

Chapter 11

Developing Robust Climate Policies: A Fuzzy Cognitive Map Approach

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Abstract Climate change has been considered one of the most significant risks for sustainability in our century; in order to move towards low-carbon and climate resilient economies, fundamental changes must take place. In this direction, the European Union has set ambitious goals regarding the transition of its Member States to low carbon societies, but the policy strategies to promote this transition must be socially acceptable and supported. So far, climate policies have been evaluated using quantitative methods, including general equilibrium and integrated assessment models but, despite their undoubted contribution to climate modeling, both the quantitative frameworks used for studying climate change and its impacts and those aiming at policy optimization or evaluation feature significant uncertainties and limitations. In order to overcome these issues, a Fuzzy Cognitive Map based approach is proposed, aiming to directly involve stakeholders and assess human knowledge and expertise. The suggested methodological framework can significantly support climate policy making, by supplementing quantitative models and exploring impacts of selected sets of policies, based on qualitative information deriving from a structured stakeholder engagement process. Finally, an innovative approach of incorporating the concept of time into the methodology is proposed and evaluated, in the aim of enhancing the robustness of transition pathways.

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11.1 Introduction

Climate change has long been considered one of the most prominent sustainability problems [70] as well as among the most significant systematic risks for global society [24] of this century. In this respect, the European Union has set ambitious goals with regard to the necessary transition of Member States to low carbon economies. The European Council has, in fact, recently mapped its envisioned requirements of a 80–95 % cut on emissions by 2050 [17], taking into account that in order to tackle the global challenge for building a sustainable future that is climate change [34] the global temperature increase should be controlled: until recently, a global average temperature increase of no more than 2 °C compared to pre-industrial levels until 2100 had been considered relatively [28, 61] safe in order for the most significant consequences to be avoided [67], although the pursuit of a newer and stricter goal of 1.5 °C was discussed and agreed upon during the latest United Nations conference on climate change [68].

It is obvious that the desired transitions cannot be achieved immediately, but require specific courses of action that can adapt to the reference concentration (and corresponding emission) trajectories, i.e. pathways, studied by the Intergovernmental Panel on Climate Change [63]. Furthermore, these transitions require radical and rapid implementation of policies that are socially and politically supported [76]. To this end, the European Union has been looking at cost-efficient ways to cut most of its greenhouse gas emissions by identifying the key sectors in this direction, as well as corresponding sectoral goals by the end of every decade until 2050, so as to achieve greater depth on costs, trade-offs and uncertainty when examining policy options [16].

So far, climate mitigation has been mostly studied through the use of quantitative methodologies. These include computable general equilibrium models that can evaluate impacts of policy reforms on the economy, revolving around the economic impacts of mitigation policies (e.g., [72]) or studied alongside climate-specific models (e.g., [40]); advanced econometric models with strong empirical background [4, 59]; dynamic stochastic general equilibrium models that emphasize economy dynamics over time, used as climate mitigation assessment tools [13, 14]; and energy-specific scenario frameworks, such as the LEAP framework [29, 42]. These models can greatly help explore implications of various scenarios in relation to climate mitigation pathways and identify effective policy drivers in quantitative terms; however, they may limit their scope to the economics of climate change, feature significant uncertainties, or fail to study all sectors in need of policy reform, and usually ignore the socio-economic dimensions of climate change.

In order to deal with the above weaknesses, integrated assessment models, that is models that draw on knowledge from multidisciplinary research [75], have been receiving increasing attention (e.g., [23, 46, 49]). These models combine economic and scientific aspects of climate change and have been proven to address issues such as evaluating climate change control policies, integrating multiple disciplines in the same framework and studying climate change in the context of both other environmental and non-environmental problems, but the degree to which their results have supported policy making is unclear [37].

Despite their undoubted contribution, all of the aforementioned quantitative models involve assumptions and simplifications [73] and, although their level of detail is limited by computing power and the need to avoid becoming too complex [47], they eventually tend to be technically too complex to construct or understand [1]. As a result, policy makers may view these models as too complicated to transform their findings into policies or as black boxes and be reluctant to trust their results [37].

It is therefore of vital importance that methods able to successfully model complex systems and at the same time easy to build by utilizing existing knowledge and experience be used. Such methods should allow for both feasible and successful policy pathways to be determined and studied, taking into account the national context and sectoral specificities of a country as well as incorporating the knowledge of experts around uncertainties and risks where quantitative data are not available or too costly.

