A Decision Making model to evaluate the reputation in Social Networks using HFLTS

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Abstract*—We present Teranga Go!, a social network with a linguistic fuzzy model which deals with HFLTS information as a practical application of decision making problems. It is defined to help members to select to whom interact based on collective information regarding real interactions with any user. In this way, we provide a tool intended to build trust among members of a sharing economy community given that is a major drawback from online transactions. As a workbench to run the linguistic decision making model, a web site and a mobile application for iOS and Android offer access to a carpooling service named Teranga Go! that seek to foster the mobility of international migration flows from Europe to Africa, based on concepts of collaborative economy and participatory consumption. The novelty of the site is the possibility of using hesitant linguistic expressions to assess a set of qualitative criteria and the use of the community members as the pool of experts. Unlike many multi criteria decision making problems we do not rank alternatives, we just qualify them using the retrieved opinions, which target a given user, and are collected over any interaction with this person along the time. Based on Computing with Words methodology where inputs are words and output are also words, we obtain from the model a linguistic value that is used to represent a *karma* property present in the user profile.

I. Introduction

Teranga Go! (http://terangago.com/) is a social network for carpooling centered at the Senegalese community, which allows to share the expenses of long car journeys as a great interest to migration flows from Europe to Africa. By developing an online community to connect people and exchange goods we align with European directives for participatory consumption as a sustainable economic model for the 21st century [2]. The main idea is to gather opinions from users of an online community about people interacting in a business relation, to create a value of confidence and reputation among members, and model it as a decision making problem. The beliefs or opinions that are generally held about someone defines its reputation, so our proposal is an innovative contribution to enhance online communities among other extended best practices [6].

The act of make a decision is a natural human activity that is heavily subjective in its basis, but also claims to be uncertain and imprecise. That it is because our brain works better with perceptions rather than with measurements. We are not aware of the implicit complexity of a problem, except when we try to build computational models to help making decisions that handle the same kind of information that our brain does. Problems defined under uncertain conditions are common in real world, but quite challenging to be modeled in a computer program due to the difficulty of dealing with uncertain information.

Computing with Words (CW) [20] *is a paradigm in which the objects of computation are words or propositions drawn from a natural language* and a way to include human sourced information in computer based decision-making programs [9]. A well known computational model that carries out CW processes without loss of information is the 2-tuple Linguistic Computational Model [4]. This model uses a pair of values called 2-tuple to represent the linguistic information. Recently it has been enabled in DM problems the possibility of provide inaccurate rates and comparative linguistic expressions by means of the use of a context-free grammar represented by a Hesitant Fuzzy Linguistic Term Set (HFLTS) [8], [11]. This way to deal with uncertainty and hesitation in the context of fuzzy decision making has been extensively used in the literature [1], [10], [12], [14], [13], [16], [17], [21].

In this work we use the online platform Teranga Go! as a workbench to run a linguistic decision making model. You can access Teranga Go! to publish and get interested in many trip planning from Spain to Senegal. Moreover, you can add opinions about the trip companions after the journey takes place. The novelty of the community is the possibility of using hesitant linguistic expressions to assess a set of qualitative criteria regarding the trip experience, and the use of the community members as the pool of experts. We do not rank alternatives, we just qualify members using retrieved opinions collected over any interaction with this person along the time.

The rest of this paper is structured as follows. Following we introduce Teranga Go!. In Section 3, a Multi-Expert Multi-Criteria Decision Making problem for an online community is presented based on 2-tuple fuzzy representation of hesitant expressions. Teranga Go! is best understood in Section 4 where an illustrative example is presented using a fictional situation reproducible in any other platform where the interchange of goods may happen. Finally, some conclusions are given.

II. A platform for collaborative consumption

Teranga Go! is an online platform for car-sharing centered on the Senegalese community that may benefit from sharing expenses in long trips from Spain to Senegal. Like any social

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network users have a profile, there is some base service, various ways to create content and facilities to search information and communicate between members of the community. The main objective of Teranga Go! is connect people: those that are drivers and publish a trip planning with those interested in join it as passengers, to send a package to their relatives using the driver as a hauler, or both things.

