Knowledge-Based Systems 165 (2019) 335–345

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

Carrying out consensual Group Decision Making processes under social networks using sentiment analysis over comparative expressions

J.A. Morente-Molinera [a], G. Kou [b], K. Samuylov [c], R. Ureña [d], E. Herrera-Viedma [a,e,*]

[a] Department of Computer Science and Artificial Intelligence, University of Granada, Granada, Spain
[b] School of Business Administration, Southwestern University of Finance and Economics, Chengdu, China
[c] Peoples' Friendship University of Russia (RUDN University), Moscow, Russian Federation
[d] IAI Institute of Artificial Intelligence, School of Computer Science, De Montfort University, Leicester, UK
[e] Department of Electrical and Computer Engineering, King Abdulaziz University, Jeddah, Saudi Arabia

ARTICLE INFO

Article history:
Received 17 August 2018
Received in revised form 18 November 2018
Accepted 4 December 2018
Available online 7 December 2018

Keywords:
Group Decision Making
Social networks
Consensus measures
Sentiment analysis

ABSTRACT

Social networks are the most preferred mean for the people to communicate. Therefore, it is quite usual that experts use them to carry out Group Decision Making processes. One disadvantage that recent Group Decision Making methods have is that they do not allow the experts to use free text to express themselves. On the contrary, they force them to follow a specific user–computer communication structure. This is against social network nature where experts are free to express themselves using their preferred text structure. This paper presents a novel model for experts to carry out Group Decision Making processes using free text and alternatives pairwise comparisons. The main advantage of this method is that it is designed to work using social networks. Sentiment analysis procedures are used to analyze free texts and extract the preferences that the experts provide about the alternatives. Also, our method introduces two ways of applying consensus measures over the Group Decision Making process. They can be used to determine if the experts agree among them or if there are different postures. This way, it is possible to promote the debate in those cases where consensus is low.

1. Introduction

With the appearance of Web 2.0 technologies [1,2], the means that people use to communicate with each other have changed completely. Thanks to social networks [3], it is possible for experts to share preferences and feelings with people located anywhere in the world. Due to this interesting capability, social networks have become quite popular. They have become the preferred method used by people to communicate, share information and carry out debates. It is also an interesting framework that can be used by the experts to carry out Group Decision Making processes [4,5]. This way, it is possible to carry out a Group Decision Making process independently of the location of the experts and without having to force them to be connected to the system at the same time.

In the recent literature, there are several Group Decision Making methods that claim to be a good choice when carrying out Group Decision Making processes over the Internet. Nevertheless, they present several drawbacks that could be solved:

- **Fixed preference providing mean**: Experts have to provide information to the system using a fixed communication mean. Therefore, they are not able to express themselves as they would like. In order to ease this situation, experts can use linguistic label sets [6,7] to provide their preferences to the system. Also, there exist methods such as multi-granular fuzzy linguistic modeling [8,9] that allow the experts to express themselves using the number of labels that they prefer. For instance, if there are three experts, $\{e_1, e_2, e_3\}$, each one can select the linguistic label set that he/she prefers. e_1 and e_2 could select a linguistic label set with 7 labels, $S_7 = \{s_1, \ldots, s_7\}$ and e_3 one with only 5 labels, $S_5 = \{s_1, \ldots, s_5\}$. With this configuration, e_3 provides a more imprecise opinion than e_1 and e_2. Nevertheless, this is not as if the experts could use their own words. Therefore, it will be desirable to develop Group Decision Making methods that allow experts to express themselves using free text.

* Corresponding author at: Department of Computer Science and Artificial Intelligence, University of Granada, Granada, Spain.
E-mail addresses: jamoren@decsai.ugr.es (J.A. Morente-Molinera), kougang@swufe.edu.cn (G. Kou), ksam@sci.pfu.edu.ru (K. Samuylov), raquel.urena@dmu.ac.uk (R. Ureña), viedma@decsai.ugr.es (E. Herrera-Viedma).

https://doi.org/10.1016/j.knosys.2018.12.006
0950-7051/

- **Not integrated in the already existing social networks**: Recent Group Decision Making methods define a separate environment for performing the preference providing, consensus calculation and alternatives ranking processes. Therefore, Group Decision Making methods that work over the Internet are designed as separate web or mobile applications [10] that must be implemented for allowing experts to use them. This approach has the disadvantage of forcing the experts to communicate using a framework that they are not used to deal with. Therefore, it would be desirable to allow them to employ their most preferred communication means in order to carry out the Group Decision Making process. One of the best solutions is to allow the experts to communicate and express themselves using their preferred social networks.
- **The process configuration is required before the participation of the experts**: In a classical Group Decision Making method, the number of experts and alternatives are fixed from the beginning. Therefore, it is not possible to include new alternatives generated over the process or invite other experts to join. Recent methods have introduced some flexibility in order to overcome this issue [11,12]. Nevertheless, they require modifications on the used applications and force new users to register. Debate and decision procedures should be designed as flexible processes where new ideas and participants can be added at any time. This issue has become a major problem now that Web 2.0 technologies and the Internet are the most preferred frameworks to carry out discussions. It is usual for users in a social network to join online conversations at any time and provide new points of view and novel ideas. In the same way that social networks allow flexibility when providing opinions and adding new participants, Group Decision Making processes should allow experts and alternatives to be modified at any time [13,14].
- **Debate and preference providing are managed as separate concepts**: Recent Group Decision Making methods separate the debate and the preference providing phase as if they were two different processes. Nevertheless, it is quite clear that new ideas are proposed and defended in the debate. Therefore, it would be much more natural to obtain the preferences directly from the debate information instead of taking them using a separated information retrieving process. From the debate it is possible to obtain a better knowledge about experts' preferences because they use the debate to share their ideas. Retrieving preferences in a separated process only makes some preference information to become lost. Also, experts have the troublesome task of providing the same information twice: one time in the debate and another one when providing their preferences to the system. Consequently, it is interesting to develop methods that are able to obtain the preferences directly from the debate and release the experts of having to provide their preferences.

The motivation of the paper is to present a novel method for overcoming the previously presented issues. Thanks to our method, experts can carry out Group Decision Making processes using their most preferred method for providing preferences, that is, natural language. Also, our method uses social networks for expert communication since this is the framework that the experts are more familiar with. A novel consensus calculation method that is based on experts' opinions is also included. It is important to develop methods that experts can use in a comfortable way since this will enhance the expert experience and improve the process results.

Our model uses sentiment analysis procedures [15–17] in order to extract the preference values from the free text used for the debate. Thanks to this, there is no need for experts to participate in a preference providing process. Furthermore, it is possible to use the novel described process over any social network since it directly works over the free text provided by the experts. For instance, when using Twitter [18,19], it is possible to use Twitter API to automatically extracts free texts from the experts. This way, there is no need for the experts to make use of any external application to provide information to the system. Instead, it is only necessary for experts to post on their social networks. The novel developed Group Decision Making method also presents two ways of applying consensus measures over the process. The first one uses the preference relation matrices extracted in the sentiment analysis procedure. The other novel approach uses the experts' opinions about other participants that are available on the social network.

The article is structured as follows. In Section 2, basis needed to understand the presented method are described. In Section 3, the novel proposed method is exposed. In Section 4, an application example in presented in order to clarify how the method works. In Section 5, advantages and drawbacks of the developed method are discussed. Finally, some conclusions are pointed out.

2. Preliminaries

In this section, basis needed to comprehend the presented method are exposed. In Section 2.1, how social networks are structured is presented. In Section 2.2 basis of Group Decision Making modeling are presented. In Section 2.3, consensus measures over the preferences are presented. Finally, in 2.4, sentiment analysis procedures are introduced.

2.1. Social networks

As it has been stated in the introduction, social networks [3] are the most preferred mean for experts to communicate over the Web. Social networks are usually implemented as web platforms that allow users to communicate and share information by using messages, posts,... Therefore, they are an interesting means to use when carrying out Group Decision Making processes.

