38}	P<	P<	R	P>	C2	C4	C2/C3/C4
a_5	R	P>	P>	P>	C1	C2	C1/C2	a_{39}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_6	P<	P<	P>	P>	C2	C3	C2/C3	a_{40}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_7	P<	P<	P>	P>	C2	C3	C2/C3	a_{41}	P<	P<	P>	P>	C2	C3	C2/C3
a_8	P<	P>	P>	P>	C1	C2	C1/C2	a_{42}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_9	P<	P>	P>	P>	C1	C2	C1/C2	a_{43}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{10}	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{44}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{11}	P<	P>	P>	P>	C1	C2	C1/C2	a_{45}	P<	P>	P>	P>	C1	C2	C1/C2
a_{12}	P<	P<	P>	P>	C2	C3	C2/C3	a_{46}	P<	P<	R	P>	C2	C4	C2/C3/C4
a_{13}	R	P>	P>	P>	C1	C2	C1/C2	a_{47}	P<	P<	R	P>	C2	C4	C2/C3/C4
a_{14}	R	P>	P>	P>	C1	C2	C1/C2	a_{48}	P<	P<	P>	P>	C2	C3	C1/C2
a_{15}	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{49}	P<	P>	P>	P>	C1	C2	C1/C2
a_{16}	R	P>	P>	P>	C1	C2	C1/C2	a_{50}	P<	R	P>	P>	C1	C3	C1/C2/C3

Table 10: (continued)

Volunteer	C_1	C_2	C_3	C_4	Optimistic	Pessimistic	Compromise	Volunteer	C_1	C_2	C_3	C_4	Optimistic	Pessimistic	Compromise
a_{17}	R	P>	P>	P>	C1	C2	C1/C2	a_{51}	P<	P>	P>	P>	C1	C2	C1/C2
a_{18}	P<	P<	R	P>	C2	C4	C2/C3/C4	a_{52}	P<	P<	P>	P>	C2	C3	C2/C3
a_{19}	P<	P>	P>	P>	C1	C2	C1/C2	a_{53}	P<	P<	P>	P>	C2	C3	C2/C3
a_{20}	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{54}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{21}	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{55}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{22}	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{56}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{23}	P<	P<	P>	P>	C2	C3	C2/C3	a_{57}	R	P>	P>	P>	C1	C2	C1/C2
a_{24}	P<	P>	P>	P>	C1	C2	C1/C2	a_{58}	P<	P<	P>	P>	C2	C3	C2/C3
a_{25}	P<	P>	P>	P>	C1	C2	C1/C2	a_{59}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{26}	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{60}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{27}	R	P>	P>	P>	C1	C2	C1/C2	a_{61}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{28}	R	P>	P>	P>	C1	C2	C1/C2	a_{62}	P<	P<	P>	P>	C2	C3	C2/C3
a_{29}	P<	P<	R	P>	C2	C4	C2/C3/C4	a_{63}	R	P>	P>	P>	C1	C2	C1/C2
a_{30}	P<	R	P>	P>	C1	C3	C1/C2/C3	a_{64}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{31}	P<	P<	P>	P>	C2	C3	C2/C3	a_{65}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{32}	P<	P>	P>	P>	C1	C2	C1/C2	a_{66}	P<	R	P>	P>	C1	C3	C1/C2/C3
a_{33}	P<	P>	P>	P>	C1	C2	C1/C2	a_{67}	P<	P<	P>	P>	C2	C3	C2/C3
a_{34}	R	P>	P>	P>	C1	C2	C1/C2								
C_1					**47**	**1**									
C2					**20**	**22**									
C3					**0**	**37**									
C4					**0**	**7**									

5. DISCUSSION

To compare of the methods separately according to the results given in the classification of volunteers for search and rescue activities, the classes of each alternative given by the TOPSIS-Sort and ORESTE-Sort optimistic approach are shown in Figure 4.

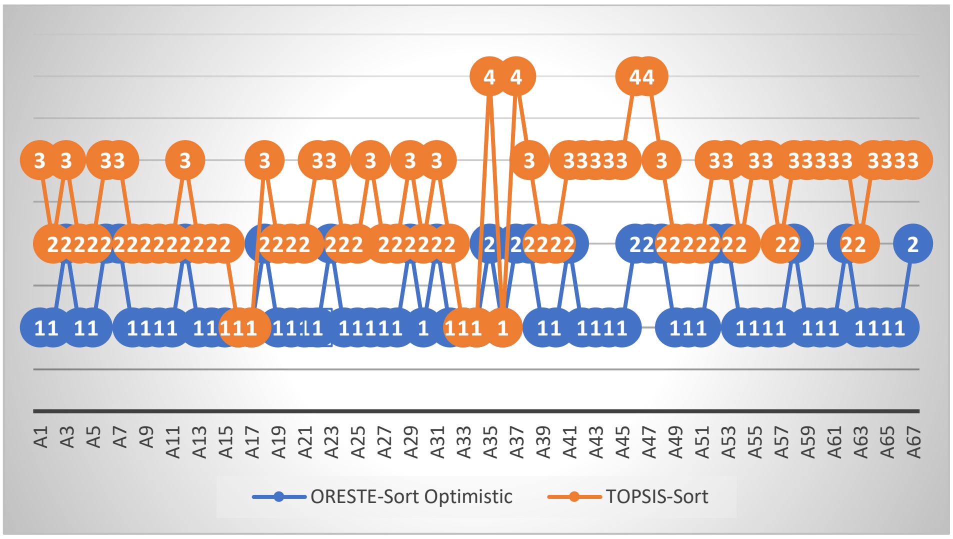

Figure 4: Comparison of the TOPSIS-Sort and ORESTE-Sort Optimistic

Depending on the results obtained between the two methods, quite different alternative classes are obtained. In both methods, only 5 of the alternatives (a_{16}, a_{17}, a_{33}, a_{34}, a_{36}) are distributed in the same class, while the other alternatives are in different classes. In addition, the alternatives (a_{35}, a_{37}, a_{46}, a_{47}) assigned to the experienced (C_2) class in the ORESTE-Sort are assigned to the insufficient (C_4) class from the TOPSIS-Sort.