Any social network that is used for collaborative or participatory consumption represents an innovative complement to a production economy and offers a way out of the economic and financial crisis, by enabling people to exchange things for others that they need. This is an idea that the European Commission is promoting as a 2020 Strategy to palliate economy crisis as can be consulted on directive 2014/C 177/01 *Collaborative or participatory consumption, a sustainability model for the 21st century* [2]. 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.

Online relationships are not free from hazards, because you start the connection online but then the interaction happens in real life. Some people may feel reluctant, for instance, to travel with a total stranger. Any social network needs to create a sense of community between members, improving participation among users, where reputation is the link making possible to establish connections over the long term. The main problem is how to build trust between users. Here we present a solution.

In a social network your reputation comes from your actions plus what others say about you. We are concerned with the second part of this brief formula. Our aim is to improve the tools that enable to give opinions about others in an online community, opinions which are subjective in their basis, to compute a property name *karma* which summarized what people say about any community member. This helpful information is visible in every profile as a non-editable field. It summarizes all the information that comes from the community (users acting as experts). Thus the *karma* term is the major output of our linguistic decision making model and it is used to help creating values of confidence and trust among members of the community.

Our proposal deals with the following objectives:

- To provide a flexible way of elicit qualitative information to assess a set of qualitative criteria. Following the bibliography, the 2-tuple fuzzy linguistic representation keeps accuracy in the processes of CW and the Hesitant Fuzzy Linguistic Term Sets (HFLTS) is an flexible tool to qualify in situations of uncertainty and hesitation in the assessments.
- To deal with undesirable situations in which opinions do not respect veracity but instead are aim to hurt someone, or just for fun. We allow the website administrator to use moderation tools (or to enable the auto-moderation option).
- To help people making a decision. It is so common nowadays to find a poorly detailed online profile with a fictional picture as an avatar, that gives no clue at all about how this person is. This impacts negatively on the overall community reputation. If we add a custom profile field based on collective assessments about some person it will definitely help, for instance, in choosing between two drivers that run the same itinerary on almost same dates. In the platform, we ask participants of a real trip to evaluate each other, providing both private and public feedback data. The private evaluations that a person have acquired along several trips and provided by various individuals are used in a CW based Multi-Expert Multi-Criteria Decision Making (ME-MCDM) model.
- To help people be subjective in their perceptions about what they would like/dislike in a journey. We have personalized the profile area to describe personal issues as if we are smokers, of if religious talks disturbs us. Moreover, the profile has a section of general traveling preferences. These are weighted significance (a percentage) assigned to different facets of a trip, such as: security, confort, cleanliness, company and conversation. Each percentage for preference is used as criterion weight in our ME-MCDM model. This information may increase the subjective information that people introduce in the system. DM processes that run over the portal will use this internal information to compute the *karma* term.
- To adapt to the level of maturity of the community. We allow scenario settings: from a naive configuration to some more complex. The scenarios allow to select assessments with or without criteria weights and with or without experts weights (a method to give priority to the opinion of those active users). In this paper we use the more complex scenario with both weights.

III. A Multi-Expert Multi-Criteria Decision Making problem for evaluating the reputation

Generally a multi-expert multi-criteria decision making (ME-MCDM) problem is defined by the alternatives to be ranked, the set of criteria which is going to be considered and the semantic of a fixed set of linguistic term set. Then, experts are asked to give linguistic preferences for each criteria and alternative according to the input set of linguistic terms S^g. Consider m criteria, n alternatives and $g+1$ linguistic terms ($g+1$ is called the granularity of the linguistic term set). Let $C_1, \ldots, C_m$ and $A_1, \ldots, A_n$ denote the criteria and alternatives respectively. Let $E_1, \ldots, E_p$ represent the total p experts involved and $s_0, \ldots, s_g$ be any single linguistic term. A decision matrix is compose of $n \times m \times p$ entries in the form of:

$$E_k \to \begin{pmatrix} y_{11k} & y_{21k} & \cdots & y_{n1k} \\ y_{12k} & y_{22k} & \cdots & y_{n2k} \\ \vdots & \vdots & \ddots & \vdots \\ y_{1mk} & y_{2mk} & \cdots & y_{nmk} \end{pmatrix} \; with \; y_{ijk} \in S^g. \quad (1)$$