In this study, Fuzzy Cognitive Maps (FCMs) are proposed as one such methodology, for modeling the complex system that is climate mitigation policy in the European Union. FCMs are fuzzy structures that strongly resemble neural networks and are often used as a useful tool for modeling complex systems [35]. Once constructed, the FCM model allows performing qualitative simulations of a system and experimenting with the model [2]. FCM simulations thus allow decision makers to examine information dynamics and uncertainty, as well as identify critical system elements and assess different decision alternatives by comparing their outcome in a holistic manner [33].

Özesmi and Özesmi [51] extensively discuss the reasons for choosing FCMs when dealing with environmental problems over other modeling methods, such as system dynamics models, multiple criteria decision analysis methodologies, expert systems and structural equation models. Most importantly though and compared to quantitative models in particular, FCMs do not depend on data availability: their robustness does not depend on any training procedures that are biased to the size of the available data sets [53]. Moreover, given the fact that they are built on human expertise and knowledge alone, they are highly flexible and easy to include social effects [69].

The following section introduces the origins and structure of Fuzzy Cognitive Maps. Section 11.3 presents the proposed FCM-based methodological framework for modeling climate policy pathways. The aim of the framework is to visualize the system dynamics deriving from both the results of other modeling methods and an effective stakeholder participatory process; quantify the knowledge and experience of the experts with regard to the success of the various transition pathways; and use all available information to simulate the impacts of the chosen policies on the respective systems, in order to gain new insight. Finally, Sect. 11.4 focuses on the assessment of simulation results, and Sect. 11.5 discusses key aspects of the proposed methodological framework.

11.2 Fuzzy Cognitive Maps

Cognitive mapping is a qualitative technique that aims to capture a person's perception of a particular issue in a diagrammatic format [20]. It provides both the analyst and the interviewee with a process that is not constrained by formal structure and through which additional insight can be gained [12]. In this context, a map focuses on the individual's values, beliefs and assumptions about a certain domain and reveals how these relate to each other, providing information about how the change of one issue can affect the others. Therefore, a cognitive map [3] can be defined as the graphical representation of a system, in which nodes represent concepts and arcs represent the perceived relationships between these concepts (Fig. 11.1).

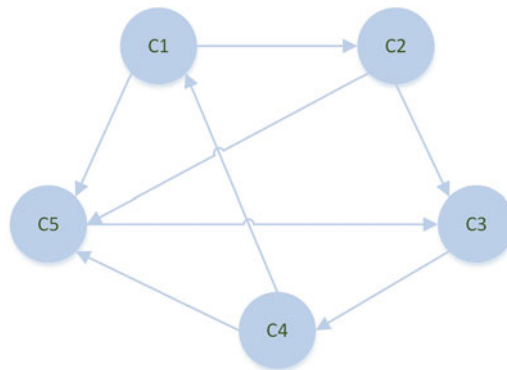


Fig. 11.1: Example of a cognitive map

Every cognitive map features a unique adjacency matrix $\mathbf{A} = [a_{ij}]$ that provides information with regard to its structure, i.e., how concepts are linked to each other [27]. The adjacency matrix is a square matrix that includes all concepts listed on both the vertical and the horizontal axis; when a causal connection from concept c_i to concept c_j exists, then $a_{ij} = 0$, otherwise $a_{ij} = 1$. In other words, if $a_{ij} = 1$, then concept c_i is considered a cause of concept c_j , and concept c_j is considered an effect of concept c_i . The adjacency matrix for the cognitive map in Fig. 11.1 is shown in Table 11.1.

Cognitive maps work as a transitional object applied by members in the aim of expressing and understanding their knowledge contents with regard to certain problem domains, as well as their structure [6]. They can be used for assessing attention, association and importance in order to identify mental connections between strategic themes; showing dimensions of categories and cognitive taxonomies in order to determine hierarchical relationships and frame the competitive environment; exploring influence, causality and system dynamics; delving into the structure of arguments and conclusion; and specifying schemas and frames [31].

