Fuzzy Cognitive Map-based selection of TRIZ trends for eco-innovation of ceramic industry products

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Abstract

Several studies have been developed implementing TRIZ (Russian acronym of Theory of Inventive Problem Solving) for eco-innovative design tasks, establishing a link between eco-efficiency and the Inventive Principles and the Contradiction Matrix. However, very few works have linked TRIZ evolution trends and eco-design.

This paper presents an innovative methodology to help designers to predict technological evolutions for more environmentally friendly products. The main novelty of our proposal is the use of Fuzzy Cognitive Maps (FCMs) to analyse, identify and quantify the relationship between the strategies of the Eco-Design Strategy Wheel and the TRIZ evolution trends. This methodology has been applied to the Spanish ceramic industry using data from a survey to their business leaders.

Results show evolution trends of ceramic products focused on Material, Design Process and Geometry are more environmentally friendly. In contrast, evolution trends included in the category Aesthetics are harmful for the environment. The methodology proposed can be applied for greener product design and technological forecasting in other industries.

Keywords: Eco-design, Fuzzy Cognitive Maps, Ceramic products design, Design for Environment, Technological forecasting, Eco-innovation

1. Introduction

Technological innovation requires some prediction of where technology will evolve towards. Here the concept of evolution trends appear, which comes from the idea that all technical systems follow the same patterns of evolution, thus making it possible to anticipate the technological changes.

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Nonetheless, these new innovation horizons have been transformed by society due to the demand of more ecological products. So, the previous technological trends in which innovation was based could be affected by this objective change, since the demand for greener products has increased in the market (Bevilacqua et al., 2007; Moreno et al., 2011) and, consequently, enterprises are obliged to design, manufacture, and deliver them in a more sustainable way (Gmelin and Seuring, 2014).

Besides the well-known and widely used trend extrapolation, Analytic Hierarchy Process (AHP) and Delphi methods, there exists a multitude of other technology forecasting methods; one of them is TRIZ trends. TRIZ (Altshuller, 1984) is the acronym of Theory of Inventive Problem Solving. This theory is composed of a set of methods and tools to generate innovative ideas and solutions (Abdalla, 2006). Some of these more popular TRIZ tools are the contradiction matrix, inventive principles, ideality, system operator, substance-field (SU-Field), and the evolution trends (Altshuller & Shulyak, 1997; Belski, 2007; Mann, 2005; Tate & Domb, 1997).

TRIZ evolution trends, as a technology forecasting method, encompasses analysing and categorizing patents in known trend phases, and depicting results on an evolutionary potential radar plot. TRIZ trend analysis allows the identifying of the evolutionary status of technologies to seek directions for further improvements of a given product or product family.

In eco-design, several lines of research have compared eco-rules and TRIZ problem solving tools (especially inventive principles and the contradiction matrix). Because of the capability of solving conflict problems, implementing TRIZ for eco-innovative design tasks have been proposed in the literature, establishing a link between eco-efficiency and the inventive principles and the contradiction matrix (Chang & Chen, 2004; Chen & Liu, 2003; Jones & Harrison, 2000; Justel et al., 2006; Strasser & Wimmer, 2003).

However, very few works have linked TRIZ evolution trends and eco-design, such as Russo et al. (2011), who propose a step-by-step TRIZ based eco-design procedure for reorganizing ideality, SU-field and evolution trends in the form of practical eco-guidelines for product innovation; Eco-MAL'IN (Samet et al., 2010), a method for integrating constraints for sustainable development in the phases of research of innovative concepts with different solving tools derived from TRIZ theory; Yang & Chen (2011) combine the innovative incremental design achieved with Case-based Reasoning (CBR) and TRIZ tools included the evolution trends; or D'Anna & Cascini (2011) who propose the SUSTAINability map, based on two key items of TRIZ: the existence of evolution trends and the system operator to identify scenarios to achieve sustainability.

In a previous work (Chulvi & Vidal, 2011), TRIZ evolution trends and the eco-design strategies were compared based on the authors' own criteria. A first conclusion was obtained: in several cases the improvement in terms of TRIZ evolution causes the ecological demands to improve too, but in other cases they make the ecological aspects worsen. This preliminary result is taken up again in this paper, improving the environmental assessment of TRIZ evolution trends using advanced technological forecasting techniques.

Traditional techniques used in technological forecasting like Delphi or AHP prioritize alternatives in decision-making and 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. To avoid this, in this paper, a Fuzzy Cognitive Map (FCM) is used to analyse the interaction between evolution trends and strategies of eco-design in different scenarios.

Our proposal goes beyond the eco-rules definition or the prioritization of eco-friendly guidelines with traditional techniques used in technological forecasting. Fuzzy cognitive maps assess TRIZ evolution trends for eco-design innovation, allowing prioritizing and further decision making based on scenario analysis.

Currently, the European Union is promoting and financing eco-innovation projects, mainly aimed at small and medium enterprises, rewarding those companies that consider the environment as an important variable in their processes of innovation, for example by reducing the consumption of materials and energy (Segarra-Ona & Peiro-Signes, 2014). We believe that our proposal can be useful to optimize these projects, since due to the current economic depression it is now more necessary than ever to make the best possible use of public funds.

This paper presents a new methodology to assess evolution trends for eco-design innovation based on FCM. The rest of this paper is organized as follows. Section 2 describes TRIZ evolution trends and strategies of eco-design. In section 3, the core, FCM, is described. In section 4 Experimental analysis, the new methodology is applied to the Spanish ceramic industry using data from a survey. In section 5 Discussion, contributions of the model and results are highlighted, discussed and compared with traditional methods like Delphi and AHP. Finally, the conclusions are presented.

2. Theoretical background

2.1. Evolution trends

Altshuller (1984) focused part of his research on discovering technological trends of evolution. At the beginning, these were discovered considering different products taken from very different situations. Some recurring changes in their evolution were highlighted and named patterns. A final synthesis of these patterns, considered altogether and independently of the specific situations generated the evolution trends.

The eight original trends are (Altshuller & Shulyak, 1997; Zanni-Merk et al., 2009):

1. Biological evolution
2. Increasing ideality
3. Evolution toward dynamization and controllability
4. Complexity-simplicity
5. Evolution with matching and mismatching elements
6. Non-uniform development
7. Evolution toward micro-level and the use of field
8. Decrease human involvement.

These eight original trends have been used in the proposal for eco-design rules by D'Anna & Cascini (2011); Russo et al. (2011); Yang & Chen (2011).