A score y_{ijk} describes the performance of alternative A_i ($i = 1, \ldots, n$) against criterion C_j ($j = 1, \ldots, m$) as given by expert E_k ($k = 1, \ldots, p$). It seems natural to represent this intensity of preference in favor of alternative as a linguistic label. Additional to this decision matrix, weights $W_C = (w_1, \ldots, w_m)$ are assigned to criteria. Weight w_j reflects the relative importance of criteria C_j to the decision, and they are assumed to be positive and normalized. The weights of the criteria are usually determined on subjective basis. Similarly we may use weight w^k for each expert, with $W_E = (w^1, w^2, \ldots, w^p)$, if we are interested in differentiate the importance of an opinion from an expert regarding others. It is based on an expertise degree, and we apply it into the *karma* calculation as it is explained at Section III-B.

Now the decision process has to be carried out to select the best alternative. Following an standard scheme of CW processes [5], this is performed in two main phases: aggregation and exploitation. However according to [3], prior to the aggregation is necessary to perform two more steps. The overall scheme we follow is:

- Establishing the linguistic expression domain. We have to choose the granularity of the linguistic term set, its labels and its semantics.
- Establishing an appropriate aggregation operator of linguistic information for aggregating and combining the linguistic performance values provided.
- An aggregation phase of the performance values with respect to all the criteria and decision makers to obtain a collective performance value for the alternatives.
- An exploitation phase to obtain a rank ordering, sorting or choice among the alternatives.

To implement a CW based ME-MCDM system, a model for linguistic data representation have to be chosen. In the following subsections we contextualize the previous computing with words processes to match and solve our particular ME-MCDM problem that computes a linguistic value for a *karma* linguistic variable. Firstly, we define our problem and the scheme to run CW processes, then we explain the use of 2-tuple linguistic information representation, describe how to elicit opinions using HFLTS, and finally it is presented how we perform the aggregate and exploitation phases.

A. Problem description and proposed CW based DM model

We propose to model what people think about a person after real interaction happened one or many times in long period trips. In this case, alternative set is just one $n = 1$, and is targeted to A_i, the person we are going to compute a *karma* profile custom field. We define a linguistic term set with a granularity of 7. The set of experts are potentially the full community minus A_i. As someone may travel many times, when a decision matrix from E_k (like in expression (1)) is given, instead of assessing different alternatives, we allow to assess many times the same alternative (think of classic n as the number of trips they have in common, n_{E_k,A_i}). Covering the retrieved data form all experts we may have a total decision matrix of $1 \times m \times t$ values with $p \leq t$ where $t = \sum_k n_{E_k,A_i}$.

Particularities of our proposal are:

- We distinguish from an input set used by the experts and an output set that applies the correct semantic to the output term. Let us have $S_{in} = \{horrible, very\,bad, bad, normal, good, very\,good, excellent\}$ and $S_{out} = \{terrible, poor, limited, satisfiable, honest, very\,good, excellent\}$. That is, under the same score (for example s_3) the term *satisfiable* suits better a property value of reputation than *normal*.
- Score y_{ijk} is a linguistic expression translated into a hesitant with the application of $env(E_{G_H}(y_{ijk}))$ (see Eq. (4) and Eq. (5)). Subsequently, it is transformed into an interval linguistic 2-tuple.
- We set $m = 4$. Our criteria refer to some aspects that need to be considered in a safe and enjoyable journey: cleanliness, company and conversation, driving security and confort.
- Criteria weights are introduced by community members in their profile, and as they can be modified at any moment, they could be different on each assessment.
- Expert weights are computed as we detail at next subsection.

