Abstract
Most decision-making processes are dynamic. Critical decisions require multiple and interrelated time-constrained decisions within strongly uncertain and so complex scenarios. The proposed methodology (mixing Delphi, Fuzzy Cognitive Maps and TOPSIS) and is a step forward with regard to the classic tools used in scenarios-based decision-support. This proposal allows managing uncertainty for improving scenarios-based decision-making. FCMs offer visual models for easier understanding by non-technical decision makers, because FCM can express human explicit and tacit knowledge. Moreover, FCM provide an intuitive, yet precise way of expressing concepts and reasoning about them at their natural level of abstraction. By transforming decision modelling into causal graphs, decision makers with no technical background can understand all of the components in a given scenario. In addition, scenarios are ranked using a multicriteria method (TOPSIS).

Keywords: Fuzzy Cognitive Maps, TOPSIS, Delphi, Scenarios, Ranking

1. Introduction
Most decision-making processes are dynamic. Critical decisions require multiple and interrelated time-constrained decisions within strongly uncertain and so complex scenarios.
Scenario analysis, also called scenario thinking or scenario planning, is a strategic planning method to make flexible long-term planification. It is in large part an adaptation and generalization of classic methods used by military intelligence. This paper propose a TOPSIS-based methodology for
ranking FCM based scenarios.

The rest of the paper is structured as follows. Section 2 presents scenarios analysis fundamentals. Next section shows the methodology proposed. The following two sections introduce the techniques included in our proposal (Fuzzy Cognitive Maps and TOPSIS). In Section 6, a numerical example is given, and conclusions are finally made in Section 7.

2. Scenario analysis

According to Kahn & Wiener (1967), a scenario can be defined as a hypothetical set of plausible (but not inevitably probable) and logical events, built to concentrate on causal processes and decision events. Scenario-based analysis is considered as a conjectural forecasting technique usually associated with future research (Shiftan et al., 2003).

Scenario analysis has been defined as an exercise in sensemaking (Roubelat, 2006) in front of tunnel vision (Jetter & Schweinfort, 2010; Schoemaker, 1995). The successful scenarios alter paradigms by overcoming the trend to naively extrapolate present environments without take into account nonlinear relationships or structural changes (van Notten et al., 2005).

Scenarios describe events and circumstances that would occur in the future world (Banuls & Salmeron, 2007). Decision and policy makers use scenario methods to build landscapes of possible futures at a national level (Godet, 1994). Based on these future perspectives, decision makers are able to explore different courses of action. Using the results of scenario-based problem solving, decision makers have a set of alternatives and outcomes associated with them with a probability or degree of occurrence (Banuls & Salmeron, 2008). In recent years, the number of potential scenario methods and applications are increasing. It is because academics and practitioners are increasing the interest about it (Harries, 2003).

In spite of the success of scenario methods support, scenario-based decision making still is not a fully structured process (Banuls & Salmeron, 2007; Chermack, 2004). The proposed methodology aims to bring methodological support to scenario-based decision making.

Scenario’s frameworks combine qualitative and quantitative scenarios, but in many cases the link between them is weak (van Vliet et al., 2010). The originality of the proposed approach with respect to other ones is that it aims to use the scenarios building, assessment and ranking as a whole. Classical approaches consider the future impact of each present entity in isolation. This assumption is a simplification of a more complex reality, in which different entities interact with each other. The model that the authors propose allows
decision and policy makers to measure the impact of entity interactions. To reach this aim, the methodology proposed combines soft computing (Fuzzy Cognitive Maps) and multicriteria (TOPSIS) techniques. Several authors discuss how multiple and diverse inputs sets should be integrated into meaningful scenarios: Intuitive techniques that lean strongly on interactive group sessions and qualitative knowledge are said to facilitate strategically relevant paradigm shifts more effectively than formal models that rely on (oftentimes historic) quantitative data and are limited in scope (de Jouvenel, 2000; van Notten et al., 2005). Proponents of quantitative models, however, point out that human brains are ill-equipped to make sense of complex systems: people regularly misjudge the behavior of complex systems because they focus on few variables, overlook feedback loops and time lags, and fall victim to decision errors such as confirmation bias and attribution errors (Senge, 1990).

