Bipolar Fuzzy Nominal Classification (BFNC) Framework

Application to Risk Analysis

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Abstract. Nominal classification (NC) is a subfield of multi-criteria decision making where an object (in a broad sense) characterized by some attributes (with their valuation belonging to an ordered set, numeric in general) must be assigned to one of pre-defined classes or categories; these classes are characterized by some numerical valued features. This is also known as supervised classification as opposed to unsupervised classification in machine learning literature. In many applications such as that of risk analysis, characterization of classes by features may not be precisely defined; they will be rather fuzzily expressed using linguistic appreciation such as high is better, low is more appreciated, medium range is better, etc. leading to what is referred to as fuzzy nominal classification (FNC). On other hand bipolar reasoning is pervasive in classification in the sense that given a couple (feature, class), there will be some values of the feature that lead to automatically assigning (respect. automatically excluding to assign) the considered object into that class leading to what we name bipolar fuzzy nominal classification or BFNC for short; the main purpose of this paper is to develop this BFNC framework with risk analysis as an illustrative application domain. The stepping stones of this framework are two indexes for each couple (class, object) known as classifiability index (that measures the extent to which the considered object can be included into that class) and the rejectability index measuring the extent to which one should avoid including this object into that class. By using two indexes for classification, many classes can be qualified for inclusion of a given object rendering this framework flexible. Analyzing risks for large-scale complex systems requires identifying, assessing, and prioritizing different risk scenarios for their appropriate treatment such as resources allocation for risk mitigation, risk prevention, risk sharing, etc. To this end and given scarcity of resources in general, one must consider first prioritizing, filtering, or scoring risks that return to assigning them to pre-defined classes or categories; that is nominally classifying them. The developed BFNC framework applied to a real world application in the domain of countries' risk classification shows its practical potentialities.

Keywords: Fuzzy nominal classification; supervised classification; bipolar analysis; risk analysis; risk scoring; synergetic aggregation.

1. Introduction

Nominal classification is pervasive in decision making; indeed, many decision problems arising in different activities and domains such as social, economics, engineering, management, marketing, among others, concern the assignment or classification of objects (to be understood in a broad sense) according to their scores for a certain number of criteria or attributes to classes that are characterized by some features. In **finance and banking** for instance, decision maker(s) face the problem of classifying customers seeking a credit or a service into classes defined by entrance thresholds with regard to their performance in some attributes (age, annual revenue, profession category, etc.) for instance or in the case of professionals which service the bank should propose to them ([1], [2]). In terms of **risk evaluation** regarding loans and credits, it is well accepted to classify loans with undue risk into three categories, namely:

substandard (for those lines of credit involving more than a normal risk due to the financial condition or unfavorable record of the obligator, insufficiency of security, or other factors noted in the examiner's comments); *doubtful credits* (the ultimate collection of which is doubtful and in which a substantial loss is probable but not yet definitely ascertainable in amount); *loss-credits* (which are regarded as uncollectible and as estimated losses which should be written off against the bank's capital), see [3]. Nominal classification is encountered in **supply chain management** mainly in the context of outsourcing. Indeed, in [4] and cited in [5], authors consider a problem of outsourcers categorization in the framework of supply chain. The problem consists in classifying prospective outsourcers into four classes, namely c_1 (suppliers for strategic partnerships), c_2 (promising suppliers that must be supported via supplier development programs), c_3 (suppliers for competitive partnerships: they have to be considered for competitive partnerships for some products), and c_4 (suppliers to be pruned: they should no longer be considered for the partnership in any level) using ten attributes: a_1 (support in product structural design), a_2 (support in process design and engineering), a_3 (design revision time), a_4 (prototyping time), a_5 (level of technology), a_6 (quality performance), a_7 (financial strength), a_8 (cost reduction performance), a_9 (delivery performance), and a_{10} (ease of communication). **International finance and commerce** is another area where nominal classification plays a great role; indeed, in this domain countries are often classified in different categories in terms of risk to which potential investors will be exposed to in these countries (country risk classification) by using a certain number of attributes such as GDP per unit of energy use, telephone mainlines per 1000 people, human development index (HDI), percentage of military expenditure of the central government expenditure and others, see [6]. During the process of selecting a candidate for a given job in the domain of **human resources management**, managers must ensure that this candidate have some attributes (diploma, communication skills, experience, etc.) that are in adequacy with the job [7]. According to the evaluation of these attributes the candidate can be accepted for the job, can be refused, or can be in position of stand by; this is a nominal classification problem as one must respond to the question, do the attributes of this candidate permit to classify him/her in a given class or reject that class. Risk scoring in the process of **project management**, see [8], consists in classifying projects into some pre-defined categories according to the evaluation of their attributes with regards to risk. In **digital marketing** [9], processes such as *segmentation* that consists in dividing a certain market into many classes known as segments with the main objective to personalizing an advertising message is typically a nominal classification problem where customer preferences for products constitute their attributes; *influencer marketing* : with the expansion of social networks, it is possible for on line advertiser to do a sort of indirect advertising by targeting some influencers or leaders (users with a great number of followers) where a leader may be seen as a representative of a certain class, so given a potential customer he/she will be included in the class of the leader with whom he/she is more closed in the attributes space; *recommender systems*: nowadays, many customers purchase their products on Internet and on line providers such as Amazon, eBay, PriceMinister, etc. offer possibilities for customer to specify his/her preferences that can be considered in terms of nominal classification as its class feature and then the recommender system of the provider will determine potential items (characterized by their contains that can be considered as their attributes) that can be recommended to that customer. One can imagine other similar situations in different socio-economic domains such **medicine** where a practitioner classifies for instance a patient as suffering a fever if its body temperature is beyond a threshold and/or if it presents some other symptoms. In **academic**, a student will get his/her diploma or degree if his/her marks in some different disciplines are beyond some thresholds. In the same way for admission process, students may be classified as definitely admitted, definitely rejected, or possibly admissible. In the context of **engineering and artificial intelligence**, constraints satisfaction for instance is the process

of finding a solution to a set of constraints which return to classifying each potential solution as feasible or not feasible; in the same way, the design of an infrastructure (a bridge, a building, etc.) must be able to support a certain load and in the same way necessitate less materials therefore any design must be judged in terms of satisfying design requirements or not.
These classification problems constitute, therefore, multi-criteria or multi-attributes (attributes of the object to classify) and multi-objectives (multi-features classes to choose) decision making problems. A unified framework is, therefore, needed to consider these problems because in the literature these two decision sub-problems have been almost always considered separately, see for instance references ([1] [7] [10] [11] [12] [13] [14]) that consider these problems in different ways.

A number of multi-criteria decision aid (MCDA) methods have been developed for nominal classification. They include multi-criteria filtering [15], a method based on concordance and non-discordance principles; PROAFTN, see [16], a multi-criteria fuzzy classification method; a method based on fuzzy integrals, see for instance [17]; TRINOMFC method [18] that computes local concordance; or the stochastic multi-criteria acceptability analysis (SMAA) method that supports incomplete or inaccurate preference, see [19]. If these methods have been successfully applied in practice, many of them do have usability limitation (with regard to final users) such as complexity of how parameters must be specified by the users.

The intention of this paper is to add a method to the panorama of existing methods that we hope will be easier (because of its flexibility) to use by the final users who in general are non specialists. In this paper we consider a method of nominal classification that is based, for a given object and a given class, on two measures corresponding respectively to what extent the object can be included in the class and to what extent it should be excluded, similar to satisficing games theory approach, see [20]. Bipolarity is pervasive in human decision process in general and classification process in particular; this bipolarity results often from uncertainty in decision making processes. For instance a medical doctor who receives a patient with a certain level of body temperature must decide if the patient is suffering of a fever or not; in general doctor may know with certainty the category of the patient if the temperature range in a certain interval and will be less certain for other range of temperature. Bipolar analysis therefore permits to manage this uncertain situation by allowing hesitation of decision maker ([21] [22] [23] [24]). The purpose of this paper that is an extension and reorganization of materials of communications [8] and [25] is to develop a framework for risk analysis with BFNC as a stepping stone of the step of scoring and filtering risks in order for their appropriate treatment.