Some software packages implementing the TRIZ theory consider and exploit these trends and thanks to them many researchers have been able to utilize TRIZ trends of evolution and customize them in order to make them applicable in several technological domains (Filippi & Barattin, 2014).

There is a certain amount of disagreement among some researchers when it comes to providing an exact definition of these evolution trends, since the original eight lines of evolution have been contracted or extended in a number of ways (Cavallucci & Rousselot, 2011; Hipple, 2005; Verhaegen et al., 2009), e.g. Rantanen & Domb (2002) developed six evolution trends; in the meantime Mann (2003) organized the evolution of a technological system into a comprehensive list of 31 trends, which is used in this paper.

2.2. Eco-design Strategies

LiDS Wheel (Brezet & Van Hemel, 1997) was chosen between other methods of eco-design rules (e.g. seven axes of eco-efficiency defined by WBCSD (1999); Eco-compass by Fussler & James (1996) by its comprehensibility and capability to plot the environmental product profile.

The LiDS (Life Cycle Design Strategy) Wheel or EcoDesign Strategy Wheel is a tool to select and communicate the eco-design strategies. This tool presents eight main levels:

1. Selection of low-impact materials

2. Reduction of material usage
3. Optimization of production techniques
4. Optimization of distribution system
5. Reduction of impact during use
6. Optimization of initial lifetime
7. Optimization of end-of-life system.
8. New concept development.

The above main levels include different environmental strategies in secondary level. For example, for *1. Selection of low-impact materials*, its secondary level includes the next environmental strategies: cleaner materials, renewable materials, lower energy content materials, recycled materials and recyclable materials.

2.3. FCM Fundamentals

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 (Papageorgiou & Salmeron, 2013, 2014; Salmeron & Gutierrez, 2012; Xirogiannis & Glykas, 2004).

The main domains where FCMs have been applied are medicine, business, information technology, industrial processes and control, engineering, environment, and agriculture. For a thorough review of the FCM research in recent years see Papageorgiou & Salmeron (2013) .

FCMs constitute neuro-fuzzy systems, which are able to incorporate experts' knowledge (Kosko, 1986; Lee et al., 2002; Papageorgiou & Groumpos, 2005; Papageorgiou & Froelich, 2012b; Salmeron, 2009; Salmeron et al., 2012). 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 (Kim & Lee, 1998; Papageorgiou & Salmeron, 2014).

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. 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 these kinds 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 the decision-making process. Furthermore, FCM provide excellent mechanisms to develop forecasting exercises, especially what-if analysis. This paper applies FCM to improve the eco-design of ceramic products.

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 discovering whether a decision made by someone is consistent with the entire collection of stated causal assertions (Bueno & Salmeron, 2008; Jetter & Schweinfort, 2010; Salmeron et al., 2012). In this sense, Cheah et al. (2011) proposed a methodology and application (FCM Constructor) to systematically acquire design knowledge from domain experts, and to construct a corresponding Bayesian Belief Networks. Despite of the many advantages of using Bayesian Belief Networks, it is less user-friendly and less flexible compared to FCM.

Fuzzy Cognitive Maps (Kosko, 1986) emerged as an extension of cognitive maps (Axelrod, 1976) for representing and studying the behaviour of systems and people. FCMs 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 FCM nodes (c_i) would represent such concepts such as costs, sales, market selection, investment, or marketing strategy, among others. 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 (Papageorgiou & Groumpos, 2005). Since FCMs are hybrid methods mixing fuzzy logic and neural networks (Kosko, 1996; Papageorgiou & Froelich, 2012a; Papageorgiou & Groumpos, 2006; Papageorgiou & Salmeron, 2013; Salmeron, 2012), 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.

2.4. 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.

$$\mathbf{A} = \begin{pmatrix} w_{11} & \dots & w_{1n} \\ \vdots & \ddots & \vdots \\ w_{n1} & \dots & w_{nn} \end{pmatrix} \tag{1}$$

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 ($\overrightarrow{C}(0)$), which represents the initial value of each variable or concept (node) (Salmeron et al., 2012). The initial vector state with n nodes is denoted as

$$\overrightarrow{C}(0) = (c_1(0) \quad c_2(0) \quad \dots \quad c_n(0)) \tag{2}$$

where $c_1(0)$ 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 $\overrightarrow{C}(t + 1)$ at the instant $t + 1$ would be

$$\begin{aligned} \overrightarrow{C}(t+1) &= f\left(\overrightarrow{C}(t) \cdot A\right) \\ &= \Big(c_1(t+1) \quad c_2(t+1) \quad \dots \quad c_n(t+1)\Big) \end{aligned} \tag{3}$$

where $\overrightarrow{C}(t)$ is the vector state at the t instant, $c_1(t)$ is the value of the i concept at the t instant, $f(\cdot)$ is the sigmoid function and A the adjacency matrix. The state changes during the process.

The component i of the vector state $\overrightarrow{C}(t)$ at the instant t would be

$$c_i(t) = \frac{1}{1 + e^{-\lambda \cdot \hat{c}_i(t-1)}} \tag{4}$$

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

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 (Papageorgiou & Salmeron, 2013; Salmeron, 2009). It happens when the error between an updated vector state $c(t)$ and the previous one $c(t-1)$ are below a tolerance level (ϵ).

$$error = |c(t) - c(t-1)| < \epsilon \tag{5}$$

where usually $\epsilon = 0.0001$

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 (Papageorgiou & Salmeron, 2013).

3. Experimental analysis

In order to investigate and demonstrate the performance of the proposed FCM model an industrial application, concerning a ceramic product design, has been considered.

3.1. Problem description

The survey has been divided into three questionnaires, product, use and manufacturing. Only the first one has been considered in this paper.

The inclusion of the 31 lines of evolution would have produced an excessively lengthy questionnaire. Typically in studies using evolution trends, only a certain number of most frequently identified trends is taken into account. This allows to focus on the most important trends and to not encumber the interpretation using radar plots. To reduce the amount of questions, the authors performed a first screening of evolutionary trends based on our opinion and experience, in a similar way as in Chulvi & Vidal (2011), although applied only to ceramic products. Evolution trends with no relation or weakly possible relations were discarded. As a result, the initial list of 31 evolution trends proposed by Mann (2003) has been reduced to 17, including only the trends that potentially could improve or worsen the eco-design

These 17 trends are the initial concepts in the FCM and to facilitate the analysis of scenarios they are classified in five categories (Table 1: material, geometry, aesthetics, functionality and design process. A brief explanation and drawings of each evolution trend was included in the questionnaire.