Furthermore, social networks structure can be used by Group Decision Making methods in order to define the decision making process over them. Sentiment analysis can also use them in order to perform accurate analysis processes. One of the most relevant features are the *hashtags*. The hashtags [20,21] are a set of keywords that are used to describe a certain user provided text. This way, it is possible to allow decision making participants to use hashtags for describing their texts and associate them to a certain Group Decision Making process in progress. Since experts are allowed to express themselves using free text, social networks provide high flexibility for experts to provide their opinions. Sometimes, the number of words allowed for a single opinion is restricted, encouraging the experts to focus on the dealt topic instead of getting sidetracked.

Since, in a social network, it is always possible to know which text belongs to which social network user, there is no doubt about who is the owner of each opinion. In order to know which alternative they are referring to, it is possible to look for specific words or allow experts to use hashtags in the text. By carrying out a sentiment analysis procedure, it is also possible to determine if the provided opinion is positive or negative. This can be done by analyzing the words meaning that are used to describe the alternatives.

Finally, it is possible to create groups of experts that agree or disagree in their opinions by analyzing texts that are written referring to them. It is common in social networks to provide the users with a special structure called *mentions* in order to refer to a specific user. In Twitter, for instance, mentions are constructed as *@username*. Therefore, by carrying out a sentiment analysis

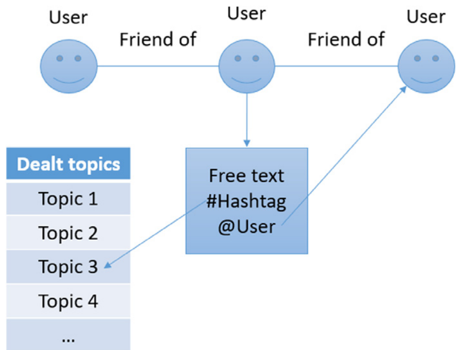

Fig. 1. Social network general scheme.

procedure of the text surrounding the mention, it is possible to determine which experts agree with his/her opinion. This can help us to determine the consensus [22–25] of the Group Decision Making process.

The described social network scheme can be seen in Fig. 1. Social networks are quite present in the recent literature since they allow us to analyze and learn a lot from users' provided information. For instance, in [26], deep convolutional neural networks are used in order to generate networks abstractions at different levels. This can help, for instance, when carrying out multi-label queries in social networks. In [27], a machine learning approach for analyzing social media is presented. In [28], graph tools that can be used for analyzing a social network are showed. Finally, in [29], a neural framework for learning node representation from social network data is presented.

2.2. Group Decision Making

Group Decision Making has been a widely studied field since its beginnings in the 70's [30,31] until nowadays [32–36]. In the last years, Group Decision Making methods have experienced a deep change due to the appearance of Web 2.0 technologies. In the beginning, Group Decision Making methods were designed for guiding a set of experts in a closed discussion that takes place in the same room. Nevertheless, nowadays, Group Decision Making methods are designed in order to carry out flexible decision processes over the Web. This way, experts do not need to reunite in the same room and they can carry out the required process independently of the moment and location.

Generally, a Group Decision Making process [37,38] can be defined as the process where a set of experts $E = \{e_1, \ldots, e_n\}$ have to sort a set of alternatives $X = \{x_1, \ldots, x_m\}$. For this purpose, they provide a set of preferences, $P = \{p_1, \ldots, p_l\}$ that represents the importance that each expert gives to each alternative.

Traditionally, a Group Decision Making method follows the next steps [39,40]:

- **Providing preferences**: Experts decide which alternatives are the most suitable and provide their opinion to the system. One of the most used methodology to carry out this process is to allow users to carry out a pairwise comparison of the alternatives [11,41,42]. This way, they can compare pairs of alternatives without having to focus on all the alternatives at the same time.
- **Calculating collective preference matrix:** Once that all the experts have provided all the alternatives, the preferences are aggregated into a single collective piece of information. Ordered Weighting Averaging (OWA) operators [43] can be used for this purpose. The obtained result contains the overall aggregated opinion of all the experts. Usually, it is represented as a square matrix where each position, p_{ij}, contains the preference of alternative x_i over x_j.
- **Creating the alternatives ranking**: Final alternatives ranking is calculated using the collective matrix. The results can be presented to the experts by showing the most voted alternative or the ranking of all the available alternatives. Selection functions of alternatives can be used for calculating the alternatives ranking. These operators are capable of calculating the alternatives ranking results using the collective preference matrix obtained in the previous step.
  In our method, the QGDD operator and a VIKOR approach will be used for computations, QGDD operator can be calculated as follows:
  $$QGDD_i = \phi(c_{ik}), k = 1 \ldots m \quad (1)$$
  Each $QGDD_i$ value represents the adequateness of alternative x_m. There can be cases where the obtained values are very close among them. In order to emphasize the differences among the alternatives, it is possible to apply a VIKOR approach. The following expression can be applied over the $QGDD$ values:
  $$RV_i = \frac{c^+ - QGDD_i}{c^+ - c^-} \quad (2)$$
  where c^+ and c^- are the ideal and anti-ideal points. Since we are carrying out a group decision making approach, c^+ and c^- can be set to the best and least obtained aggregated result. Both approaches have been used in the recent literature, as it can be seen in [44,45].
- **Measuring consensus**: Before obtaining the decision results, it is important to encourage experts to maintain an intense debate about the dealt topic. It is important to allow the experts to adequately communicate and make them reach a common conclusion before making a final decision [24,46]. The more the experts agree on the final ranking, the more reliable the results will be. If the consensus among the experts is high enough, it means that they all agree and, therefore, no more discussions are needed. Consequently, the last calculated decision results are taken as the final ones. On the contrary, if consensus is low, experts need to modify their preferences in another debate round. This will allow experts to try to bring their opinions closer. Since, it is sometimes impossible for all the experts to agree on an alternatives ranking, a maximum number of decision making rounds must be established. If this limit is reached, the decision results on the current round are considered as the final ones. In Section 2.3, how to calculate consensus measures over the preferences is showed. In Section 3.5.1, a novel approach that uses experts' opinions is presented.

The described Group Decision Making scheme can be seen graphically on Fig. 2. In the novel developed method, experts' preferences are extracted from social networks like the one described in Fig. 1 by using a sentiment analysis procedure over their contributions.

To facilitate the way experts use to provide their preferences, it is usual to employ linguistic modeling techniques [47–49]. Thanks to them, experts can provide their preferences in a linguistic and imprecise way. They ease the human–system communication and allow the experts to provide their preferences in a more comfortable way. The main problem of this approach is that the experts that participate in the Group Decision Making process are forced to use a fixed linguistic label set. Although methodologies such as multi-granular linguistic modeling methods [9] have been developed, they only solve the problem partially since what experts

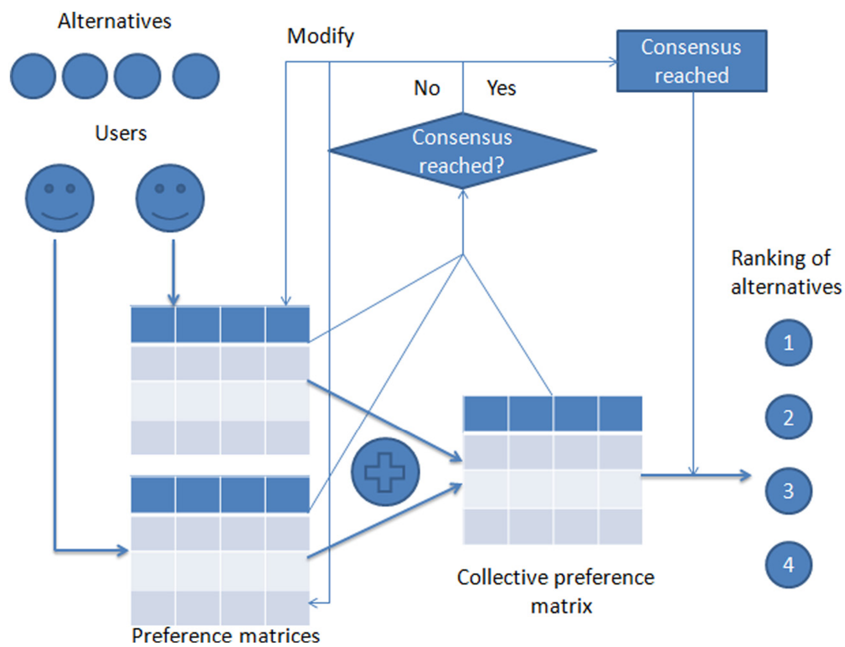

Fig. 2. Group Decision Making general scheme.

really want is to express themselves using free text, without having to withhold their expressiveness using just a small set of words. This is the reason why in the novel developed method, experts are asked to provide their preferences using free texts and preferences are automatically calculated using sentiment analysis procedures. Thanks to this freedom, they can express themselves better and, also, preferences can be extracted directly from the texts used for debate releasing the experts from the duty of providing the same information twice.