The remainder of this paper is organized as follows: in the second section, BFNC framework is presented (necessary materials to be used to measure the classifiability and rejectability of an object are presented); third section is devoted to risk analysis processes (risk assessment and risk treament); section four considers illustrating the approach developed in the paper to a problem of country risk characterization; and finally a conclusion is given in the fifth section.

2. BFNC Framework: Presentation

In this section, we will formulate BFNC framework going from objects characterization through fuzzyfication of classes features and aggregation to obtain classifiability and rejectability degrees till the final assignment procedure. Formally nominal classification problem considered in this paper is defined by the following materials.

- An object u to be classified is characterized by a set of m numeric attributes or criteria and the value of attribute l is given by x_l so that this object can be designated by its attributes vector $x \in R^m$ (where R^m represents the set of real vectors of dimension m); that is $x = \left[x_1\ x_2\ ...\ x_m\right]^T$ where M^T stands for the transpose of vector or matrix M.
- The former defined object must be assigned to one of the n classes or categories of the set $C = \{c_1, c_2, ..., c_n\}$; each class or category c_j is characterized by n_j features, conditions, or constraints through scalar functions $f_j^k(x) \in R,\ j = 1,\ 2,\ ...,\ n_j$ of the attributes vector $x \in R^m$; a feature is a mapping from attributes evaluation space R^m onto the real number set R. A class is therefore completely determined by its features vector $F_j(x) = \left[f_j^1(x)\ f_j^2(x)\ ...\ f_j^{n_j}(x)\right]^T$.

This classification proceddure is schematically illustrated on Fig. 1 where classes' labels may represent risk score such as low (L), medium (M), high (H), etc.

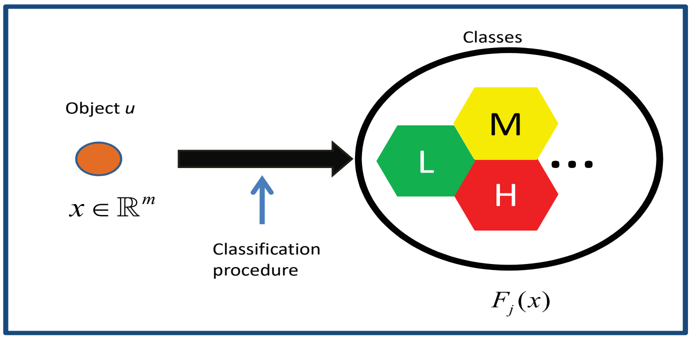

Fig. 1. Scheme of nominal classification

In practice it is rather rare that features $f_j^k(x) \in R,\ j = 1,\ 2,\ ...,\ n_j$ of classes be determined exactly. Most of the time they will be described only up to some degree of uncertainty with linguistic characterization such as if $f_j^k(x)$ is high, low, mean, approximatively, near to, etc. then one should privilege a particular class compared to other classes for the inclusion of the corresponding object. The purpose of fuzzy nominal classification methods or algorithms is then to establish a procedure that select the most appropriate class where to include the considered object; one may notice that this is an absolute decision making process as objects to classify are not compared with each other. Bipolar reasoning constitutes a sort of divide to better apprehend paradigm; indeed uncertainty resulting from fuzzy characterization of classes by their features appeals for a flexible classification procedure. To this end, we use the concept of bipolar analysis as the underlying methodology to derive flexible classification algorithms. The stepping stones in BFNC are the classifiability and rejectability measures $\mu_C^j(u)$ and $\mu_R^j(u)$ given a class c_j and an object u similar to selectability and rejectability degrees in the case of alternatives selection problems [2] [21] [22] [23] [24] ; so their derivation is an important step towards a sound classification algorithm.

These measures must be established considering the performance of the considered object with regard to the considered class. As each feature k characterizing a class is fuzzily described, to consider that the object u characterized by vector x belongs to the class c_j if one were to decide only based on feature k, we consider the range of $f_j^k(x)$ to be partitioned into two labels or zones: rejection zone (**R zone**), that is if $f_j^k(x)$ belongs to this zone one should categorically exclude including object u in the corresponding class c_j and classification zone (**C zone**) where if $f_j^k(x)$ lays in, one should consider including the object u in this class; finally there is a zone where decision of including or excluding is not obvious that we refer to as doubtful or gray zone. Let us define by $m_C^{j,k}(x)$ and $m_R^{j,k}(x)$ the membership degrees of **C zone** and **R zone** respectively. Examples of membership degrees for a particular feature k for three classes low (L), medium (M), and high (H) where the green curve represents the classifiability membership degree and the red curve that of rejectability membership degree are depicted on Fig. 2. One should notice that the shapes of these curves that represent a feature k behaving in the sense low is better in terms of risk are just illustrative and one can imagine many other shapes. With regard to a class c_j, an object u

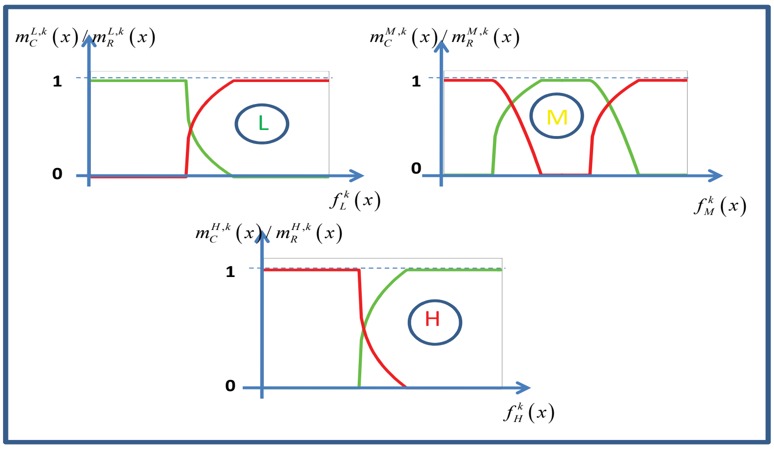

Fig. 2. Examples of membership degrees shapes

with attributes vector x will therefore be characterized by two vectors $m_C^j(x)$ and $m_R^j(x)$ gathering its membership functions as $m_\times^j(x) = \left[m_\times^{j,1}(x)\, m_\times^{j,2}(x) \ldots m_\times^{j,n_j}(x) \right]^T$ where $\times$ stands for R or C.

The classifiability and rejectability measures $\mu_C^j(u)$ and $\mu_R^j(u)$ are then obtained as equation (1)

$$\mu_C^j(u) = \frac{G(m_C^j(x))}{\sum_l \left(G(m_C^l(x)\right)}; \mu_R^j(u) = \frac{G(m_R^j(x))}{\sum_l \left(G(m_R^l(x)\right)} \tag{1}$$

where G is a certain aggregation operator. Given the synergy obtained by considering separately, classifiability and rejectability zone, it is obvious of considering a synergistic aggregation operator. Furthermore, features characterizing classes do not necessarily have the same importance in the classification process and experts may be able to weight them through a normalized vector ω. In this case, Choquet integral associated with a weighted cardinal fuzzy measure (wcfm) [26] is a suitable aggregation operator that permits to overcome difficulties due to the dimension of the vector to aggregate encountered in the literature [27] because a straightforward formula does exist.

