

Teranga Go!: Carpooling Collaborative Consumption Community with multi-criteria hesitant fuzzy linguistic term set opinions to built confidence and trust

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Abstract

Boosting collaborative or participatory consumption is a priority for the European Commission. It is in line with the provisions of the Europe 2020 Strategy, which proposes that consumption of goods and services should take place in accordance with smart, sustainable and inclusive growth. These have motivated us to develop an online community for collaborative consumption centered in the Senegalese community that travels by car from Europe to Africa named Teranga Go!. Carpooling relationships are based on the sense of a real existing community, social experiences among users, and connection through technology, where confidence is the key concept. To help creating values of confidence, trust and safety among the members of the Teranga Go! community, we have implemented an intelligent decision support system in the platform based on computing with words. The participants of a carpooling experience act as experts that assess the driver aptitudes and determine, together with the history of the driver, a linguistic value for the driver's *karma* which represents the collective opinion of people that have travelled with the driver. The *karma* is a public label attached to the site user profiles. A MultiExpert Multi-Criteria Decision Making model is applied using Hesitant Fuzzy Linguistic Terms to represent the expert opinions.

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1. Introduction

The concept of collaborative or participatory consumption provides an opportunity to develop online communities to connect people and exchange things [6]. Most vulnerable groups of people can benefit from accessing to limited resources. For instance, think in the goods migrants traveling between Europe and Africa may need for purchasing. In this case, sharing the expenses of a journey that might take five or ten days by car has a great interest and it can be modeled as a decision making problem.

Social media and the Internet are changing our everyday habits [15; 31]. It is absolutely common to: listen music online, read digital newspapers, do shopping for Christmas on big web stores, buy plane tickets, check-in at the airport, or share our family pictures on Social Networks. In a social network your reputation comes from your actions plus what others say about you. In this work we are concerned with the second part of this small formula. Our aim is to improve the tools that enable to give opinion about others in an online community, opinion with is subjective in its basis, and support decision making problems.

We have developed Teranga Go! (<http://terangago.com/>) as an online facility for carpooling centered at the Senegalese community. It provides a mobile app and a website with a set of tools to post a new journey or communicate interested in travel from Spain to Senegal, and get detailed information of the event. People using online car sharing communities may feel reluctant to travel with a total stranger because sometimes the profile gives not enough information, or you have to blind choose between two drivers that run the same itinerary on the same dates. Concerned with this situation, the proposal of this work is to implement Teranga Go! with an extra feature: an intelligent support system to help making decisions to users of an online community, to help creating values of confidence, trust and safety by using the Teranga community members.

Every day people are challenged with multiple acts of decision as it is a natural human activity. Decision Making (DM) [29] is the process of selecting a logical choice from the available options, and sometimes is a rough task for people. There are computational models for DM that helps with the implicit complexity of real problems. In decision problems, each decision

maker considers a set of alternatives, that are assessed by a pool of experts regarding a set of criteria. Later, alternatives are compared considering all this information and the best alternative is selected. This kind of problems are known as Multiple Expert - Multiple Criteria Decision Making (MEMCDM) [11].

Computing with Words (CW) [36; 37] is a methodology for reasoning and computing with perceptions rather than measurements. CW is able to empower applications that involve people expressing their preferences about particular issues. In this work we operate with the fuzzy linguistic approach, that represents qualitative aspects as linguistic values by means of linguistic variables [35]. The linguistic approach deals well with how people think and it is also preferable because experts are allowed to evaluate closer to natural language. Often, decision situations are defined under uncertainty, and the fuzzy linguistic approach provides tools to model and manage it. Problems defined under uncertain conditions are common in real world, but difficult to be modeled in a computer program due to the complication of dealing with uncertain information. We include the possibility of provide inaccurate and uncertain rates by means of the use of a context-free grammar represented by a Hesitant Fuzzy Linguistic Term Set (HFLTS).

In this context, our aims in this paper are:

- To model opinions of users of a online community about people interacting in a business relation, trust and reputation.
- To present a practical application of decision making with a linguistic fuzzy model that deals with imprecise information represented as HFLTS, and the final linguistic information represented to 2-tuple linguistic intervals.
- To compute a *karma* value as custom profile field in an online community using **Teranga-IDSS**, our proposal for an intelligent decision support system that could be reused in any online community.
- And finally, to ensemble all these elements in a real online community for carpooling collaborative consumption released under the GNU Public License v2.

Our carpooling online service for putting in practice a sharing economy approach, is based on the open source framework ELGG, and was released

covering the migration flows between Spain and Senegal on April 2016. The novelty of the site is the possibility of using hesitant linguistic expressions to assess a set of qualitative criteria, the use of the community members as the pool of experts and the idea that alternatives are the experts themselves. The linguistic information is used to set a linguistic variable named *karma* in the profile of each user.

The remainder of the paper is organized as follows. Section 2 focus in the importance of online use-base offering economic communities and how to improve trust within their members. In Section 3, the representation of qualitative data and how to deal with the elicitation of hesitant information is described. The community of Teranga Go! is explained with some illustrative figures in Section 4. Section 5 describes our ME-MCDM problem based on 2-tuple fuzzy representation of hesitant expressions and the model's scenarios. Here, two scenarios outputs are compared by using the same assessment data in the input of **Teranga-IDSS**. Finally in Section 6 conclusions are given.

2. Online Communities, Trust and Reputation

In this section we introduce first online communities and then the importance of building trust and reputation in them. Finally, we shortly introduce the Teranga Intelligent Decision Support System.

2.1. Online Communities for Collaborative Consumption

In opinion of the European Economic and Social Committee set out on directive 2014/C 177/01 *Collaborative or participatory consumption, a sustainability model for the 21st century* [6] enabling tools that promotes sharing economy practices has become a priority for the European Union. Collaborative or participatory consumption represents an innovative complement to a production economy in the form of a use-based economy offering economic, social and environmental benefits. It also offers a way out of the economic and financial crisis, by enabling people to exchange things for others that they need. It represents an opportunity to build sustainable economic, social and human development in an environmentally-friendly way. The key issue is linking people who need a resource with others that have these resources. This relationship is based on a sense of community, sharing and participation among users, where trust is the link making possible to establish connections, develop an alternative form of consumption and, over the long term, maintain the relationships that are created. In this way, Internet is the best place

to let these interactions to happen as it is everywhere, every time and world wide.

The power of collaboration and sharing through technology will change the way we think about business relations [14]. The product is no longer just sold, but is also hired, redistributed or shared. As a result of the economic crisis, platforms have emerged, for example, for the buying and selling of second-hand wedding dresses and accessories, for private accommodation, or the rental of cars. We have a special interest in online communities for carpooling services because of a number of direct effects of car sharing: a lower resource consumption and CO2 emissions; it is benefiting for different users and could be repeated; it improves social interaction, community development and trust among individuals; it encourages access to a service for lower-income consumers and can also have other indirect effects such as local tourism development.

2.2. Building confidence and trust in an online community

To have a digital identity and have presence in many social networks has become fundamental. It is a digital competency which is frequently required in the profile of the candidate for a job vacancy. Social networks usually demand a profile description and an image avatar to build up an identity, then we interact within the community by sell our old stuff, win an auction, comment and like pictures and videos or share a car. These activities are performed under the assumption that people respect a Code of Honor implicit in the website, but it does not help much in building an online community that built trust [1].

Trust mechanisms for online communities are generally employed to reinforce confidence [13]. Some of them are:

- Member ratings. Allows a member to grade any other user with a point award, which usually goes from 1 to 5 stars.
- Friendship request management. Let users request friendship to any other member of the platform. This would send a solicitude that can be rejected or approved by the target user. Any approved friendship could be canceled at any time.
- Report an abuse. There are actually some rules and regulations that go along with participating in social media. Any member that detect bad content like spamming can report this circumstance to the site

administrator. The responses vary from delete the content or penalize the spammer user.

- Block the content from a user. Action consequence of a bad use of the social network, for instance posting copyrighted content.
- User banning. The site administrator can temporarily deny access to the site to a particular user that does not respect the rules and regulations of the community.