2.3. Consensus measures over the preferences

The consensus approach that is presented in this section is based on the preferences extracted from the debate texts. The obtained results are based in the similarity of the preferences provided by every possible pair of experts.

In order to calculate the consensus between two specific experts, e_i and e_j, the Euclidean distance between their preferences values can be applied:

$$CN_{ij} = \sqrt{(p^i_{kl} - p^j_{kl})^2}, k, l = 1 \dots m \tag{3}$$

In order to calculate the global consensus value, the consensus obtained between every two experts can be aggregated as follows:

$$GC = \phi(CN_{ij}), i, j = 1 \dots n \tag{4}$$

Similar approaches have been applied in recent papers such as [50].

2.4. Sentiment analysis

Human–computer communication is an issue that is still quite challenging nowadays. While computers are used to work using numbers, humans are more used to communicate using feelings and concepts. The sentiment analysis procedure goal is to allow computers to measure how a human is feeling by analyzing free texts written by them. It is based in the idea that if a person is using words such as *interesting*, *good* or *amazing*, then he/she has positive feelings about what he/she is talking about. Otherwise, if he/she employs words such as *negative* or *demoralizing* then, the feelings that the person is experimenting are negative ones.

Generally, in order to carry out a sentiment analysis procedure, the following steps are followed:

- **Selecting the goal sentiment:** First of all, it is necessary to determine which sentiments are we trying to identify. Depending on our purpose, it is possible to carry out a positive/negative sentiment analysis or search for more specific feelings.
- **Generating a list of words:** A list of words according to each feeling that we want to identify must be generated. Each list must contain words related to the associated feeling. For instance, if we want to determine if a person is experimenting anger in their comments, words that are typically used when a person is angry must be included in the anger word list.
- **Analyzing free texts:** Every word from the texts is searched in the lists. If the process finds out that several words are included in the same list, then the probability that the person is experiencing the list associated feeling is quite high.
- **Presenting final results:** Once that the analysis is complete, found feelings are listed. It is possible that a user is experiencing more than one feeling at the same time. A minimum number of words that must be found in the lists in order to consider a feeling to be present in a text/person can be established.

The exposed scheme can be seen in Fig. 3. Sentiment analysis is a topic that is quite present in the recent literature. For instance, in [51], hierarchical fusion with context modeling is applied in order to solve multimodal sentiment analysis problems. In, [52], a prototype tool that is capable of carrying out dynamic sentiment analysis of textual content from websites is presented. In [53], a specific neural network structure is built in order to carry out sentiment analysis procedures.

3. A Group Decision Making method to analyze social network discussions

Sentiment analysis is a quite useful tool when trying to figure out how people felt when they wrote a specific text. Therefore, it

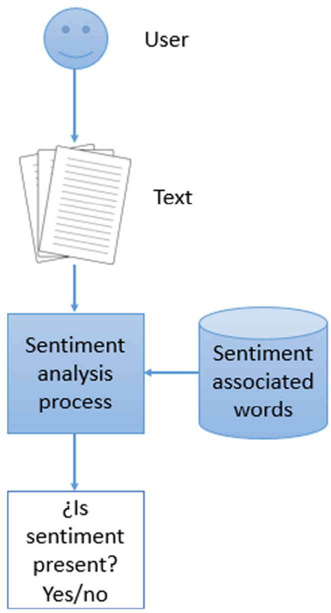

Fig. 3. Sentiment analysis general scheme.

can be applied over Group Decision Making debate texts in order to obtain information about how experts feel about the alternatives that they are discussing about. The novel developed method has the following steps:

- **Extracting debate texts from experts**: Texts from the debate are extracted from the social network used. As an example, we will be using Twitter, but our method is compatible with any social network. This is because our method is focused on the texts not on any specific social network structure.
- **Calculating expert's preferences values:** Once that the experts texts have been retrieved, a sentiment analysis procedure is applied in order to extract the preference values to be used in the Group Decision Making process.
- **Calculating collective preference matrix**: Preferences are aggregated into a single collective piece of information that represents the overall opinion of all the experts. Preference relation matrices are used.
- **Creating the alternatives ranking**: Selection procedures are applied in order to calculate the alternatives ranking.
- **Calculating consensus**: Consensus analysis is performed in order to determine if the experts agree on the results or if there are different opinions. Two ways of carrying out this step are proposed.

All the presented steps are described in more detail on the following subsections.

3.1. Extracting debate texts from experts

First of all, texts referring to the Group Decision Making process must be extracted from the social network. In order to carry out this process the next steps are followed:

- **Establishing a Group Decision Making process hashtag**: First of all, a hashtag that represents the Group Decision Making process must be selected. Experts are asked to use it in any debate text that they provide to the system. Thanks to this, it is easier for the Group Decision Making method to retrieve all the required information from the social network.
- **Selecting experts' accounts**: Each expert that participates in the process has an associated social network account. If it is not clear how many experts are participating, it is possible to retrieve all the accounts that use the hashtag that has been established in the previous step.
- **Selecting Group Decision Making debate texts**: Once that the experts that participate in the process are known and their social network accounts are located, it is time to extract all the texts that are related to the Group Decision Making process. For this purpose, texts that include the hashtag are selected from each expert's account. If no hashtag is used, it is possible to create a list of words related to the dealt topic and select the contributions that have several words that belong to that list. After this step is performed, we have determined a set of experts, $E = \{e_1, \ldots, e_n\}$ and a set of associated texts $A = \{A_1, \ldots, A_n\}$ that have been written by each expert.

Once that all the texts related to the Group Decision Making process have been extracted, it is time to generate the preferences values using them.

3.2. Calculating preferences

Once that the debate texts have been extracted, the natural free writing used by experts in their debates must be converted into a set of preference values that will be used by the Group Decision Making process to calculate the ranking of alternatives. For this purpose, sentiment analysis procedures are used. Since, for the problem solved, we only need to determine if there are positive, neutral or negative feelings about two specific alternatives, three lists of words are used. In the first one, words determining positive feelings are used. If several of these words are used by the experts in their texts, it means that they prefer the first alternative over the second. In the second one, negative words are stored. If these words are employed, it means that the experts do not prefer the first alternative over the second. Finally, the third list contains words that are frequently used when stating that something is similar. We will call these lists *P*, *NP* and *S* (preferred, not preferred and similar) respectively. Since experts are comparing alternatives, it is interesting to focus on comparatives structures instead of adjectives. This way, it is possible to analyze the sentences where the alternatives are mentioned and determine the preference among them employing on the words used by the experts for comparing them.

Each of the lists *PL*, *NPL* and *SL* is built as a matrix where each row is structured as follows:

- **Comparative expression**: An expression used for comparing two elements.
- **Comparative strength degree**: Preference degree of one alternative over another. The assigned value depends on the meaning of the comparative expression used. This way, expressions that emphasize a lot the preference of one alternative over another have a higher strength degree than expressions whose meaning do not imply that there is much difference between them.