Given a numerically valued n dimension vector θ with a relative importance vector ω, Choquet integral of x associated to a weighted cardinal fuzzy measure with relative importance vector ω is give by equation (2)

$$C_{\omega}^{wcfm}(x) = \sum_{k=1}^{n} \left\{ \varphi\left(A_k\right) \left(\theta_{\sigma(k)} - \theta_{\sigma(k-1)}\right) \right\} \tag{2}$$

where $\varphi\left(A_k\right)$ is a weighted cardinal fuzzy measure of subset A_k given by equation (3)

$$\varphi\left(A_k\right) = \left(\frac{n-(k-1)}{n}\right) \left(\sum_{j \in A_k} \omega_j\right) \tag{3}$$

and A_k is defined as equation (4)

$$A_k = \{\sigma(k), \sigma(k+1), ..., \sigma(n)\} \tag{4}$$

where σ is a permutation over x as given by equation (5)

$$x_{\sigma(1)} \leqslant x_{\sigma(2)} \leqslant ... \leqslant x_{\sigma(n)}; x_{\sigma(0)} = 0 \tag{5}$$

The operator $G(.)$ of equation (1) is therefore given by $C_{\omega_j}^{wcfm}(.)$ where ω_j is the relative importance weights vector of features characterizing the class c_j.

From classifiability and rejectability measures $\mu_C^j(u)$ and $\mu_R^j(u)$ one can define the classifying set $C(u)$ (classes where u can be classified) of object u as given by equation (6)

$$C(u) = \left\{ c_j : \mu_C^j(u) \geqslant q\left(\mu_R^j(u)\right) \right\} \tag{6}$$

where q is a non decreasing function representing the caution or boldness attitude of decision maker. One should notice that many categories or classes may be qualified for inclusion of a given object so that the ultimate class $c^*(u)$ in which to include the object can be selected by optimizing (let say maximizing) an index $\pi(u)$, for instance $\pi(u) = \mu_C^j(u) - q(\mu_R^j(u))$ or other as given by equation (7).

$$c^*(u) = arg\{max_{v \in C(u)}(\pi(v))\} \tag{7}$$

The overall BFNC framework that consists basically in five main steps is illustrated by Fig. 3

In the following section we will apply BFNC in the context of risk analysis by showing mainly that risk scoring is a mater of nominal classification.

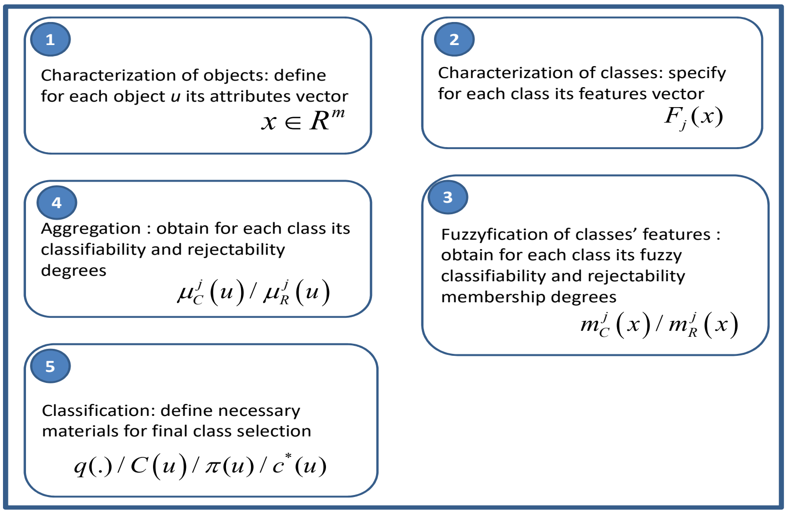

Fig. 3. Main steps of BFNC framework

3. Risk analysis

As stated in the preface of [28] concerning projects management, "every project involves risks and every project needs to have a management strategy for dealing with threats and opportunities represented by each risk"; this assertion can apply to almost any human activity as uncertainty is inherent to it. Risk analysis of human activities becomes therefore an important issue that must be addressed with appropriate scientific tools and methods; indeed risk arises from the incapacity of human to predict precisely the outcomes of their activities or external events. Today, an ever-increasing number of professionals and managers in industry, government, and academia are devoting a larger portion of their time and resources to the task of improving their approach to, and understanding of, risk-based decision making. Integration of risk factor in decision making or risk informed decision making is receiving a great attention by researchers and decision makers in many domains such as *engineering* (designing technical systems that meet some requirements in terms of safety), *finance* (set up norms to monitor finance activities in order to avoid companies collapse), *environment* (develop sustainable agriculture and natural resources extraction), *science and medical research* (monitoring scientists activity by the society to avoid creating new threats) to name few. But to address correctly (in terms of resources allocation for instance) important risks, decision makers must consider discriminating, categorizing or scoring them; this process consists basically in assigning them to predefined classes, categories, or scores that is nominal classification problem. The purpose of this section is to establish a risk analysis framework in terms of risk assessment; risk scoring, filtering and/or categorization; and risk management (resources allocation for risk prevention and/or mitigation, etc.); the first step is to assess risks namely to identify and evaluate them.

3.1. Risk assessment

Risk assessment is organized around two main activities: risk identification (looking for what can go wrong) and risk evaluation mainly evaluation of severity (the impact of the things that may go wrong);

these two activities are considered in the subsequent sections.

3.1.1. Risk identification and evaluation

In terms of risk assessment, risky attributes that characterize any activity or decision may come from different horizons; so before starting any activity or implementing any decision, one must identify all potential threats using different methods and tools among which the past experience, the opinion of members and/or stakeholders concerned by the activity or decision, etc.. Identification process is a purely analytic activity that can be based on proven methods such as the following ones adapted from [28].

- **Documentation reviews.** This consists in structured reviews of all documentation including plans, assumptions, preview activities files, contracts, etc. to possibly identify risky attributes of the activity.
- **Assumptions analysis.** In practice, each activity is based on a set of hypotheses, scenarios, or assumptions; the purpose of assumptions analysis is to explore the validity of assumptions in order to detect possibly inaccuracy, inconsistency or incompleteness that may constitute sources of risk.
- **Fishbone Diagrams.** Fishbone diagrams are risk diagramming techniques that include cause and effect diagrams useful for identifying risky attributes of an activity.
- **SWOT (Strength, Weakness, Opportunities, Threats) analysis.** SWOT analysis consists in looking at the activity from the perspective of its internal strengths and weakness as well as external opportunities, and threats; this is a very useful approach for risky attributes identification of an activity.

The main purpose of these approaches is to have an answer to the following triple questions [29].

- What can go wrong ? Identification of all events or sequences of events (or scenarios) that may have an (negative) effect on the activities that we referred to here as risky attributes of the activity.
- What is the likelihood that it would go wrong ? The probability of occurrence of that events or attributes.
- And, what are the consequences ? Characterization of the impact on the activity if undesired events do really occur.

Answers to these questions help risk analysts identify, measure, quantify, and evaluate risks and their consequences and impacts. Once the identification process is finished, one must consider evaluating different identified risky attributes. Technically speaking, risk is jointly associated with the likelihood (probability) of something (a risky attribute or event) happening and the impact (severity, gravity of that thing) which arises if it does actually happen. Thus and formerly, the risk $R_u(a_i)$ related to an attribute a_i of an activity or decision u (an object in the language of BFNC) is defined by two measures: the probability of occurrence $Pr(a_i)$ of that attribute and its severity $\sigma(u/a_i)$ (impact of event a_i on the activity u). The severity measures the negative impact on the activity that are generally expressed by the amount of some losses (economic loss, lives loss, etc.) or by the probability of no satisfaction of objectives. In the literature risk is defined by the measure known as the criticality that is the product of the probability of occurrence and the severity; thus the measure $x_i(u)$ of risk related to attribute a_i on activity u is given by equation (8).

$$x_i(u) = R_u(a_i) = Pr(a_i)\sigma(u/a_i) \tag{8}$$

Finally each activity or object u will be completely characterized by its risk vector $x(u)$ as given by equation (9) if m primary risky attributes have been identified.

$$x(u) = [x_1(u), x_2(u), ..., x_m(u)] \tag{9}$$

The following subsection go further in the process of evaluating the severity $\sigma(u/a_i)$ of the attribute a_i on the considered activity u.

