A Linguistic Approach to Structural Analysis in Prospective Studies

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Abstract. One of the methodologies more used to accomplish prospective analysis is the scenario method. The first stage of this method is the so called structural analysis and aims to determine the most important variables of a system. Despite being widely used, structural analysis still presents some shortcomings, mainly due to the vagueness of the information used in this process. In this sense, the application of Soft Computing to structural analysis can contribute to reduce the impact of these problems by providing more interpretable and robust models. With this in mind, we present a methodology for structural analysis based on computing with words techniques to properly address vagueness and increase the interpretability. The method has been applied to a real problem with encouraging results.

Keywords: intelligent systems, soft computing, computing with words, scenario method, structural analysis

1 Introduction

Prospective analysis is a differentiating factor in innovation management and decision-making. The competitive advantages of organizations are achieved by accurately identifying the scenarios they must address. Organizations rely on systems that perform prospective analysis to be ahead of the changes in the environment. One of the most widely employed methodologies to accomplish prospective analysis is the scenario method proposed by Godet [4]. This method helps to determine the possible futures by means of the definition of scenarios and establishes five stages to accomplish it: structural analysis, strategies of the actors, morphological analysis, expert methods and multi-criteria decision making. In this work we deal with the first one, structural analysis. Concretely we will focus on the tool provided by Godet to support this stage, the Impact Matrix Cross-Reference Multiplication Applied to a Classification (MICMAC) [4, 6].

Structural analysis aims to determine the most important variables of a system from a matrix that establishes the relation among them. It has been increasedly used in a number of applications in various domains since the middle

1980's, within businesses as well as on society-related topics. Qureshi et al. [12] employed MICMAC to measure the key guidelines of 3PL services providers. Arya et al. [1] applied it in environmental trend analysis. Shivraj et al. [9] evaluated the effectiveness of information systems. Sharma et al. [13] considered waste management with MICMAC. In [10] the structure of international conflict is described with the tools of structural analysis to enhance the understanding of multilateral conflict-communication relations and to predict the conflict structure with existing international relations theories.

Despite being a widely used approach, structural analysis and MICMAC method still presents some shortcomings. The information used in this process comes from various experts and is obtained through opinion pools, panels, etc. Such information is inherently vague due to the subjective character of the data, imprecision on the opinions, and not enough consensus among experts.

In this sense, the application of Soft Computing to structural analysis can contribute to reduce the impact of these problems by providing more interpretable and robust models that lead to a better representation of the scenarios and therefore, of the possible futures [3, 14]. With this idea in mind, we present a methodology based on fuzzy sets and linguistic labels for structural analysis that extends and improves MICMAC by properly addressing vagueness and increasing interpretability.

The contribution is structured as follows. Section 2 reviews the MICMAC method. Section 3 explains the novel approach, and Section 4 shows its application to a real problem. Finally, Section 5 is devoted to conclusions and further work.

2 MICMAC

The MICMAC method for structural analisys is aimed at dermining the most important variables within a system, among a set of variables specified by an expert commitee. Basically, MICMAC is composed of the following three steps:

- Define the relevant variables.
- Specify the relations between the variables.
- Identify the key variables among all the variables proposed by the experts.

Define relevant variables. The variables in complex systems are defined with the opinion of several experts, brainstorming and literature review. An unsorted list variables is given as an output in this phase. Of course, not all the experts may agree in the importance of the variables or even in identifying what aspects should be formalized as a variable or which should not. Let n be the number of variables identified.

Specify the relations between the variables. The group of experts provide a n x n integer matrix that states the influence that each variable has over the rest of variables of the system. This matrix is called the *Matrix of Direct Influence*, MDI or, from now, M, and it is created on the basis of the experts' own knowledge and expertise. Every cell m_{ij} of M denotes to what extent variable i influences variable j, and this value can be

- 0 if variable i has no influence on variable j.
- 1 if variable i has a weak influence on variable j.
- 2 if variable i has a strong influence on variable j.
- 3 if variable i has a very strong influence on variable j.

The cells m_{ii} of the diagonal are all set to 0. According to Godet [4], in real systems only about 30 % of the cells of the MDI matrix have values different from 0.