In this sense, causal cognitive mapping, a qualitative method that captures the mental models of experts in simple loop and arrow causal maps, has long been proposed as a solution to the problem (Warren, 1995). Cognitive mapping captures individuals unique views of their world, either through interviews that are later transcribed into causal maps (Figure 2). The resulting causal maps show the subjective knowledge of individuals. The mapping process fosters system thinking and enables subject matter experts to become aware of flaws in their own mental models, such as inconsistencies, ignorance of (de-)stabilizing feedback loops, and unquestioned assumptions. More critically, the resulting causal maps allow others to gain insights into the formerly tacit mental models of individual experts and decision makers. In academic research, these insights are frequently used to assess decision-making and to understand managerial actions as a result of commonalities and differences in the worldviews of the management team (Axelrod, 1976). In scenario development and strategic planning knowledge of mental maps is used to identify key issues of the scenario domain and guide the exploration of alternative futures in a group setting.

3. Proposed methodology

Scenarios describe events and situations that would occurred in the future real-world. Policy makers use scenario methods as a tool to build landscapes of possible futures at a national level (Godet, 1994). Based on these future visions, policy and decision-makers are able to explore different courses of action. Using the results of scenario-based problem solving, decision makers have a set of alternatives and outcomes associated with them
with a probability or degree of occurrence. In recent years, the number of potential scenario methods is increasing. It is because academics and practitioners are increasing the interest about it (Harries, 2003).

In spite of the success of scenario methods’ support, scenario-based decision making still is not a fully structured process (Chermack, 2004). The proposed methodology aims to bring methodological support to scenario-based decision making in scenario analysis.

The originality of the proposed approach with respect to other ones is that it aims to use the scenarios’ assessment and ranking as a whole. Traditional approaches consider the future impact of each present entity in isolation. This assumption is a simplification of a more complex reality, in which different entities interact with each other. The model that the authors propose allows decision and policy makers to measure the impact of a entity interactions. To reach this aim, the proposal combine Delphi method, soft computing (Fuzzy Cognitive Maps) and multicriteria (TOPSIS) techniques. The whole methodology proposed is shown in the Figure 1. The proposal is composed by three blocks.

![Figure 1: FCM layers](image)

1. Building FCM models with Delphi. Each expert or data source can generate a FCM. Various methodologies could be used in order to add
FCMs or to reach a consensus among the experts in FCM (Bryson, Mobolurin & Joseph 1997).

2. Scenarios simulation. The simulation is composed of a couple of stages. The first one is the scenario definition and the second one is the FCM inference. This block will be run once by scenario. Each execution is independent to the other ones, but the FCM model must to be the same for ranking.

(a) Defining initial stimuli. We can divide the FCM in layers as a classical neural network (input, hidden and output) like is shown in Figure 2.

![Figure 2: FCM layers examples](image)

The nodes belonging to the input layer ($x^{in}$) are the nodes acti-
vated at the initial time. These are the nodes with states different to zero at the first time. The hidden layer is composed by non-activate nodes \((x^h)\) at the first time. Note that the hidden layers could be empty. Finally, the output layer has the nodes \((x^{out})\) composing the future scenario to analyze. Note that a node could belongs to input and output layer at the same time. It happens when the initial state of a scenario’s node has influence on one of more nodes in the output layer even itself. Furthermore, a scenario is the state of the \(x^{out}\) nodes.

(b) FCM dynamics. At this block the FCM is running iterations up to the stability is reached. The output is the final state of all the nodes. The states of \(x^{out}\) nodes are the only relevant for next stage, because those are the scenario components. The results are the set of \(x^{out}\) nodes’ state, each for scenario to analyze.