3.1.2. Severity evaluation process

The process of evaluating the severity $\sigma(u/a_i)$ of an attribute a_i may be not straightforward in general; indeed, elicitation process begins most of the time by establishing a primary list of risky attribute which evaluation will characterize the concerned activity as defined by equation (9). But, in practice one may need to split each primary attribute into many other sub attributes hierarchically until an operational level (a level where one can assign a score to attributes' severity) is reached as shown by Fig. 4. Furthermore and as shown on Fig. 4, at each level there may exist interactions between corresponding attributes so that for a sound evaluation these interactions must be taken into account. One possible tool in the literature that permit to evaluate interactions between entities is the so called "Decision-Making Trial and Evaluation Laboratory" or DEMATEL technique for short [30] [31] [32] which is briefly described in the following steps.

- **Step 1: Generating the direct-relation matrix** by measuring the relationship between elements, attributes, criteria or entities in four levels: 0 (no influence), 1 (very low influence), 2 (low influence), 3 (high influence) and 4 (very high influence); one should notice that nothing prevent using any other scale to measure influence strength; the result of this process is the direct-relation matrix which is a square matrix A where a_{ij} is the degree to which the attribute a_i affects (influences) attribute a_j.
- **Step 2: Normalizing the direct-relation matrix.** On the basis of the direct-relation matrix A, the normalized direct relation matrix X can be obtained as given by equation (10) that is relating each influence degree to the maximum influence (received or dispatched) flowing through the network defined by A.

$$X = \frac{A}{\max\left\{\max_i\left\{\sum_{j=1}^n a_{ij}\right\}, \max_j\left\{\sum_{i=1}^n a_{ij}\right\}\right\}} \tag{10}$$

- **Step 3: Attaining the total-relation matrix.** In fact influence will circulate among elements until a steady state is reached; so one needs to compute the total relation matrix. Once the normalized direct-relation matrix X is obtained, the total relation matrix T is calculated as shown by equation (11)

$$T = \sum_{k=1}^{\inf} X^k = X(I-X)^{-1} \tag{11}$$

where I is the identity matrix; the total matrix does exist thanks to Perron-Frobenius theorem [33] as the spectral radius of X is less than 1 by construction (in general).

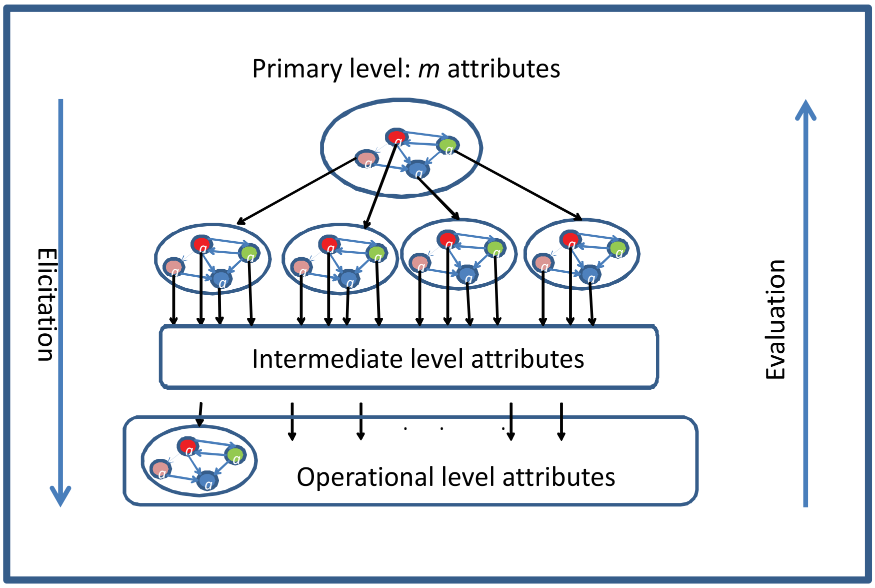

Fig. 4. Hierarchy and interactions in severity evaluation of risky attributes

From the total interaction matrix, one can determine some indexes (namely the dispatching index d_i and receiving index r_i for attribute i) that can be used to estimate the power or the influence degree of each attribute; these indexes are given by equation (12).

$$d_i = \sum_{j=1}^{n} T[i,j]; r_i = \sum_{j=1}^{n} T[j,i] \tag{12}$$

The importance of attributes at each level can be analyzed using $d_i + r_i$ and $d_i - r_i$ as they convey following properties.

- $d_i + r_i$ represents relationships importance or connectivity degree of attribute a_i within the network either as a dispatcher or a receiver;
- $d_i - r_i$ represents the influence degree and characterizes the attribute a_i as a dispatcher or a receiver: indeed, if $d_i - r_i > 0$ then the corresponding attribute influences more other attributes than it is

influenced and constitute therefore a dispatcher of influence; it will be consider as a receiver of influence otherwise.

Connectivity degree $d_i + r_i$ and influence degree $d_i - r_i$ can be used to categorize attributes for management purpose as described by Fig. 5. In terms of evaluation, once interactions parameters are determined at each level, one will propagate the values going from operational attributes for which one can evaluate until first level attributes that constitute the final evaluation vector x of the considered activity is reached (see Fig. 4). As shown by Fig. 4, whereas elicitation process goes from primary attributes to operational attributes, evaluation process goes in the counter sense that is from operational level to primary level by possible weighting the contribution of each attribute according to its importance as sketched above at each cluster.

3.2. *Risk scoring*

Decision regarding the considered activity will depend on the risk category, class, or score it belongs to as defined by the organization. Thus when risky attributes are elicited and evaluated, one must consider classifying the activity into the appropriate class. In terms of BFNC framework, at this stage one disposes of attributes vector x for each object u. Subsequent steps of BFNC concerning particular case of risk scoring are discussed in the following items.

- Definition and characterization of risk classes; this issue is a matter of top management decision makers mainly in what concerns the number of classes or categories.
- Definition of relationship between classes and attributes according to their evaluation score in general relies on experience of mangers and/or experts knowledge to arrive to a suitable characterization; this process will end up with fuzzy membership degrees of classifiability and rejectability of the BFNC framework.
- Aggregation of the relationship strength between classes and attributes may be a challenging task as attributes may be evaluated using heterogeneous units and scales; so the analyst needs to transform these evaluations into a unique transparent evaluation scale that allow sound aggregation procedure; meanwhile top managers and/or experts are needed to adjust or establish weighting obtained from DEMATEL analysis.
- Final scoring will necessitate the intervention of mangers to define the caution function q, the trade-off function π and to give their opinion regarding ultimate score or class c^*.

Once the process of scoring risk is ended, one can consider going further in risk analysis by considering risk management (resources allocation for risks sharing, avoiding, preventing, or mitigating, etc. for instance).