Figure 1 [10] shows our DM scheme, which combines the HFLTS and 2-tuple representations in the following processes of CW:

1) Unification phase. Each alternative is valued by each expert over a set of criteria. Decision matrices are provided by experts by using linguistic expressions constructed with a grammar G_H (more information in Section III-C). Some experts would give single term valuations, and others, due to hesitation, would need to elicit comparative preferences values. So, a unification phase is needed to homogenize all the assessments. Transformation function E_{G_H} (using Eq. 4) is applied to the composite preference relations getting a matrix of $m \times t$ HFLTSs with elements h_{ijk}.
2) Interval calculation phase. To operate with linguistic intervals we calculate the envelope of the HFLTS. In this stage every single valuation is noted as $[s_a, s_b]$.
3) 2-tuple transformation phase. The linguistic intervals are represented using the 2-tuple fuzzy linguistic computational approach. They are translated to $[(s_a, 0), (s_b, 0)]$.
4) Aggregation phase. We choose aggregation operators which deal with the existence of weights in data. Here we obtain a collective performance value β_i for the implicit alternative A_i. Following [18], the translation phase would imply a backward re-translation phase (using the inverse of Eq. 6) to convert from β_i to a 2-tuple, and then into a single term s_i.
5) Exploitation phase. The ranking of alternatives is the last phase to the solution of an ME-MCDM problem. We don't have to sort to find the best value, we just have to change the semantic of the computed term $s_i \in S_{in}$ to $s_o \in S_{out}$ with $o = i$. As the last action, we insert the linguistic term solution s_o as a *karma* label into the profile of user A_i.

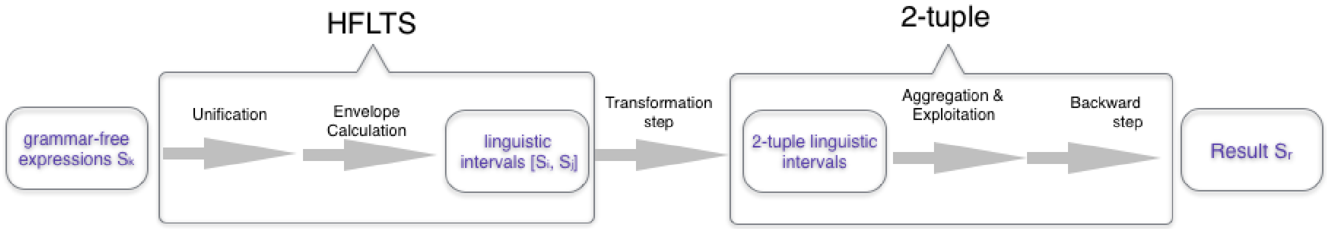

Fig. 1. Computing with Words scheme using 2-tuples and HFLTS [10].

B. Computing the expert weights

We are interested in modeling the relative importance of an opinion against others. These are the expert weights. We calculate them considering a gamification technique consisting in assigning points to users. People want to gain points, have more than others, and be shown on top of a ranking list. After a trip, participants of that journey can assess each other (not only the driver but also any other passenger). If the moderation process grant the data given, then a point is awarded to the evaluator. The fact is that: a user is experienced in this type of real life interactions if s/he have travelled a lot. Community users gain points with the more assessing forms filled and thus, we can estimate the number of trips of a member.

Suppose the total set of community members is noted $TC = (TC_1, TC_2, \ldots, TC_q)$ with $q \geq 2$. 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 $1 \leq e \leq q$. We can compute $\max_{e=0}^{q} \phi(TC_e)$ with $(e = 1, 2, \ldots, q)$ the maximum number of points a user has gained with the submission of assessment forms.

The function that returns the *expertise degree* of any community member is $\varepsilon : TC \rightarrow [0, 1]$. This is part of the expert weight $w^e \in [0, 1]$ and reflects about the user relative importance in the full community regarding participation in journeys promoted through the platform.