3. Ranking scenarios with TOPSIS. A rank of those scenarios is done using TOPSIS. The closer scenario to the positive-ideal scenario is the best solution.

The approach proposed here is a step forward with regard to the classic tools used in scenario-based decision-support. Delphi help to reach experts’ consensus. FCMs have simulation and prediction capabilities. This tool allows managing uncertainty for improving scenarios-based decision-making. In addition, FCMs offer visual models for easier understanding by non-technical decision makers, because FCM can express human explicit and tacit knowledge. Moreover, FCM provide an intuitive, yet precise way of expressing concepts and reasoning about them at their natural level of abstraction. By transforming decision modelling into causal graphs, decision makers with no technical background can understand all of the components in a given situation. In addition, with FCM, it is possible to identify and consider the most relevant factor that seems to affect the expected target variable. The following sections describe the methodological components of our proposal.

3.1. Delphi method

The Delphi method was developed in the Rand Corporation during the 50s (Helmer and Rescher, 1959). It is a well-known method used to reach experts' groups consensus regarding a complex problem (Dalkey & Helmer, 1963). The Delphi methodology application to FCMs offers the possibility of reaching measures about the intensity and sign of the relationship by means of consulting a panel of experts (Bueno & Salmeron, 2008). One of
the main features of the Delphi study is when the experts receive feedback reports, they have the opportunity of changing their initial opinion based on this feedback (Akkermans et al., 2003; Dalkey & Helmer, 1963). At the beginning of each round (but the first one) the experts receive the aggregate results as feedback. The aggregate feedback was done using Augmented FCMs (Kosko, 1996) approach (adding the adjacency matrix of each expert or data source). This was done through anonymous consultations of two rounds. Anonymity is required in the sense that no one knows who else is participating. Managing anonymous data in this way avoids opinion leaders bias (Linstone and Turoff, 2002).

3.2. Fuzzy Cognitive Maps
3.2.1. FCM Fundamentals

Cognitive Maps (Axelrod, 1976) is a signed digraph designed to capture the causal assertions of a person with respect to a certain domain and then use them to analyze the effects of alternatives, e.g. policies or business decisions in respect to achieving certain goals. A Fuzzy Cognitive Map (FCM) is a graphical representation consisting of nodes indicating the most relevant factors of a decisional environment; and links between these nodes representing the relationships between those factors (Kosko, 1986). FCM is a modelling methodology for complex decision systems, which has originated from the combination of fuzzy logic and neural networks. A FCM describes the behaviour of a system in terms of concepts; each concept representing an entity, a state, a variable, or a characteristic of the system (Xirogiannis & Glykas, 2004).

FCMs constitute neurofuzzy systems, which are able to incorporate experts’ knowledge (Kosko, 1986; Lee et al., 2002; Papageorgiou & Groumpos, 2005; Salmeron, 2009). FCM describes a cognitive map model with two characteristics. From an Artificial Intelligence perspective, FCMs are supervised learning neural systems, whereas more and more data is available to model the problem, the system becomes better at adapting itself and reaching a solution (Rodriguez-Repiso et al., 2007).

Firstly, causal relationships between nodes have different intensities, represented with a number from 0 to 1. As we analyze the cognitive maps, the causal value that they establish is the sign plus or minus. However, a FCM substitutes these signs by a fuzzy value between -1 and +1 where the zero value indicates the absence of causality. Secondly, it involves feedback, where the effect of change in a concept node may affect other concept nodes. In addition, one assumes that the decision makers can construct an accurate representation of a decision problem, that there is unlimited time for
making a choice, and that the context is static, as it does not change autonomously or as a consequence of the decision maker’s choices. This also assumes that decision-making is often constrained by a limitation of both external resources, such as time limitations, and human cognitive resources, such as memory capacity. Real-world challenges are usually characterized by a number of components interrelated in many complex ways. They are often dynamic, that is, they evolve with time through a series of interactions among related concepts.