A list composition example can be observed in Table 1. A [1,5] scale has been used in order to determine the preference value strength. The higher the value, the more preferred is one alternative over the other. Strength values can be configured and fixed according to the decision making environment. Also, different words can be added or removed in order for the list to accommodate to the discussion environment. It is also important to remark that *SL* list does not really need a strength value since the process assigns the middle label of the used linguistic label set in the cases where two alternatives are considered as similar ones.

Table 1
Comparative word list examples.

Comparative	Value
Better	4
Much better	5
Smarter	2
Cheaper	2
Much cheaper	3

It is important to remark that it is possible to apply any other sentiment analysis procedure to the novel developed method. The only requirement is that the applied process must be able to transform the debate texts where the alternatives are mentioned into numerical preference values. For testing purposes, three toy lists that follows the provided description have been developed. *PL* has 304 entries, *NL* has 308 entries and *SL* has 116 entries.

The mentioned preferences calculating step can be performed as follows:

- **Identify alternatives keywords**: Before carrying out any computation, a set of keywords, $KX = \{kx_1, \dots, kx_m\}$, is associated to each alternative. Thanks to these, it is possible to identify which alternatives the experts are discussing about. Each kx_i value is formed by a set of words that are typically used when the alternative x_i is being discussed.
- **Extracting comparative sentences related to the alternatives**: All the sentences belonging to all the experts that participate in the process are analyzed. All the sentences that have at least one of the expressions located in the word lists are extracted from the main texts. As a result of this process, each expert, e_i, is associated with three sets of comparative sentences, spl_i, $snpl_i$ and ssl_i. spl_i stores the sentences that mention two alternatives and have one comparative expression belonging to the *PL* list. $snpl_i$ and ssl_i contain sentences that have comparative expressions belonging to the *NPL* and *SL* lists respectively. Each sentence must contain a comparative expression and some of two alternatives keywords in order to be valid.
- **Grouping sentences that compare the same alternatives**: Now that, for each expert, spl_i, $snpl_i$ and ssl_i values have been extracted, we need to calculate the preference degree of each pair of alternatives, p_{ij}. This process is performed by associating the strength value of the comparative expression used for comparing alternatives x_i and x_j. In the case that several comparative sentences are available for the same pair of alternatives, we select the most extreme value. For instance, if alternatives x_i and x_j have two comparatives sentences from *PL* with a strength value of 2 and 3, value 3 is assigned to p_{ij}. In the case that no comparative sentence is assigned to some pair of alternatives, some incomplete preference relation managing method can be used to fill the gap [54] or expert can be specifically asked to provide the required value to the preference relation matrix. From now on, it is assumed that there is enough information to fill the preferences matrix without leaving any gap in it.

  After assigning the strength value, it must be transformed depending on the comparative list:

  - **The comparative expression belongs to** *PL*: No change is applied over the strength value. For instance, if the comparative word used for comparing x_i and x_j has a strength value of 3, then $p_{ij} = 3$.
  - **The comparative expression belongs to** *NPL*: The strength value is negated. For instance, if the comparative expression has a strength value of 3, then $p_{ij} = -3$.
  - **The comparative expression belongs to** *SL*: In this case, $p_{ij} = 0$.

  After performing this process, a preference matrix, p_{ij}, that is conformed by integer values belonging to the interval [−g,g] is generated. g is the highest strength value of the lists. Once that numbers have been assigned to the preference matrix, a linguistic label from a specific linguistic label set is assigned to each of the preference values. This way, it is possible to operate and present final decision results to the experts using linguistic modeling.
- **Fixing the preference value interval**: Although it is possible to associate labels from a linguistic label set to the integer values that conform P when it is represented by values in the interval [−g,g], it may occur that we are not interested in maintaining negative indexes or that we prefer a linguistic label set with another granularity value. In order to fix this, it is possible to transform the obtained preference representation in order to reduce/augment granularity and remove the negative values. The following procedures can be optionally applied in order to obtain the desired representation:

  - **Remove negative values**: The obtained preliminary representation generates labels whose indexes belong to the interval [−g,g]. If negative indexes are not desired, it is possible to apply a domain change and express all the information using indexes from the interval $[0, (2 \cdot g)]$. In such a way, if the linguistic label set S_{2g} is used, s_0 in p_{ij} indicates that x_i is totally not preferred to x_j while $s_{2 \cdot g/2}$ indicates similarity between them. The following expression can be applied for carrying out the transformation:

  $$p_{ij}^{[0,(2\cdot g)]} = p_{ij}^{[-g,g]} + g \tag{5}$$

  - **Modify the linguistic label set granularity**: It is possible that, for precision or comprehension purposes, the granularity of the linguistic label set used does not fit our expectations. This can be easily fixed by applying any multi-granular fuzzy linguistic modeling method [9] over the preference values. In such a way, it is possible to adjust the granularity of the linguistic label set to our needs.

Once that the preferences matrices of all the experts are calculated, the decision making process can continue. Temporary ranking of alternatives and the consensus values can be calculated. These processes are described in more detail in the following subsections.

A graphical scheme of this process can be seen in Fig. 4.

3.3. Calculating the collective preference matrix

Before calculating the alternatives ranking, a collective preference matrix containing the overall aggregated opinion of all the experts that participate in the Group Decision Making process must be calculated. Any aggregation operator can be applied for this purpose. For instance, the mean operator or some OWA operator [43,55] are the most used choices.

If the same representation is chosen for all the preference values provided the experts, P^i, then the aggregation process is quite straightforward.

In the developed method, we will apply the weighted aggregator (WA) as it is done in [56]. Therefore, it is possible to calculate the collective preference matrix, C, as follows:

$$c_{ij} = \sum_{k=1}^{n} w_k \cdot p_{ij}^{k}, i, j = 1 \dots m \tag{6}$$

where n is the number of experts and m the number of alternatives.

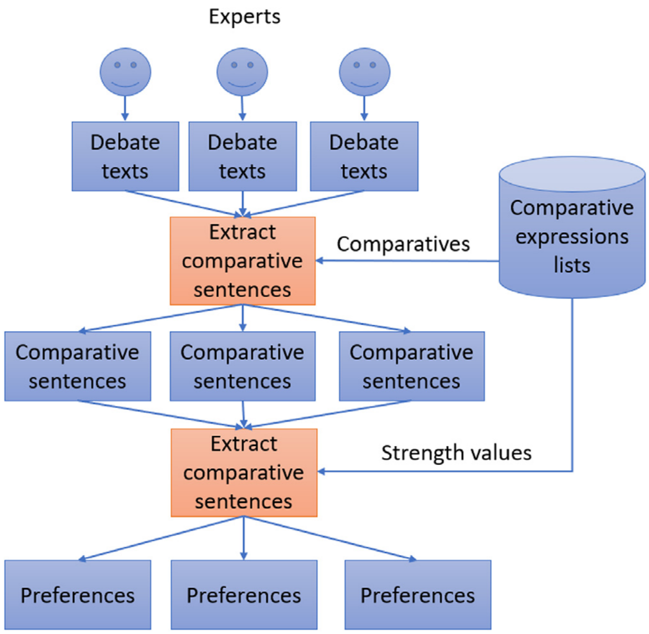

Fig. 4. Preference calculating step scheme.

3.4. Ranking alternatives

Once that the collective preference matrix has been calculated, alternatives need to be ranked. For this purpose, it is possible to use the process that has been exposed in Section 2.2. Expressions (1) and (2) can be applied over collective matrix in order to obtained the required ranking.

It is important to notice that, in order to increase the presented results comprehension, it is possible to transform the obtained RV values into linguistic labels. This way, experts better understand the obtained alternatives ranking and it will be easier for them to understand the overall preference degree over a specific alternative. For this purpose, 2-tuple linguistic representation model [57] and a multi-granular fuzzy linguistic modeling method that is capable of working with that representation [58] can be applied. This way, by interpreting the RV values as β values that are located in the interval [0,1], it is possible to apply the 2-tuple linguistic representation model in order to assign a specific label to each obtained result.