Nevertheless, these mechanisms does not help much to confer a reputation to their members. Today, we have to think more about reputation management even more than we did in the past. Not only is necessary to create a great impression in real life but we also have to be aware of how we come across online. We are prompted to create a strong reputation currency online as we interact in many ways through the Internet (as professionals, as customers, as friends, etc). In these days, it is a challenge to be certain about the identity of the people to whom we interact. Leaving apart the case of knowing in real life the other person, you decide to engage with another user only by a glance of a picture and a brief personal profile. If we are able to use the collective information about a particular user (what others say about you), to compute a value for the reputation of a person, the social network will create an online community centered on the trust between users.

The key idea in Teranga Go! is to add a custom profile field name *karma* to reflect the reputation of a person. The *karma* label is computed using **Teranga-IDSS** which will be fully detailed in Section 5.

2.3. Teranga Intelligent Decision Support System

To help creating values of confidence, trust and safety among the members a community, we have implemented an intelligent decision support system named **Teranga-IDSS** based on computing with words. We offer this tool in a public GitHub repository to be reused in any online community as a plugging. We have foreseen four scenarios to model the maturity of the community: from a young community with few opinion data to a grown community with long-term interactions between users. So the more assessments from users to users (lets say, user generated content), the better for the maturity of the online community. The webmaster might establish the model parameters and set the default scenario.

Motivated by the use of gamification techniques¹ in online collaborative communities, we consider the description of the expertise of a user in our CW based ME-MCDM model. This is a way of introducing levels of consistency and confidence in our model, which in decision-making situations is exploited by assigning a relative importance weight to each one of the experts in arriving to a collective opinion.

3. Decision Making with Hesitant Fuzzy Linguistic Term Sets

To our interest, CW based DM problems can deal with inaccurate rates and comparative linguistic expressions by means of the use of HFLTS [19; 24]. A HFLTS represents a context-free grammar that enables the experts to elicit assessments with uncertainty and hesitation in the context of fuzzy decision making. HFLTS derives from the original idea of Torra's hesitant fuzzy sets (HFS) [28], and it is present in many research works relate to DM [2; 5; 17; 18; 19; 20; 21; 22; 25; 26; 33; 32; 30; 39; 40; 23]. In [26; 27] a review of HFLTS advances and discussion of its use are presented.

In the following subsections we present the 2-tuple model to represent the linguistic information and we define a HFLTS as a tool to elicit linguistic expressions under uncertainty. Finally, we describe how we aggregate linguistic information.

3.1. The 2-tuple fuzzy linguistic computational model

A linguistic variable can take values only in a finite set of eligible values that are defined by the linguistic term set $S = \{s_0, \dots, s_g\}$, in which $g + 1$ is called the cardinality of S and usually is an odd number. The more terms in S the more precise an evaluation could be, but on the contrary, it also may imply hesitation to the expert. The linguistic terms $s_k \in S$ are defined by triangular membership functions uniformly distributed. These assumptions guarantee that the 2-tuple linguistic computational model [8] is precise and effective.

Definition 1. [8]: *Let S be a linguistic term set, and $\beta \in [0, g]$. Then*

¹Gamification is defined by [4] as *a process of enhancing a service with affordances for gameful experiences in order to support the user's overall value creation.*

the 2-tuple is defined as:

$$\begin{aligned} \Delta : [0, g] &\rightarrow S \times [-0.5, 0.5) \\ \Delta(\beta) &= (s_i, \alpha), \text{ with } \begin{cases} s_i, i = \text{round}(\beta), \\ \alpha = \beta - i \end{cases} \end{aligned} \quad (1)$$

The 2-tuple becomes a equivalent representation of any term $s_i \in S$. The inverse function $\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g]$ is defined in [8] by $\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$. The value of $\alpha \in [-0.5, 0.5)$ is known as the symbolic translation. In CW processes, a linguistic term $s_i \in S$ will transform into $(s_i, 0)$.

A comparison rule is needed if we rate two alternatives assessed with a linguistic variable represented with a 2-tuple. A valid comparison rule is [8]:

1. if $n < m$, then (s_n, α_1) is smaller than (s_m, α_2)
2. if $n = m$, then
 - (a) if $\alpha_1 = \alpha_2$, then (s_n, α_1) and (s_m, α_2) are the same
 - (b) if $\alpha_1 < \alpha_2$, then (s_n, α_1) is smaller than (s_m, α_2)
 - (c) if $\alpha_1 > \alpha_2$, then (s_n, α_1) is bigger than (s_m, α_2)

Definition 2. Let $X = \{(r_1, \alpha_1), \dots, (r_n, \alpha_n)\}$ be a set of 2-tuples and $W = \{w_i/i = 1, \dots, n\}$ an associated weighting vector. Consider W' the normalized version of W with $w'_i \in [0, 1]$ and $\sum_{i=1}^n w'_i = 1$. The arithmetic weighted extended mean \bar{x}^e is defined in [8] as:

$$\bar{x}^e(X) = \Delta \left(\frac{\sum_{i=1}^n \Delta^{-1}(r_i, \alpha_i) w_i}{\sum_{i=1}^n w_i} \right) = \Delta \left(\sum_{i=1}^n \beta_i w'_i \right). \quad (2)$$

Definition 3. Let $S = \{s_0, \dots, s_g\}$ be a fixed set of linguistic terms. An interval 2-tuple linguistic variable is the composition of two 2-tuples denoted by $[(s_i, \alpha_i), (s_j, \alpha_j)]$, where $i \leq j$. Both s_i and s_j represent a label of the pre-defined linguistic term set S . Respectively, α_1 and α_2 represent the symbolic translation. The equivalent information of the interval 2-tuple corresponds to an interval value $[\beta_1, \beta_2]$ with $\beta_1, \beta_2 \in [0, g]$ and $\beta_1 \leq \beta_2$, derived by using an extension of function (1).

$$\begin{aligned} &\beta_1, \beta_2 \in [0, g] \quad \beta_1 \leq \beta_2 \\ \Delta([\beta_1, \beta_2]) &= [(s_i, \alpha_1), (s_j, \alpha_2)] \text{ with } \begin{cases} s_i, i = \text{round}(\beta_1), \\ s_j, j = \text{round}(\beta_2), \\ \alpha_1 = \beta_1 - i, \\ \alpha_2 = \beta_2 - j, \end{cases} \quad (3) \\ &s_i, s_j \in S \quad i \leq j \quad S = \{s_0, \dots, s_g\} \end{aligned}$$

To convert from an interval 2-tuple to an interval value $[\beta_1, \beta_2]$ a function Δ^{-1} is applied:

$$\begin{aligned} \Delta^{-1} : S \times [-0.5, 0.5] &\rightarrow [0, g] \\ \Delta^{-1}[(s_i, \alpha_1), (s_j, \alpha_2)] &= [i + \alpha_1, j + \alpha_2] = [\beta_1, \beta_2] \end{aligned} \quad (4)$$

3.2. The Hesitant Fuzzy Linguistic Term Set

To handle imprecise information we need to model hesitation in the elicitation of linguistic information. In a quantitative setting, the concept of HFS was introduced in [28] to allow decision makers the consideration of several values to determine the membership of an element to a set. The concept of HFS has proved to be applicable to DM, evaluation and clustering techniques [26]. An extension known HFLTS was presented in [24] to be used in linguistic fuzzy decision making situations.

Definition 4. [24]: Let $S = \{s_0, \dots, s_g\}$ be a fixed set of linguistic term set, and g a parameter known as the granularity of the linguistic term set. A HFLTS H_S , is an ordered finite subset of the consecutive linguistic terms of S .

1. Empty HFLTS: $H_S(\vartheta) = \{\}$,
2. Full HFLTS: $H_S(\vartheta) = S$.
3. Other HFLST: formed with at least one linguistic term in S .