To represent how much we want to rely in the $\varepsilon(TC_e)$ value, we offer a percentage parameter $B \in [0, 1]$ named *base expertise*. 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 share the same weight. Any value of B in between, creates some confidence in users with few expertise. The *expertise degree* is updated on every rewarding point, and it considers the full community members q:

$$\varepsilon(TC_e) = B + \frac{1 - B}{\max_{r=1}^{q} \phi(TC_r)} \phi(TC_e) \tag{2}$$

When p experts are selected and the decision matrix is retrieved from internal database, we compute the weighting vector $W_E = (w^1, w^2, \ldots, w^t)$ with $(e = 1, \ldots, t)$. Repetitions of $\varepsilon(TC_e)$ are allowed to match the number of times that an expert evaluates, filling from p to t values. We normalize the expertise degree of the trip companions for the driver A_i only in the process of *karma* computation, by using this expression:

$$w^e = \frac{\varepsilon(TC_e)}{\sum_{k=1}^{t} \varepsilon(TC_k)} \tag{3}$$

C. Eliciting opinions from experts

Experts can express their preferences giving a linguistic term (atomic answers) or composite terms generated through comparative linguistic expressions. An HFLTS [8], [11] represents a context-free grammar G_H that enables the experts to elicit assessments with uncertainty and hesitation in the context of fuzzy linguistic decision making.

According to Rodriguez et al. [11], an HFLTS H, is an ordered finite subset of the consecutive linguistic terms of S. Here we use a very simply context-free grammar, but it is posible to implement many more comparative linguistic expressions in a website [10]. We allow to elicit a single precise linguistic value, as well as, the use of linguistic expressions based on the *between* operator. The former are composite expressions that need to be transformed into something useful to carry out the CW processes. The following transformation function E_{G_H} [11] is used to generate an HFLTS from a comparative linguistic expression.

$$E_{G_H}(between\ s_i\ and\ s_j) = \{s_k | s_k \in S\ and\ s_i \leq s_k \leq s_j\} \tag{4}$$

Following the scheme shown in Fig. 1 we need to compute the envelope of an HFLTS. As it is defined [11], the envelope $env(H)$ is a linguistic interval whose limits are obtained by means of its upper bound H^+ and lower bound H^-. The envelope is computed as:

$$env(H) = [H^-, H^+]\ \ with\ \ H^- \leq H^+ \tag{5}$$

where

$$H^+ = \max\{s_i\} = s_j,\ s_i \leq s_j\ and\ s_i \in H,\ \forall i,$$
$$H^- = \min\{s_i\} = s_j,\ s_i \geq s_j\ and\ s_i \in H,\ \forall i.$$

D. Representation of linguistic data

We have chosen to apply the 2-tuple linguistic computational model [4]. It represents a transformation of a linguistic variable suitable for computations without any lost of information, is precise and effective. Let S be a linguistic term set, and $\beta \in [0, g]$. Then the 2-tuple is defined as:

$$\Delta : [0, g] \rightarrow S \times [-0.5, 0.5)$$
$$\Delta(\beta) = (s_i, \alpha),\ with \begin{cases} s_i, i = round(\beta), \\ \alpha = \beta - i \end{cases} \tag{6}$$

The value of $\alpha \in [-0.5, 0.5)$ it is known as the symbolic translation. The 2-tuple is an equivalent representation of a term $s_i \in S$. In [4] the inverse function $\Delta^{-1} : S \times [-0.5, 0.5) \rightarrow [0, g]$ is also defined by $\Delta^{-1}(s_i, \alpha) = i + \alpha = \beta$. So, a linguistic term $s_i \in S$ is transformed into $(s_i, 0)$ in CW processes.

E. The choice of an aggregation operator

In our scheme, the first stage comes from the unification and translation of assessments to HFLTS. Information is internally managed as linguistic intervals, so we apply the envelope of an HFLTS before translation to the 2-tuple linguistic representation. Aggregation comes as two rounds of computations with the application of the generalized users' criteria weights and the computed expert weights.