Identify the key variables. This is the main step of the method. Some important measures that give us a clue of the degree of importance of the variables can be computed from M after simple operations. The *direct method* estimates the overall direct influence and direct dependence of a variable in the system directly from the MDI matrix, while the *indirect method* estimates the overall influence and dependence of a variable through other variables of the system.

a) Direct method. The *direct influence* of a variable k over the rest is computed as the sum of all the values of row k of M. Similarly, the *direct dependence* of a variable k from the rest is computed as the sum of all the values of column k. Therefore we have two different measures associated with every variable k:

$$I_k = \sum_{j=1}^{n} m_{kj} \ (k = 1, 2, ..., n) \qquad (1) \qquad D_k = \sum_{i=1}^{n} m_{ik} \ (k = 1, 2, ..., n) \qquad (2)$$

With this information, an influence ranking σ_I^M and a dependence ranking σ_D^M are built by sorting the variables according to their influence and dependence, respectively. Both rankings serve as a first indicator of the importance of each variable in the system. These calculations are known as the *direct method*.

b) Indirect method. The influence and dependence rankings become stable (i.e. don't change) when they are built not directly upon matrix M but from matrix M^δ with δ a low integer (according to Godet [4], 7 or 8 is an usual value that guarantees ranking convergence). This means that the influence and dependence rankings built upon M^8 are the same as those built upon M^r for any $r > 8$. The pow of a fuzzy matrix is defined in the same way that with a matrix of scalars: $M^p = \prod_p M$.

It is possible to build other more informative rankings following the so-called *indirect method*, which is an iterative process in two steps aimed at finding the value δ that makes the rankings not change:

1. Initialization step. Let σ_I and σ_D be the influence and dependence rankings obtained with the direct method. Initialize A to be the original MDI matrix M.
2. Iteration:
   - Do $A = A$ x M and compute the new influence and dependence rankings σ_I^A and σ_D^A with the resulting matrix, as explained above.

- Compare σ_I^A with σ_I and σ_D^A with σ_D.
- If both comparisons match, finalize. Otherwise, update the old rankings: let $\sigma_I = \sigma_I^A$ and let $\sigma_D = \sigma_D^A$ and go to step 2 again.

Now let $M' = M^\delta$ which is the matrix obtained in the last iteration. M' is known as the *Matrix of Indirect Influence* (MII). The *indirect influence* of a variable k over the rest is computed as the sum of all the values of row k of M'. Similarly, the *indirect dependence* of a variable k from the rest is computed as the sum of all the values of column k of M'. Therefore we have another two different measures computed over M' and associated with every variable k:

$$I'_k = \sum_{j=1}^{n} m'_{kj} \ (k = 1, 2, ..., n) \quad (3) \qquad D'_k = \sum_{i=1}^{n} m'_{ik} \ (k = 1, 2, ..., n) \quad (4)$$

3 Fuzzy MICMAC

The main idea to ease the implantation of MICMAC is to enable the user to give qualitative values instead of quantitative ones in the influence matrix, and use such qualitative values in all the calculations of the method. Many times, it is easier for the experts to use linguistic terms when giving an evaluation of certain aspects within their domains of expertise. Therefore, the use of *linguistic variables* is a valid solution. Since Zadeh [17] introduced the concept of fuzzy set and subsequently went on to extend the notion via the concept of linguistic variables, the popularity and use of fuzzy sets has been extraordinary. We are particularly interested in the role of linguistic variables as an ordinal scale and their associated mathematical representation, in this case triangular fuzzy numbers, to be used in the structural analysis. By a linguistic variable [16] we mean a variable X whose values are words or sentences in a natural or artificial language. A strict ordering must exist over the possible values of X so that all the values are comparable. As mentioned above, it is also necessary to have a mathematical structure behind such linguistic labels to enable calculations. Every linguistic term (value) has an underlying fuzzy set [2, 8] associated to it. Here we will focus on *triangular fuzzy numbers*. A triangular fuzzy number (TFN) is a fuzzy number whose membership function is defined by three real numbers a, b, c, where $a < b < c$. Thus a TFN can be mathematically described as [11]:

$$f_A(u) = \begin{cases} (u-a)/(b-a) & a \le u \le b \\ (c-u)/(c-b) & b < u \le c \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

With regard to the fuzzy numbers, we will show only the mathematical operations that will be used throughout the development of the algorithm. Let *T1*, *T2* be two positive triangular fuzzy numbers defined by the triplets $[a_1,b_1,c_1]$ and $[a_2,b_2,c_2]$, respectively. Then we can define mathematical operations between them such as:

- Addition: $T_1 \oplus T_2 = [a_1 + a_2,\ b_1 + b_2,\ c_1 + c_2]$

- Multiplication: $T_1 \otimes T_2 = [a_1 \times a_2, b_1 \times b_2, c_1 \times c_2]$
- Distance between TFN's:

$$d(T_1, T_2) = \frac{|a_1 - a_2| + 4|b_1 - b_2| + |c_1 - c_2|}{6} \tag{6}$$

- Defuzzification method [5]

$$c(T_1) = \frac{a_1 + 4b_1 + c_1}{6} \tag{7}$$

3.1 Fuzzy Modifications to MICMAC

In general, structural analysis is easier when the influence and dependence are described in terms of linguistic labels. On the other hand, we also want to calculate an absolute measure of how important a variable is within the system, yet in an interpretable way. In those cases, the concept of linguistic label is more suitable than a real number. In our proposal, we use a linguistic computational model based on membership functions [7]. The experts use linguistic labels to evaluate the influence between the variables, and all the computations of the method are done with their underlying fuzzy numbers. We also output a linguistic measure of the influence and dependence of each variable as described in detail in steps 1 and 2 of the fuzzy direct method, later in this section. The following aspects should be modified in the original MICMAC method to implement this new approach.

Define a set of linguistic labels. A set of linguistic labels must be defined by the experts to evaluate the relations between the variables. A first approach may use the labels {No influence, Weak influence, Strong influence, Very strong influence}; we will abide to this division during the remainder of this paper but any other division and number of labels can be valid as well. We will refer to these labels as $\{l_0, l_1, ..., l_N\}$ so in our case $N = 3$. The universe of discourse and the shape and parameters of the underlying TFN's may also be predefined or customized by the user. This way the original MDI becomes a fuzzy MDI, i.e. a matrix in which every cell is a linguistic label with a TFN associated to it, as shown in Table 1. The cells that are set to *No influence* are ignored (discarded) for all the computations because *No influence* is not really a linguistic label but is equivalent to an empty cell.

Table 1. Linguistic MDI

	V_1	V_2	...	V_n
V_1	No influence	Weak	...	Very strong
V_2	Strong	No influence	...	Strong
...	...	...	...	...
V_n	Weak	No influence	...	No influence

Compute the direct and indirect dependence and influence. Both the direct and the indirect method remain unchanged from a high-level perspective. It must be only taken into account that the sums of the cells indicated in expressions (2), (3), (4), (5) now turn into sums of TFN's and the product of fuzzy matrices should now be defined in terms of sums and products of the TFN's of the cells as defined in the previous section. Thus the direct influence and direct dependence of a variable are now TFN's, as well as the indirect influence and the indirect dependence.

However, an additional step should be considered here. Since the direct and indirect influence and dependence are TFN's, they should be interpretable also in linguistic terms: it would be desirable to know for instance if the resulting direct influence of a variable is *Weak*, *Strong* or *Very strong* because that is more informative than having only the triplet $[a, b, c]$ of the resulting TFN. Actually this is a very important point and in the case of the indirect method it requires adapting the universe of the discourse of the TFN's obtained as results of the computations to a new scale in order to assign a linguistic term to every output TFN. In other words, it is necessary to define the underlying TFN's for the labels {No influence, Weak influence, Strong influence, Very strong influence} when they are referred *to the resulting direct/indirect influence/dependence* instead of referring to the influence that one variable has over another variable. Note that both universes must be different because the TFN's representing the overall direct and indirect influences and dependences will have much higher values $[a, b, c]$ than the original labels, so it is necessary to have a way to map such big triplets to their corresponding linguistic labels.

a) Fuzzy direct method: in addition to obtaining a ranking of the variables according to their (fuzzy) influence and dependence, the secondary goal is to assign linguistic labels to the TFN's representing such direct influence and direct dependences to make them more informative. The steps are:

1. *Computation of the TFN defining each linguistic term at the output.* For each $p = 1, ..., N$ do:
   (a) Take the MDI matrix containing linguistic labels and substitute all the cells that are different of *No influence* by the linguistic label l_p. Let M_{l_p} be the matrix after the substitutions, which we will call the p-th ideal matrix.
   (b) For every variable k compute the fuzzy *direct influence* $I_k^{l_p}$ and fuzzy *direct dependence* $D_k^{l_p}$ over M_{l_p}. As a result, we obtain two lists $\{[a_k, b_k, c_k], k = 1, ..., n\}_{inf}^{l_p}$ and $\{[a_k, b_k, c_k], k = 1, ..., n\}_{dep}^{l_p}$ of TFN's.
   (c) Compute the minimum of the left-side values of influence and dependence of all the TFN's obtained, the maximum of the right-side values and the median of the central values:

$$
\begin{aligned}
a_{inf}^{l_p} &= min\{a_k, k = 1, ..., n\}_{inf}^{l_p} & a_{dep}^{l_p} &= min\{a_k, k = 1, ..., n\}_{dep}^{l_p} \\
c_{inf}^{l_p} &= max\{c_k, k = 1, ..., n\}_{inf}^{l_p} & c_{dep}^{l_p} &= max\{c_k, k = 1, ..., n\}_{dep}^{l_p} \\
b_{inf}^{l_p} &= median\{b_k, k = 1, ..., n\}_{inf}^{l_p} & b_{dep}^{l_p} &= median\{b_k, k = 1, ..., n\}_{dep}^{l_p}
\end{aligned}
$$

These are, respectively, the left-side, right-side and the central values of the TFN's that we will use as references to categorize the TFN's of direct influence and direct dependence.

(d) Now we have two new TFN's $\delta_{l_p}^{inf} = [a_{inf}^{l_p}, b_{inf}^{l_p}, c_{inf}^{l_p}]$ and $\delta_{l_p}^{dep} = [a_{dep}^{l_p}, b_{dep}^{l_p}, c_{dep}^{l_p}]$ that define two linguistic labels whose linguistic term is l_p (the same as the original) but whose underlying TFN's are different in order to properly adapt to the new range of values of the fuzzy direct influence and fuzzy direct dependence.

2. *Compute influence and dependence as TFN and assign a linguistic term.* Up to now we have obtained two sets of linguistic labels, one for influence called $\Delta_{inf} = \{\delta_1^{inf}, ..., \delta_N^{inf}\}$ and one for dependence called $\Delta_{dep} = \{\delta_1^{dep}, ..., \delta_N^{dep}\}$, which are the same as the original but have different underlying TFN's. Now for each $k = 1, ..., n$:
   (a) Compute the fuzzy direct influence I_k and fuzzy direct dependence D_k of variable k over the original fuzzy MDI matrix M.
   (b) Find the linguistic label in Δ_{inf} that is closest to I_k according to the distance stated in (6), and assign that label to I_k. Do the same with D_k and the set of labels Δ_{dep}. [1]
3. *Build the fuzzy influence and dependence rankings.* First, defuzzify the values I_k and D_k according to (7) to obtain the crisp values $\bar{I_k}$ and $\bar{D_k}$. Then build the influence and dependence rankings by sorting the variables according to such crisp influence and dependence values respectively, $\bar{I_k}$ and $\bar{D_k}, \quad i = 1, ..., n$.

Notice that after step 2(b), the fuzzy direct influence and fuzzy direct dependence of each variable are much more informative than the integer numbers of the original MICMAC method, as they have a linguistic term associated.

b) Fuzzy indirect method: the steps are exactly the same as in the direct method except step 1(a) which should be replaced by the following:

1. (a) Take the MDI matrix containing linguistic labels and substitute all the cells that are different of *No influence* by the linguistic label l_p. Then, using the addition and product for TFN's defined above, compute the 8th power of this matrix. Let M_{l_p} be the matrix after the power operation, which we will call the p-th ideal matrix.

Again, indirect influence and dependence rankings are obtained from the indirect method, together with two linguistic labels per variable describing the absolute influence and dependence of the variable in a linguistic way. As can be seen, the main concern of the above algorithms is to define properly the shape of the TFN's that underlie the output linguistic terms. If this is achieved, the TFN obtained at the end representing the overall direct (indirect) influence (dependence) of a variable can be assigned an interpretable linguistic term. The

[1] The TFN's I_k and D_k computed initially are not replaced; only a linguistic label is assigned to them.

calculation process itself with TFN's is basically analogous to that proposed by Godet for the crisp discrete valuations 1, 2 and 3, but the latter does not output any interpretable information about such overall dependence or influence.