Similarly, when comparing the Pessimistic approach of the ORESTE-Sort with the TOPSIS-Sort, to obtain closer results than the optimistic approach (Figure 5).

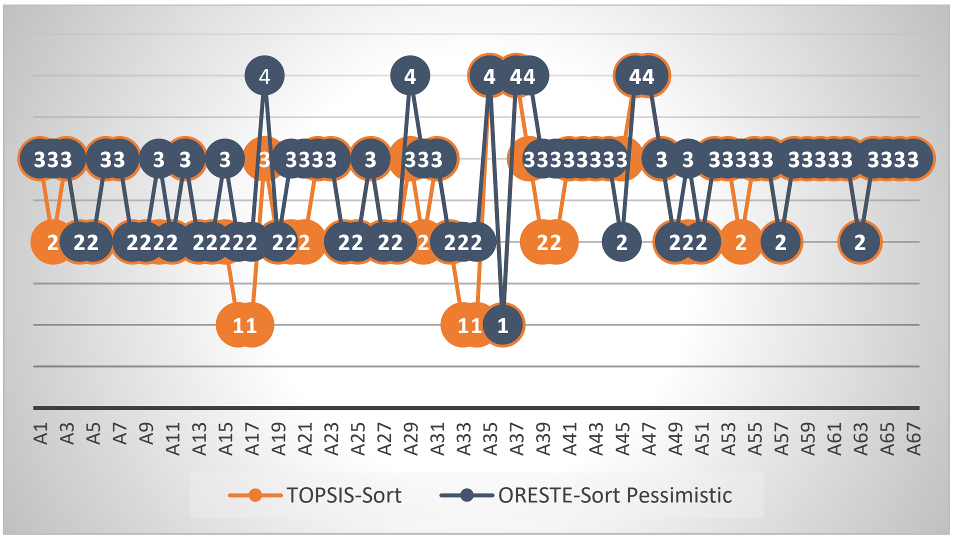

Figure 5: Comparison of the TOPSIS-Sort and ORESTE-Sort Pessimistic

In the two methods, 49 of the 67 alternatives are assigned to the same class. Among the alternatives that are not assigned to a similar class in the two methods, only a_{45} (C_2) is assigned to a better class in ORESTE-Sort Pessimistic than the TOPSIS-Sort (C_3). The same results for all three methods are that only a_{36} is assigned to the C_1 class.

This study has several limitations that should be taken into account when interpreting the findings. The participant group consisted of volunteers, a relatively small group. This limited sample size inherently limits the extent to which the results can be generalised and applied to broader, more diverse populations. Furthermore, the classification of the volunteer group, which is relevant only to the pre-response planning domain of disaster management, lacks practical impact simulations or real-world scenario testing in the study design, undermining the study's general applicability and ability to provide concrete guidance for real-world situations. Furthermore, the classification of the methods was based on nine criteria. The criteria for search and rescue efforts were not broken down into subgroup criteria and addressed in greater depth, revealing the physical, mental, or emotional characteristics of the volunteers.

The comparative analysis and sensitivity analysis of the two methods in the current study are subject to some limitations stemming from the limited size of the available dataset. To more definitively validate the practical applicability of these methods and effectively address the challenges associated with solution complexity, it is important to include significantly larger and more comprehensive datasets. Furthermore, the study only focuses on the strengths and weaknesses of ORESTE-Sort and TOPSIS-Sort by comparing them, without mentioning other methods such as VIKOR, PROMETHEE, and ELECTRE-Sort to determine the most suitable classification approach.

5.1. Managerial Insights

The result is analysed test statistics to determine if there is a significant difference between the ORESTE-Sort (Optimist and Pessimist approaches) and TOPSIS-Sort.The Wilcoxon signed-rank test is a nonparametric hypothesis test used to assess the statistical significance of the difference between two related groups after evaluating the results of two methods and calculating the number of similar and different classes for each alternative [28]. The steps of the test are as follows:

- Calculate the difference(D_i) between two measurements for each of the n items in a sample.
- The absolute differences are given by $|D_i|$ for i = 1,2,..., n.
- To get accurate magnitude estimates, consider only the n non-zero absolute difference scores.
- Rank each absolute difference score $|D_i|$ from 1 to n, assigning rank 1 to the smallest and rank n to the largest. In case of ties, assign the average rank.
- Assign a "+" or "–" symbol to each of the n ranks R_i based on the initial sign of D_i.
- The W-statistic uses the smaller of two sums to assess the significance of observed differences.
- Determine if the calculated W statistic is significant compared to a predefined significance level (e.g., $\alpha = 0.05$).

Comparing the ORESTE-Sort optimistic approach with the TOPSIS-Sort, the test statistics are calculated with n=62 because 5 of the 67 alternatives yielded identical results. With n>30, the critical value(T^c) of z-table is -1.645 is used, corresponding to a 5% confidence level. The absolute values of the differences between the two methods for each alternative are ranked. The sum of the positive ($T^+ = 0$) and negative ($T^- = 1931$) ranks are calculated. The evaluation of the H_0 null hypothesis (similarity between the two methods) is as follows:

$$Tmin(T^+, T^-) = 0$$

$$\mu_t = \frac{n*(n+1)}{4} = \frac{62*63}{4} = 976.5$$

$$\sigma_t = \sqrt{\frac{n*(n+1)*(2n+1)}{24}} = 142.6315$$

$$Z = \frac{T-\mu_t}{\sigma_t} = -6.84631$$

Since $Z < T^c$ the H_0 hypothesis is rejected. That is, there are significant differences between the results of the two methods.