We consider a ceramic product design problem. It consists of seventeen concepts (c_1 to c_{17}) with influence over nine output concepts (c_{18} to c_{26}), as depicted in Fig. 1. The adjacency matrix is shown at eq. 6. Note that columns 1-17 are 0.0. For the sake of simplicity, the null rows and columns are summarized at eq. 6.

$$A = \begin{pmatrix}
.00 & \dots & .00 & .12 & .06 & .15 & .42 & .18 & .12 & .03 & .09 & .45 \\
.00 & \dots & .00 & -.06 & .09 & .30 & -.09 & -.21 & -.27 & .63 & .36 & .69 \\
.00 & \dots & .00 & .15 & .36 & .06 & .12 & .09 & .09 & .85 & .21 & -.15 \\
.00 & \dots & .00 & .09 & .06 & .12 & .33 & .18 & .33 & .27 & .12 & .18 \\
.00 & \dots & .00 & .15 & .42 & .15 & .12 & .06 & .18 & .76 & .03 & -.33 \\
.00 & \dots & .00 & .09 & -.03 & .09 & -.06 & .06 & .03 & .00 & .00 & .12 \\
.00 & \dots & .00 & .09 & .39 & .03 & .03 & .06 & .03 & .76 & .70 & -.27 \\
.00 & \dots & .00 & .09 & -.33 & .00 & -.21 & -.18 & .00 & -.15 & -.27 & .12 \\
.00 & \dots & .00 & .03 & -.06 & .03 & .03 & .00 & -.03 & -.03 & .00 & -.03 \\
.00 & \dots & .00 & -.36 & -.09 & -.03 & -.15 & -.09 & -.24 & .00 & .00 & -.03 \\
.00 & \dots & .00 & -.15 & .00 & -.33 & -.06 & -.03 & -.09 & -.12 & .03 & -.09 \\
.00 & \dots & .00 & .06 & .18 & -.03 & .33 & .12 & .12 & -.12 & -.09 & .03 \\
.00 & \dots & .00 & .00 & .03 & .12 & .12 & .00 & -.24 & -.03 & -.12 & .06 \\
.00 & \dots & .00 & .00 & -.15 & .03 & -.21 & -.06 & .00 & .06 & -.03 & .24 \\
.00 & \dots & .00 & .12 & .03 & .09 & -.03 & -.03 & -.03 & .00 & .09 & .18 \\
.00 & \dots & .00 & .18 & .00 & .09 & .18 & .06 & .03 & .06 & .03 & .48 \\
.00 & \dots & .00 & .27 & .21 & .18 & -.03 & .09 & .12 & .18 & .15 & .54 \\
.00 & \dots & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 \\
\dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\
.00 & \dots & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00 & .00
\end{pmatrix} \tag{6}$$

The eco-design strategies on product are the output concepts. They have been selected from the second level of LiDS Wheel (Brezet & Van Hemel, 1997), corresponding to four categories in the first level of LiDS Wheel (Table 2).

The questionnaire asked if each evolution trend (input parameter) improves or worsens each eco-design strategy (output concept). Initially a Likert scale of 7 points was used as follows

3 Strongly improve

2 Improve

Table 1: Input concepts from evolution trends

Input category	Code	Evolution trend
Material	c_1	Smart materials
	c_2	Web and fibres
	c_3	Decreasing density
Geometry	c_4	Object segmentation
	c_5	Space segmentation
	c_6	Surface segmentation
	c_7	Macro to nano scale
	c_8	Increasing asymmetry
Aesthetics	c_9	Increasing use of senses
	c_{10}	Increasing use of colours
	c_{11}	Increasing transparency
Functionality	c_{12}	Mono-bi-poly-Similar Objects
	c_{13}	Mono-bi-poly-Various objects
	c_{14}	Mono-bi-poly-Increasing differences
Design process	c_{15}	Boundary breakdown
	c_{16}	Design point
	c_{17}	Design methodology

1 Slightly improve

0 Neither improve, nor worsen

-1 Slightly worsen

-2 Worsen

-3 Strongly worsen

This Likert scale was used in the questionnaire with the experts. During the data pre-processing phase, this scale was normalized in the range $[-1, +1]$. The opposite values -1 and $+1$ refer to the environmental efficiency, being -1 totally environmentally inefficient and $+1$ totally environmentally efficient. Qualitatively, environmental effectiveness relates to environmental efficiency and resources. The more innovations pursued presumably means that more resources will be needed to achieve them.

3.2. FCM static analysis

Considering the nine eco-design strategies are equipotential, the mean of the normalised values of evolution trends over all eco-design strategies

Table 2: Output concepts from eco-design strategies

Output category	First level in LiDS Wheel	Code	Output concepts from Second level LiDS Wheel
O_1	(1) Selection of low-impact materials	c_{18} c_{19} c_{20}	Cleaner materials Lower energy content materials Recycled materials
O_2	(2) Reduction of material usage	c_{24} c_{25}	Reduction in weight Reduction in (transport) volume
O_3	(6) Optimisation of initial lifetime	c_{26}	Reliability and durability
O_4	(7) Optimisation of end-of-life system	c_{21} c_{22} c_{23}	Reuse of product Remanufacturing Recyclable materials