4 A Real Example

Our fuzzy methodology has been applied to a real case study about the determinants of the rural spaces on the 2010 time horizon. This example comes with the MICMAC tool included in the software package developed by the LIPSOR research group[2] so the results can be compared. The system has 50 variables. Some of them are listed below with informational purposes.

1. Metropolization
2. Organization of the international market
3. Food demand
4. Contribution of migration
5. Job market
6. Elderly
7. Social politics

The results are shown in Tables 2, 3, 4 and 5. The ranking obtained with Godet's crisp method is shown next to the one obtained with our fuzzy MICMAC proposal for comparison. As can be seen, both rankings are almost identical in the direct method but also very similar in the indirect method. This represents a quite remarkable result since the operations involving fuzzy matrix products followed by defuzzifications carried out by the indirect method are rather different from the original crisp operations but lead to similar results, which confirms the validity of our approach. In addition, we were able to output linguistic labels for the influence and dependence of the variables in the direct method, which are more informative than the crisps values as mentioned in previous sections.

5 Conclusions and Further Work

A fuzzy extension has been proposed to the MICMAC method for structural analysis in the scenario method for prospective studies. It allows to give linguistic valuations to the influence of a variable over the others, and to get a qualitative measure at the output representing the overall influence and dependence of a variable in the system. The results are easier to interpret and the qualitative information about the absolute overall influence and dependence of a variable can be understood by the user, which would not occur with the crisp values of the original MICMAC method. Our proposal has shown good results when compared with the original crisp MICMAC over a real example. As future work we will focus on solving the retranslation problem in the indirect method [15] in order to get more informative labels.

[2] http://en.laprospective.fr/methods-of-prospective/downloading-the-applications.html

Table 2. Prominent variables ranked according to direct influence with the crisp and fuzzy MICMAC methods

Variable	Crisp infl.	Label	Crisp rank	Fuzzy rank
37	59	V. strong	1	1
5	49	V. strong	2	2
4	46	V. strong	3	3
32	46	V. strong	4	4
33	43	V. strong	5	6
19	43	V. strong	6	5
18	42	Strong	7	7
14	42	Strong	8	8
23	41	Strong	9	10
25	41	Strong	10	9

Table 3. Prominent variables ranked according to direct dependence with the crisp and fuzzy MICMAC methods

Variable	Crisp depend.	Label	Crisp rank	Fuzzy rank
37	59	V.strong	1	1
24	52	V.strong	2	2
32	51	V.strong	3	3
35	51	V.strong	4	4
5	50	V.strong	5	5
14	49	V.strong	6	6
46	48	V.strong	7	7
43	46	V.strong	8	8
20	45	V.strong	9	10
48	45	V.strong	10	9

Table 4. Prominent variables ranked according to indirect influence with the crisp and fuzzy MICMAC methods

Variable	Crisp infl.	Label	Crisp rank	Fuzzy rank
37	$5.57 \cdot 10^{13}$	Weak	1	1
19	$4.82 \cdot 10^{13}$	Weak	2	5
5	$4.66 \cdot 10^{13}$	Weak	3	3
25	$4.34 \cdot 10^{13}$	Weak	4	7
32	$4.28 \cdot 10^{13}$	Weak	5	2
4	$4.23 \cdot 10^{13}$	Weak	6	4
23	$4.21 \cdot 10^{13}$	Weak	7	8
18	$4.18 \cdot 10^{13}$	Weak	8	6
14	$4.07 \cdot 10^{13}$	Weak	9	10
24	$3.83 \cdot 10^{13}$	Weak	10	12

Table 5. Prominent variables ranked according to indirect dependence with the crisp and fuzzy MICMAC methods

Variable	Crisp depend.	Label	Crisp rank	Fuzzy rank
37	$6 \cdot 10^{13}$	Weak	1	1
35	$5.20 \cdot 10^{13}$	Weak	2	2
43	$5.01 \cdot 10^{13}$	Weak	3	7
14	$4.94 \cdot 10^{13}$	Weak	4	4
24	$4.72 \cdot 10^{13}$	Weak	5	3
32	$4.63 \cdot 10^{13}$	Weak	6	6
46	$4.57 \cdot 10^{13}$	Weak	7	5
5	$4.43 \cdot 10^{13}$	Weak	8	8
4	$4.40 \cdot 10^{13}$	Weak	9	12
48	$4.31 \cdot 10^{13}$	Weak	10	11

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