3.3. *Risk management*

Risk management is decision making under uncertainty; it consists in defining control variables or management actions that are things or procedures that can be realized in order to achieve objectives; it seeks therefore answering questions such as the following ones [29]: what can be done ? what are available options ? what are associated trade offs, etc.. Risk management actions will act primarily on risky attributes identified in the previous section. For this purpose DEMATEL analysis presented in the previous section can be very useful to optimize and organize how to effectively control risky attributes. Indeed, from the influence degree $d-r$ and connectivity degree $d+r$ obtained from DEMATEL analysis and by setting a threshold (C^{th}) (that corresponds in general to the mean value) on the connectivity degree, one can obtain four categories of attributes as depicted on Fig.5

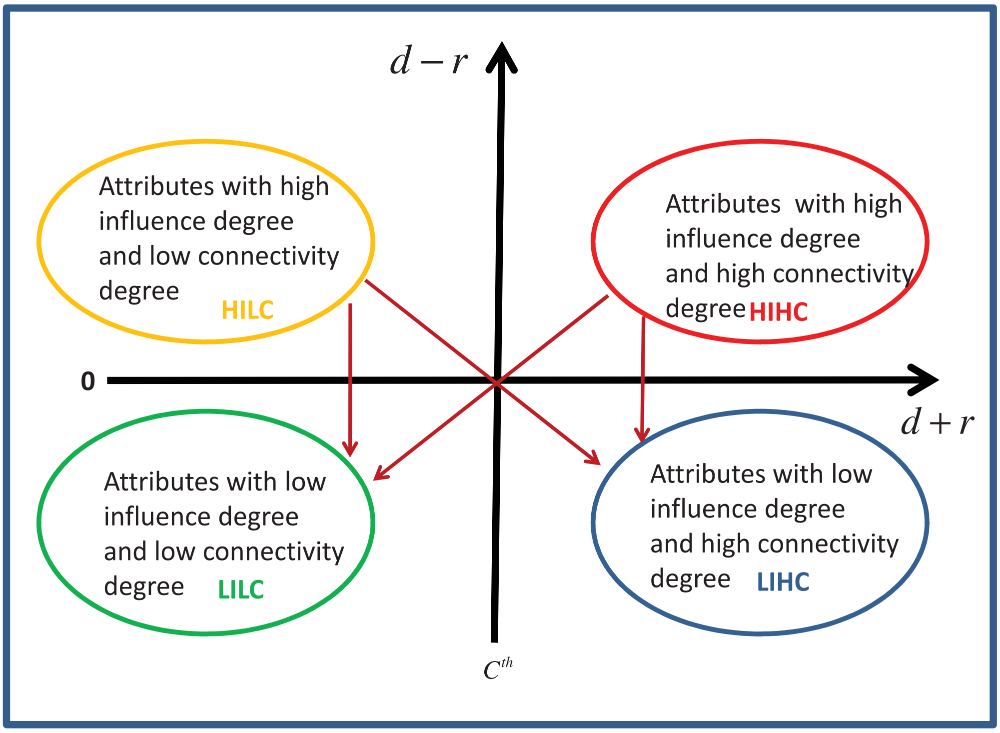

Fig. 5. Categorization of attributes according to their influence and connectivity degrees

Appropriate treatment of attributes as management action may rely on this categorization as described in the following items.

- *Attributes with high influence degree and high connectivity degree (**HIHC attributes**)*. These attributes have a great influence degree and inverter-connection degree. These causal attributes have high prominence, so their occurrence invokes a wide range of influences and interactions, such that they may trigger or exaggerate the other attributes and induce feedback. With such a high risk level, top priority management interventions are required. Response strategies should be *proactive*, such as avoidance strategies to eliminate the risk factors or mitigation efforts to lessen their potential impacts to an acceptable level.
- *Attributes with high influence degree and low connectivity degree (**HILC** attributes)*. Their emergence produces effects on only certain attributes, so improving these attributes might have limited

impacts on overall adjustments or optimization of the activity. The best response strategy might be *acceptance*, with contingent plans, or mitigation to minimize their impacts.

- *Attributes with low influence degree and high connectivity degree (**LIHC** attributes).* These attributes have high prominence; they are among the most important attributes and demand greater attention. Their risk levels are associated with their dependence on others and how well their cause attributes (**HIHC** and/or **HILC** attributes) can be managed. In addition, these attributes might generate feedback effects due to their high levels of interaction with other attributes which should affect management actions. Accordingly, these attributes are *avoided* or mitigated through careful monitoring of the source attributes by which they are influenced.
- *Attributes with low influence degree and low connectivity degree (**LILC** attributes).* These attributes are characterized by their minor influences and interactions with other factors. They are independent and isolated, so they may be judged as *acceptable* in ordinary situations.

The influence graph sketched on Fig. 5 can be refined to obtain what is known in the literature as influential network relation map (INRM) [34] which is a directed acyclic graph (DAG). To this end we propose to use the following procedure to determine wether attribute a_i does influence attribute a_j or not ? Let us define by δ_{ij} a parameter that measure the extent to which attribute a_i does influence attribute a_j; it is given by the difference of their respective influence degrees as shown by equation (13).

$$\delta_{ij} = (d_i - r_i) - (d_j - r_j) = (d_i - d_j) + (r_j - r_i) \tag{13}$$

To avoid no significant influence, one may set up a threshold $\delta^* > 0$ so that attribute a_i is considered to influencing attribute a_j if and only if $\delta_{ij} > \delta^*$.

In the following section we will consider a problem of risk analysis in the domain of international trade (selecting suppliers from foreign countries, outsourcing activities in foreign countries, investing in infrastructures development in foreign countries, etc.). To undertake such projects, investors must measure the risk on their investment performance given the situation of the targeted country.

4. Illustrative application

4.1. Presentation

The illustrative application considers the problem of classifying countries in terms of risk some actors such as investors may face by investing in these countries. In international trade context, risk classification of countries relies mainly on the Worldwide Governance Indicators (WGI) that determine the level of risks related to Governance in sourcing countries. There are 6 WGI, attributes, dimensions, or indicators of governance identified by the World Bank for this purpose that are briefly described in the following points [35].

1. Voice and Accountability (**VA**): perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media.
2. Political Stability and Absence of Violence/Terrorism (**PV**): perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including politically-motivated violence and terrorism.

3. Government Effectiveness (**GE**): capturing perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.
4. Regulatory Quality (**RQ**): perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development.
5. Rule of Law (**RL**): capturing perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence.
6. Control of Corruption (**CC**): perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.

So a project consisting in considering investing in a country to classify will be characterized by a 6 dimension vector x given by equation (14)

$$x = [VA, PV, GE, RQ, RL, CC]. \tag{14}$$

Data concerning 209 countries were evaluated and registered in 2014 by Foreign Trade Association(FTA) (a Brussels based organization working for European enterprises) and their statistics are shown on Table 1 [35]; how these data are obtained, the units and scales of the evaluation, are not the matters of this paper, we just use them for illustration purpose; one should also notice that all dimensions are evaluated in the sense of higher is the score better is the dimension in terms of risk minimization. Two

Table 1
Statistics of registered data of the considered application

	VA	**PV**	**GE**	**RQ**	**RL**	**CC**
min	0	0	0	0	0	0
max	100	100	100	100	100	100
mean (m)	49.7	49.6	50.3	50.3	49.8	50.0
std (σ)	29.1	29.1	29.1	29.1	29.1	29.3

classes were considered by [35]: risk countries and low-risk countries and the classification procedure is as following.

- **Risk countries**: countries with WGI average rating between 0 and 60 or three or more individual below 60.
- **Low-Risk countries**: countries with WGI average rating higher than 60 and no more than two individual dimensions rated below 60.

Fig. 6 shows an excerpt of the classification file by FTA where the names of corresponding countries are masked for confidentiality reason, (a) risk countries and (b) low-risk countries. In this paper we consider three categories of risks namely low risk (L), medium risk (M), and high risk (H) with the membership function of each of 6 attributes or dimensions given by Fig. 7. We also consider that all dimensions are equally important so that the weighting vector ω to be used in Choquet integral (reduced in this case to the mean value) of x associated to a weighted cardinal fuzzy measure of equation (2) is given by $\omega = [1/6, 1/6, 1/6, 1/6, 1/6, 1/6]$.