When comparing the ORESTE-Pessimist and TOPSIS-Sort method, 18 out of 67 alternatives will be considered (since the others give the same result). Since the sample n=18<30, the T statistic will be used, and the critical value will be taken as 40 in the 0.05 confidence interval according to the Wilcoxon Signed-Rank Test Critical Values Table. According to the differences between the two methods for 18 alternatives, T^+ =9.5 and T^-=161.5 are found, and since the $Tmin(T^+, T^-)$=9.5 value is smaller than the critical value, the Ho hypothesis is rejected, and similarly, there is a significant difference between the two methods.

The Wilcoxon test reveals statistically significant differences between TOPSIS-Sort and ORESTE-Sort optimistic and pessimistic approaches. These inconsistencies arise partly because TOPSIS-Sort requires a method for calculating criterion weights, whereas ORESTE-Sort only needs the criterion importance order. Furthermore, TOPSIS-Sort offers clearer classification results but lacks in-depth comparative analysis between alternatives and center profiles. Conversely, ORESTE-Sort assigns alternatives with values close to center profiles to higher (optimistic) or lower (pessimistic) center profiles, leading to notable implementation differences. Moreover, its ARDA rule necessitates three thresholds (β , γ, C^*) that influence classification, a feature absent in TOPSIS-Sort.

5.2. Sensitivity Analysis of ORESTE-Sort

In the ORESTE-Sort method, the threshold values β, γ, and $C*$ are crucial for classifying alternatives. These values define indifference, incomparability, and preference thresholds, and their modification influences the classification outcomes. A sensitivity analysis will be performed to assess the impact of varying these values on the classification. Given that β equals 0.0015, all alternatives in this study surpassed the absolute net preference relationship ($|NC(a_v, cp_k)| >$ β) rendering the $C*$ value is unnecessary for classification. Consequently, decreasing β does not alter the ranking of alternatives. When the β value increases by at least 400%, the $C*$ number is used to evaluate alternatives 15 and 59. Their absolute net preference relationship is less than β; their classification remains stable despite changes in β, and $C*$.

When the γ value is examined for the changes of alternative classes, increasing the γ=1.8 value by approximately 2% initially impacted alternative 18, decreasing its classification from C_2 to C_3 under the optimistic approach. Similarly, if the γ increased by approximately 25%, it is seen that it falls to a lower class than the class range where there are 11 alternatives, such as 19,22, and 63. Conversely, a 10% reduction in γ shifts alternative 12 from class C_2 to C_1 (optimistic approach). Lowering γ by 25% reassigns alternatives 38 and 47 from C_4 to C_3 (pessimistic approach) and triggers a one-class re-evaluation for 8 alternatives (optimistic approach). Table 11 shows the impact of a ±25% change in γ on previous and newly assigned volunteer classes.

Table 11: The effect of ±25% change in γ value on ORESTE-Sort classification

Volunteer	Class(Ci)	New Class(Ci)	Volunteer	Class(Ci)	New Class(Ci)
3	2	1	**38**	4	3
8	2	1	**42**	3	2
12	2	1	**47**	4	3
18	2	3	**50**	1	2
19	1	2	**51**	2	1
22	1	2	**55**	3	2
26	1	2	**57**	1	2
28	1	2	**60**	3	2
32	2	1	**63**	1	2
33	2	1			

Sensitivity analysis reveals that the ORESTE-Sort method's classification of volunteer classes (Figure 3) is sensitive to changes in the γ number, while B and C threshold values have no significant impact. The γ value's effect varies between the method's optimistic and pessimistic approaches, with the optimistic approach being more significantly affected by the change of γ. This is because a lower γ threshold leads to increased indecision and incomparability when determining preference relationships of the center profiles, whereas a higher threshold reduces incomparability (R).

5.3. General evaluation of the two methods

The general characteristics of both methods and their evaluation according to the method steps are summarised in Table 12. The advantages and disadvantages of the methods are as follows, respectively.

Table 12: General comparison of the two methods

	TOPSIS-Sort	***ORESTE-Sort***
Usage in literature	*Quite common*	*Rare*
Criterion Weights	*Must be calculated*	*Sorting is enough*
Preference relationship	*Not used*	*Each alternative is examined*
Solution method	*Simpler*	*Complicated*
Approaches	*Not used*	*Three different approaches*

In classification methods, criteria are ranked in line with expert opinions or by determining the importance of the criteria for the decision maker. In the TOPSIS-Sort method, criterion weights are calculated according to the order of importance among the criteria with the help of the AHP or Best-Worst method. Although the ORESTE-Sort method is not as widely used as the TOPSIS-Sort method, it is a flexible and effective multiple sorting method that can be implemented to vary problems such as risk, inventory, and personnel selection. When determining the weights of the criteria, the criteria are ordered from the most important to the least important, then preferences and alternatives are ranked with the help of the Besson mean ranking.

In the TOPSIS-Sort method, the *P*, *I,* and *R* relationship between the preferences is not used, and it is only checked whether they are between the specified lower and upper limits. In the ORESTE-Sort method, the *P* and *I* importance preference relationship is calculated by comparing the lower and upper limit values of the class ranges of each alternative, and the limits of these parameters can also be determined. Additionally, the incomparability relationship between alternatives and classes is examined with the help of the *R* threshold value.

ORESTE-Sort Optimistic, Pessimistic, and Compromise approaches are evaluated separately for each alternative, resulting in 3 different results, and the solution method is more complex and requires more time. Since there are no different approaches in TOPSIS-Sort, it is possible to reach a single solution in a shorter time.