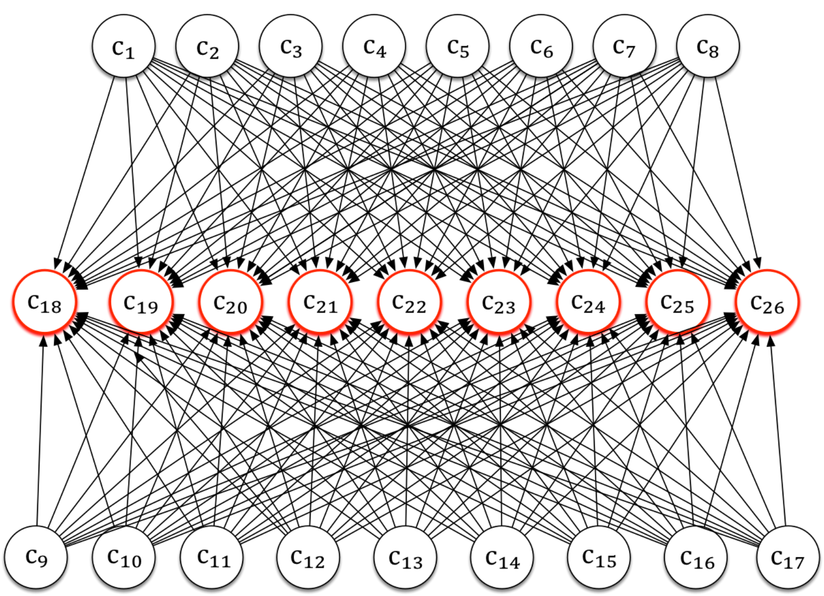

Figure 1: FCM model for ceramic product design

Table 3: Statistics of the evolution trends over eco-design strategies

	Mean c_i	O_1	O_2	O_3	O_4	Mean O_f
c_1	0.18	0.11	0.06	0.45	0.24	0.215
c_2	0.16	0.11	0.50	0.69	-0.19	0.276
c_3	0.20	0.19	0.53	-0.15	0.10	0.168
c_4	0.19	0.09	0.20	0.18	0.28	0.186
c_5	0.17	0.24	0.40	-0.33	0.12	0.106
c_6	0.03	0.05	0.00	0.12	0.01	0.045
c_7	0.20	0.17	0.73	-0.27	0.04	0.168
c_8	-0.10	-0.08	-0.21	0.12	-0.13	-0.075
c_9	-0.01	0.00	-0.02	-0.03	0.00	-0.011
c_{10}	-0.11	-0.16	0.00	-0.03	-0.16	-0.088
c_{11}	-0.09	-0.16	-0.05	-0.09	-0.06	-0.089
c_{12}	0.07	0.07	-0.11	0.03	0.19	0.046
c_{13}	-0.01	0.05	-0.08	0.06	-0.04	-0.001
c_{14}	-0.01	-0.04	0.02	0.24	-0.09	0.031
c_{15}	0.05	0.08	0.05	0.18	-0.03	0.069
c_{16}	0.12	0.09	0.05	0.48	0.09	0.176
c_{17}	0.19	0.22	0.17	0.54	0.06	0.246

(Mean c_i) are in Table 3. Columns O_1 to O_4 are the mean of the evolution trends for each output category according to Table 1, and the last column is the mean of the four output categories.

The individual results of the evolution trends range from slightly worsen to slightly improve eco-design strategies as a whole. The concepts c_{10} (increasing use of colours), and c_3 (decreasing density) are the worst and the best environmental friendly, respectively.

The lowest result is for the pair $c_{10} - c_{18}$, this means that the evolution trend Increasing use of colours is supposed to strongly impair the environmental strategy Cleaner materials. It should be mentioned that many of the pigments used in ceramic colours are highly toxic. Conversely, the highest result is for the pair $c_3 - c_{24}$, Decreasing density improves Reduction in weights.

3.3. FCM dynamic analysis

Tables 4 and 5 show seven experiments (scenarios), where $c_i(0)_k$ is the initial state of the node i of the k scenario and $c_i(t)_k$ is the steady (final) state of the former node and scenario. Figures 2 - 8 show the FCM dynamics of the scenarios.

Table 4: Experiments (Scenarios 1-4)

Node	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
c_i	$c_i(0)_1$	$c_i(t)_1$	$c_i(0)_2$	$c_i(t)_2$	$c_i(0)_3$	$c_i(t)_3$	$c_i(0)_4$	$c_i(t)_4$
c_1	1	0.0250	1	0.0271	0	0	0	0
c_2	1	0.0250	1	0.0271	0	0	0	0
c_3	1	0.0250	1	0.0271	0	0	0	0
c_4	1	0.0250	0	0	1	0.0269	0	0
c_5	1	0.0250	0	0	1	0.0269	0	0
c_6	1	0.0250	0	0	1	0.0269	0	0
c_7	1	0.0250	0	0	1	0.0269	0	0
c_8	1	0.0250	0	0	1	0.0269	0	0
c_9	1	0.0250	0	0	0	0	1	0.0296
c_{10}	1	0.0250	0	0	0	0	1	0.0296
c_{11}	1	0.0250	0	0	0	0	1	0.0296
c_{12}	1	0.0250	0	0	0	0	0	0
c_{13}	1	0.0250	0	0	0	0	0	0
c_{14}	1	0.0250	0	0	0	0	0	0
c_{15}	1	0.0250	0	0	0	0	0	0
c_{16}	1	0.0250	0	0	0	0	0	0
c_{17}	1	0.0250	0	0	0	0	0	0
c_{18}	0	0.5651	0	0.3626	0	0.4752	0	-0.4403
c_{19}	0	0.5923	0	0.4764	0	0.4752	0	-0.3352
c_{20}	0	0.5746	0	0.4764	0	0.4381	0	-0.4288
c_{21}	0	0.5392	0	0.4588	0	0.3616	0	-0.3551
c_{22}	0	0.3955	0	0.2428	0	0.3444	0	-0.3122
c_{23}	0	0.3179	0	-0.2428	0	0.4912	0	-0.4403
c_{24}	0	0.7605	0	0.6472	0	0.6589	0	-0.3352
c_{25}	0	0.6233	0	0.5143	0	0.5060	0	0.1994
c_{26}	0	0.6990	0	0.5778	0	-0.3444	0	-0.3352

Table 5: Experiments (Scenarios 5-7)

Node	Scenario 5		Scenario 6		Scenario 7	
c_i	$c_i(0)_5$	$c_i(t)_5$	$c_i(0)_6$	$c_i(t)_6$	$c_i(0)_7$	$c_i(t)_7$
c_1	0	0	0	0	0	0
c_2	0	0	0	0	0	0
c_3	0	0	0	0	1	0.0297
c_4	0	0	0	0	0	0
c_5	0	0	0	0	0	0
c_6	0	0	0	0	0	0
c_7	0	0	0	0	0	0
c_8	0	0	0	0	0	0
c_9	0	0	0	0	0	0
c_{10}	0	0	0	0	0	0
c_{11}	0	0	0	0	0	0
c_{12}	1	0.0309	0	0	0	0
c_{13}	1	0.0309	0	0	0	0
c_{14}	1	0.0309	0	0	0	0
c_{15}	0	0	1	0.0281	0	0
c_{16}	0	0	1	0.0281	0	0
c_{17}	0	0	1	0.0281	0	0
c_{18}	0	0.2534	0	0.4980	0	0.3357
c_{19}	0	0.2534	0	0.3826	0	0.4409
c_{20}	0	0.3167	0	0.4337	0	0.2502
c_{21}	0	0.3939	0	0.3073	0	0.3127
c_{22}	0	0.2534	0	0.3073	0	0.2852
c_{23}	0	-0.3167	0	0.3073	0	0.2852
c_{24}	0	-0.2888	0	0.3826	0	0.5661
c_{25}	0	-0.3600	0	0.3969	0	0.3733
c_{26}	0	0.4346	0	0.6158	0	-0.3357