Example 1: Let S be a linguistic term set, $S = \{s_0 : \text{very low}, s_1 : \text{low}, s_2 : \text{weakly low}, s_3 : \text{medium}, s_4 : \text{weakly high}, s_5 : \text{high}, s_6 : \text{very high}\}$, two different HFLTS might be:

- $H_S(\vartheta_1) = \{\text{low}, \text{weakly low}, \text{medium}\} = \{s_1, s_2, s_3\}$.
- $H_S(\vartheta_2) = \{\text{medium}, \text{weakly high}, \text{high}\} = \{s_3, s_4, s_5\}$.

The HFLTS is a flexible tool to represent hesitant qualitative information and can be used to elicit several linguistic values for a linguistic variable. The use of a context-free grammar G [24] increases the flexibility of the model by including the possibility to generate linguistic terms and linguistic expressions

Definition 5. [24]: Let G_H be a context-free grammar, and let S be a linguistic term set. The elements of $G_H = (V_N, V_T, I, P)$ are defined as follows:

- $V_N = \{\langle \text{primary term} \rangle, \langle \text{composite term} \rangle, \langle \text{unary relation} \rangle, \langle \text{binary relation} \rangle, \langle \text{conjunction} \rangle\}$,
- $V_T = \{\text{lower than, greater than, between, } s_0, s_1, \dots, s_g\}$,
- $I \in V_N$, and
- P is the set of production rules defined in an extended Backus-Naur form [19].

Definition 6. [24]: Let E be a function that transforms G_H linguistic expressions (LE), which are obtained by G_H into a HFLTS H_S , where S is the linguistic term set that is used by G_H . Thus, $E_{G_H} : LE \rightarrow H_S$.

The linguistic expressions will be transformed into HFLTS in different ways according to their meaning:

- $E_{G_H}(s_i) = \{s_i | s_i \in S\}$;
- $E_{G_H}(\text{less than } s_i) = \{s_j | s_j \in S \text{ and } s_j \leq s_i\}$;
- $E_{G_H}(\text{greater than } s_i) = \{s_j | s_j \in S \text{ and } s_j \geq s_i\}$;
- $E_{G_H}(\text{between } s_i \text{ and } s_j) = \{s_k | s_k \in S \text{ and } s_i \leq s_k \leq s_j\}$.

Definition 7. [19]: Let H_S be an ordered finite subset of the consecutive linguistic terms of S , the envelope of a HFLTS, $env(H_S)$, is a linguistic interval whose limits are obtained by means of its upper bound H^+ and lower bound H^- :

$$\begin{aligned} H_S^+ &= \max\{s_i | s_i \in H_S\} \\ H_S^- &= \min\{s_i | s_i \in H_S\} \end{aligned} \quad (5)$$

The original envelope is computed as $env(H_S) = [H_S^-, H_S^+]$, $H_S^- \leq H_S^+$, though it is also possible to compute such linguistic intervals by means of a fuzzy envelope of HFLTS [19].

Example 2. Following the previous example of $H_S(\vartheta_2)$, the envelope is:

$$env(H_S(\vartheta_2)) = [s_3, s_5] = [\text{medium}, \text{high}].$$

The inverse operation is feasible. Given a linguistic interval, a HFLTS can be obtained by including all the terms that lay between the lower and the upper interval bounds.

$$[s_a, s_b] = env(H_S) \rightarrow H_S = \{s_a, s_k, s_b | s_a \leq s_k \leq s_b \text{ and } k \in \{a, \dots, b\}\}$$

Example 3. Consider the linguistic interval $[s_2, s_4]$ which can be the result of the envelope of the expression *between weakly low and weakly high*.

$$[s_2, s_4] = env(H_S(\vartheta_3)) \rightarrow H_S(\vartheta_3) = \{s_2, s_3, s_4\}$$

3.3. Aggregating HFLTSs

According to [24], aggregation of the assessments represented by HFLTS can be performed with two symbolic aggregation operators: the *min_upper* operator that obtains the minimum of the maximum linguistic terms, and the opposite *max_lower* operator that obtains the maximum of the minimum linguistic terms.

Definition 8. [24]: Let $h_i (i = 1, 2, \dots, n)$ be a collection of hesitant fuzzy linguistic term sets, $H = \{h_1, h_2, \dots, h_n\}$. The *min_max_HFLA* aggregation operator θ performs the following steps:

1. Apply the *min_upper* operator: This is a symbolic aggregation operator that gets the upper bound of each hesitant (with Eq.5) and computes the minimum linguistic term $min_upper = \min\{h_i^+ \mid i \in \{1, \dots, n\}\}$.
2. Apply the *max_lower* operator: This is a symbolic aggregation operator that gets the lower bound of each hesitant (with Eq. 5) and computes the maximum linguistic term $max_lower = \max\{h_i^- \mid i \in \{1, \dots, n\}\}$.

The result of these operators are two linguistic terms that will be used to build a linguistic interval r :

$$min_max_HFLA(H) = \theta(h_1, h_2, \dots, h_n) = [min_upper, max_lower] \quad (6)$$

Example 4: To aggregate $h_1 = H_S(\vartheta_1)$ and $h_2 = H_S(\vartheta_2)$ from example 1, with operator *min_max_HFLA*, we first compute the upper bounds $h_i^+ = \{s_3, s_5\}$ and the lower bounds $h_i^- = \{s_1, s_3\}$ with $i = 1, 2$. Later, we select the minimum term from h_i^+ and the maximum term from h_i^- . As a result we get $[s_3, s_3]$ which is the hesitant $h_3 = \{s_3\}$.

The *min_max_HFLA* operator cannot deal with the situation where the importance weights of criteria or experts are to be considered. Literature brings the option to use alternatives to aggregate several HFLTS considering them of different weights. In [16] the authors use the concept of likelihood-based comparison relations of HFLTS to propose a similarity measure between hesitant fuzzy linguistic term sets. They also propose definitions for several the hesitant fuzzy linguistic operators, such as the weighted average

(HFLWA) operator. Nevertheless these operators do not adapt to our ME-MCDM problem because the result of an aggregation is a number and not a HFLTS. In [33] the authors bring in a HLWA operator which generalizes the Linguistic Weighted Averaging operator to aggregate HFLTS by using the convex combination.

Definition 9. [33]: Let $h_i (i = 1, 2, \dots, n)$ be a collection of hesitant fuzzy linguistic term sets, $H = \{h_1, h_2, \dots, h_n\}$, and $w = (w_1, \dots, w_n)$ a weighting vector of H with $w_j \geq 0 (j = 1, \dots, n)$ and $\sum_{j=1}^n w_j = 1$, the HLWA operator θ is defined as follows:

$$\begin{aligned} HLWA(H) &= \theta(h_1, h_2, \dots, h_n) = C^k(w_j, h_j, j = 1, \dots, n) \\ &= w_1 \odot h_1 \oplus (1 - w_1) \odot C^{k-1}\{w_t / \sum_{j=2}^n w_j, h_t\} \\ &\text{with } t = \{2, \dots, n\}. \end{aligned} \quad (7)$$

Definition 10. [33]: The convex combination for h_1 and h_2 is as follows:

$$C^2(w_1, h_1, w_2, h_2) = w_1 \odot h_1 \oplus w_2 \odot h_2 = \{C^2(w_1, s_i, w_2, s_j) \mid s_i \in h_1, s_j \in h_2\}$$

where $w_k \geq 0 (k = 1, 2)$ and $w_1 + w_2 = 1$.

Now we just have to deal with the convex combination of two linguistic terms [3], which it is also a linguistic term. The HLWA aggregator operator is better for us because the combination of the input HFLTSs is also a HFLTS. The major drawback of the HLWA operator is that it needs to rank the HFLTS to compare and aggregate them and weights do not naturally link with each hesitant but with its ranking position. After the collection H is ranked, w_0 is assigned to the first ranked hesitant and w_n is assigned to the last one in the convex combination of HFLTS. In this way weights naturally reflect a risk criteria of sorting and not the importance of the HFLTS, but we still can use this θ operator if we maintain the implicit hesitant weight in our computational processes.

4. The Teranga Go! Community. A GNU Public License Software

The aim of Teranga Go! is to foster the mobility of international migration flows based on concepts of collaborative economy and participatory consumption. People share not only a car but also lifetime experiences.