Classical decision-making techniques cannot support this kind of environments. For that reason, this paper proposes a soft computing technique called Fuzzy Cognitive Map (FCM). FCM is an innovative and flexible technique for modelling human knowledge in decision-making process. In addition, FCM provide excellent mechanisms to develop forecasting exercises, specially what-if analysis. This paper applies FCM in ERP risks management.

Cognitive maps (Axelrod, 1976) and, after, Fuzzy Cognitive Maps (Kosko, 1986), have emerged as alternative tools for representing and studying the behaviour of systems and people. Cognitive maps are a collection of nodes linked by arcs or edges. The nodes represent concepts or variables relevant to a given domain. The causal links between these concepts are represented by the edges, which are oriented to show the direction of influence. The other attribute of an edge is its sign, which can be positive (a promoting effect) or negative (an inhibitory effect).

The main goal of building a cognitive map (or FCM) around a problem is to be able to predict the outcome by letting the relevant issues interact with one another. These predictions can be used for finding out whether a decision made by someone is consistent with the entire collection of stated causal assertions.

FCMs were proposed as an extension of cognitive maps. FCM was proposed by Kosko (1986) to describe a cognitive map model with two significant characteristics. The first one, causal relationships between nodes have different intensities. These are represented by fuzzy numbers (a number from 0 to 1). The second one, the system is dynamic, that is, it evolves with time. It involves feedback, where the effect of change in a concept node may affect other concept nodes, which in turn can affect the node initiating the change.

After an inference process, the FCM reaches either one of two states following a number of iterations. It settles down to a fixed pattern of node values, the so-called hidden pattern or fixed-point attractor. Alternatively, it keeps cycling between several fixed states, known as a limit cycle. Using
a continuous transformation function, a third possibility known as a chaotic attractor exists. This occurs when, instead of stabilizing, the FCM continues to produce different results (known as state-vector values) for each cycle. The FCM nodes \( x_i \) would represent such concepts as costs, sales, market selection, investment, or marketing strategy, to name a few (Figure 3). The relationships between nodes are represented by directed edges. An edge linking two nodes models the causal influence of the causal variable on the effect variable (e.g.: the influence of the price to sales). Since FCMs are hybrid methods mixing fuzzy logic (Zadeh, 1965, Bellman and Zadeh, 1970) and neural networks (Kosko, 1992), each cause is measured by its intensity \( w_{ij} \in [0, 1] \), where \( i \) is the pre-synaptic (cause) node and \( j \) the post-synaptic (effect) one.

3.2.2. FCM dynamics

An adjacency matrix \( A \) represents the FCM nodes connectivity. FCMs measure the intensity of the causal relation between two factors and if no
causal relation exists it is denoted by 0 in the adjacency matrix.

\[
A = \begin{pmatrix}
  x_1 & \ldots & x_n \\
  w_{11} & \ldots & w_{1n} \\
  \vdots & \ddots & \vdots \\
  x_n & \ldots & w_{nn}
\end{pmatrix}
\] (1)

FCMs are dynamical systems involving feedback, where the effect of change in a node may affect other nodes, which in turn can affect the node initiating the change. The analysis begins with the design of the initial vector state \(\overrightarrow{X^0}\), which represents the initial value of each variable or concept (node). The initial vector state with \(n\) nodes is denoted as

\[
\overrightarrow{X^0} = (x_1^0, x_2^0, \ldots, x_n^0)
\] (2)

where \(x_i^0\) is the value of the concept \(i = 1\) at instant \(t = 0\).