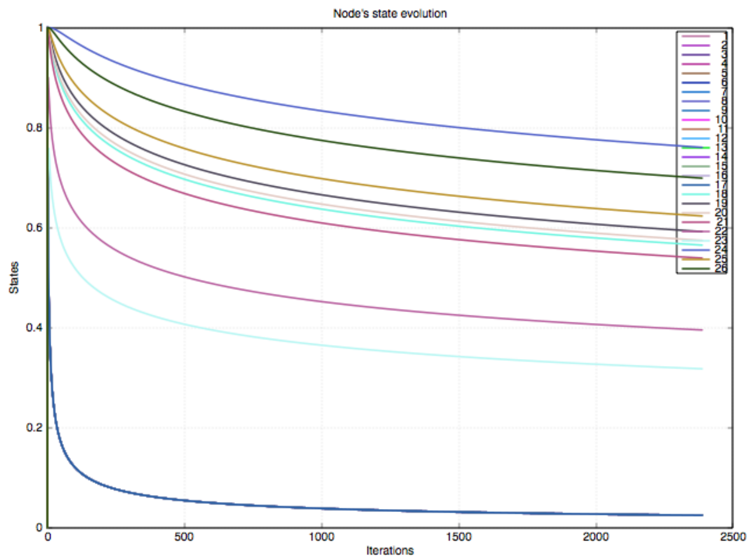

Figure 2: FCM dynamics (Scenario 1)

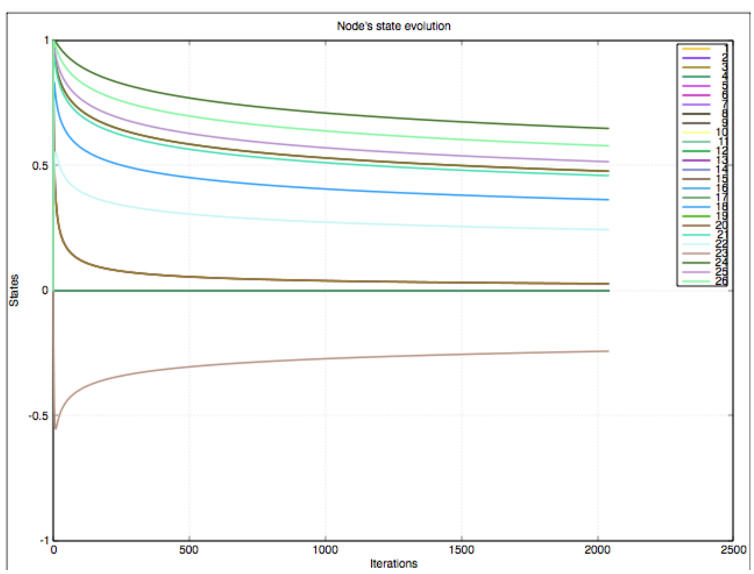

Figure 3: FCM dynamics (Scenario 2)

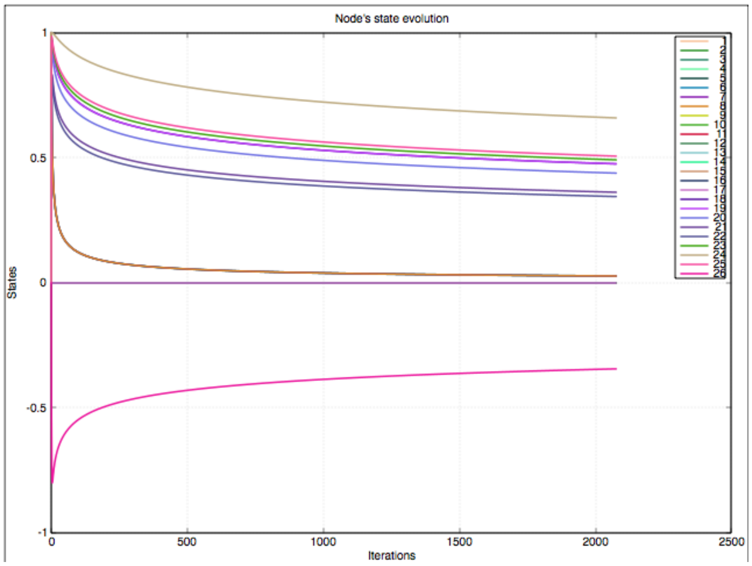

Figure 4: FCM dynamics (Scenario 3)

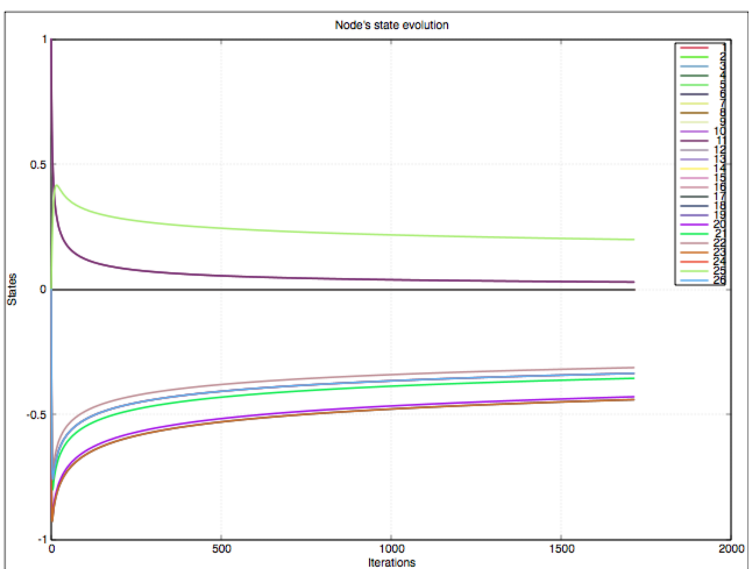

Figure 5: FCM dynamics (Scenario 4)