To aggregate 2-tuples, the arithmetic mean can be adapted to be applied to the 2-tuple representation. Let $x = \{(s_1, \alpha_1), \ldots, (s_n, \alpha_n)\} = \{\beta_1, \ldots, \beta_n\}$ be a set of linguistic values represented as 2-tuple, W a weighting vector ($\{w_i/i = 1, \ldots, n\}$), and W' its normalized version ($\{w'_i/i = 1, \ldots, n\}$), i.e. $\sum_{i=1}^{n} w'_i = 1$. The arithmetic weighed extended mean $\bar{x}^e$ is defined as:

$$\bar{x}^e(x) = \Delta\left(\frac{\sum_{i=1}^{n} \Delta^{-1}(s_i, \alpha_i) \cdot w_i}{\sum_{i=1}^{n} w_i}\right) = \Delta\left(\frac{1}{n}\sum_{i=1}^{n} \beta_i w'_i\right). \quad (7)$$

Literature also brings specific operators for aggregating a collection of HFLTS $H = \{h_1, h_2, \ldots, h_n\}$. An operator defined in [7] uses a function that computes the likelihood-based comparison relation applying the weights of each HFLTS h_i. Nonetheless, the result of aggregation is a number and not an HFLTS, so it does not adapt well to our ME-MCDM problem. Wei et al. [15] present an HLWA operator based on the convex combination of two linguistic terms which it is also a linguistic term. The HLWA aggregator operator is viable for us, as the combination of the input HFLTSs is also an HFLTS. It is included in the implementation of Teranga Go! and can be enabled at the settings page. For simplicity, we refer only to operator $\bar{x}^e$.

IV. Computing the karma term: a case study

This section presents a case of study with a community with $q = 4$ fictional users named *spring*, *summer*, *autumn*, and *winter*.

In Teranga Go!, general trip preferences are expressed using weighted significance assigned to different facets of a trip. Our criteria are: cleanliness, company and conversation, driving security and confort. Assessments and criteria weights are a double subjective information that we store and use in our model. Preferences over criteria might change along the time, so they are stored and used in our CW computational model. Table I summarizes internal static information that can be retrieved at any time from the platform using the community administrative tools.

Let us suppose a situation where the users *spring*, *summer*, *autumn* and *winter* have interacted in one trip. Also *winter* and *summer* travelled together two more times. We choose to display the profile of *summer*, triggering the computation of the *karma* term for this user. We have $n = 1$, $m = 4$ and $p = 3$, and the base expertise is set to $B = 0.2$. Now is time to collect what people say about this user. Initial assessments are in the form of linguistic hesitant expressions. The retrieved $t = 5$ assessments data are shown in Table II.

TABLE I
EXPERTISE DEGREE AND TRIP GENERAL PREFERENCES OF MEMBERS.

	ε	C_1	C_2	C_3	C_4
spring	0.36	1.0	1.0	1.0	1.0
summer	0.52	0.6	0.6	0.6	0.6
autumn	0.68	1.0	1.0	1.0	1.0
winter	1.0	0.8	0.4	0.2	0.6

TABLE II
PULL OF ASSESSMENTS TARGETED TO USER *summer*.

E	C_1	C_2	C_3	C_4
spring	very bad	very bad	bad	very bad
autumn	normal	very good	very good	normal
winter	between good and very good	normal	normal	normal
winter	between normal and very good	normal	good	very good
winter	very good	betw. very good and excellent	between normal and excellent	between normal and good

TABLE III
HESITANT DECISION MATRIX TARGETED TO USER *summer*.

E	C_1	C_2	C_3	C_4
spring	$\{s_1\}$	$\{s_1\}$	$\{s_2\}$	$\{s_1\}$
autumn	$\{s_3\}$	$\{s_5\}$	$\{s_5\}$	$\{s_3\}$
winter	$\{s_4, s_5\}$	$\{s_3\}$	$\{s_3\}$	$\{s_3\}$
winter	$\{s_3, s_4, s_5\}$	$\{s_3\}$	$\{s_4\}$	$\{s_5\}$
winter	$\{s_5\}$	$\{s_5, s_6\}$	$\{s_3, s_4, s_5, s_6\}$	$\{s_3, s_4\}$

TABLE IV
MATRIX WITH COMPUTED HESITANT ENVELOPES.