Average rating	Voice and Accountability	Political Stability and Absence of Violence	Government Effectiveness	Regulatory Quality	Rule of Law	Control of Corruption
21.1	**23.0**	38.7	**7.6**	**17.5**	**23.5**	**16.6**
52.3	58.2	78.8	42.7	**28.9**	57.3	47.9
56.8	62.9	51.9	63.0	63.5	49.8	49.8
47.1	35.7	39.2	56.9	46.4	51.2	53.1
51.9	43.7	**17.9**	65.4	65.4	57.7	61.1
11.5	**0.9**	54.7	**4.3**	**1.9**	**4.7**	**2.4**
50.3	70.0	96.2	**23.7**	**9.0**	64.3	38.4
32.7	**30.0**	**15.1**	37.4	49.8	43.7	**19.9**
30.3	46.5	41.5	**21.8**	**31.8**	**23.0**	**17.1**
11.2	**1.9**	**27.4**	**24.6**	**3.8**	**5.2**	**4.3**

(a): risk counries

Average rating	Voice and Accountability	Political Stability and Absence of Violence	Government Effectiveness	Regulatory Quality	Rule of Law	Control of Corruption
92.0	93.4	96.2	91.0	93.8	89.2	88.2
89.7	80.8	99.5	91.0	90.0	88.7	88.2
75.5	64.3	80.7	67.8	72.5	79.8	88.2
88.6	91.1	94.3	85.8	89.1	87.3	83.9
92.3	95.3	73.6	95.3	96.7	96.2	96.7
92.6	94.4	89.6	93.4	91.5	97.2	89.6
77.9	76.1	87.7	78.2	68.2	68.1	89.1
86.5	89.2	93.4	90.0	71.1	82.2	93.4
88.7	93.9	75.5	93.8	86.7	89.7	92.4
84.4	80.8	82.1	80.6	90.0	85.0	88.2

(b): low-risk countries

Fig. 6. An excerpt of FTA registered data

4.2. Results and comments

Classification results obtained by applying the BFNC framework developed in this paper are depicted on Fig. 8. The column FTA of this Fig.8 corresponds to the original classification by FTA where red color refer to risk countries and the green color to low-risk countries. The classification obtained by BFNC by using the index $\pi(u) = \mu_C(u) - \mu_R(u)$ is given under the column No. with following legend: green for low risk (L), yellow for medium risk (M), and red for high risk (H). We can notice that for low risk, our classification matches perfectly with that of FTA whereas for countries classified by FTA as risk countries that we have interpreted as high risk, there are cases where the considered countries are classified as medium or low risk by our BFNC approach. The aggregation method used by BFNC seems to be more smooth than the classification procedure used by FTA.

4.3. Risk management possibilities

As there are two main stakeholders (investors on one hand and country authorities on other hand), risk management process can be viewed in two directions according to the profile of decision maker. For instance authorities of a given country may like to invest or to act to improve some of the 6 WGI in order to enhance their position regarding the perception of risk by potential investors; investors on other hand, may like to know most influencing WGI toward risk for sequential preemptive decision making process for instance. In both two cases, interactions between the 6 WGI can be done do deduce an INRM

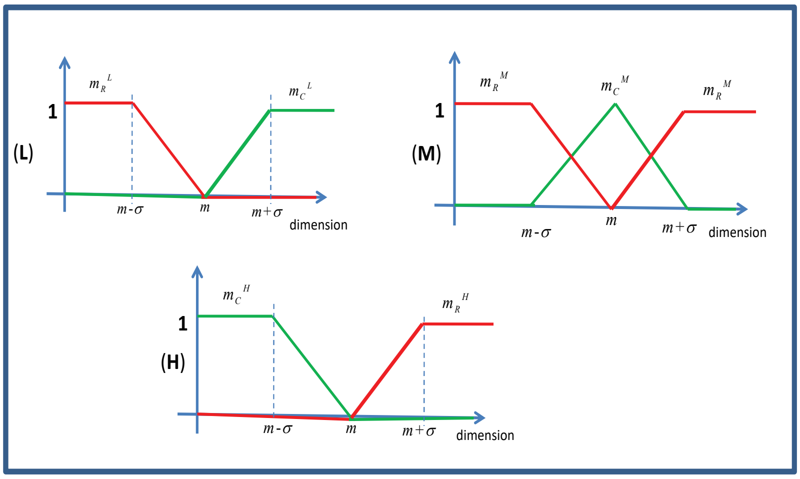

Fig. 7. Classifiability and rejectability membership functions of each dimension with regard to each class of the considered application

that can be used as a decision support tool. To this end, and as we dispose with relatively large data, we choose to construct the direct interaction matrix A as given by equation (15)

$$A = \frac{1}{209}\sum_{k=1}^{209} A_k = \begin{bmatrix} 0.00 & 157.39 & 3.84 & 1.30 & 32.96 & 15.00 \\ 8.31 & 0.00 & 1.64 & 4.19 & 1.50 & 1.42 \\ 8.15 & 1.84 & 0.00 & 3.53 & 1.22 & 1.22 \\ 1.26 & 157.17 & 3.60 & 0.00 & 32.79 & 14.79 \\ 8.08 & 1.35 & 1.20 & 3.61 & 0.00 & 1.12 \\ 7.97 & 1.58 & 1.15 & 3.59 & 1.11 & 0.00 \end{bmatrix} \tag{15}$$

where A_k is the direct interaction matrix of the 6 WGI for the country k and the influence degree $A_k(i, j)$ of WGI i on WGI j is given by equation (16)

$$A_k(i, j) = \frac{Data(k, j)}{Data(k, i)} \tag{16}$$

with $Data$ being a 209×6 matrix of registered data; and to avoid dividing by 0 we add 10^{-3} to each registration.