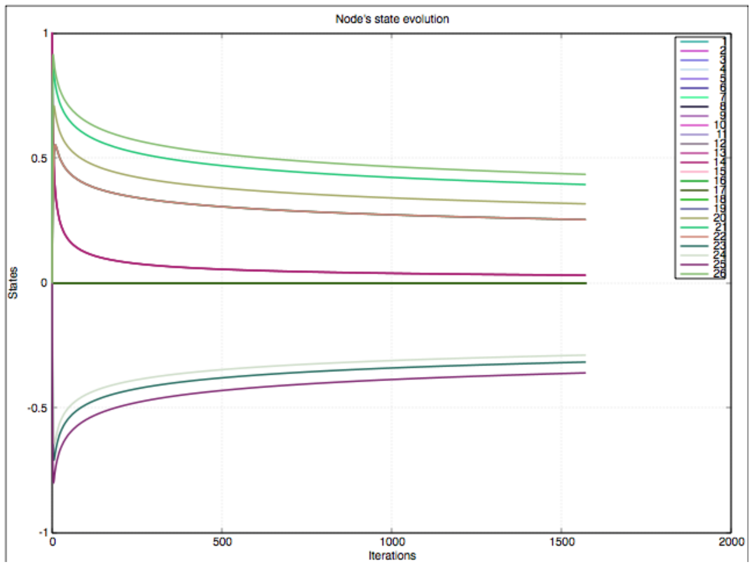

Figure 6: FCM dynamics (Scenario 5)

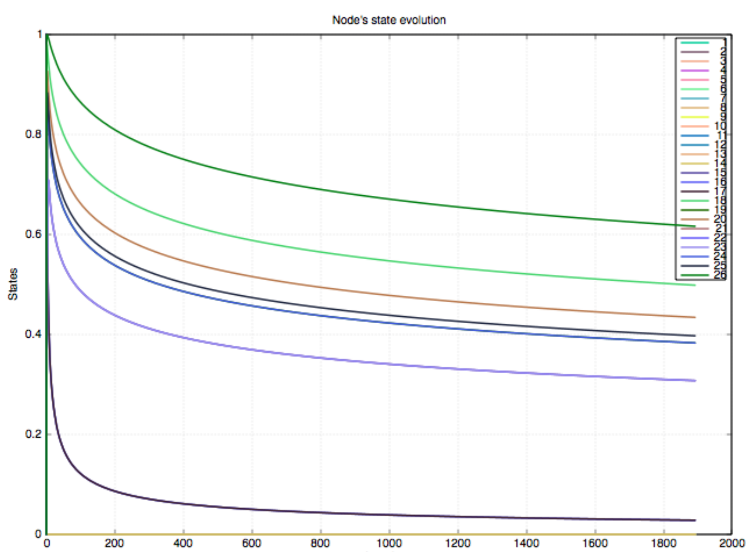

Figure 7: FCM dynamics (Scenario 6)

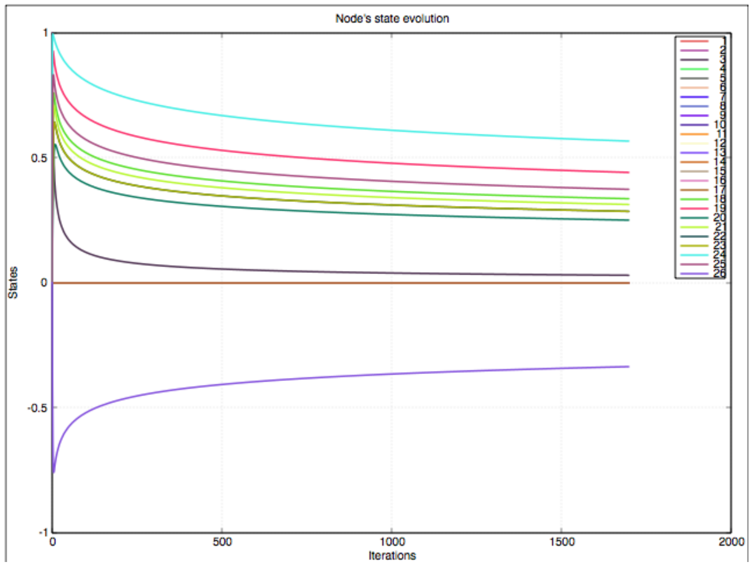

Figure 8: FCM dynamics (Scenario 7)

Table 6: Results aggregated in output categories

	S1	S2	S3	S4	S5	S6	S7
O_1	0.577	0.438	0.463	−0.401	0.275	0.438	0.342
O_2	0.692	0.581	0.582	−0.068	−0.324	0.390	0.470
O_3	0.699	0.578	−0.344	−0.335	0.435	0.616	−0.336
O_4	0.418	0.153	0.399	−0.369	0.110	0.307	0.294
Mean	0.596	0.437	0.275	−0.293	0.124	0.438	0.193

The results of the output concepts were equipotentially aggregated in the four output categories (Table 6). The overall mean was calculated supposing all output categories were equally weighted.

The activation of all concepts in Scenario 1 improves the four output categories. This scenario achieves the better results, but considering the greater effort required, the environmental effectiveness would be low.

Although its environmental efficiency is lower, scenario 7 has better effectiveness, which includes only the activation of the concept with better total environmental performance.

This initial stimulus improves three of the four output categories, only the output concept c_{26} (reliability and durability) is reduced. It should be noted that a decrease in the lifetime of the product does not always mean a global environmental deterioration, for example, reducing the thickness of plastic T-shirt bags used in supermarkets has the positive consequence that resource consumption is reduced, and in principle as a negative consequence its duration is decreased. But if you consider that this kind of bag usually has only one or two uses (if used for waste disposal), reducing the thickness continues to ensure its functionality while reducing resource consumption.

The environmental efficiency of scenarios 1 and 7 are shown in the radar chart (Fig. 9). Each axis corresponds to a label whose scale varies from -1 to $+1$. It has to be noted that the opposite values -1 and +1 refer to the extremes of environmental efficiency, being negative values inefficient environmentally and positive values being efficient environmentally. The value -1 is located in the centre of the graph and the value $+1$ at the end. For each scenario, the values for each axis are joined forming a polygon, the outermost vertices indicate better environmental performance.