6. CONCLUSION AND RECOMMENDATIONS

This study applies the ORESTE-Sort method with TOPSIS-Sort for volunteer selection in disaster management. By classifying volunteers based on emergency knowledge, the study placed particular emphasis on the ORESTE-Sort method compared with TOPSIS-Sort, providing a detailed discussion of its inherent strengths and weaknesses. This discussion offers a nuanced perspective on how ORESTE-Sort performs in relation to the TOPSIS-Sort method, highlighting areas where it excels and areas where it may fall short. According to the results obtained, although the TOPSIS-Sort method gives some similar results to the Pessimistic approach of ORESTE-Sort, quite different results are obtained compared to the ORESTE-Sort Optimistic. Moreover, in all methods, only one alternative is assigned to the same class, and in ORESTE-Sort Optimistic, no alternatives are assigned to classes C_3 and C_4. When the relationship between the methods is examined by the Wilcoxon signed-rank test , there is a significant difference between the two methods.

The pros and cons of both methods are presented in a table and critically evaluated. While TOPSIS-Sort offers a simpler and faster solution, ORESTE-Sort, unlike TOPSIS-Sort, which relies on methods like BWM for criteria weighting, employs Besson's mean ranking for a more objective assessment of criteria importance and handles the evaluation of relationships (preference, indifference, incomparability) between alternatives and classes under three approaches (optimist, pessimist, compromise).

This study enables flexible decision-making in disaster response by classifying volunteers according to the situation. When immediate intervention is needed and all volunteers must be evaluated, the optimistic ORESTE-Sort approach can be used to ensure no volunteer is overlooked. If only a few volunteers are needed and expertise is critical, a pessimistic approach can identify and utilize only the most experienced volunteers, maximizing benefit while minimizing risk. In contrast,ORESTE-Sort's classification process is more complex than TOPSIS-Sort due to its three threshold values and the ARDA rule. These thresholds, as shown in the sensitivity analysis, impact classification results; optimistic versus pessimistic approaches can yield significantly different classifications for the same alternative. This, combined with a large number of alternatives, increases variability, complexity, and computational difficulty. Consequently, TOPSIS-Sort is better suited when a single result is desired with numerous alternatives and classifications.

The current study limits volunteer classification to nine criteria. Adding new criteria to include mental and emotional dimensions could significantly expand the scope of volunteer classification for search and rescue operations. Combining mental qualities such as time management, sociability, self-confidence, and active participation with emotional qualities such as empathy, stress tolerance, and sensitivity would provide a more comprehensive assessment.

Further research is needed to fully understand ORESTE-Sort's capabilities and limitations. This method can be used to analyse various areas, such as the economic ranking of companies and the classification of countries by carbon footprint, using alternative and central profiles. Moreover, to gain a more complete understanding of ORESTE-Sort's strengths and weaknesses, comparative analyses against the Multiple Criteria Sorting Methods like VIKOR, PROMETHEE, and ELECTRE-Sort are needed. Such comparisons would be instrumental in identifying the most appropriate classification approach for various types of decision-making problems, enabling practitioners to select the method best suited to their specific needs and objectives.

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APPENDIX

Table 2: The questionnaire results of the volunteers with classes

Volunteer	Criteria									Volunteer	Criteria								
	First Aid (p1)	*Search and Rescue (p2)*	*Computer (p3)*	*Teamwork (p4)*	*Learning Ability (p5)*	*Experience (p6)*	*Physical ability (p7)*	*Equipment and device (p8)*	*Language Ability (p9)*		*First Aid (p1)*	*Search and Rescue (p2)*	*Computer (p3)*	*Teamwork (p4)*	*Learning Ability (p5)*	*Experience (p6)*	*Physical ability (p7)*	*Equipment and device (p8)*	*Language Ability (p9)*
a_1	3	3	3	9	9	1	5	1	3	a_{35}	1	3	5	5	1	1	1	1	3
a_2	5	5	3	7	7	5	7	5	3	a_{36}	9	9	7	9	9	9	9	9	5
a_3	5	3	5	7	7	3	5	3	1	a_{37}	3	1	3	5	1	1	5	1	3
a_4	7	7	3	7	9	5	7	5	1	a_{38}	7	3	1	1	5	1	3	1	7
a_5	7	7	1	9	9	7	9	5	3	a_{39}	7	7	3	9	7	3	5	1	3
a_6	5	3	5	7	5	3	5	3	1	a_{40}	7	7	1	5	9	3	3	1	9
a_7	3	5	3	5	5	3	5	3	1	a_{41}	5	3	5	1	7	3	5	5	3
a_8	7	5	3	9	7	5	9	7	5	a_{42}	3	5	3	3	5	7	5	3	9
a_9	5	5	5	7	7	5	5	5	3	a_{43}	3	1	1	5	7	5	7	7	5
a_{10}	5	7	5	7	7	5	3	5	1	a_{44}	5	1	1	7	7	7	5	3	9
a_{11}	5	5	5	7	7	5	7	5	1	a_{45}	5	3	5	7	7	5	7	7	5
a_{12}	5	5	1	5	7	3	5	5	1	a_{46}	3	1	1	3	7	1	1	1	7
a_{13}	7	7	5	9	9	5	5	7	1	a_{47}	1	1	1	5	5	3	1	3	9
a_{14}	7	7	7	9	9	7	7	9	1	a_{48}	3	3	5	7	5	3	3	5	5
a_{15}	5	5	3	7	9	3	7	5	1	a_{49}	5	5	5	7	7	3	7	7	9
a_{16}	7	7	5	9	7	9	9	9	3	a_{50}	5	5	1	9	7	7	7	5	5
a_{17}	9	9	1	9	9	9	5	7	1	a_{51}	7	9	5	9	9	3	3	1	5
a_{18}	5	3	3	5	3	3	3	3	1	a_{52}	5	3	5	5	5	1	3	1	5
a_{19}	9	5	5	7	9	5	5	3	5	a_{53}	5	3	5	7	5	1	3	1	7
a_{20}	7	5	5	7	5	3	5	3	1	a_{54}	7	5	3	5	7	5	3	3	5
a_{21}	5	5	1	7	7	7	5	5	3	a_{55}	5	5	3	5	7	3	5	1	7
a_{22}	5	5	5	9	5	3	3	3	3	a_{56}	5	5	7	9	9	3	5	1	3
a_{23}	5	3	3	5	5	1	5	5	3	a_{57}	7	5	5	9	9	5	3	3	9
a_{24}	5	5	5	7	7	9	7	5	5	a_{58}	5	3	3	5	5	3	3	5	5
a_{25}	7	7	3	7	7	9	7	5	3	a_{59}	3	5	1	7	5	5	7	5	9
a_{26}	5	3	5	7	7	3	5	3	3	a_{60}	3	5	1	3	7	3	3	5	9
a_{27}	5	9	5	9	9	7	5	7	3	a_{61}	5	3	3	9	5	5	3	1	7
a_{28}	5	9	5	9	9	7	5	9	1	a_{62}	3	3	5	5	5	3	5	1	3
a_{29}	5	3	1	3	5	3	5	3	1	a_{63}	5	7	5	9	9	5	3	3	9
a_{30}	7	5	5	7	5	3	5	1	9	a_{64}	3	3	5	9	9	3	3	5	5
a_{31}	3	5	9	5	3	1	5	1	3	a_{65}	5	3	1	7	7	5	7	5	9
a_{32}	5	5	3	9	9	5	9	7	1	a_{66}	5	5	1	5	9	3	3	5	9
a_{33}	9	7	5	7	7	7	7	5	3	a_{67}	3	5	1	3	5	5	3	1	7
a_{34}	9	7	5	7	9	9	9	9	3										
C_1	7	7	7	7	7	7	7	7	7										
C_2	5	5	5	5	5	5	5	5	5										
C_3	3	3	3	3	3	3	3	3	3										
C_4	2	2	2	2	2	2	2	2	2										