We have developed an online community that uses the CW based ME-MCDM model discussed in this paper. The site includes an Intelligent Decision Support System named **Teranga-IDSS**, that computes the label *karma*

of any user platform by collecting other people opinions about this driver. This will be further explain in Section 5. The platform also fully implements the service of car-sharing.

Teranga Go! is based on the open source framework ELGG (<http://elgg.org/>). The specific modules used to run the linguistic DM model are publicly available at GitHub. At <http://terangago.com/comunidad> you find the log-in/register form to join Teranga Go! community.

Once logged in Teranga Go! community you can get engaged in a trip, connect with other users and leave an opinion about the driver after your trip have finished. In the following subsections we explain the interface of the platform² focusing only in the parts that are relevant to understand how **Teranga-IDSS** works.

Firstly, in subsection 4.1 we cover how users can customize their personal space and how they access to the linguistic output *karma*. Later, in subsection 4.2 we describe the assessment form that should be filled to create our assessment data. The assessment form is attached to a trip planning space and it is enabled only when the status of the participants match the given restrictions. The software installation is briefly covered at subsection 4.3. We also present the administration tools which set **Teranga-IDSS** parameters in subsection 4.4.

4.1. The User Profile Area

Teranga Go! supports a ME-MCDM model under hesitation and it is used to compute a linguistic label named *karma* that reflects the collective opinion of people that have travelled with a driver. The *karma* is dynamically computed with every profile display to reflect any new information (new assessments, changes of reputation of the trip companions (i.e. the expertise property), or to reflect new community settings (a new base expertise for all community users). This up-to-date compromise helps to built a trusted online community, as the profile of a person includes not only the avatar and personal information, but also it tells other users the level of experience of the driver in sharing trips. In Teranga Go! following the Members menu, we can check on every user's profile to see what is the collective opinion of the members that already travelled with the user, as the assessment is performed

²A complete manual of Teranga Go! can be found at http://terangago.com/wp-content/uploads/2016/04/teranga_user_guide_en.pdf

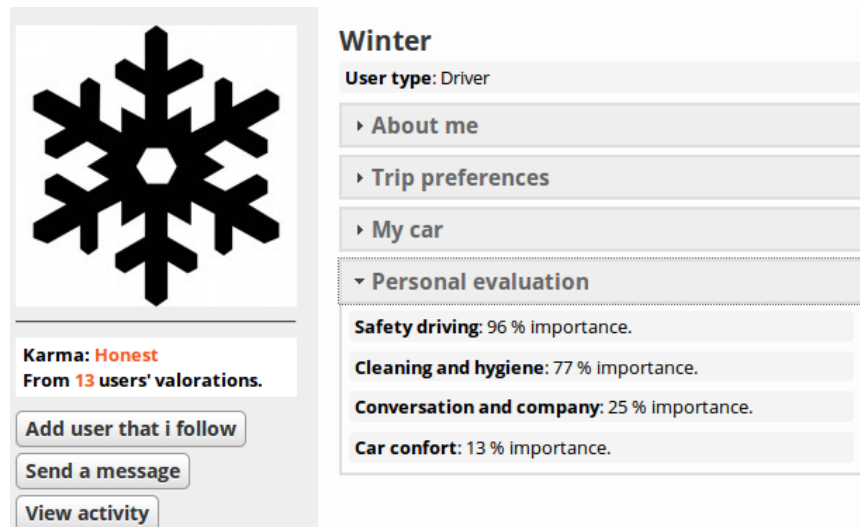


Figure 1: The profile of a trip companion candidate informs about *karma*, personal information and general trip preferences.

on the basis that they interacted in real life. Figure 1 gives an example of a user profile.

A user profile provides detailed and visual information about a user grouped into these categories:

- **Avatar:** It is a picture that represents the person. It could not be real. Below is the *karma* label and the numbers of assessments received.
- **About me:** A brief description of the user, country, interests, phone number or Twitter account.
- **Trip preferences:** Personal preferences about places to stops, tobacco habits, or religion link that defines the user’s affinities.
- **My car:** People can select as profile type field values of Passenger or Driver. When Driver is selected, the platform will recommend to fill information regarding the vehicle to be used.
- **Personal valuation:** General traveling preferences. These are expressed using weighted significance assigned to different facets of a trip. Our criteria are: security, confort, cleanliness, company and conversation. Each percentage for preference is used as criterion weight w_{C_j} .



Figure 2: The trip planning page shows general trip information. Below is the module of Trip companions' comments. You get information about your assessments under My status block.

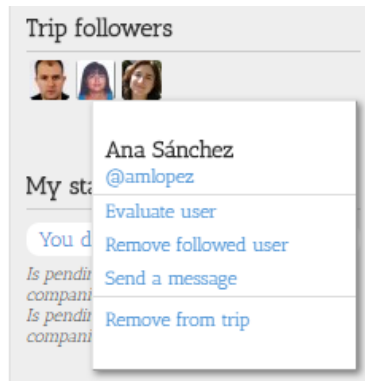


Figure 3: You start an assessment selecting the target user.

So assessments and criteria weights are a double subjective information that we store when a user evaluates other people in scenarios third and fourth.

4.2. Creating opinions using the HFLTS representation

Participants of a trip are able to assess any of the other confirmed passengers and driver after the trip. This is an innovative tool that the site enables as a service. In Fig.2 we show an example of a trip planning. Some users that traveled from Granada (Spain) to Dakar (Senegal) express their opinion about the other participants. In the region **My status** that appears at the right column of Fig. 2, the platform shows who the logged user have assessed and who is pending of him/her evaluation. In this case, Rosana has made an assessment concerning Maria Teresa and Lisa (the three have traveled together). To get access to the evaluation form, you just have to click at each avatar and select **Evaluate user** as it is shown in Fig. 3.

We have predefined four main criteria in Teranga Go! mostly directed to the driver but also to the car maintenance state which this person is responsible of. The criteria are $\{C_1$: safety in driving, C_2 : cleaning and hygiene, C_3 : conversation and company, C_4 : car confort $\}$. Note that it also correspond with the facets used in the personalized profile area.

Within the platform, the evaluation form has two parts:

- Private questions. Trip Companions that assess each other participants of the trip can use qualitative information under hesitation to express their opinions about the evaluated person. A view of the input form when a user is assessed is shown in Figure 4. It is possible to assess someone that does nothing to do with a criterion such as the security of the car (think in a rental car). Thanks to the use of HFLTS it is suitable to select the full set S to give a null answer.
- Public questions. Additionally a person could give recommendations and comments expressed as free text (see Figure 5). Only the answers of these questions are shared with participants interested in the trip (trip planning area with the Trip Companions' comment module appears at the bottom of Figure 2).

4.3. Installing and setting Teranga Go!

Teranga Go! is a social community for sharing economy that builds upon ELGG v1.12.14 open source framework and some of its open plugins, such as `customindex`, `renamefriend`, `externalpages`, `messages` or `elgghtml5`. The previous packages are external dependencies that have to be installed and activated in addition to the ELGG core. The specific development made

Personal valoration of:
 María Teresa - Teranga

Safety driving
 Horrible Very bad Bad Normal Good Very good Excellent
General opinion about the driving style (you could choose more than one answer regarding their are consecutive).

Cleaning and hygiene
 Horrible Very bad Bad Normal Good Very good Excellent
General opinion about the person (you could choose more than one answer regarding their are consecutive).

Conversation and company
 Horrible Very bad Bad Normal Good Very good Excellent
General opinion about the person (you could choose more than one answer regarding their are consecutive).

Car confort
 Horrible Very bad Bad Normal Good Very good Excellent
General opinion about the car (you could choose more than one answer regarding their are consecutive).

Figure 4: Trip evaluation form private part. The user can make accurate assessments or express doubt by checking more than one value in response.

Will recommend the driver to other users?

Public answer together with comments. Not mandatory.

Was the driver faithful to the agreements previously negotiated?

Public answer together with comments. Not mandatory.

Other comments
 María Teresa was very nice with me. I traveled with flu and she took care of me.