E	C_1	C_2	C_3	C_4
spring	$[s_1, s_1]$	$[s_1, s_1]$	$[s_2, s_2]$	$[s_1, s_1]$
autumn	$[s_3, s_3]$	$[s_5, s_5]$	$[s_5, s_5]$	$[s_3, s_3]$
winter	$[s_4, s_5]$	$[s_3, s_3]$	$[s_3, s_3]$	$[s_3, s_3]$
winter	$[s_3, s_5]$	$[s_3, s_3]$	$[s_4, s_4]$	$[s_5, s_5]$
winter	$[s_5, s_5]$	$[s_5, s_6]$	$[s_3, s_6]$	$[s_3, s_4]$

The *karma* linguistic term for A_i =*summer* can be computed following these steps:

1) Data phase. Compute normalized criteria weights and expert weights from the stored data of Table I. We get $W_C = \{0.88, 0.64, 0.52, 0.76\}$ and $W_E = \{0.089, 0.168, 0.247, 0.247, 0.247\}$. Also, we gather data from Table II.
2) Unification phase. Apply the transformation function Eq. (4) to get HFLTS values, as those presented in Table III.

TABLE V
FIRST AGGREGATION APPLIES $\theta_1(env(h_{i\cdot k}))$ WITH $(j = 1, \ldots, 4)$.

C_1	C_2	C_3	C_4
$[1.336, 1.633]$	$[0.777, 0.826]$	$[0.502, 0.576]$	$[0.965, 1.039]$

3) Interval calculation phase. Calculate the envelope $env(h_{ijk}) = [h^-_{ijk}, h^+_{ijk}]$ of each HFLTS h_{ijk} by using Eq. (5). Table IV summarizes these operations.
4) First aggregation. Apply operator $\theta_1 = \bar{x}^e$ from Eq. (7) to both ends of the intervals, using W_C. Current Table V includes the result of this first aggregation step which reduces the information detailed for each criterion.
5) Second aggregation. Compute a collective evaluation by applying the aggregator operator $\theta_2 = \bar{x}^e$ on the assessments given globally by each trip companion, using W_E this time. We get $[3.581, 4.076]$ or equivalently $[(s_4, -0.419), (s_4, 0.076)]$ if we use the function Δ from Eq. (6).
6) Exploitation phase. Translate the interval 2-tuple solution into a single 2-tuple. As a compromise option, the middle term $[s_4, -0.1715]$ is selected. The final computed term is $s_4 \in S_{in}$. To change the semantic of the output we simply retrieve $s_4 \in S_{out}$. We update the profile of user A_i from *karma* = *unknown* (if there is less than 2 assessments) to the linguistic term *honest*.

Now the profile of *summer* informs not only about personal information and general trip preferences (which are optional fields) but it also displays the linguistic term *honest*. The *karma* value represents what others say about any user on the basis of knowing this person after real interactions. This is good for the reputation of *summer*, and for new members that are searching for good trip companion candidates for traveling.

V. CONCLUSIONS

We have presented a CW based DM model to support reputation evaluation in the recently emerged online platforms that tries to find a solution to the economic crisis. We are able to use the collective information about a particular user (what others say about you), to compute a value of reputation for a person, so the social network will create an online community centered on the trust between users.

Our carpooling online service for putting in practice a sharing economy approach, 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 https://github.com/rosanamontes/teranga.go. You can join Teranga Go! community registering at http://terangago.com/comunidad

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. It is a real application of an ME-MCDM problem. It benefits from the use of the fuzzy linguistic approach and the techniques available for CW. We apply the 2-tuple linguistic representation model to keep accuracy in the processes of CW and the HFLTS to qualify for situations of uncertainty and hesitation in the assessments.

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