3.5. Calculating consensus

Determining the consensus reached among experts in a Group Decision Making process is a critical part of the process. Thanks to it, experts can know if they are reaching an agreement or, on the contrary, there are different positions among them. Therefore, consensus measures can be used to decide if experts should carry out more debate or if they have already reached an agreement.

In the novel developed method, two ways of carrying out this process are presented. One is based on the preferences generated after analyzing the debate texts. The other one is based exclusively on information provided by the experts about the rest of the people involved in the decision. By carrying out a sentiment analysis procedure over this information, it is possible to determine if they agree with the other experts or if they have different opinions.

There are no clear criteria that help us to select one consensus method or another. It all depends on how consensus wants to be calculated. Centering consensus in preferences can be probably seen as a more objective approach since it totally relies on experts' preferences. On the contrary, centering the consensus on experts' opinions means that the consensus results will be based on how experts feel about the rest of the people that participate in the discussion. Therefore, it is a more subjective approach.

Regarding to the convergence of the consensus reaching process, we should point out that our consensus approach controls the decision making process finishes by using a variable of maximum number of rounds. On the other hand, the experts are free to express their preferences and it is clear that we cannot force them to converge, although we could guide them with feedback methods [35,59]. In our model in each round we provide them with a consensus graph that shows every expert his/her position regarding to the rest of experts. This information is useful to guide the changes of expert preferences in order to guarantee the convergence of the consensus reaching process. In such a way, we provide a special feedback to aid in the convergence process.

In Section 2.3, consensus is calculated over the generated preferences values. In Section 3.5.1, a novel consensus approach that uses experts' debate information is presented.

3.5.1. Consensus over the experts

One way of determining if there is consensus in the Group Decision Making process is to analyze what experts think about the rest of participants contributions to the debate. Thanks to sentiment analysis procedures, it is possible to carry out a thorough analysis about these opinions and calculate a consensus value based on them. It should be noticed that, using the obtained procedure results, it is possible to create a network that connects all the experts according to their ideas. This can help to visually determine which ones agree and which one have different opinions.

In this case, the application of sentiment analysis procedures have the purpose of identifying which experts have positive or negative opinions about what other experts are stating in their contributions. For this purpose, two lists of words will be used. The first one will contain words that, if present, they will indicate that the experts agree and defend each other. On the contrary, the second word list will contain expressions that state disagreement among them. The lists used for this task will be the ones provided in [60]. Since there are two lists available, one for positive feelings and another for negative ones, they adapt perfectly to the required analysis.

The procedure that our method follows to obtain the consensus results is specified below:

- **Extracting the required texts**: For each expert's account, texts referring directly to other experts that participate in the process are retrieved. Mentions can be used for an easier identification. For instance, in Twitter, debate texts that include the syntax *@nickname*, where *nickname* refers to one of the Group Decision Making participants, can be selected.
- **Establishing a pairwise expert comparison value**: In order to obtain the consensus value between experts e_i and e_j, cs_{ij}, the following process is followed:
  - **Establishing the agreement level**: Sentences relating experts e_i and e_j are analyzed. The number of words belonging to the positive word list are counted. This number is considered as $pwcount_{ij}$ and measures the agreement between experts e_i and e_j. It is important to notice that, in this case, $pwcount_{ij} = pwcount_{ji}$.
  - **Establishing the disagreement level**: The number of words from the selected sentences that are located in the negative word list is counted. This value, $nwcount_{ij}$, provide us with a measure of the disagreement between experts e_i and e_j.

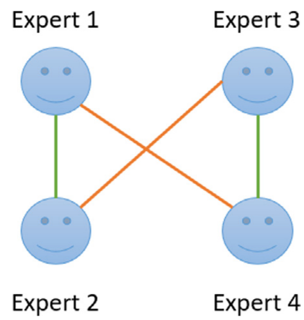

Fig. 5. Example of a Group Decision Making process consensus graph.

- **Calculating the pairwise consensus value**: Finally, using $pwcount_{ij}$ and $nwcount_{ij}$, the following expression is applied in order to calculate the consensus value between e_i and e_j:

$$cs_{ij} = \frac{pwcount_{ij} - nwcount_{ij}}{pwcount_{ij} + nwcount_{ij}} \quad (7)$$

The obtained value is located in the interval [−1,1]. A linear transformation can be applied in order to convert the obtained values into the interval [0,1]. This process can be performed as follows:

$$cs_{ij}^{[0,1]} = \frac{(cs_{ij}^{[-1,1]} + 1)}{2} \quad (8)$$

As it can be observed, the lower the value, the more disagreement there are between e_i and e_j. Since the obtained value is independent of the total of words found on the word lists, it is possible to compare consensus among different pair of experts by using their obtained consensus value. It is also possible to employ this information in order to build a graph that interconnects the experts that agree.

For instance, imagine that we have the set of experts $E = \{e_1, e_2, e_3, e_4\}$ and the following consensus values between them:

$$CS = \begin{pmatrix} - & 0.8 & 0.3 & 0.1 \\ 0.8 & - & 0.3 & 0.4 \\ 0.3 & 0.3 & - & 0.9 \\ 0.1 & 0.4 & 0.9 & - \end{pmatrix} \quad (9)$$

As it can be seen, due to the way that the computations have been carried out, $cs_{ij} = cs_{ji}$. Using this information, it is possible to build a graph where experts that have high consensus between them are interconnected by green lines. On the contrary, experts that disagree can be interconnected by red lines or not be connected. Value 0.5 can be used as the threshold value for the graph. In such a way, consensus values lower than 0.5 indicate disagreement while values higher than 0.5 mean that there is agreement between experts. In Fig. 5, the graph associated to the consensus matrix exposed in (9) is shown.

- **Calculating the global consensus value**: It is possible to obtain the Group Decision Making process summary consensus value, GCS, by calculating the mean among all the cs_{ij} values. This can be done by applying the next expression:

$$GCS = \phi(cs_{ij}), i, j \in \{1, n\}, i \neq j. \quad (10)$$

4. Illustrative example

In order to enhance the comprehension of the presented method, an application example is shown in this section. Imagine that a set of four experts $E = \{e_1, e_2, e_3, e_4\}$ want to discuss about where some money should be invested. There are four options, $X = \{x_1, x_2, x_3, x_4\}$, that are described in Table 2. Texts from the experts are extracted from the social network using a pre-specified hashtag.

Table 2
Description of alternatives.

X	Description	Keywords
x_1	More resources	resources, stock
x_2	New employees	employees
x_3	Hire another building	hire, new building
x_4	Save the money for the future	save, put away

First of all, a set of keywords, KX, must be established for each alternative in order to use them for detecting the debate texts that discuss those alternatives. Column 3 of Table 2 shows a possible set of keywords for each alternative. The set of keywords size depends on the precision required for identifying the alternative in the text analysis process and the expected alternatives synonyms that the experts can use to express themselves.

After establishing all the required parameters, a sentiment analysis procedure over the debate texts provided by the experts can be performed. For instance, in Table 3, some examples of some possible sentences that the experts could have written about the topic are presented. In order to convert them into preference values, we need to check the strength values associated to each comparative word. In the case of the comparative expressions presented in Table 3, values are listed in Table 4.

Strength values are expressed using the [0,5] interval in the lists. The strength values that belong to NP are negated since they indicate lack of preference. 0 value is assigned to any comparative expression that indicates high similarity. Therefore, the strength values that are finally assigned to the comparative expressions are located in the interval [−5,5].