The new values of the nodes are computed in an iterative vector-matrix multiplication process with an activation function, which is used to map monotonically the node value into a normalized range \([0, 1]\). The sigmoid function is the most used one (Bueno & Salmeron, 2009) when the concept (node) value maps in the range \([0, 1]\). The vector state \(\overrightarrow{X^{t+1}}\) at the instant \(t + 1\) would be

\[
\overrightarrow{X^{t+1}} = f(\overrightarrow{X^t} \cdot A) = f(\overrightarrow{\hat{x}^t}) = (f(\hat{x}_1^t), f(\hat{x}_2^t), \ldots, f(\hat{x}_n^t)) = (x_1^{t+1}, x_2^{t+1}, \ldots, x_n^{t+1})
\] (3)

where is the vector state at the \(t\) instant, \(x_i^t\) is the value of the \(i\) concept at the \(t\) instant, \(f(x)\) is the sigmoid function and \(A\) is the adjacency matrix.

The state is changing along the process.

The component \(i\) of the vector state \(\overrightarrow{X^{t+1}}\) at the instant \(t + 1\) would be

\[
\overrightarrow{x_i^{t+1}} = \frac{1}{1 + e^{-\lambda \cdot \hat{x}_i^t}}
\] (4)

where \(\lambda\) is the constant for function slope (degree of normalization). The value of \(\lambda = 5\) provides a good degree of normalization (Bueno & Salmeron, 2009) in \([0, 1]\).

The FCM inference process finish when the stability is reached. The final
vector state shows the effect of the change in the value of each node in the FCM. After the inference process, the FCM reaches either one of two states following a number of iterations. It settles down to a fixed pattern of node values, the so-called hidden pattern or fixed-point attractor. Alternatively, the state could keep cycling between several fixed states, known as a limit cycle. With a continuous function, a third possibility would be a chaotic attractor. This occurs when, instead of stabilizing, the FCM continues to produce different results (state vector values) for each cycle.

3.3. TOPSIS method
3.3.1. Concept

The Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) is a multicriteria method to detect the best alternative from a finite set of ones (Hwang & Yoon, 1981). The chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The positive ideal solution is composed of all best values attainable from the criteria, whereas the negative ideal solution consists of all worst values attainable from the criteria (Wang & Elhag, 2006).

General TOPSIS process is briefly explained in the next section.

3.3.2. TOPSIS process

Let us define the set of alternatives as \( A = \bigcup_{i=1}^{n} A_i \) and the set of criteria as \( C = \bigcup_{i=1}^{m} C_i \). Furthermore, let us assume a decision matrix, \( D \), be defined as

\[
D = \begin{pmatrix}
A_1 & C_1 & \ldots & C_m \\
\vdots & \vdots & \ddots & \vdots \\
A_n & x_{11} & \ldots & x_{1m} \\
\end{pmatrix}
\]  \hspace{1cm} (5)

where \( D \) is composed of \( n \) alternatives (scenarios in this proposal) and \( m \) attributes (nodes’ values in this proposal); \( x_{ij} \) denotes the value of the \( i \)th alternative with respect to the \( j \)th criterion or attribute.

The procedure of TOPSIS technique can be expressed in the following stages.

**Stage 1.** Determine the normalized decision matrix \( (R = [r_{ij}]) \). The raw decision matrix is normalized for criteria comparability. The normalized value of \( x_{ij}, r_{ij} \), can be obtained by

\[
r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}, \quad j = 1, \ldots, m, \quad i = 1, \ldots, n
\]  \hspace{1cm} (6)
Stage 2. Compute the weighted normalized decision matrix \((V = [v_{ij}])\).
The weighted normalized value of \(r_{ij}\) will be denoted by \(v_{ij}\) and can be computed by

\[
v_{ij} = r_{ij} \cdot w_j
\]

Note that \(w_j\) is the weight of the \(j\)th criterion and \(\sum_{j=1}^{m} w_j = 1\).