Figure 5: Trip evaluation form public part. The platform allows to share your opinion with other participants.

to configure a carpooling service and the **Teranga-IDSS** that computes the *karma* label is available at Rosana Montes's GitHub: <https://github.com/rosanamontes/teranga.go>. The following set of plugins brings to live Teranga Go!:

1. **teranga-theme**: original plugin that implements the site theme, including aspect elements and text translations to Spanish, English and French.
2. **teranga-idss**: original plugin that fully implements **Teranga-IDSS** proposal. Its configuration is covered in the next subsection. It includes the algorithm to solve a ME-MCDM problem and the set of HFLTS aggregation operations described in Section 3.3.
3. **mytrips**: an adaptation of the **group** plugin. It enables a space to publish and share a trip planning. People that get interested in a trip, automatically are subscribed to Trip Discussion forums and Trip companions' comments.
4. **profiles-go**: an adaptation of the **profilemanager** plugin that set the user profile area. Two profile types are enabled: driver or passenger, each one with a set of customized profile fields.
5. **trip-companions**: original plugin that implements the trip assessment form. It allows to create opinions using the HFLTS representation which help the expert to elicit hesitant linguistic information.
6. **terangapp**: original plugin that set a banner that announce TerangaUGR App and links to the Android and iOS markets.

It has to be noted that the order of the plugin activation is important, as a plugin below other might override some of its functionality. For that reason in the elgg plugin configuration area, core ELGG elements are in first order (as it appears after first installation), followed by the external dependencies, and at the bottom must be the set of plugins specific for Teranga Go!.

4.4. *Teranga-IDSS Configuration Area*

The webmaster can access to the configuration area of any enabled plugin. In Fig. 6 a view of the **teranga-idss** plugin settings is shown. In this area, we get access to the following parameters:

1. IDSS parameters: display karma flag and auto-moderation of trip assessments. Assessment collected from the evaluation form can be moderated previous to their storage, the point awarding and its use as data

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Chose the methods to run as linguistic models in the decision making process.

Aggregation operator

Given a set of hesitant, compute the aggregate hesitant according one of these operators

Linguistic terms

Linguistic Term set to be used in the decision-making linguistics.

Display karma on users profile?

The driver karma is the result of the decision making process considering overall satisfaction with the driver and his vehicle, and for all trips and valorations.

Auto-Moderation

If enabled, assessments would be automatically archived (no manual moderation)

Consider expertise

Allow many assessments from one user to other in the context of a trip

Base expertise

In case of considering expertise, this is a value in $[0,1]$ that determines how to include the expertise characterization. 0=all from the platform
1=ignore the platform information (i.e. all user are equal).

Consider preferences

Activates the use of importance per criteria and per expert (dual subjective information)

Figure 6: Settings for visualization options and Teranga-IDSS parameters.

for the ME-MCDM model. This will avoid wrong data from malicious users. We have implemented an auto-moderation option that the web-master can select at any time.

2. ME-MCDM parameters: choose HFLTS aggregation operator θ from min_max_HFLA or $HFLW(H)$ and the granularity g or the numbers of linguistic terms. It also includes the scenario selection and the parameter B which represent the overall confidence in the community.

It may be noted that these parameter configuration could be done in any online community, as it is not specific only for Teranga Go!.

5. Intelligent Decision Support System for Online Collaborative Communities

An important contribution of this paper is an intelligent decision support system for online communities based on computing with words, called **Teranga-IDSS**, that we have applied in a community for carpooling name Teranga Go!. We have foreseen **Teranga-IDSS** as an application for on-line communities that computes a *karma* value for each user. In the case

of Teranga Go! the *karma* of a traveller –someone involved in driving for short or long periods of the journey– reflects how good was that experience and, in some way, it allows to share this information with other community members.

In subsection 5.1, we explore the ME-MCDM parameters that set up the four scenarios of the model. In subsection 5.2 some considerations are given to represent levels of expertise among active users. The core of our intelligent decision support system are the processes for computing the *karma* term, which are detailed at subsection 5.3.

5.1. Discussing Teranga-IDSS Scenarios

We use a simple but not simplistic CWDM model to compute collective judgements of users that will represent the *karma* of a person, so the output of the model is a linguistic term. Users of an online community may have roles. We consider two roles: (1) the driver, who is the alternative being assessed and (2) the trip companions *TC*, one or more users that eventually have shared a journey with the driver.

Teranga-IDSS accepts some setting parameters that configure its input data and elements:

- Assessments. Clearly in our problem the assessments focus on people with the responsibility of driving. The model uses linguistics expressions under hesitation or linguistic single term values, and symbolic aggregation operators. We let trip companions to elicit several linguistic values by using HFLTS in an input predefined linguistic term set.
- Evaluation Criteria *C*. These are the properties under evaluation for the alternative that are evaluated.
- Alternatives *A*. For us, alternatives are platform users that might play a role in a trip, sometimes as drivers. We do not rank alternatives because we only have one alternative (the driver) each time that the model run. We run the model every time that a profile of a user is consulted.
- Experts. The users that share a trip with a driver are the experts that evaluate the driving experience, and the output of the decision model is a linguistic value from a second term set –to represent a linguistic

variable *karma*— which models the general satisfaction of participants with the trip promoter.

- Personal preferences. In ME-MCDM problems, criteria may have different importance in determining the result of exploitation phase. It is intuitive that the more important a criterion is, the more it should affect the aggregated score.
- Expertise weight. As with criteria, we have weights to distinct the opinion of a person that has traveled many times (a trip companion with more experience in travelling) with respect to the information that comes from newbie users. Nevertheless, the intuition of people with low expertise can be adjusted with a parameter B called base expertise. A value closer to 1 might be used in a community with many newbies and low or null experienced users.

	Expertise=Y	Expertise=N
Preferences=Y	Scenario 4	Scenario 3
Preferences=N	Scenario 2	Scenario 1

Table 1: Parameters combination for Scenario selection.

Thus we have a ME-MCDM model that also considers expertise degree and criteria weights. We have depicted four distinct situations or scenarios (which the website administrator can set in the Teranga-IDSS Configuration Area) which are also summarized at Table 1:

1. Scenario 1 of equity consideration: no weights are assumed to evaluate each criteria, neither weights are imposed to each trip companion.
2. Scenario 2 with expertise on: the system assigns a weight to each trip companion (in fact, to any user) that represents the expertise of the user on real trips. Each criterion is considered of the same importance.
3. Scenario 3 with criteria on: with any assessment, a weight to each criteria (representing individual preferences of the evaluator) is applied. Each expert is considered of the same relevance.
4. Scenario 4 of dual weights: expertise degree is considered for each trip companion, and using the profile information, their individual preferences on criteria are applied as criteria weights.

5.2. Expertise Computation in Teranga-IDSS

Our ME-MCDM model uses a linguistic term set of granularity $g = 6$: $S_{in} = \{Horrible, Verybad, Bad, Normal, Good, Very good, Excellent\}$. It also is defined by p valuations with $k = 1, 2, \dots, p$ and $p \geq 2$, n alternatives $A_i (i = 1, 2, \dots, n)$ and m evaluation criteria $C_j (j = 1, 2, \dots, m)$ fixed to $m = 4$. Let us note t the number of experts or trip companions $TC = (TC_1, TC_2, \dots, TC_t)$. Hypothetically t could be the total community members minus 1. As people may travel as many times as they like, we do not impose restrictions on repetitions and thus $t \leq p$. It means that if we have for instance four trip companions ($t = 4$), we could have the same number of assessments ($p = 4$) if they are distinct, or we could have any other number if some of them have traveled more than once together ($p = 8$, if all companions have travelled twice with the driver).

Online participation can be increased with the use of gamification techniques such as: user points, user badges, community activity, wire notification, etc. In fact, platforms can collect many information relative to online activity that could be used to assign a expertise value to community members. Trip Companions that assess each other participants of the trip may have different backgrounds and might have participated in a varied number of real journeys, so this situation is what we need to model as expertise. In our case, we collect assessments submitted after a real trip. That is why our

gamification techniques should focus on promoting trip evaluation forms as a way to feed our assessment data.