Strength values can be converted to the interval [0,10] by following expression (5). Results can be observed in the third column of Table 3. The obtained results have been represented using the linguistic label set $S = \{s_0, \ldots, s_{10}\}$. Preferences obtained by the application of the sentiment analysis procedure on the extracted texts are shown below:

$$P_1 = \begin{pmatrix} - & s_4 & s_3 & s_8 \\ s_9 & - & s_1 & s_7 \\ s_9 & s_8 & - & s_{10} \\ s_1 & s_3 & s_2 & - \end{pmatrix} P_2 = \begin{pmatrix} - & s_3 & s_2 & s_7 \\ s_{10} & - & s_2 & s_6 \\ s_{10} & s_{10} & - & s_9 \\ s_1 & s_1 & s_4 & - \end{pmatrix}$$

$$P_3 = \begin{pmatrix} - & s_1 & s_2 & s_9 \\ s_7 & - & s_2 & s_8 \\ s_8 & s_8 & - & s_8 \\ s_3 & s_4 & s_2 & - \end{pmatrix} P_4 = \begin{pmatrix} - & s_3 & s_3 & s_{10} \\ s_8 & - & s_3 & s_7 \\ s_9 & s_9 & - & s_{10} \\ s_4 & s_3 & s_3 & - \end{pmatrix}$$

Once that the preference matrices of all the experts have been obtained, the collective preference matrix can be calculated. Since all the experts have the same importance, the weight vector $W = \{0.25, 0.25, 0.25, 0.25\}$ is used. After aggregating all the indexes of the labels of the preference relation matrices, the following collective preference matrix is obtained:

$$C = \begin{pmatrix} - & 2.75 & 2.5 & 8.5 \\ 8.5 & - & 2 & 7 \\ 9 & 8.75 & - & 9.25 \\ 2.25 & 2.75 & 2.75 & - \end{pmatrix}$$

Finally, using the collective matrix, the final ranking results are calculated. The process specified in Section 2.2 is applied. Results can be seen in Table 5.

After calculating the first round results, a consensus analysis can be carried out to see if the experts have similar opinions

Table 3
Sentences and associated preference value.

Sentences	Strn. value	Pref. value
We need resources more than employees.	4	$p_{12} = s_9$
Hire another building is a better option than put away the money.	3	$p_{34} = s_8$
It is more necessary to save the money than to spend it in hiring more employees.	4	$p_{42} = s_9$
It is better to hire new employees than to invest in another building.	4	$p_{23} = s_9$
It would be similar to me to invest the money in a new building or in new employees	0	$p_{32} = s_5$
It would be worse to save the money than to invest it in hire new employees	−3	$p_{42} = s_2$

Table 4
Comparatives and associated preference values.

Comparative	Strn. value
Need more than	4
Better option	3
More necessary	4
Better	4
Similar	–
Worse	3

Table 5
Alternatives ranking.

	x_1	x_2	x_3	x_4
QGDD	4.583	5.833	9	2.583
Ranking value	0.6436	0.4712	0.0344	0.9195
Ranking	x_3	x_2	x_1	x_4

Table 6
Consensus over preference relations.

Experts	Consensus
e_1, e_2	4
e_1, e_3	3
e_1, e_4	8
e_2, e_3	1
e_2, e_4	4
e_3, e_4	5
Global consensus	4.166

Table 7
Consensus over experts debate texts.

Exp.	$pwcount_{ij}$	$nwcount_{ij}$	$cs_{ij}^{[-1,1]}$	$cs_{ij}^{[0,1]}$
e_1, e_2	5	0	1	1
e_1, e_3	6	1	0.8571	0.928
e_2, e_3	8	2	0.8	0.9
e_2, e_4	5	1	0.83	0.915
e_1, e_4	7	0	1	1

or if there are disagreement among them. First, it is possible to apply consensus measures over the preferences relation matrices generated by the sentiment analysis procedure over the debate texts. When the procedure exposed in Section 2.3 is applied, results exposed in Table 6 are obtained.

The other presented way of calculating consensus is by using experts' texts that refer to other decision making participants. As exposed in Section 3.5.1, we need to retrieve the texts belonging to each pair of experts and count the number of positive and negative words that are included on them. For this purpose, the positive and negative word lists from [60] are used. Consensus values obtained for each two pair of experts are exposed in Table 7.

It is possible to obtain a summary consensus value by applying the mean operator over the obtained consensus values as follows:

$$\phi(1, 0.928, 0.9, 0.915, 1) = 0, 9486$$

As it can be seen, consensus reached in both consensus measuring approaches are quite high. Therefore, it is possible to accept the generated alternatives ranking as the final one.

The efficiency of the method depends on different aspects of the process:

- **Number of experts and alternatives,** NE **and** NA: The number of experts and alternatives have a clear impact in the number of computations that must be performed. The more experts involved in the process, the more contributions that need to be analyzed and, consequently, the more time the process will need to be accomplished.
- **Number of contributions of each expert,** NC_i: The more contributions that each expert generates, the more time will be consumed by the preferences calculation process.
- **Number of hashtags for each alternative,** NH_i: Each alternative hashtag needs to be searched in the experts' contributions. Therefore, the more hashtags are introduced, the more time the preference calculating step will take.

The main computational effort of the method consists in searching words over the experts' contributions. Since the number of experts that participate in a Group Decision Making process and their contributions are usually limited and not quite high, the described method is not computationally intensive. An estimation of a Group Decision Making round number of computations can be calculated using the following expression:

$$\begin{aligned} CompNumber &= \{NE \cdot (NA \cdot NA - NA) \cdot NH_\phi \cdot NC_\phi\} \\ &\quad + \{(NA \cdot NA - NA) \cdot NE\} \end{aligned} \tag{11}$$

where the first bracket refers to the preferences extraction step and the second one to the collective matrix calculation. NH_ϕ is the mean number of hashtags and NC_ϕ the mean number of contributions per expert. Ranking calculation, since it is carried over a unique $NA \cdot NA$ matrix is considered negligible. The size of the contributions, since they are considered as short ones is considered negligible too.

Taking into account the presented example, the estimated number of computations that have been carried out in one Group Decision Making round is:

$$CompNumber = 4 \cdot (4 \cdot 4 - 4) \cdot 2 \cdot 3 + (4 \cdot 4 - 4) \cdot 4 = 288 + 48 = 336$$

In a more complex example with 9 experts, 7 alternatives, 4 hashtags per alternative and 5 contributions per expert the number of computations rise to:

$$CompNumber = 9 \cdot (7 \cdot 7 - 7) \cdot 4 \cdot 5 + (7 \cdot 7 - 7) \cdot 9 = 7560 + 378 = 7938$$

Since we are dealing with low effort operations, 7938 is still a quite low computational effort. The number of experts and alternatives that are dealt in a typical debate does not usually exceeds too much making the presented method efficient enough for any debate scene.

5. Discussion

The presented Group Decision Making method has the main novelty of using sentiment analysis procedures over free texts provided by the experts in order to fill the preference relation matrices. Thanks to this, experts do not have to participate in a tiring and uncomfortable preference providing process. In this way, they can talk and debate freely in social networks without worrying about having to explicitly provide their preferences to the system. The use of social networks for Group Decision Making processes have made that our method presents the following advantages:

- **Organized debates:** Social networks allow us to carry out Group Decision Making processes in an organized way. Since it is clear which contribution belongs to each expert and all the contributions are ordered by the posting time, it is easy to follow the debate.
- **Transcribed text of the debate:** Since the provided opinion and debate texts are stored in the social network, it is easy to access and analyze them using the sentiment analysis procedures.
- **Hashtags and mentions**: The hashtags and mentions to other experts participating in the decision making process help the sentiment analysis procedures to find and catalog the texts according to the requirements. For instance, hashtags can help us to select the debate texts that discuss the Group Decision Making process topic. Also, mentions to other experts can help the sentiment analysis procedures to find debate texts referring to other experts' opinions.
- **Preferred mean for communication**: Social networks are the communication method preferred by users. Meeting face-to-face can become troublesome due to the need of reuniting in the same place at the same time. Thanks to social networks, it is possible to carry out a debate at any time from anywhere.

The other important advantage that has been presented in this paper is a novel consensus measuring method based on experts' opinions about other experts contributions to the debate. This consensus approach is more subjective and imprecise due to the fact that is based on opinions and feelings that the experts have about the other people that participate in the debate. Nevertheless, it has the advantage of obtaining the values directly from the sentences where the other experts are mentioned. That is, it is centered in the debate text used for commenting other experts' contributions.