Table 11.1: The adjacency matrix of the example cognitive map

	C_1	C_2	C_3	C_4	C_5
C_1	0	1	0	0	1
C_2	0	0	1	0	1
C_3	0	0	0	1	0
C_4	1	0	0	0	1
C_5	0	0	1	0	0

Kosko [39] was the first to introduce the notion of Fuzzy Cognitive Maps (FCMs), by suggesting that cognitive maps are too binding for knowledge-base building because causality is fuzzy, admits of vague degrees and thus cannot be fully described by arcs that connect concepts with one another. Among Huff’s five types of cognitive maps, FCMs fall under the third category: they are fuzzy-graph structures for representing causal reasoning and consist of concepts that interact with each other, enabling the mapper to show the dynamics of a particular system [25]. The main difference between FCMs and cognitive maps lies in the fact that causal relation values are also defined and quantified, meaning that links between concepts are weighted.

As a result, a fuzzy cognitive map does not have only a unique adjacency matrix but a weight matrix $\mathbf{W} = [w_{ij}]$ as well. Entries in an FCM weight matrix are not of binary form (either 0 or 1), but can be of any numerical value within the interval $[-1, 1]$. If there exists a causal connection from concept c_i to concept c_j , then $[w_{ij} \in (0, 1]$ if a positive change in concept c_i leads to an increase in concept c_j , or $[w_{ij} \in [-1, 0)$ if a positive change in concept c_i leads to a decrease in concept c_j ; otherwise, if no connection exists between the two concepts then $w_{ij} = 0$.

A causal map, and therefore a fuzzy cognitive map as well, includes concepts that can be one of three types: transmitters, receivers and ordinary concepts [21]. A transmitter is a concept that can be perceived only as a cause to other elements within the system under examination; a receiver is a concept that can be perceived only as an effect of other elements; and ordinary concepts are those elements that have both at least one cause and at least one effect relationship. These three types can also be defined by their indegree and outdegree functions. The indegree or generalized indegree of a node is the number of paths leading to this particular node from others, while the (generalized) outdegree of a node is the number of paths leading from this node to others [9]. As a result, a transmitter is a concept with zero indegree and non-zero outdegree; a receiver is a concept with non-zero indegree and zero outdegree; and an ordinary concept is a concept with both indegree and outdegree non-zero [50]. An example of these structural criteria can be viewed in Fig. 11.2, which is inspired by the work of Lopolito et al. [45].

Other than assessing the structure of a map, the indegree and outdegree functions can also contribute to drawing comparisons between FCMs, as they are used to calculate centrality of concepts, which is the summation of their indegree and