Let call $\phi : TC \rightarrow \mathbb{N}^+$ the function that returns the overall points awarded to community members, so $\phi(TC_e) \geq 0$ with $1 \leq e \leq t$. We can compute $\max_{e=0}^t \phi(TC_e)$ with $(e = 1, 2, \dots, t)$ the maximum number of points a user have gained with the submission of assessment forms.

Let call $\varepsilon : TC \rightarrow [0, 1]$ the function that returns the expertise degree of any community member. We want to compute this value because we need to assign a weight $w^e \in [0, 1]$ to each community member to reflect his/her relative importance in the community regarding the participation in journeys promoted through the platform.

Teranga-IDSS uses a percentage parameter $B \in [0, 1]$ named *base expertise* that represents a guaranty of expertise and reflects about how much we generally rely in the expertise degree $\varepsilon(TC_e)$ value. When $B = 0$, we fully believe that the more journeys and assessments done, the more importance has the opinion of experienced users. When $B = 1$, we set expertise off and all the users are of equal weight. Any value of $B \in [0, 1]$, creates some confidence in users with lower expertise.

In our model, we compute w^e as:

$$\varepsilon(TC_e) = B + \frac{1 - B}{\max_{e=0}^t \phi(TC_e)} \phi(TC_e) \quad (8)$$

$$w^e = \frac{\varepsilon(TC_e)}{\sum_{k=1}^p \varepsilon(TC_k)} \quad (9)$$

The weighting vector $W_{TC} = (w^1, w^2, \dots, w^p)$ with $(e = 1, \dots, p)$ is the normalized version of the expertise degree (allowing $t \leq p$ and repetitions of w^e).

Example 6: A community with $B = 100\%$ and $t = p = 4$ would use $W_{TC} = \{0.25, 0.25, 0.25, 0.25\}$ in a scenario of equality, but we now want to consider a value of 20% as base expertise. We also know that the number of points awarded to them is $\phi = \{1, 2, 3, 5\}$ so $\max(\phi) = 5$. According to Eq. 8:

$$\begin{aligned} \varepsilon(TC_1) &= 0.2 + \frac{0.8}{5} = 0.36 \\ \varepsilon(TC_2) &= 0.2 + \frac{0.8}{5} 2 = 0.52 \\ \varepsilon(TC_3) &= 0.2 + \frac{0.8}{5} 3 = 0.68 \\ \varepsilon(TC_4) &= 0.2 + \frac{0.8}{5} 5 = 1 \end{aligned}$$

Following Eq. 9, the resulting normalized expertise weighting vector with $B = 20\%$ is $W_{TC} = \{0.14, 0.2, 0.26, 0.39\}$.

5.3. *Karma Computation in Teranga-IDSS*

The flowchart shown in Fig. 7 summarizes the processes of computing with words that we describe here. Note that it is necessary to repeat these steps for any $A_i (i = 1, 2, \dots, n)$ independently.

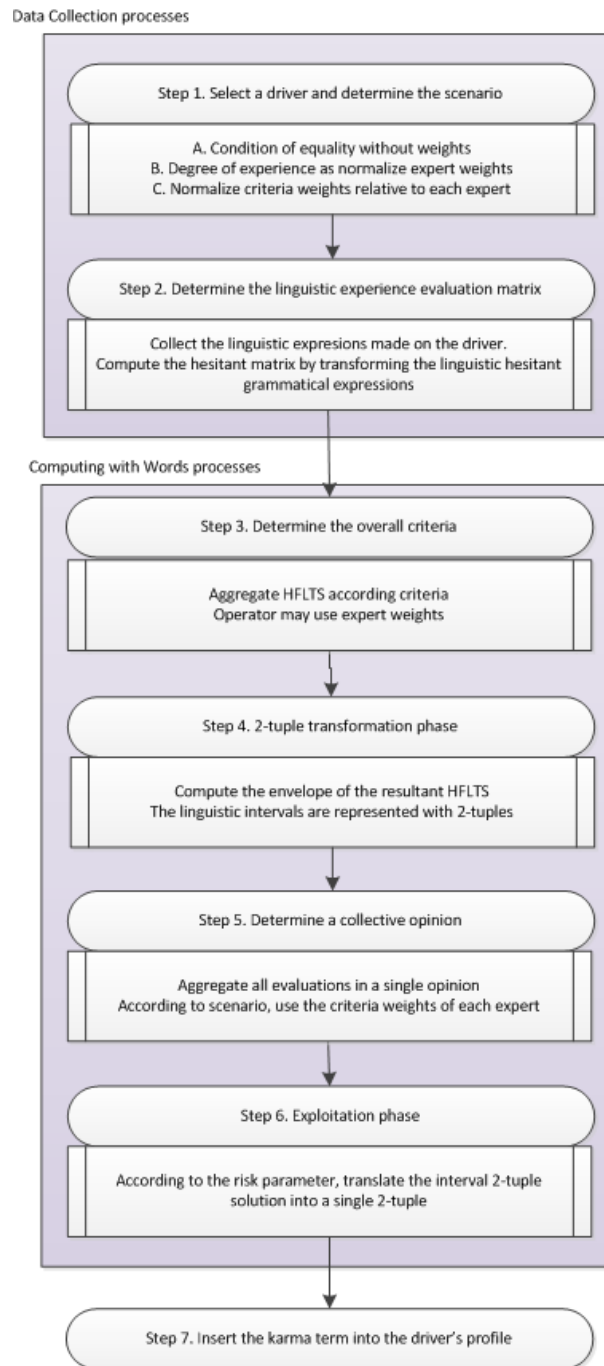


Figure 7: Flowchart of the proposed karma computation model for each user.

Step 1: Data phase

The *karma* computation starts with the selection of a driver A_i . Then, it collects the linguistic valuations F made from all the A_i 's trip companions considering any journey made in the past. Supposing a scenario of equal opportunities (Scenario 1) we just have to compose the linguistic experience evaluation matrix F of $n \times m \times p$ linguistic expressions LE in $H_{S_{in}}$. Unlike most of the ME-MCDM models, we do not rank or compare alternatives as our objective is to value alternatives individually, so $n = 1$ and our matrix reduced to $m \times p$ values.

$$A_i \rightarrow F = \begin{pmatrix} LE_{i,1}^1 & LE_{i,2}^1 & \cdots & LE_{i,m}^1 \\ LE_{i,1}^2 & LE_{i,2}^2 & \cdots & LE_{i,m}^2 \\ \vdots & \vdots & \vdots & \vdots \\ LE_{i,1}^p & LE_{i,2}^p & \cdots & LE_{i,m}^p \end{pmatrix}$$

Note that $LE_{i,j}^k$ could be a precise term or a hesitant expression. By considering many scenarios, we would also need to collect the normalized expert weights $W_{TC} = \{w^1, \dots, w^p\}$ with $\sum_{e=1}^p w^e = 1$ or the normalized criteria weights $W_C(TC_e) = \{w_{C_1}, \dots, w_{C_m}\}$ with $\sum_{j=1}^m w_{C_j} = 1$ associated with the person that makes the assessments.

Step 2: Unification phase

Our model enables the use of precise linguistic values, as well as, the use of linguistic expressions based on the *between* operator. To homogenize all the assessments, we apply the transformation functions of E_{GH} to get HFLTS values. This results in the linguistic hesitant matrix $H = (h_{ij}^k)$ of $m \times p$ HFLTS. Consequently each entry of matrix H is homogeneously a hesitant.

Step 3: Interval calculation phase

To operate with linguistic intervals we calculate the envelope of each HFLTS with Eq. 5. For each HFLTS h_{ij}^k , its envelope $env(h_{ij}^k) = [h_{ij}^{k-}, h_{ij}^{k+}]$, represents a linguistics interval $[s_a, s_b]$ with $s_a, s_b \in S_{in}$. We operate with linguistic intervals by using the 2-tuple fuzzy linguistic computational approach, so they are translated to $[(s_a, 0), (s_b, 0)]$. Equivalently we write $[(s_a, 0), (s_b, 0)] = r_{ij}^k$ to represent the original LE_{ij}^k opinion under this linguistic representation.