Although the presented advantages make this method quite interesting to be applied over social networks, there are several issues that should be polished in order to improve its effectiveness in real life applications. As it has been stated, it is possible that the experts do not provide any information in the debate about two concrete alternatives. This leads to a missing piece of information in the preference relation matrix. This problem can be easily solved by applying incomplete preference relation matrices management methods [54] or asking experts to fill the gaps in the generated preference relation matrices. The method has been tested using a toy problem. As future work, we will improve the comparative word lists used in order to include more expressions and we will test the method in real world problems.

The presented Group Decision Making method deals with the problem of how to design clear means for the experts to provide their preferences to the system. Also, it includes a novel consensus model based on experts' opinions about the rest of the experts. There are already articles describing Group Decision Making methods in the literature that deals with this issue. For instance, in [61], the trust among the experts is measured in order to identify groups of experts that have similar opinions. It should be noticed that this is a similar approach that the one taken in the second presented consensus model. Nevertheless, our method uses sentiment analysis procedures over the experts' opinions to extract the information while in [61] they use a previously built trust information graph. In [62], they also improve the preference providing system by establishing semantic models for the experts. Nevertheless, they still need that the experts focus on providing labels from linguistic label sets instead of allowing them to use free text. In [63], authors provide a type-2 fuzzy sets environment for the experts providing step. Although, thanks to this, experts can provide more imprecise information, free text is a more comfortable way for the experts to provide their preferences.

6. Conclusions

In this paper, a new method of Group Decision Making is presented based on the communication of users through social networks. Traditional Group Decision Making methods have always introduced a separation between the debate carried out by the experts and the preferences providing process. Since it is in the debate where experts express their opinions, we have developed a novel Group Decision Making method that is capable of extracting preferences directly from experts' contributions. This is possible thanks to the application of sentiment analysis procedures. By identifying comparative expressions over the alternatives in the debate texts, it is possible to automatically generate preference relations that can be used for carrying out the Group Decision Making process. Thanks to this, experts do not have to replicate the debate information in a preference providing step.

Since social networks are the most preferred mean to communicate over the Internet, this is the environment chosen for carrying out the Group Decision Making processes. Thanks to social networks and the Internet, experts can carry out Group Decision Making procedures at any time and any where.

The novel developed method also implements a novel consensus measuring method based on the opinions that the experts have of the rest of decision making participants. Thanks to sentiment analysis, it is possible to analyze texts referring to other experts and determine if they agree or if there is differences among them. It is also possible to calculate consensus analyzing the preference relation matrices that the sentiment analysis procedure generates.

Acknowledgments

The authors would like to thank FEDER financial support from the Project TIN2016-75850-P and the RUDN University Program 5-100 (Russian Federation).

References

[1] K. Huffman, Web 2.0: beyond the concept practical ways to implement rss, podcasts, and wikis, Educ. Lib. 29 (2017) 12–19.
[2] P.R. Humanante-Ramos, F.J. García-Peñalvo, M.Á. Conde-González, Electronic devices and web 2.0 tools: usage trends in engineering students, Int. J. Eng. Educ. (IJEE) 33 (2017).
[3] J. Scott, Social Network Analysis, Sage, 2017.
[4] J.H. Davis, H. Brandstätter, G. Stocker-Kreichgauer, Group Decision Making, European Association of Experimental Social Psychology by Academic Press, 1982.
[5] D.J. Packer, N.D. Ungson, Group decision-making, Soc. Psychol.: Revisiting Classic Stud. (2017) 182.
[6] F. Herrera, S. Alonso, F. Chiclana, E. Herrera-Viedma, Computing with words in decision making: foundations, trends and prospects, Fuzzy Optim. Decis. Mak. 8 (2009) 337–364.
[7] L.A. Zadeh, Fuzzy logic= computing with words, IEEE Trans. Fuzzy Syst. 4 (1996) 103–111.
[8] J.A. Morente-Molinera, J. Mezei, C. Carlsson, E. Herrera-Viedma, Improving supervised learning classification methods using multi-granular linguistic modelling and fuzzy entropy, IEEE Trans. Fuzzy Syst. 25 (2017) 1078–1089.
[9] J.A. Morente-Molinera, I.J. Pérez, M.R. Ureña, E. Herrera-Viedma, On multi-granular fuzzy linguistic modeling in group decision making problems: a systematic review and future trends, Knowl.-Based Syst. 74 (2015) 49–60.
[10] S. Alonso, E. Herrera-Viedma, F. Chiclana, F. Herrera, A web based consensus support system for group decision making problems and incomplete preferences, Inform. Sci. 180 (2010) 4477–4495.
[11] J. Morente-Molinera, G. Kou, R. González-Crespo, J. Corchado, E. Herrera-Viedma, Solving multi-criteria group decision making problems under environments with a high number of alternatives using fuzzy ontologies and multi-granular linguistic modelling methods, Knowl.-Based Syst. 137 (2017) 54–64.
[12] I.J. Pérez, F.J. Cabrerizo, S. Alonso, E. Herrera-Viedma, A new consensus model for group decision making problems with non-homogeneous experts, IEEE Trans. Syst. Man Cybern.: Syst. 44 (2014) 494–498.
[13] I.J. Perez, F.J. Cabrerizo, S. Alonso, Y. Dong, F. Chiclana, E. Herrera-Viedma, On dynamic consensus processes in group decision making problems, Inform. Sci. 459 (2018) 20–35.