Table 4: The weighted normalized decision matrix with ideal and anti-ideal solutions

Weighted Normalized Decision Matrix									
Volunteer	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
a_1	0,014	0,019	0,003	0,012	0,007	0,002	0,011	0,002	0,003
a_2	0,023	0,032	0,003	0,009	0,006	0,009	0,015	0,008	0,003
a_3	0,023	0,019	0,006	0,009	0,006	0,005	0,011	0,005	0,001
a_4	0,033	0,045	0,003	0,009	0,007	0,009	0,015	0,008	0,001
a_5	0,033	0,045	0,001	0,012	0,007	0,012	0,019	0,008	0,003
a_6	0,023	0,019	0,006	0,009	0,004	0,005	0,011	0,005	0,001
a_7	0,014	0,032	0,003	0,007	0,004	0,005	0,011	0,005	0,001
a_8	0,033	0,032	0,003	0,012	0,006	0,009	0,019	0,012	0,006
a_9	0,023	0,032	0,006	0,009	0,006	0,009	0,011	0,008	0,003
a_{10}	0,023	0,045	0,006	0,009	0,006	0,009	0,006	0,008	0,001
a_{11}	0,023	0,032	0,006	0,009	0,006	0,009	0,015	0,008	0,001
a_{12}	0,023	0,032	0,001	0,007	0,006	0,005	0,011	0,008	0,001
a_{13}	0,033	0,045	0,006	0,012	0,007	0,009	0,011	0,012	0,001
a_{14}	0,033	0,045	0,008	0,012	0,007	0,012	0,015	0,015	0,001
a_{15}	0,023	0,032	0,003	0,009	0,007	0,005	0,015	0,008	0,001
a_{16}	0,033	0,045	0,006	0,012	0,006	0,015	0,019	0,015	0,003
a_{17}	0,042	0,057	0,001	0,012	0,007	0,015	0,011	0,012	0,001
a_{18}	0,023	0,019	0,003	0,007	0,002	0,005	0,006	0,005	0,001
a_{19}	0,042	0,032	0,006	0,009	0,007	0,009	0,011	0,005	0,006
a_{20}	0,033	0,032	0,006	0,009	0,004	0,005	0,011	0,005	0,001
a_{21}	0,023	0,032	0,001	0,009	0,006	0,012	0,011	0,008	0,003
a_{22}	0,023	0,032	0,006	0,012	0,004	0,005	0,006	0,005	0,003
a_{23}	0,023	0,019	0,003	0,007	0,004	0,002	0,011	0,008	0,003
a_{24}	0,023	0,032	0,006	0,009	0,006	0,015	0,015	0,008	0,006
a_{25}	0,033	0,045	0,003	0,009	0,006	0,015	0,015	0,008	0,003
a_{26}	0,023	0,019	0,006	0,009	0,006	0,005	0,011	0,005	0,003
a_{27}	0,023	0,057	0,006	0,012	0,007	0,012	0,011	0,012	0,003
a_{28}	0,023	0,057	0,006	0,012	0,007	0,012	0,011	0,015	0,001
a_{29}	0,023	0,019	0,001	0,004	0,004	0,005	0,011	0,005	0,001
a_{30}	0,033	0,032	0,006	0,009	0,004	0,005	0,011	0,002	0,010
a_{31}	0,014	0,032	0,010	0,007	0,002	0,002	0,011	0,002	0,003
a_{32}	0,023	0,032	0,003	0,012	0,007	0,009	0,019	0,012	0,001
a_{33}	0,042	0,045	0,006	0,009	0,006	0,012	0,015	0,008	0,003
a_{34}	0,042	0,045	0,006	0,009	0,007	0,015	0,019	0,015	0,003
a_{35}	0,005	0,019	0,006	0,007	0,001	0,002	0,002	0,002	0,003
a_{36}	0,042	0,057	0,008	0,012	0,007	0,015	0,019	0,015	0,006
a_{37}	0,014	0,006	0,003	0,007	0,001	0,002	0,011	0,002	0,003
a_{38}	0,033	0,019	0,001	0,001	0,004	0,002	0,006	0,002	0,008
a_{39}	0,033	0,045	0,003	0,012	0,006	0,005	0,011	0,002	0,003
a_{40}	0,033	0,045	0,001	0,007	0,007	0,005	0,006	0,002	0,010
a_{41}	0,023	0,019	0,006	0,001	0,006	0,005	0,011	0,008	0,003
a_{42}	0,014	0,032	0,003	0,004	0,004	0,012	0,011	0,005	0,010
a_{43}	0,014	0,006	0,001	0,007	0,006	0,009	0,015	0,012	0,006
a_{44}	0,023	0,006	0,001	0,009	0,006	0,012	0,011	0,005	0,010
a_{45}	0,023	0,019	0,006	0,009	0,006	0,009	0,015	0,012	0,006
a_{46}	0,014	0,006	0,001	0,004	0,006	0,002	0,002	0,002	0,008
a_{47}	0,005	0,006	0,001	0,007	0,004	0,005	0,002	0,005	0,010
a48	0,014	0,019	0,006	0,009	0,004	0,005	0,006	0,008	0,006
a49	0,023	0,032	0,006	0,009	0,006	0,005	0,015	0,012	0,010
a50	0,023	0,032	0,001	0,012	0,006	0,012	0,015	0,008	0,006
a51	0,033	0,057	0,006	0,012	0,007	0,005	0,006	0,002	0,006
a52	0,023	0,019	0,006	0,007	0,004	0,002	0,006	0,002	0,006