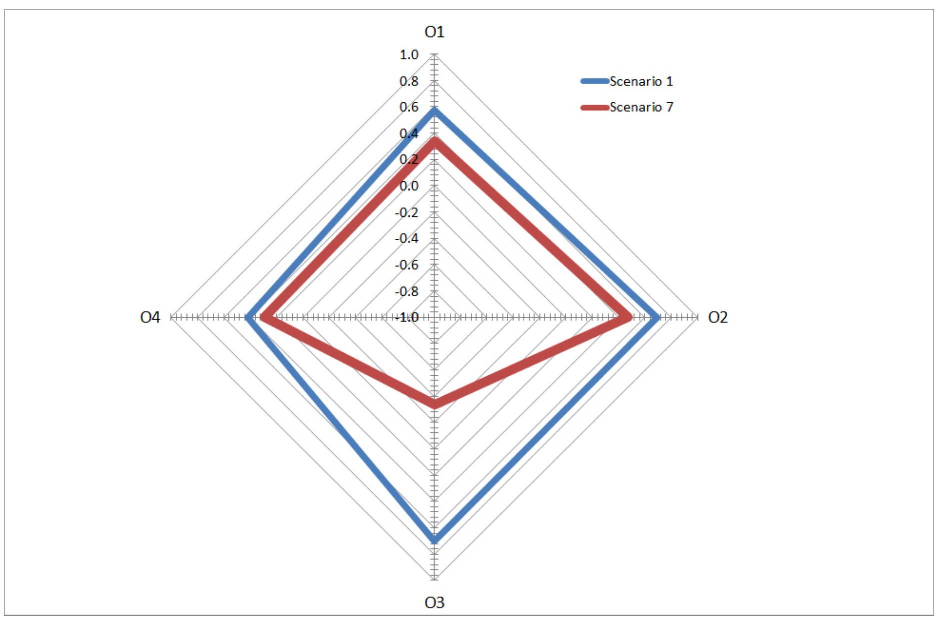

Figure 9: Radar chart for scenario 1 and 7

Two input categories, Material (initial stimulus I2) and Design Process (initial stimulus I6) improve the four output categories. In addition, all output concepts are improved in scenario 6, and in scenario 2, only the concept c_{23} (recyclable materials) worsens because smart materials, and composite materials with fibres make recyclability difficult. As far as we can conclude, evolution trends for ceramic products centered in Material and Design Processes are environmentally friendly.

In contrast, initial stimulus I4 worsens the four output categories. In this stimulus, the three concepts included in the category Aesthetics (c_9 increasing use of senses, c_{10} increasing use of colours and c_{11} increasing transparency) clearly are harmful for the environment.

The scenario 3 which corresponds to the activation of the input category Geometry, the results follow the same trend as in Scenario 7 and the same explanation is valid. This initial stimulus improves three of the four output categories, only the output concept c_{26} (reliability and durability), is reduced.

Finally, in scenario 5 with activation of the input category Functionality, the output category O_2 (reduction of material usage), and the output concept c_{23} (recyclable materials) worsen. The remaining categories and output concepts are improved.

4. Discussion

In this section, our methodology, based on FCM, to assess TRIZ evolutions trends for eco-design innovation is compared and discussed with traditional techniques used in technological forecasting like Delphi and AHP. As a result, the different environmental performance of each TRIZ evolution trend, and their combinations in potential scenarios, are highlighted.

The Delphi method is a well-known method used to reach expert group consensus regarding a complex problem (Dalkey & Helmer, 1963). This could be done through anonymous consultations. Anonymity is required in the sense that no one knows who else is participating. In our experimental analysis, a Delphi first round was used and experts answered the questionnaire explained in 4.1.

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. In the second round of our experimental analysis, feedback was received from four experts focusing on the choice between results obtained by applying directly classical statistics compared to expert opinion in the first round or by applying FCM.

Scenario 7 is the only one of the scenarios analysed available for this because it has only one input concept (c_3), the other scenarios have more than one input concept and their results cannot be drawn directly from Delphi first round. The question was: Which option do you think is the

Table 7: Feedback options for scenario 7

		Option 1	Option 2
O_1	Selection of low-impact materials	0.19	0.34
O_2	Reduction of material usage	0.53	0.47
O_3	Optimisation of initial lifetime	-0.15	-0.34
O_4	Optimisation of end-of-life system	0.10	0.29

more accurate to assess the effect of innovation by decreasing density on eco-design of ceramic products?

The environmental efficiency of each option for the four first levels of LiDS wheel are in Table 7 normalized in the range $[-1, +1]$. Experts could post comments explaining their choice. The first option is the result of classical statistics and the second one from FCM. All experts selected Option 2 with the results from FCM. Favourable comments for Option 2 are related to more realistic values for each O_i.

Traditional techniques used in technological forecasting like Delphi or AHP allow the prioritization of alternatives in decision making. Fuzzy Cognitive Maps applied in our methodology prioritize and also allow further decision making based on scenario analysis (Lopez & Salmeron, 2013; Salmeron, 2012; Salmeron et al., 2012).

Scenarios describe events and situations that could happen in the future real-world. 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.

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 makers to measure the impact of entity interactions.

To highlight these differences, the rating method in the AHP processes has been applied to the same problem, with the same answers from eleven experts (Chulvi & Vidal, 2012). Delphi method would require at least a full second round; meantime AHP requires expert opinion only once.

The Analytic Hierarchy Process (AHP) is a method proposed by Saaty (1977) and it is used with two types of measurement, relative and absolute. In both, paired comparisons are performed to derive priorities for criteria with respect to the goal.

Rating alternatives in the AHP or Absolute AHP Saaty (2005) involves

Table 8: Priorities

	Strongly worsen	Worsen	Slightly worsen	Neutral	Slightly improve	Improve	Strongly improve	Normalized Priorities1
Strongly worsen	1.00	0.50	0.33	0.25	0.20	0.17	0.14	0.144
Worse	2.00	1.00	0.67	0.50	0.40	0.33	0.29	0.284
Slightly worsen	3.00	1.50	1.00	0.75	0.60	0.50	0.43	0.428
Neutral	4.00	2.00	1.33	1.00	0.80	0.67	0.57	0.572
Slightly improve	5.00	2.50	1.67	1.25	1.00	0.83	0.71	0.716
Improve	6.00	3.00	2.00	1.50	1.20	1.00	0.86	0.856
Strongly improve	7.00	3.50	2.33	1.75	1.40	1.17	1.00	1.000

making paired comparisons but the criteria just above the alternatives, known as the covering criteria, are assigned intensities that vary in number and type. These intensities themselves are also compared pairwise to obtain their priorities as to importance, and they are then put in normalized form by dividing by the largest value (Table 8). To avoid negative intensities, the initial scale $[-3, +3]$ has been modified to $[1, 7]$.

Priorities are calculated with the principal right eigenvector of the reciprocal matrix of intensities (Saaty, 1977) with the help of PriEsT (Siraj et al., 2013). This software tool also estimates several measures of inconsistency in judgments like Consistency Ratio (CR) (Saaty, 1977), which must be about 0.10 or less to be acceptable ($CR = 0$ in priorities of Table 8). Finally each input concept $(c_1, \ldots, c_{17})$ is assigned an intensity result of the geometric mean of the expert opinions, along with its accompanying priority, for each output concept $(c_{18}, \ldots, c_{26})$.