Stage 3. Define the positive-ideal and negative-ideal alternatives. The values of the criteria in the positive-ideal alternative correspond to best level. On the other hand, the values of the criteria of the negative-ideal correspond to the worst level.
Denote the positive-ideal alternative, \(A^+\), and the negative-ideal alternative, \(A^-\), as

\[
A^+ = \{ (\max_{i=1}^{n} v_{ij} | j \in I^+) , (\min_{i=1}^{n} v_{ij} | j \in I^-) \} = [v_1^+, v_2^+, \ldots, v_m^+],
\]

and

\[
A^- = \{ (\min_{i=1}^{n} v_{ij} | j \in I^+) , (\max_{i=1}^{n} v_{ij} | j \in I^-) \} = [v_1^-, v_2^-, \ldots, v_m^-],
\]

where \(I^+\) and \(I^-\) are the criteria sets of the benefit and cost type, respectively.

Stage 4. Compute the distance measures with the well-known Euclidean distance for m-dimensional vectors. The separation of each alternative to the positive-ideal alternative, \(d_i^+\), is denoted as

\[
d_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^+)^2}, \quad i = 1, \ldots, n
\]

In addition, the distance to the negative-ideal alternative, \(d_i^-\), is denoted as

\[
d_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)^2}, \quad i = 1, \ldots, n
\]

Stage 5. Compute the relative closeness to the ideal alternative and rank the preference order. The relative closeness of the \(i\)th alternative, \(C_i^+\), with respect to the ideal alternative is defined as

\[
C_i^+ = \frac{d_i^-}{d_i^+ + d_i^-}, \quad i = 1, \ldots, n
\]
Since $d^+_i \geq 0$ and $d^-_i \geq 0$, then $C^+_i \in [0, 1]$.
A set of alternatives then can be preference ranked according to the
descending order of $C^+_i$; then larger $C^+_i$ means better alternative.

For illustrating our methodological proposal the next section exposes a num-
merical example.

4. A numerical example

For illustrating our proposal a numerical example have been desgined.
Figure 4 shows a FCM model with twelve nodes and twenty-six edges (in-
cluding recursive ones).

![Figure 4: FCM experiment](image)

The FCM layers is defined with all the nodes within input and output layers,
as Figure 2d. Furthremore, five initial stimuli have been defined as follows
(Table 1). Each of initial stimuli vector is used for generating FCM-based
scenarios.

Next stage is the FCM dynamics. The results are shown in Table 2. In ad-
dition, the final scenarios are represented graphically at Figure 5. Note that
Table 1: Initial stimuli

<table>
<thead>
<tr>
<th>Nodes</th>
<th>Initial stimuli ($I_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1$</td>
<td>1.0 1.0 0 1.0 1.0</td>
</tr>
<tr>
<td>$x_2$</td>
<td>1.0 1.0 0 0 1.0</td>
</tr>
<tr>
<td>$x_3$</td>
<td>1.0 0 0 0 1.0</td>
</tr>
<tr>
<td>$x_4$</td>
<td>1.0 0 0 1.0 1.0</td>
</tr>
<tr>
<td>$x_5$</td>
<td>0 1.0 0 0 1.0</td>
</tr>
<tr>
<td>$x_6$</td>
<td>0 1.0 0 1.0 1.0</td>
</tr>
<tr>
<td>$x_7$</td>
<td>0 0 1.0 0 1.0</td>
</tr>
<tr>
<td>$x_8$</td>
<td>0 0 1.0 0 1.0</td>
</tr>
<tr>
<td>$x_9$</td>
<td>0 0 1.0 0 1.0</td>
</tr>
<tr>
<td>$x_{10}$</td>
<td>0 0 1.0 0 1.0</td>
</tr>
<tr>
<td>$x_{11}$</td>
<td>0 0 1.0 0 1.0</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td>0 0 1.0 0 1.0</td>
</tr>
</tbody>
</table>