Table 4: (continued)

Volunteer	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
a_{53}	0,023	0,019	0,006	0,009	0,004	0,002	0,006	0,002	0,008
a_{54}	0,033	0,032	0,003	0,007	0,006	0,009	0,006	0,005	0,006
a_{55}	0,023	0,032	0,003	0,007	0,006	0,005	0,011	0,002	0,008
a_{56}	0,023	0,032	0,008	0,012	0,007	0,005	0,011	0,002	0,003
a_{57}	0,033	0,032	0,006	0,012	0,007	0,009	0,006	0,005	0,010
a_{58}	0,023	0,019	0,003	0,007	0,004	0,005	0,006	0,008	0,006
a_{59}	0,014	0,032	0,001	0,009	0,004	0,009	0,015	0,008	0,010
a_{60}	0,014	0,032	0,001	0,004	0,006	0,005	0,006	0,008	0,010
a_{61}	0,023	0,019	0,003	0,012	0,004	0,009	0,006	0,002	0,008
a_{62}	0,014	0,019	0,006	0,007	0,004	0,005	0,011	0,002	0,003
a_{63}	0,023	0,045	0,006	0,012	0,007	0,009	0,006	0,005	0,010
a_{64}	0,014	0,019	0,006	0,012	0,007	0,005	0,006	0,008	0,006
a_{65}	0,023	0,019	0,001	0,009	0,006	0,009	0,015	0,008	0,010
a_{65}	0,023	0,019	0,001	0,009	0,006	0,009	0,015	0,008	0,010
a_{66}	0,023	0,032	0,001	0,007	0,007	0,005	0,006	0,008	0,010
a_{67}	0,014	0,032	0,001	0,004	0,004	0,009	0,006	0,002	0,008
C_1	0,033	0,045	0,008	0,009	0,006	0,012	0,015	0,012	0,008
C_2	0,023	0,032	0,006	0,007	0,004	0,009	0,011	0,008	0,006
C_3	0,014	0,019	0,003	0,004	0,002	0,005	0,006	0,005	0,003
C_4	0,009	0,013	0,002	0,003	0,002	0,003	0,004	0,003	0,002
Ideal	0,042	0,057	0,010	0,012	0,007	0,015	0,019	0,015	0,010
Anti ideal	0,005	0,006	0,001	0,001	0,001	0,002	0,002	0,002	0,001

Table 7: Normalize alternatives and central profiles

Normalized Matrix									
Volunteer	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
a_1	0,25	0,25	0,25	1	1	0	0,5	0	0,25
a_2	0,5	0,5	0,25	0,75	0,75	0,5	0,75	0,5	0,25
a_3	0,5	0,25	0,5	0,75	0,75	0,25	0,5	0,25	0
a_4	0,75	0,75	0,25	0,75	1	0,5	0,75	0,5	0
a_5	0,75	0,75	0	1	1	0,75	1	0,5	0,25
a_6	0,5	0,25	0,5	0,75	0,5	0,25	0,5	0,25	0
a_7	0,25	0,5	0,25	0,5	0,5	0,25	0,5	0,25	0
a_8	0,75	0,5	0,25	1	0,75	0,5	1	0,75	0,5
a_9	0,5	0,5	0,5	0,75	0,75	0,5	0,5	0,5	0,25
a_{10}	0,5	0,75	0,5	0,75	0,75	0,5	0,25	0,5	0
a_{11}	0,5	0,5	0,5	0,75	0,75	0,5	0,75	0,5	0
a_{12}	0,5	0,5	0	0,5	0,75	0,25	0,5	0,5	0
a_{13}	0,75	0,75	0,5	1	1	0,5	0,5	0,75	0
a_{14}	0,75	0,75	0,75	1	1	0,75	0,75	1	0
a_{15}	0,5	0,5	0,25	0,75	1	0,25	0,75	0,5	0
a_{16}	0,75	0,75	0,5	1	0,75	1	1	1	0,25
a_{17}	1	1	0	1	1	1	0,5	0,75	0
a18	0,5	0,25	0,25	0,5	0,25	0,25	0,25	0,25	0
a19	1	0,5	0,5	0,75	1	0,5	0,5	0,25	0,5
a20	0,75	0,5	0,5	0,75	0,5	0,25	0,5	0,25	0
a21	0,5	0,5	0	0,75	0,75	0,75	0,5	0,5	0,25
a22	0,5	0,5	0,5	1	0,5	0,25	0,25	0,25	0,25
a23	0,5	0,25	0,25	0,5	0,5	0	0,5	0,5	0,25
a24	0,5	0,5	0,5	0,75	0,75	1	0,75	0,5	0,5
a25	0,75	0,75	0,25	0,75	0,75	1	0,75	0,5	0,25
a26	0,5	0,25	0,5	0,75	0,75	0,25	0,5	0,25	0,25