In Table 9, like in Tables 1 and 6, output concepts were considered equipotential and aggregated in four output categories (Table 2). The priority of each intensity is summed over the weighted intensities for each input concept to obtain that input concept's final rating that also belongs to a ratio scale.

Ranking obtained with Table 9 is similar to the statistical results of Table 1 although with different scale and consequently different intensities. Best and worst input concepts are also c_2 and c_{11}, respectively. It should be noted that the neutral is 0.572; below this value the product innovation would be worse from an environmental point of view. From these two results we can categorize the 17 evolution trends in three groups according to their environmental performance:

Table 9: Rating results

	O_1	O_2	O_3	O_4	Mean
C_1	0.61	0.60	0.78	0.68	0.67
C_2	0.60	0.81	0.90	0.46	0.69
C_3	0.65	0.82	0.48	0.62	0.64
C_4	0.60	0.64	0.66	0.70	0.65
C_5	0.67	0.74	0.40	0.62	0.61
C_6	0.59	0.57	0.62	0.56	0.58
C_7	0.63	0.90	0.42	0.59	0.64
C_8	0.52	0.44	0.62	0.49	0.52
C_9	0.56	0.56	0.55	0.57	0.56
C_{10}	0.48	0.57	0.55	0.48	0.52
C_{11}	0.48	0.54	0.52	0.53	0.52
C_{12}	0.60	0.50	0.57	0.66	0.58
C_{13}	0.59	0.51	0.58	0.53	0.55
C_{14}	0.55	0.55	0.68	0.51	0.57
C_{15}	0.61	0.59	0.67	0.54	0.60
C_{16}	0.60	0.59	0.79	0.61	0.65
C_{17}	0.67	0.65	0.81	0.59	0.68

- Group A, very slightly worsen: c_8, c_9, c_{10}, c_{11}, c_{13}.
- Group B: neutral: c_6, c_{12}, c_{14}, c_{17}.
- Group C, very slightly improve: c_1, c_2, c_3, c_4, c_5, c_7, c_{16}, c_{17}.

The main advantage of our methodology is the analysis of scenarios, without having to consult the experts directly. The total number of possible scenarios is 2^n, where n is the number of alternatives or input concepts. In our experimental analysis, the total number of possible scenarios was 131,072, from them, only seven scenarios were strategically chosen in section 4.3. for FCM dynamic analysis.

One particular case is when the scenarios are formed with only one input concept that could be analyzed with classical tools like AHP. Still, the results are different (e.g. c_3 in scenario 7 of Table 5 and in Table 9) because in classical tools, the context is static, in FCM the context is dynamic, that is, they evolve with time through a series of interactions in related concepts.

In general terms, an FCM is built by mixing the available experience and knowledge regarding a problem (Froelich & Salmeron, 1996; Papageorgiou et al., 2013). This can be achieved by using a human experts' team to describe the problem's structure and behaviour in different conditions. FCM is a straightforward way to find which factor should be modified and how.

An FCM is 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.

The approach proposed here is a step forward with regard to the classic tools used in scenario-based decision-support. Delphi, AHP and other methods help to reach relationships between concepts. FCMs have simulation and prediction capabilities. This tool allows managing uncertainty for improving scenario-based decision-making. In addition, FCMs offer visual models for easier understanding by non-technical decision makers, because FCM can represent explicit and tacit human knowledge.

Moreover, FCMs provide an intuitive, yet precise way of expressing concepts and reasoning of them at their natural level of abstraction. By transforming decision modelling into causal graphs, decision makers without a technical background can understand all of the components in a given situation (Salmeron, 2009). Furthermore, with FCMs, it is possible to identify and consider the most relevant factor that seems to affect the expected target variable.

Our proposal goes beyond the eco-rules definition based on TRIZ evolution trends as previous researchers have done, like D'Anna & Cascini (2011); Russo et al. (2011); Yang & Chen (2011).

Results of Table 9 prioritize TRIZ evolution trends according to their environmental effectiveness and it should be noted that some of them very slightly worsen the environment. Furthermore, results of Table 6 quantify the environmental efficiency for 7 scenarios, obtained as combinations of evolution trends, in the case example of the ceramic products.

The results of our methodology can be used together with methods based on patent analysis and TRIZ trends to identify possible improvements in invention concepts. Verhaegen et al. (2009) and Yoon & Kim (2012) measure the maximum and the average evolutionary potential of a product related to the collected patents. If the average evolution phase of a trend is low and the difference between average evolution phase and maximum evolution phase in the trend is zero, then the trend is an untapped area, this indicates the trend has room for further improvements (Yoon & Kim, 2012). If this evolution trend improves the environment using our methodology, then this trend has room for further eco-design.

As a novelty, evolution trends, and also their combinations, that improve or worsen the environment are identified and their environmental efficiency is quantified. This significant result should be considered in future eco-rules definitions based on TRIZ evolution trends.

5. Conclusions

There exists a lot of useful technology forecasting methods but their validity for eco-design has to be tested. One of them is TRIZ evolution trends, the question that arises is if these evolution trends are also valid for eco-design.

In this paper, an innovative methodology is proposed for environmental friendly product forecasting.

Our proposal goes beyond the eco-rules definition or the prioritization of eco-friendly guidelines with traditional techniques used in technological forecasting. Fuzzy Cognitive Maps assess TRIZ evolution trends for eco-design innovation, allowing prioritizing and further decision making based on scenario analysis. Based in a field survey, this paper also shows that it is possible to forecast environmental friendly ceramic products.

From a static point of view, the FCMs can indicate the relationships between the evolution trends and the strategies of eco-design. The individual results of the evolution trends range from slightly worsen to slightly improve eco-design strategies as a whole. Increasing use of colours and Decreasing density are the worst and the best environmentally friendly evolution trends, respectively.

From a dynamic point of view, FCMs can make what-if simulations and forecasting greener products according to previously established conditions. In this case, seven scenarios have been analysed and their environmental performance has been performed for four strategies of the first level in LiDS Wheel. Compliance with all evolution trends simultaneously achieves the best efficient eco-design but at low effectiveness.

However, there are evolution trends with good environmental performance. Evolution trends of ceramic products focused on Material, Design Process and Geometry are environmentally friendly. In contrast, evolution trends included in the category Aesthetics are harmful for environment.

Future research will include other real applications, linking different environmentally friendly product categories with FCMs and its extensions for greener product forecasting.

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