To operate with the linguistic information contained on the envelope, Eq. 4 is applied to both sides of the 2-tuple linguistic interval r_{ij}^{k-} and r_{ij}^{k+}

respectively. Following a standard scheme from words to words of CW processes [34], this would imply a final re-translation phase to obtain a qualitative result (refer to Eq. 3).

$$\begin{aligned}\Delta^{-1}(r_{ij}^{k+}) &= v_{ij}^k \quad \text{with } v_{ij}^k \in [0, 1] \\ \Delta^{-1}(r_{ij}^{k-}) &= u_{ij}^k \quad \text{with } u_{ij}^k \in [0, 1]\end{aligned}\tag{10}$$

Step 4: First aggregation phase

At this stage we operate with the interval linguistic 2-tuple matrix $R = ([u_{ij}^{k-}, v_{ij}^{k+}])$. The objective of this process is to reduce the overall information about the selected driver by bringing together all evaluations for each criteria given by experts into 2-tuple intervals. This is performed by applying a hesitant linguistic aggregating operator θ to the left and the right intervals respectively.

Our model has to choose between the aggregating operator *min_max_HFLA* (given in Eq. 6) if scenario 1 is enabled, or HLWA(H) (from Eq. 7) in case of using W_C (scenarios 2 and 4). Our implementation allows the use of these operators indistinctly with HFLTS or 2-tuple linguistic intervals.

$$\begin{aligned}\theta(h_{i1}^{k+}, \dots, h_{im}^{k+}) &= \theta(\Delta^{-1}(r_{ij}^{k+})) = \theta(v_{i1}^k, \dots, v_{im}^k) = v_i^k \quad \forall j \in \{1, \dots, m\} \\ \theta(h_{i1}^{k-}, \dots, h_{im}^{k-}) &= \theta(\Delta^{-1}(r_{ij}^{k-})) = \theta(u_{i1}^k, \dots, u_{im}^k) = u_i^k \quad \forall j \in \{1, \dots, m\}\end{aligned}\tag{11}$$

Step 5: Second aggregation phase

Previous step results in a matrix of p numeric intervals where each element is noted as $[u_i^k, v_i^k] = r_i^k$. Next, we compute a collective evaluation by a second aggregation on the assessments given globally by each trip companion. The arithmetic weighted extended mean explained at Section 3.1 solves the fifth step in any model scenario: with W_{TC} at scenario 3 and 4, or without them at scenario 1 and 2. Finally we get a single 2-tuple interval $r_i = [u_i, v_i]$:

$$\phi = \bar{x}^e(u_i^1, \dots, u_i^p) = [u_i, v_i] \quad \forall k \in \{1, \dots, p\}\tag{12}$$

Steps 6-7: Exploitation phase

Now we translate the interval 2-tuple solution into a single 2-tuple. This operation might consider a risk parameter $\chi \in [0, 1]$ that determines the convex combination of the interval 2-tuple upper and 2-tuple lower limits. When the χ value is close to 0 we represent a pessimistic point of view regarding the maturity of the members. When it is near 1, we are confident of the goodness of the community's assessments.

$$(s_i, \alpha_i) = \Delta((1 - \chi) u_i + \chi v_i) \quad (13)$$

The resulting 2-tuple for alternative A_i (the driver) is (s_i, α_i) . The semantic of the output needs a different linguistic term set S_{out} with the same granularity that S_{in} but able to describe the values of the linguistic variable *karma*:

$$S_{out} = \{Terrible, Poor, Limited, Satisfiable, Honest, Very good, Excellent\}.$$

Finally, output term is s_k with $s_i \in S_{in}$, $s_k \in S_{out}$, and $k = i$. As the last action, we insert the linguistic term solution s_k as a *karma* label into the profile of user A_i .

6. Teranga-IDSS Case Studies

Teranga-IDSS can be run under four different scenarios (see Section 5.1). In conditions of equity (Scenario 1), the assessments are the only information required. On the contrary (Scenario 4), we may use both the experts preferences and the relative experts importance or expertise. These two scenarios reflect extreme cases of use of our intelligent decision support system. The differences over *karma* output under the same set of assessments, highlight the flexibility of our proposal.

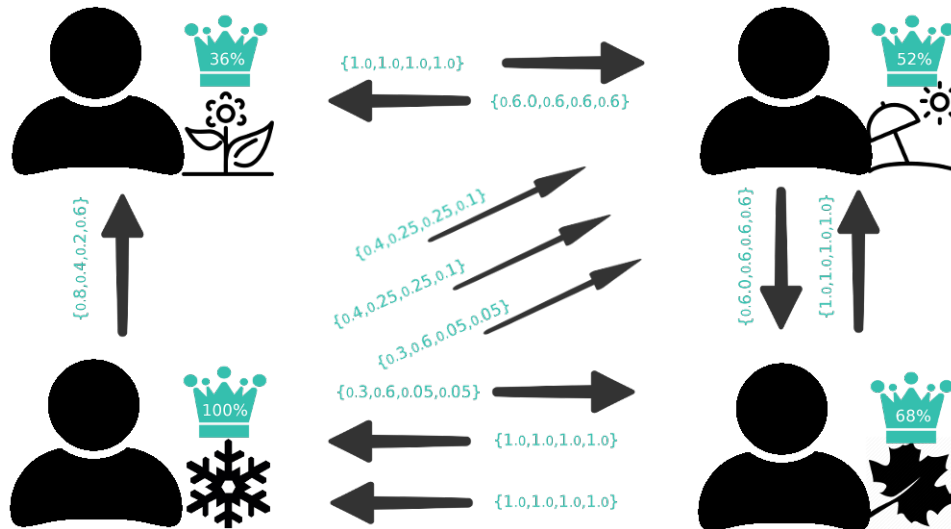


Figure 8: Visualization of our case study indicating who assess whom, criteria weights used in the valuation and the expertise degree of them.

6.1. Scenario 1. Conditions of Equity

Consider here a community with four users as in Example 4 with base expertise of 20%. For simplicity, let's suppose that each user name is: *spring*, *summer*, *autumn* and *winter*. In this section we are going to compute the *karma* term of each of them under the assumption of criteria have the same importance and experts share the same weight. The linguistic data is at Table 2, together with a graphical representation at Fig. 8 to get the flux of assessments between members.

$A_1 = \textit{spring}$	C_1	C_2	C_3	C_4
$TC_{\textit{summer}}$	very bad	between horrible and very bad	good	bad
$TC_{\textit{winter}}$	very bad	bad	horrible	between horrible and very bad
$A_2 = \textit{summer}$	C_1	C_2	C_3	C_4
$TC_{\textit{spring}}$	very bad	very bad	bad	very bad
$TC_{\textit{autumn}}$	normal	very good	very good	normal
$TC_{\textit{winter}}$	between good and very good	normal	normal	normal
$TC_{\textit{winter}}$	between normal and very good	normal	good	very good
$TC_{\textit{winter}}$	very good	between very good and excellent	between normal and excellent	between normal and good
$A_3 = \textit{autum}$	C_1	C_2	C_3	C_4
$TC_{\textit{summer}}$	very bad	between horrible and very bad	good	bad
$TC_{\textit{winter}}$	very bad	bad	horrible	between horrible and very bad
$A_4 = \textit{winter}$	C_1	C_2	C_3	C_4
$TC_{\textit{summer}}$	very bad	between horrible and very bad	good	bad
$TC_{\textit{winter}}$	very bad	bad	horrible	between horrible and very bad

Table 2: Assessments as linguistic expressions that A_1 gets from A_2 and A_4 , A_2 gets from A_3 and A_4 , A_3 gets from A_2 and A_4 , and A_4 gets from A_3 in two different trips.