Table 7: (continued)

Volunteer	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
a_{27}	0,5	1	0,5	1	1	0,75	0,5	0,75	0,25
a_{28}	0,5	1	0,5	1	1	0,75	0,5	1	0
a_{29}	0,5	0,25	0	0,25	0,5	0,25	0,5	0,25	0
a_{30}	0,75	0,5	0,5	0,75	0,5	0,25	0,5	0	1
a_{31}	0,25	0,5	1	0,5	0,25	0	0,5	0	0,25
a_{32}	0,5	0,5	0,25	1	1	0,5	1	0,75	0
a_{33}	1	0,75	0,5	0,75	0,75	0,75	0,75	0,5	0,25
a_{34}	1	0,75	0,5	0,75	1	1	1	1	0,25
a_{35}	0	0,25	0,5	0,5	0	0	0	0	0,25
a_{36}	1	1	0,75	1	1	1	1	1	0,5
a_{37}	0,25	0	0,25	0,5	0	0	0,5	0	0,25
a_{38}	0,75	0,25	0	0	0,5	0	0,25	0	0,75
a_{39}	0,75	0,75	0,25	1	0,75	0,25	0,5	0	0,25
a_{40}	0,75	0,75	0	0,5	1	0,25	0,25	0	1
a_{41}	0,5	0,25	0,5	0	0,75	0,25	0,5	0,5	0,25
a_{42}	0,25	0,5	0,25	0,25	0,5	0,75	0,5	0,25	1
a_{43}	0,25	0	0	0,5	0,75	0,5	0,75	0,75	0,5
a_{44}	0,5	0	0	0,75	0,75	0,75	0,5	0,25	1
a_{45}	0,5	0,25	0,5	0,75	0,75	0,5	0,75	0,75	0,5
a_{46}	0,25	0	0	0,25	0,75	0	0	0	0,75
a_{47}	0	0	0	0,5	0,5	0,25	0	0,25	1
a_{48}	0,25	0,25	0,5	0,75	0,5	0,25	0,25	0,5	0,5
a_{49}	0,5	0,5	0,5	0,75	0,75	0,25	0,75	0,75	1
a_{50}	0,5	0,5	0	1	0,75	0,75	0,75	0,5	0,5
a_{51}	0,75	1	0,5	1	1	0,25	0,25	0	0,5
a_{52}	0,5	0,25	0,5	0,5	0,5	0	0,25	0	0,5
a_{53}	0,5	0,25	0,5	0,75	0,5	0	0,25	0	0,75
a_{54}	0,75	0,5	0,25	0,5	0,75	0,5	0,25	0,25	0,5
a_{55}	0,5	0,5	0,25	0,5	0,75	0,25	0,5	0	0,75
a_{56}	0,5	0,5	0,75	1	1	0,25	0,5	0	0,25
a_{57}	0,75	0,5	0,5	1	1	0,5	0,25	0,25	1
a_{58}	0,5	0,25	0,25	0,5	0,5	0,25	0,25	0,5	0,5
a_{59}	0,25	0,5	0	0,75	0,5	0,5	0,75	0,5	1
a_{60}	0,25	0,5	0	0,25	0,75	0,25	0,25	0,5	1
a_{61}	0,5	0,25	0,25	1	0,5	0,5	0,25	0	0,75
a_{62}	0,25	0,25	0,5	0,5	0,5	0,25	0,5	0	0,25
a_{63}	0,5	0,75	0,5	1	1	0,5	0,25	0,25	1
a_{64}	0,25	0,25	0,5	1	1	0,25	0,25	0,5	0,5
a_{65}	0,5	0,25	0	0,75	0,75	0,5	0,75	0,5	1
a_{66}	0,5	0,5	0	0,5	1	0,25	0,25	0,5	1
a_{67}	0,25	0,5	0	0,25	0,5	0,5	0,25	0	0,75
C_1	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
C_2	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5	0,5
C_3	0,25	0,25	0,25	0,25	0,25	0,25	0,25	0,25	0,25
C_4	0,125	0,125	0,125	0,125	0,125	0,125	0,125	0,125	0,125