No.	FTA	L	M	H
1		-0,50	-0,50	1,00
2		-0,32	0,20	0,12
3		-0,50	-0,43	0,93
4		-0,50	-0,48	0,98
5		-0,31	0,17	0,13
6		-0,36	0,16	0,20
7		-0,50	-0,43	0,93
8		0,38	-0,31	-0,06
9		-0,50	-0,45	0,95
10		-0,50	-0,47	0,97
11		-0,27	0,19	0,08
12		-0,34	0,06	0,28
13		0,41	-0,29	-0,12
14		-0,50	-0,09	0,59
15		-0,47	0,14	0,33
16		0,19	0,26	-0,44
17		0,26	0,24	-0,50
18		-0,50	0,19	0,31
19		-0,50	-0,50	1,00
20		-0,50	-0,38	0,88
21		-0,50	-0,49	0,99
22		-0,50	-0,50	1,00
23		-0,50	-0,50	1,00
24		-0,41	-0,08	0,49
25		-0,14	0,19	-0,05
26		-0,50	-0,42	0,92
27		-0,50	-0,50	1,00
28		-0,50	-0,48	0,98
29		-0,50	-0,50	1,00
30		-0,23	-0,15	0,38
31		-0,44	-0,20	0,64
32		-0,49	0,14	0,34
33		-0,50	-0,41	0,91
34		-0,50	-0,24	0,74
35		-0,06	0,27	-0,22
36		-0,50	-0,47	0,97
37		-0,50	-0,48	0,98
38		-0,50	-0,41	0,91
39		-0,50	-0,22	0,72
40		-0,43	-0,29	0,72
41		-0,50	0,06	0,44
42		0,12	0,04	-0,16
43		0,18	0,32	-0,50
44		-0,50	-0,17	0,67
45		-0,50	-0,50	1,00
46		-0,50	-0,49	0,99
47		-0,49	0,17	0,32
48		-0,50	-0,49	0,99
49		-0,50	-0,17	0,67
50		-0,24	0,12	0,11
51		-0,50	0,03	0,47
52		-0,50	-0,48	0,98
53		-0,50	-0,50	1,00
54		-0,03	0,16	-0,13
55		0,05	0,08	-0,13
56		-0,50	-0,09	0,59
57		-0,50	-0,25	0,75
58		0,38	-0,39	0,01
59		-0,50	-0,49	0,99
60		-0,50	0,00	0,50
61		0,16	0,17	-0,33
62		-0,50	-0,38	0,88
63		-0,50	-0,47	0,97
64		-0,47	-0,15	0,62
65		-0,20	0,20	0,00
66		-0,50	-0,34	0,84
67		-0,50	-0,50	1,00
68		-0,10	0,29	-0,19
69		-0,50	-0,34	0,84
70		-0,49	0,26	0,24
71		0,44	-0,08	-0,36
72		-0,50	0,17	0,33
73		-0,46	-0,14	0,60
74		0,16	-0,25	0,10
75		-0,50	-0,47	0,97
76		-0,10	0,12	-0,02
77		0,21	-0,33	0,12
78		-0,48	0,28	0,20
79		-0,33	0,16	0,18
80		0,17	0,33	-0,50
81		-0,48	0,36	0,13
82		-0,41	0,14	0,27
83		-0,50	-0,50	1,00
84		0,37	0,13	-0,50
85		0,45	-0,36	-0,08
86		-0,50	-0,45	0,95
87		-0,50	-0,25	0,75
88		-0,50	-0,18	0,68
89		-0,50	-0,47	0,97
90		0,46	-0,12	-0,34
91		-0,50	-0,47	0,97
92		0,41	-0,48	0,07
93		0,10	0,21	-0,32
94		-0,50	-0,34	0,84
95		-0,50	-0,30	0,80
96		-0,17	0,15	0,02
97		-0,44	0,03	0,41
98		0,16	0,28	-0,44
99		-0,50	-0,34	0,84
100		-0,14	0,16	-0,02
101		-0,45	0,01	0,44
102		-0,35	0,19	0,16
103		-0,50	0,12	0,38
104		-0,11	0,28	-0,17
105		0,29	0,07	-0,36
106		-0,50	-0,29	0,79
107		-0,38	-0,09	0,48
108		-0,50	-0,50	1,00
109		0,33	0,15	-0,48
110		-0,50	-0,50	1,00
111		-0,38	0,25	0,14
112		-0,50	-0,50	1,00
113		-0,12	0,27	-0,15
114		-0,50	-0,11	0,61
115		-0,50	-0,44	0,94
116		-0,50	-0,50	1,00
117		-0,50	0,16	0,34
118		-0,26	0,14	0,12
119		-0,47	-0,44	0,92
120		-0,50	-0,45	0,95
121		0,04	0,08	-0,12
122		0,16	0,33	-0,50
123		-0,25	0,26	-0,02
124		0,20	0,02	-0,22
125		-0,47	-0,49	0,96
126		0,19	-0,39	0,20
127		-0,50	-0,10	0,60
128		-0,50	-0,25	0,75
129		-0,50	-0,48	0,98
130		0,40	-0,12	-0,27
131		-0,50	-0,50	1,00
132		-0,46	0,02	0,44
133		-0,44	-0,33	0,77
134		-0,50	-0,50	1,00
135		-0,38	0,06	0,32
136		-0,50	-0,50	1,00
137		1,00	-0,50	-0,50
138		1,00	-0,50	-0,50
139		0,90	-0,40	-0,50
140		1,00	-0,50	-0,50
141		0,99	-0,49	-0,50
142		1,00	-0,50	-0,50
143		0,92	-0,42	-0,50
144		0,99	-0,49	-0,50
145		1,00	-0,50	-0,50
146		1,00	-0,50	-0,50
147		0,79	-0,29	-0,50
148		0,92	-0,52	-0,40
149		1,00	-0,50	-0,50
150		0,59	-0,09	-0,50
151		0,97	-0,47	-0,50
152		0,99	-0,49	-0,50
153		0,67	-0,17	-0,50
154		0,47	0,03	-0,50
155		0,98	-0,48	-0,50
156		0,98	-0,48	-0,50
157		1,00	-0,50	-0,50
158		0,79	-0,29	-0,50
159		0,98	-0,48	-0,50
160		1,00	-0,50	-0,50
161		0,99	-0,49	-0,50
162		0,97	-0,47	-0,50
163		0,99	-0,49	-0,50
164		0,44	0,02	-0,45
165		1,00	-0,50	-0,50
166		0,44	0,06	-0,50
167		0,80	-0,30	-0,50
168		0,98	-0,48	-0,50
169		0,83	-0,33	-0,50
170		1,00	-0,50	-0,50
171		1,00	-0,50	-0,50
172		0,89	-0,54	-0,35
173		0,62	-0,12	-0,50
174		1,00	-0,50	-0,50
175		1,00	-0,50	-0,50
176		0,86	-0,36	-0,50
177		0,73	-0,23	-0,50
178		1,00	-0,50	-0,50
179		0,79	-0,29	-0,50
180		1,00	-0,50	-0,50
181		0,82	-0,32	-0,50
182		1,00	-0,50	-0,50
183		0,87	-0,37	-0,50
184		0,85	-0,35	-0,50
185		1,00	-0,50	-0,50
186		0,91	-0,41	-0,50
187		1,00	-0,50	-0,50
188		1,00	-0,50	-0,50
189		0,92	-0,42	-0,50
190		0,97	-0,47	-0,50
191		0,73	-0,23	-0,50
192		0,85	-0,50	-0,35
193		0,96	-0,46	-0,50
194		0,35	0,07	-0,42
195		0,96	-0,49	-0,46
196		0,90	-0,40	-0,50
197		0,97	-0,47	-0,50
198		0,96	-0,46	-0,50
199		0,93	-0,43	-0,50
200		0,92	-0,42	-0,50
201		0,94	-0,44	-0,50
202		1,00	-0,50	-0,50
203		1,00	-0,50	-0,50
204		0,98	-0,48	-0,50
205		0,80	-0,46	-0,33
206		0,98	-0,48	-0,50
207		0,98	-0,48	-0,50
208		0,88	-0,38	-0,50
209		0,95	-0,45	-0,50

Fig. 8. Countries risk classification obtained by established BFNC procedure

By applying DEMATEL approach presented previously to this matrix, we obtain the matrix of influence indexes of equation (13) as shown by equation (17)

$$[\delta_{ij}] = \begin{bmatrix} 0.00 & 1.60 & 0.54 & -0.07 & 0.74 & 0.62 \\ -1.60 & 0.00 & -1.06 & -1.67 & -0.90 & -0.98 \\ -0.54 & 1.06 & 0.00 & -0.61 & 0.20 & 0.08 \\ 0.07 & 1.67 & 0.61 & 0.00 & 0.81 & 0.69 \\ -0.74 & 0.86 & -0.20 & -0.81 & 0.00 & -0.13 \\ -0.62 & 0.98 & -0.08 & -0.69 & 0.12 & 0.00 \end{bmatrix} \tag{17}$$

that leads to the INRM depicted on Fig. 9 by considering that i influence j if $\delta_{ij} > 0$. The network of this Figure can be used in many ways to assist making decisions: for an investor, this Figure suggests to pay attention particularly to regulatory quality (**RQ**) and voice of accountability (**VA**) when judging a country in terms of investment risk; on other side, country authorities can use this network to optimize resources allocation for improvement of the risk reduction of their country.

5. Conclusion

The issue of deriving a framework that permit to classifying, categorizing, or scoring activities (investment projects, industrial activities, marketing projects, infrastructures maintenance activities, etc.) for

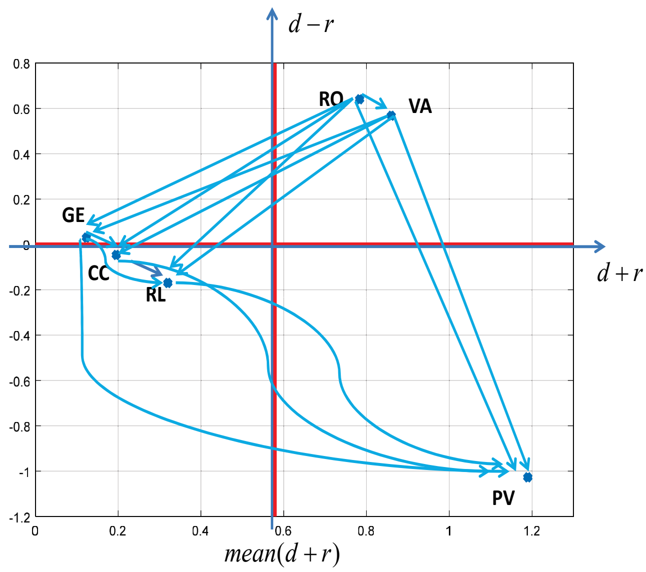

Fig. 9. INRM of the 6 WGI for the considered application

their appropriate treatment toward some stakes such as risks has been considered in this paper. Scoring consists in deriving classification algorithms that use activities risky attributes values as input information to assign them into pre-defined classes that are characterized by some fuzzily defined features. The established framework contributes in terms of risk analysis in the following three main directions.