We start this case study by selecting the profile of *spring*, as alternative A_1 . Following the steps indicated at Section 3, we collect the linguistic valuations F made from all past trip companions as shown Table 2. The platform finds that A_1 has two trip companions ($p = 2$). The unification phase computes the matrix of hesitant H :

$$A_1 \rightarrow H_1 = \begin{pmatrix} \{s_1\} & \{s_0, s_1\} & \{s_3\} & \{s_2\} \\ \{s_1\} & \{s_2\} & \{s_0\} & \{s_0, s_1\} \end{pmatrix}$$

To start any computing with word processes we need to transform H_1 into the linguistic 2-tuple interval matrix R_1 , after the computation of every envelope (see Eq. 5).

$$R_1 = \begin{pmatrix} [(s_1, 0), (s_1, 0)] & [(s_0, 0), (s_1, 0)] & [(s_3, 0), (s_3, 0)] & [(s_2, 0), (s_2, 0)] \\ [(s_1, 0), (s_1, 0)] & [(s_2, 0), (s_2, 0)] & [(s_0, 0), (s_0, 0)] & [(s_0, 0), (s_1, 0)] \end{pmatrix}$$

We apply aggregation operator θ as referred by Eq. 11, to aggregate the opinion of the two experts. After a second aggregation following Eq. 12 we get the interval of β values $[0.75, 2]$. For the exploitation phase, lets suppose that our case sample community sets the risk parameter to a compromise value $\chi = 0.5$ that determines that the convex combination of the interval 2-tuple upper and 2-tuple lower limits is the average of them, that is 1.375. We just have to retranslate to get the 2-tuple $(s_1, 0.375)$ which corresponds with term $s_1 \in S_{out}$. So *karma* linguistic term for user *spring* is *poor*.

User *summer* is alternative A_2 with $p = 5$, because *summer* has traveled many times with *winter*. Linguistic hesitant expressions for *summer* are shown in Table 2. After collected data we apply the transformation functions of E_{GH} , so elements of matrix H_2 are HFLTS values. Similarly, matrixes H_3 for *autumn* and H_4 for *winter* would be computed in similar steps.

$$A_2 \rightarrow H_2 = \begin{pmatrix} \{s_1\} & \{s_1\} & \{s_2\} & \{s_1\} \\ \{s_3\} & \{s_5\} & \{s_5\} & \{s_3\} \\ \{s_4, s_5\} & \{s_3\} & \{s_3\} & \{s_3\} \\ \{s_3, s_4, s_5\} & \{s_3\} & \{s_4\} & \{s_5\} \\ \{s_5\} & \{s_5, s_6\} & \{s_3, s_4, s_5, s_6\} & \{s_3, s_4\} \end{pmatrix}$$

Following step 3, or interval calculation phase, we get the matrix $R = (r_{ij}^k)$

as:

$$R_2 = \begin{pmatrix} [(s_1, 0), (s_1, 0)] & [(s_1, 0), (s_1, 0)] & [(s_2, 0), (s_2, 0)] & [(s_1, 0), (s_1, 0)] \\ [(s_3, 0), (s_3, 0)] & [(s_5, 0), (s_5, 0)] & [(s_5, 0), (s_5, 0)] & [(s_3, 0), (s_3, 0)] \\ [(s_4, 0), (s_5, 0)] & [(s_3, 0), (s_3, 0)] & [(s_3, 0), (s_3, 0)] & [(s_3, 0), (s_3, 0)] \\ [(s_3, 0), (s_5, 0)] & [(s_3, 0), (s_3, 0)] & [(s_4, 0), (s_4, 0)] & [(s_5, 0), (s_5, 0)] \\ [(s_5, 0), (s_5, 0)] & [(s_5, 0), (s_6, 0)] & [(s_3, 0), (s_6, 0)] & [(s_3, 0), (s_4, 0)] \end{pmatrix}$$

The subsequent steps may vary according to the Scenario selection. The linguistic *karma* terms for our four users are summarized at Table 4 in which they are compared with the *karma* computation with the same assessments but under a different scenario, as we describe in the next subsection.

6.2. Scenario 4. Condition of Expertise and Personal Preferences

Lets suppose that community administration parameters (as shown in Fig. 6) set Scenario 4. This mode increases the collected data from the community, that in the case of user *summer*, that we are going to use as example here, weights are depicted in Table 3 but also are shown in Fig 8. Note that some users may have changed their profile preferences (criteria weights) in any moment.

	$\varepsilon(TC)$	C_1	C_2	C_3	C_4
TC_{spring}	0.36	1	1	1	1
TC_{autumn}	0.68	1	1	1	1
TC_{winter}	1.0	0.4	0.25	0.25	0.1
TC_{winter}	1.0	0.4	0.2	0.1	0.3
TC_{winter}	1.0	0.3	0.6	0.05	0.05

Table 3: Criteria weights used when summer is assessed by spring, autumn and winter.

Lets see how this scenario affect the *karma* computation of user *summer*. We already have H_2 and R_2 from the previous section. Using data from Table 3, we have to compute both normalized versions of our weighting vectors: $W_{TC} = \{0.089, 0.168, 0.247, 0.247, 0.247\}$ assuming $B = 20\%$ and $W_C = \{0.88, 0.64, 0.52, 0.76\}$.

To run both aggregation phases we have to chose as operator the one given in Eq. 7 because we are using both W_C and W_{TC} (the first aggregation θ_1 is over R_2 with W_C and the second aggregation θ_2 is also over the previous but with W_{TC}), instead of the given in Eq. 6. The collective expert decision regarding each criteria is computed using the translation of each 2-tuple to β values, that later is aggregated as the final collective interval:

$$\theta_1(R_2, W_C) \rightarrow ([1.33, 1.63] \quad [0.77, 0.82] \quad [0.50, 0.57] \quad [0.96, 1.03])$$

$$\theta_2(\theta_1(R_2, W_C), W_{TC}) \rightarrow [3.581, 4.076]$$

Exploitation phase maintains the risk parameter $\chi = 0.5$, which gives a $\beta = 3.829$ that retranslates to $(s_4, -0.17)$. According to S_{out} the *karma* term to show in the user profile is *honest*. In comparison with the results of this user in a scenario of equity conditions (see Table 4), we realize how conditions may change the *feelings* of a community under the same data gathered from the trip companions. We found that is very positive to allow the system administrator or webmaster to control some of the parameters of our ME-MCDM model to reflect what is the general contribution of the members of the community. For instance, if very few members update their profiles to reflect about their personal valuations, then a scenario of equity conditions is perfectly assumed. But if the community quickly grows, is best to adapt the model to the variety of users and personal considerations.

User	Scenario 1: <i>karma</i> term		Scenario 4: <i>karma</i> term	
<i>spring</i>	$(s_1, 0.375)$	poor	$(s_1, 0.18)$	poor
<i>summer</i>	$(s_3, 0)$	satisfiable	$(s_4, -0.17)$	honest
<i>autumn</i>	$(s_4, 0)$	honest	$(s_5, -0.42)$	very good
<i>winter</i>	$(s_4, 0.125)$	honest	$(s_4, 0)$	honest

Table 4: Profile *karma* of the four users in two distinct scenario settings.

7. Conclusions

Through Information and communications technology and social networks, people with different backgrounds and origins come together to work and to share ideas or resources. One of the benefit of a social network may come by the collaborative or participatory consumption, an idea that the European Commission is promoting as a 2020 Strategy to palliate economy crisis. These have motivated us to built an online community for carpooling centered in the Senegalese community in accordance with smart, sustainable and inclusive growth of migrants. Social experiences among users, may happen in real life but also on the Internet. We know that connection through technology is growing very fast, and that a key point to consider is to create values of confidence, trust and safety among the members of a community. That is why we propose an intelligent decision support system named **Teranga-IDSS**, to be used in an online community such as Teranga Go!. The participants of a carpooling experience act as experts that assess the driver aptitudes and determines a linguistic value for the driver's *karma* which represents the collective opinion that may help to improve the information which is shown in their profile.

Establishing an applicable intelligent decision support system for online communities have been our main objective, to prove that research can be transferrable to society. We have presented here a social community for carpooling but it could be used in many contexts and for many purposes. It is implemented under public license for an open source award-winning social networking engine named ELGG. It delivers the building blocks that enable businesses, schools, universities and associations to create their own fully-featured social networks and applications. We use it to build Teranga Go! community which is accessible not only by an internet browser but also by a native mobile application for iOS and Android.

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