Table 8: Bessian Ranking results of alternatives and central profiles

Bessian Rank Matrix									
Volunteer	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
a_1	517,5	477,5	432,5	67,5	122,5	625	296	571	413
a_2	326	255	432,5	280	355,5	220,5	100	220,5	413
a_3	326	477,5	184,5	280	355,5	454,5	296	394,5	593,5
a_4	75	44	432,5	280	122,5	220,5	100	220,5	593,5
a_5	75	44	611	67,5	122,5	100	14,5	220,5	413
a_6	326	477,5	184,5	280	534	454,5	296	394,5	593,5
a_7	517,5	255	432,5	488	534	454,5	296	394,5	593,5
a_8	75	255	432,5	67,5	355,5	220,5	14,5	75	275,5
a_9	326	255	184,5	280	355,5	220,5	296	220,5	413
a_{10}	326	44	184,5	280	355,5	220,5	499	220,5	593,5
a_{11}	326	255	184,5	280	355,5	220,5	100	220,5	593,5
a_{12}	326	255	611	488	355,5	454,5	296	220,5	593,5
a_{13}	75	44	184,5	67,5	122,5	220,5	296	75	593,5
a_{14}	75	44	593,5	67,5	122,5	100	100	24	593,5
a_{15}	326	255	432,5	280	122,5	454,5	100	220,5	593,5
a_{16}	75	44	184,5	67,5	355,5	29,5	14,5	24	413
a_{17}	100	3	611	67,5	122,5	29,5	296	75	593,5
a_{18}	326	477,5	432,5	488	635	454,5	499	394,5	593,5
a_{19}	100	255	184,5	280	122,5	220,5	296	394,5	275,5
a_{20}	75	255	184,5	280	534	454,5	296	394,5	593,5
a_{21}	326	255	611	280	355,5	100	296	220,5	413
a_{22}	326	255	184,5	67,5	534	454,5	499	394,5	413
a_{23}	326	477,5	432,5	488	534	625	296	220,5	413
a_{24}	326	255	184,5	280	355,5	29,5	100	220,5	275,5
a_{25}	75	44	432,5	280	355,5	29,5	100	220,5	413
a_{26}	326	477,5	184,5	280	355,5	454,5	296	394,5	413
a_{27}	326	3	184,5	67,5	122,5	100	296	75	413
a_{28}	326	3	184,5	67,5	122,5	100	296	24	593,5
a_{29}	326	477,5	611	573,5	534	454,5	296	394,5	593,5
a_{30}	75	255	184,5	280	534	454,5	296	571	56,5
a_{31}	517,5	255	33	488	635	625	296	571	413
a_{32}	326	255	432,5	67,5	122,5	220,5	14,5	75	593,5
a_{33}	100	44	184,5	280	355,5	100	100	220,5	413
a_{34}	100	44	184,5	280	122,5	29,5	14,5	24	413
a_{35}	625	477,5	184,5	488	638,5	625	632	571	413
a_{36}	100	3	593,5	67,5	122,5	29,5	14,5	24	275,5
a_{37}	517,5	582	432,5	488	638,5	625	296	571	413
a_{38}	75	477,5	611	634	534	625	499	571	136
a_{39}	75	44	432,5	67,5	355,5	454,5	296	571	413
a_{40}	75	44	611	488	122,5	454,5	499	571	56,5
a_{41}	326	477,5	184,5	634	355,5	454,5	296	220,5	413
a_{42}	517,5	255	432,5	573,5	534	100	296	394,5	56,5
a_{43}	517,5	582	611	488	355,5	220,5	100	75	275,5
a_{44}	326	582	611	280	355,5	100	296	394,5	56,5
a_{45}	326	477,5	184,5	280	355,5	220,5	100	75	275,5
a_{46}	517,5	582	611	573,5	355,5	625	632	571	136
a_{47}	625	582	611	488	534	454,5	632	394,5	56,5
a_{48}	517,5	477,5	184,5	280	534	454,5	499	220,5	275,5
a_{49}	326	255	184,5	280	355,5	454,5	100	75	56,5
a_{50}	326	255	611	67,5	355,5	100	100	220,5	275,5
a_{51}	75	3	184,5	67,5	122,5	454,5	499	571	275,5
a_{52}	326	477,5	184,5	488	534	625	499	571	275,5

Table 8: (continued)

Volunteer	P_1	P_2	P_3	P_4	P_5	P_6	P_7	P_8	P_9
$\mathbf{a_{53}}$	326	477,5	184,5	280	534	625	499	571	136
$\mathbf{a_{54}}$	75	255	432,5	488	355,5	220,5	499	394,5	275,5
$\mathbf{a_{55}}$	326	255	432,5	488	355,5	454,5	296	571	136
$\mathbf{a_{56}}$	326	255	593,5	67,5	122,5	454,5	296	571	413
$\mathbf{a_{57}}$	75	255	184,5	67,5	122,5	220,5	499	394,5	56,5
$\mathbf{a_{58}}$	326	477,5	432,5	488	534	454,5	499	220,5	275,5
$\mathbf{a_{59}}$	517,5	255	611	280	534	220,5	100	220,5	56,5
$\mathbf{a_{60}}$	517,5	255	611	573,5	355,5	454,5	499	220,5	56,5
$\mathbf{a_{61}}$	326	477,5	432,5	67,5	534	220,5	499	571	136
$\mathbf{a_{62}}$	517,5	477,5	184,5	488	534	454,5	296	571	413
$\mathbf{a_{63}}$	326	44	184,5	67,5	122,5	220,5	499	394,5	56,5
$\mathbf{a_{64}}$	517,5	477,5	184,5	67,5	122,5	454,5	499	220,5	275,5
$\mathbf{a_{65}}$	326	477,5	611	280	355,5	220,5	100	220,5	56,5
$\mathbf{a_{66}}$	326	255	611	488	122,5	454,5	499	220,5	56,5
$\mathbf{a_{67}}$	517,5	255	611	573,5	534	220,5	499	571	136
$\mathbf{C_1}$	75	44	593,5	280	355,5	100	100	75	136
$\mathbf{C_2}$	326	255	184,5	488	534	220,5	296	220,5	275,5
$\mathbf{C_3}$	517,5	477,5	432,5	573,5	635	454,5	499	394,5	413
$\mathbf{C_4}$	593,5	552,5	510	629,5	637	562	593,5	489	509