- *Scoring by BFNC*: the established scoring algorithms transform fuzzily defined features characterizing classes that are functions of activities attributes values into two bipolar membership functions namely *classifiability* (measuring the extent to which the given activity must be included into the considered class using a specific feature) and *rejectability* (measuring the extent to which one should avoid including the former activity into the later class) membership functions with possible use of experts knowledge. As there are many features characterizing a class, former obtained membership functions are aggregated using a Choquet integral associated to a weighted cardinal fuzzy measure (wcfm) to take into account synergy between attributes, to finally obtain classifiability and rejectability measures that will be used for final assignment process. This way of scoring has two main advantages: there is no need for raw data (that is the original attributes vector) to be normalized nor to be evaluated on the same scale as the transformation into membership functions is transparent; with this approach many classes may be qualified for a given activity rendering this approach very flexible as decision makers' attitude such as hesitation can be revealed.
- *Risk assessment*: a procedure for elicitation and evaluation of risky attributes of activities taking into account possible hierarchy and interactions has been established. Taking into account interac-

tions between attributes is very important as interactions may exacerbate or attenuate the effect of particular attribute.

- *Risk management*: in terms of risk management, the ultimate stage of risk analysis process, the established framework permits, mainly through the so called influence network relations map (INRM), to optimize actions such as resources allocation by targeting most influential attributes.

The application of the developed approach framework to a real world problem in terms of classification of countries by the potential risks investors in these countries may face show interesting possibilities of this framework.

References

[1] Rigopoulos G, Patras J, Askounis D. A Decision Support System for Supervised Assignment in Banking Decisions. Journal of Applied Science. 2008; 8(3): 443.

[2] Tchangani AP. Selectability/Rejectability Measures Approach for Nominal Classification. Journal of Uncertain Systems. 2009; 3(4): 257.

[3] Spong K, Hoenig T. Bank Examination Classifications and Loan Risk. Economic Review. 1979; 15.

[4] Araz C, Ozkarahan I. Multi-criteria based novel strategic sourcing methodologies. Ph.D. Thesis. Izmir Dokuz Eylul University; 2007.

[5] Nemery de Bellevaux P. On the use of multicriteria ranking methods in sorting problems. PhD Thesis. Bruxelles: Université Libre de Bruxelles; 2008.

[6] Wang X. Country risk classification and multicriteria decision-aid. MSc. Thesis. Ontario: McMaster University; 2004.

[7] Pomerol JC, Barba-Romero S. Choix multicritÃÍre dans l'entreprise, principe et pratique. Paris: Hermes; 1993.

[8] Tchangani AP. Scoring Risk of Investment Projects Using Nominal Classification. 12th International Conference on MOdeling, Optimization and SIMulation (MOSIM18); 2018.

[9] Tchangani AP. Fuzzy Nominal Classification using Bipolar Analysis. In: Kumar A, Kumar Dash M, editors. Fuzzy Optimisation and Multi-Criteria Decision Making in Digital Marketing. Hershey: IGI Global; 2016. 233.

[10] Brans JP, Mareschal B, Vincke P. PROMETHEE: A new family of outranking methods in multicriteria analysis. In: Brans JP, editor. Operational Research 84. North Holland; 1984. 477.

[11] Brans JP, Mareschal B, Vincke P. How to select and how to rank projects: the PROMETHE method. European Journal of Operational Research. 1986; 24(2): 228.

[12] Roy R, Bouyssou D. Aide Multicritere a la Decision: Methodes et Cas. Paris: Edition Economica; 1993.

[13] Saaty T. Theory and Applications of the Analytic Network Process: Decision Making with Benefits, Opportunities, Costs, and Risks.Pittsburgh: RWS Publications; 2005.

[14] Steuer RE. Muticriteria Optimization: Theory, Computation, and Application. New York: Wiley; 1986.

[15] Perny P. Multicriteria filtering methods based on concordance and non-discordance principles. Annals of Operations Research. 1998; 80(1): 137.

[16] Belacel N. Multicriteria assignment method PROAFTN: methodology and medical applications. European Journal of Operational Research. 2000; 125(1): 175.

[17] Guzman LM. Fuzzy measures and integrals in MCDA sorting problematic: methodology and application to diagnostics of firms. Ph.D. Thesis. Bruxelles: University of Bruxelles; 2003.

[18] Leger J., Martel JM. A multicriteria assignment procedure for nominal sorting problematic. European Journal of Operational Research. 2002; 138(2): 349.

[19] Yevseyeva I. Solving Classification Problems with Multicriteria Decision Aiding Approaches. Academic Dissertation. University of Jyaskyla; 2007.

[20] Stirling WC. Satisficing Games and Decision Making: With Applications to Engineering and Computer Science. Cambridge: Cambridge University Press; 2003.

[21] Bouzarour-Amokrane Y., Tchangani AP, Pérès F. A bipolar consensus approach for group decision making problems. Expert Systems with Applications. 2015; 42(3): 1759.

[22] Tchangani AP. Considering Bipolarity of Attributes with regards to Objectives in Decisions Evaluation. Inzinerine Ekonomika - Engineering Economic. 2010; 21(5): 475.

[23] Tchangani AP, Bouzarour Y, Pérès F. Evaluation Model in Decision Analysis: Bipolar Approach. INFORMATICA: an International Journal. 2012; 23(3): 461.

[24] Tchangani AP, Pérès F. BOCR Framework for Decision Analysis. In: Borne P, Filip Florin G, editors. Proceedings of 12th IFAC Symposium on Large Scale Complex Systems Theory and Applications; 2010; 507.

[25] Tchangani AP, Pérès F. Filtering Risk uusing Bipolar Fuzzy Nominal Classfication. 5th International Conference on Control, Decision and Information Technologies (CoDIT). 2008; 170.
[26] Tchangani AP. Bipolar Aggregation Method for Fuzzy Nominal Classification using Weighted Cardinal Fuzzy Measure (WCFM). Journal of Uncertain Systems. 2013; 7(2): 138.
[27] Grabisch M. The application of fuzzy integrals in multicriteria decision making. European Journal of Operational Research. 1996; 89(3): 445.
[28] Newton P. Managing Project Risk. Free Management E-Books; 2015.
[29] Haimes YY, Kaplan S, Lambert JH. Risk Filtering, Ranking, and Management Framework Using Hierarchical Holographic Modeling. Risk Analysis. 2002. 22(2): 383.
[30] Fontela E., Gabus A. The DEMATEL observer, DEMATEL 1976 Report. Switzerland Geneva: Battelle Geneva Research Center; 1976.
[31] Gabus A, Fontela E. World problems and invitation to further thought within the framework of DEMATEL. Switzerland Geneva: Battelle Geneva Research Centre; 1972.
[32] Gabus A, Fontela E. Perceptions of the World problematic: Communication procedure, communicating with those bearing collective responsibility (DEMATEL Report No. 1)?. Switzerland Geneva: Battelle Geneva Research Centre; 1973.
[33] Meyer C. Matrix analysis and applied linear algebra. SIAM; 2000.
[34] Wang WC, Lin YH, Lin CL, Chung CH, Lee MT. DEMATEL-based model to improve the performance in a matrix organization. Expert Systems with Applications. 2012; 39(5): 4978.
[35] Foreign Trade Association. [https://www.foreigntradeassociation.com/]. Bruxelles: Business Social Compliance Initiative (BSCI); 2014 [cited 2019 Juanuary 22]. Availlable from: https://www.amfori.org/resource/countries-risk-classification.