[14] F.J. Pérez, E. Herrera-Viedma, A mobile decision support system for dynamic group decision-making problems, IEEE Trans. Syst. Man Cybern. Part A: Syst. Hum. 40 (2010) 1244–1256.
[15] E. Cambria, Affective computing and sentiment analysis, IEEE Intell. Syst. 31 (2016) 102–107.
[16] R.M. Cantón Croda, D.E. Gibaja Romero, Development of injuries prevention policies in mexico: A big data approach., Int. J. Interact. Multimedia Artif. Intell. 4 (2018).
[17] H. Saif, Y. He, M. Fernandez, H. Alani, Contextual semantics for sentiment analysis of twitter, Inf. Process. Manage. 52 (2016) 5–19.
[18] M. Cha, H. Haddadi, F. Benevenuto, P.K. Gummadi, Measuring user influence in twitter: The million follower fallacy, Icwsm 10 (2010) 30.
[19] I. Himelboim, M.A. Smith, L. Rainie, B. Shneiderman, C. Espina, Classifying Twitter Topic-Networks Using Social Network Analysis, Vol. 3, Social Media+ Society, 2017, 2056305117691545.
[20] G. Enli, C.A. Simonsen, social media logicmeets professional norms: Twitter hashtags usage by journalists and politicians, Inf. Commun. Soc. (2017) 1–16.
[21] G. Veletsianos, Toward a generalizable understanding of twitter and social media use across moocs: who participates on mooc hashtags and in what ways? J. Comput. Higher Educ. 29 (2017) 65–80.
[22] F.J. Cabrerizo, J. López-Gijón, M. Martínez, J.A. Morente-Molinera, E. Herrera-Viedma, A fuzzy linguistic extended libqual+ model to assess service quality in academic libraries, Int. J. Inf. Technol. Decis. Mak. 16 (2017) 225–244.
[23] F.J. Cabrerizo, R. Ureña, W. Pedrycz, E. Herrera-Viedma, Building consensus in group decision making with an allocation of information granularity, Fuzzy Sets and Systems 255 (2014) 115–127.
[24] C. De Maio, G. Fenza, V. Loia, F. Orciuoli, Linguistic fuzzy consensus model for collaborative development of fuzzy cognitive maps: a case study in software development risks, Fuzzy Optim. Decis. Mak. 16 (2017) 463–479.
[25] Ureña R., F. Chiclana, M. Guy, E. Herrera-Viedma, A social network based approach for consensus achievement in multiperson decision making, Inf. Fusion 47 (2019) 72–87.
[26] I. Chaturvedi, S. Cavallari, E. Cambria, V. Zheng, Learning word vectors in deep walk using convolution, in: Proceedings of the Thirtieth International Florida Artificial Intelligence Research Society Conference, 2017, pp. 323–328.
[27] Z. Munawar, B. Siswoyo, N.S. Herman, Machine learning approach for analysis of social media, ADRI Int. J. Inf. Technol. 1 (2017) 5–8.
[28] N. Akhtar, M.V. Ahamad, Graph tools for social network analysis, in: Graph Theoretic Approaches for Analyzing Large-Scale Social Networks, IGI Global, 2018, pp. 18–33.
[29] L. Liao, X. He, H. Zhang, T.S. Chua, Attributed social network embedding, IEEE Trans. Knowl. Data Eng. (2018).
[30] J.D. Cole, A.P. Sage, Multi-person decision analysis in large scale systems-roup decision making, J. Franklin Inst. B 299 (1975) 245–268.
[31] B.E. Collins, H.S. Guetzkow, A Social Psychology of Group Processes for Decision-Making, Wiley New York, 1964.
[32] N. Banaeian, H. Mobli, B. Fahimnia, I.E. Nielsen, M. Omid, Green supplier selection using fuzzy group decision making methods: A case study from the agri-food industry, Comput. Oper. Res. 89 (2018) 337–347.
[33] G. Baudry, C. Macharis, T. Vallee, Range-based multi-actor multi-criteria analysis: A combined method of multi-actor multi-criteria analysis and monte carlo simulation to support participatory decision making under uncertainty, European J. Oper. Res. 264 (2018) 257–269.
[34] F. Liu, Y.H. Wu, W. Pedrycz, A modified consensus model in group decision making with an allocation of information granularity, IEEE Trans. Fuzzy Syst. (2018).
[35] J. Wu, L. Dai, F. Chiclana, H. Fujita, E. Herrera-Viedma, A minimum adjustment cost feedback mechanism based consensus model for group decision making under social network with distributed linguistic trust, Inf. Fusion 41 (2018) 232–242.
[36] H. Zhang, Y. Dong, E. Herrera-Viedma, Consensus building for the heterogeneous large-scale gdm with the individual concerns and satisfactions, IEEE Trans. Fuzzy Syst. 26 (2018) 884–898.
[37] J. Kacprzyk, Group decision making with a fuzzy linguistic majority, Fuzzy Sets and Systems 18 (1986) 105–118.
[38] W. Liu, Y. Dong, F. Chiclana, F.J. Cabrerizo, E. Herrera-Viedma, Group decision-making based on heterogeneous preference relations with self-confidence, Fuzzy Optim. Decis. Mak. 16 (2017) 429–447.
[39] N. Capuano, F. Chiclana, H. Fujita, E. Herrera-Viedma, V. Loia, Fuzzy group decision making with incomplete information guided by social influence, IEEE Trans. Fuzzy Syst. 26 (2018) 1704–1718.
[40] Y. Dong, S. Zhao, H. Zhang, F. Chiclana, E. Herrera-Viedma, A self-management mechanism for non-cooperative behaviors in large-scale group consensus reaching processes, IEEE Trans. Fuzzy Syst. (2018).
[41] F.J. Cabrerizo, E. Herrera-Viedma, W. Pedrycz, A method based on PSO and granular computing of linguistic information to solve group decision making problems defined in heterogeneous contexts, European J. Oper. Res. 230 (2013) 624–633.
[42] J.A. Morente-Molinera, R. Wikström, E. Herrera-Viedma, C. Carlsson, A linguistic mobile decision support system based on fuzzy ontology to facilitate knowledge mobilization, Decis. Support Syst. 81 (2016) 66–75.
[43] X. Liu, B. Han, H. Chen, L. Zhou, The probabilistic ordered weighted continuous owa operator and its application in group decision making, Int. J. Mach. Learn. Cybern. (2017) 1–11.
[44] F.J. Cabrerizo, R. Al-Hmouz, A. Morfeq, A.S. Balamash, M. Martínez, E. Herrera-Viedma, Soft consensus measures in group decision making using unbalanced fuzzy linguistic information, Soft Comput. 21 (2017) 3037–3050.
[45] Z. Ren, Z. Xu, H. Wang, Dual hesitant fuzzy vikor method for multi-criteria group decision making based on fuzzy measure and new comparison method, Inform. Sci. 388 (2017) 1–16.
[46] F.J. Cabrerizo, F. Chiclana, R. Al-Hmouz, A. Morfeq, A.S. Balamash, E. Herrera-Viedma, Fuzzy decision making and consensus: challenges, J. Intell. Fuzzy Syst. 29 (2015) 1109–1118.
[47] L.A. Zadeh, The concept of a linguistic variable and its application to approximate reasoning-I, Inf. Sci. 8 (1975) 199–249.
[48] L.A. Zadeh, The concept of a linguistic variable and its application to approximate reasoning-II, Inf. Sci. 8 (1975) 301–357.
[49] L.A. Zadeh, The concept of a linguistic variable and its application to approximate reasoning-III, Inf. Sci. 9 (1975) 43–80.
[50] Y. Zhang, Z. Xu, H. Liao, A consensus process for group decision making with probabilistic linguistic preference relations, Inform. Sci. 414 (2017) 260–275.
[51] N. Majumder, D. Hazarika, A. Gelbukh, E. Cambria, S. Poria, Multimodal sentiment analysis using hierarchical fusion with context modeling, Knowl.-Based Syst. (2018).
[52] I.M. de Diego, A. Fernández-Isabel, F. Ortega, J.M. Moguerza, A visual framework for dynamic emotional web analysis, Knowl.-Based Syst. 145 (2018) 264–273.
[53] K. Shuang, Z. Zhang, H. Guo, J. Loo, A sentiment information collector–extractor architecture based neural network for sentiment analysis, Inform. Sci. 467 (2018) 549–558.
[54] R. Ureña, F. Chiclana, J.A. Morente-Molinera, E. Herrera-Viedma, Managing incomplete preference relations in decision making: A review and future trends, Inform. Sci. 302 (2015) 14–32.
[55] R.R. Yager, Quantifier guided aggregation using OWA operators, Int. J. Intell. Syst. 11 (1996) 49–73.
[56] C.C. Li, R.M. Rodriguez, L. Martinez, Y. Dong, F. Herrera, Consensus building with individual consistency control in group decision making, IEEE Trans. Fuzzy Syst. (2018).
[57] L. Martínez, F. Herrera, An overview on the 2-tuple linguistic model for computing with words in decision making: Extensions, applications and challenges, Inform. Sci. 207 (2012) 1–18.
[58] F. Herrera, L. Martínez, A model based on linguistic 2-tuples for dealing with multigranular hierarchical linguistic contexts in multi-expert decision-making, IEEE Trans. Syst. Man Cybern. B 31 (2001) 227–234.
[59] M.J. del Moral, F. Chiclana, J.M. Tapia, E. Herrera-Viedma, A comparative study on consensus measures in group decision making, Int. J. Intell. Syst. 33 (2018) 1624–1638.
[60] M. Hu, B. Liu, Mining and summarizing customer reviews, in: Proceedings of the Tenth ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, ACM, 2004, pp. 168–177.
[61] J. Wu, F. Chiclana, H. Fujita, E. Herrera-Viedma, A visual interaction consensus model for social network group decision making with trust propagation, Knowl.-Based Syst. 122 (2017) 39–50.
[62] C.C. Li, Y. Dong, F. Herrera, E. Herrera-Viedma, L. Martínez, Personalized individual semantics in computing with words for supporting linguistic group decision making. an application on consensus reaching, Inf. Fusion 33 (2017) 29–40.
[63] J. Qin, X. Liu, W. Pedrycz, An extended todim multi-criteria group decision making method for green supplier selection in interval type-2 fuzzy environment, European J. Oper. Res. 258 (2017) 626–638.