Table 2: FCM dynamics results

<table>
<thead>
<tr>
<th>Nodes</th>
<th>Scenarios ($S_i$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_1$</td>
<td>$S_1$ 0.9811 0.8962 0.9767 0.9669 0.9312</td>
</tr>
<tr>
<td>$x_2$</td>
<td>$S_2$ 0.9042 0.8352 -0.8129 0.8352 -0.7710</td>
</tr>
<tr>
<td>$x_3$</td>
<td>$S_3$ 0.8195 0.0 0.0 0.0 0.8195</td>
</tr>
<tr>
<td>$x_4$</td>
<td>$S_4$ 0.8106 0.8966 0.8891 0.8966 0.6689</td>
</tr>
<tr>
<td>$x_5$</td>
<td>$S_5$ 0.0 0.9527 0.0 0.0 0.9527</td>
</tr>
<tr>
<td>$x_6$</td>
<td>$S_6$ 0.9612 0.9543 0.9905 0.9543 0.9845</td>
</tr>
<tr>
<td>$x_7$</td>
<td>$S_7$ 0.6915 -0.3040 0.7262 -0.3040 0.8328</td>
</tr>
<tr>
<td>$x_8$</td>
<td>$S_8$ 0.7621 0.4904 0.7789 0.4905 0.8248</td>
</tr>
<tr>
<td>$x_9$</td>
<td>$S_9$ 0.8705 0.7244 0.9918 0.7244 0.9927</td>
</tr>
<tr>
<td>$x_{10}$</td>
<td>$S_{10}$ 0.0 0.0 0.9527 0.0 0.9527</td>
</tr>
<tr>
<td>$x_{11}$</td>
<td>$S_{11}$ 0.0 0.0 0.9527 0.0 0.9527</td>
</tr>
<tr>
<td>$x_{12}$</td>
<td>$S_{12}$ 0.0 0.0 0.9527 0.0 0.9527</td>
</tr>
</tbody>
</table>
the figure suggests the fifth scenario as the best one, but there is not more information about the preference between the different scenarios. After FCM dynamics, the next stage is to rank scenarios with TOPSIS. We assume that all the nodes are benefits (higher scores are better). According to this, the positive-ideal scenario (PIS) is composed by the higher scores of each node and the negative-ideal one (NIS) is composed by the lower scores of each node.

After TOPSIS algorithm, the results are detailed at Table 3. Finally the simulated scenarios are ranked as $S_5 \succ S_3 \succ S_1 \succ S_2 \succ S_4$.

5. Conclusions

Scenarios describe events and situations that would occurred in the future real-world. The originality of the proposed approach with respect to
other ones is that it aims to use the scenarios’ built, assessment and ranking as a whole. Traditional approaches consider the future impact of each present entity in isolation. This assumption is a simplification of a more complex reality, in which different entities interact with each other. The model that the authors propose allows decision and policy makers to measure the impact of a entity interactions. The methodology proposed is a step forward with regard to the classic tools used in scenarios based scenarios’ decision-support, mixing Delphi method, soft computing (Fuzzy Cognitive Maps) and multicriteria (TOPSIS) techniques. In addition, the proposed methodology was validate with a numerical example. The results confirm that it is a worthy proposal.

Acknowledgements

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References


<table>
<thead>
<tr>
<th>$S_i$</th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
<th>$S_4$</th>
<th>$S_5$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_i^+$</td>
<td>1.3603</td>
<td>1.6482</td>
<td>1.2441</td>
<td>1.7460</td>
<td>0.8284</td>
</tr>
<tr>
<td>$d_i^-$</td>
<td>1.3224</td>
<td>0.9987</td>
<td>1.4486</td>
<td>0.8155</td>
<td>1.7458</td>
</tr>
<tr>
<td>$C_i^+$</td>
<td>0.4929</td>
<td>0.3773</td>
<td>0.5380</td>
<td>0.3184</td>
<td>0.6782</td>
</tr>
<tr>
<td>Rank</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>5</td>
<td>1</td>
</tr>
</tbody>
</table>