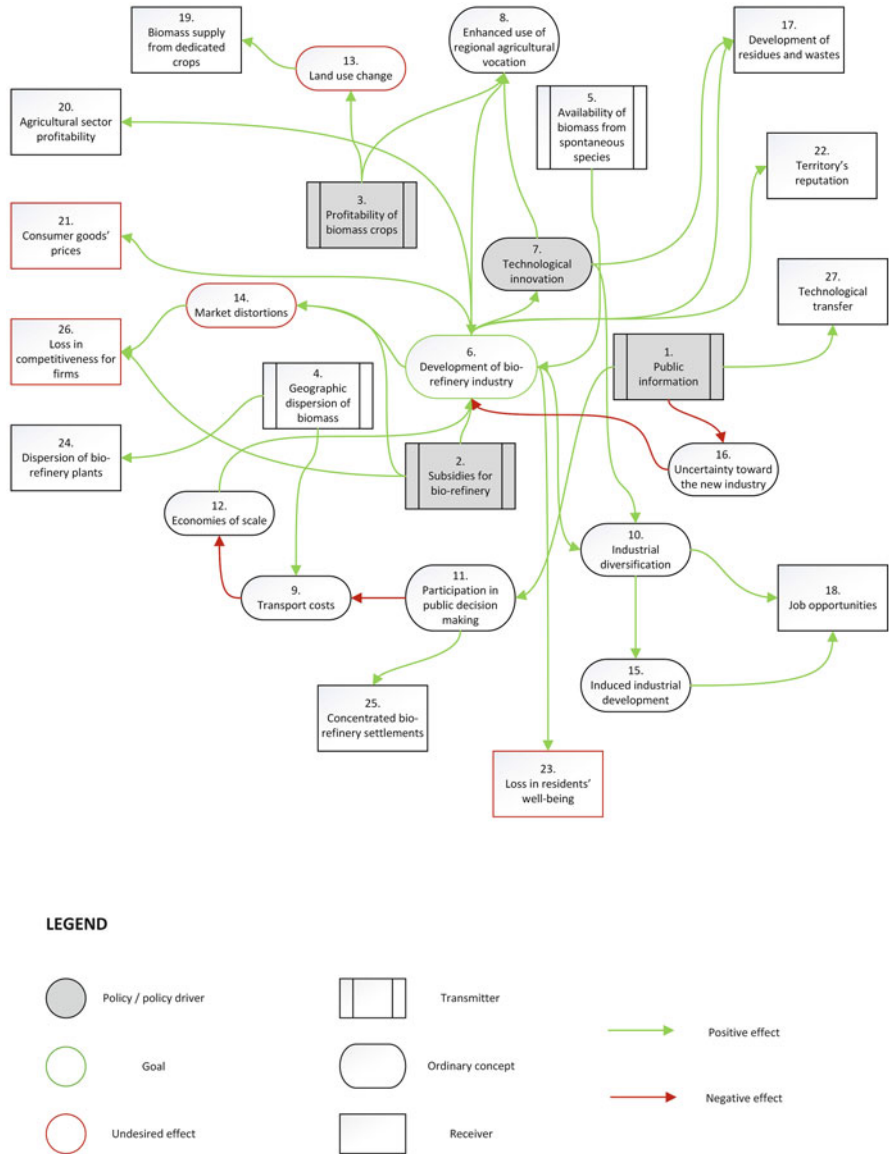


Fig. 11.2: Transmitter, receiver and ordinary variables of a causal map, based on Lopolito et al. [45]

outdegree [27], as well as complexity, which is defined as the ratio of number of receivers to the number of transmitters [51].

In a fuzzy cognitive map, concepts represent key factors and stand for events, goals, inputs, outputs, states, variables and trends of the modeled system [25]. For example, in the context of developing robust mitigation policy pathways, these can

be events, policy-defined goals, system trends, transition drivers and barriers (such as risks and uncertainties) and other variables acting within each national (or sectoral) system.

After a fuzzy cognitive map has been drawn, using techniques from neural networks, the systematic causal propagation [39] of the map can be analytically traced through a simulation process [52]. Using a simulation driver function, the value of a concept during each iteration depends on its value at the beginning of the current step and the values of the concepts that causally point to it, as well as the causal weights of the respective interconnections. At the end of each iteration, new values are normalized within the interval $[0, 1]$ using a transfer function (also known as threshold or transformation function). Simulations may converge to a steady state vector (fixed point), a limit cycle where the concept values fall into a loop of numerical values, a limit torus, or a highly unstable strange (chaotic) attractor in the fuzzy cube [19], where concept values randomly reach varying values. The result to which the simulated system will converge depends on the initial state vector, given a fixed model structure.

This analysis allows the modeler to explore what-if scenarios, by performing simulations of the FCM for various initial state vectors, i.e., for different sets of activated policies or different levels of activation of certain policies. Comparisons between the results can be used to support decision making or scenario building [62].

It is noteworthy to mention that there exist many applications of Fuzzy Cognitive Mapping in literature, with regard to climate change and environmental planning and assessment, among which many focus on improving the methodological process as well, while others aim to either stress the participatory methodology or exploit the FCM methodology for building scenarios [48].

11.3 The Methodological Framework

Regardless of how FCM simulation results have been evaluated and supported decision and policy making, FCMs have so far been used to model and simulate various systems from different disciplines, in problems that feature significant uncertainties linked to the social factor to some (e.g., [2, 45, 52, 78]), great (e.g., [8]) or no extent at all (e.g., [43, 64]). When considering the many risks and uncertainties associated with climate change policy [22] as well as issues concerning public acceptance of low-carbon technologies and policies, one can understand the logic behind using fuzzy cognitive mapping in this context. However, as already discussed and unlike many of the domains in which FCMs have previously been used, there exist a large number of quantitative frameworks that can support climate mitigation policy making and that have, to some degree, tackled many uncertainty issues.

The aim of this approach, therefore, is not to avoid the necessary quantitative models used for optimizing, evaluating and selecting policies that can deliver the desired transition goals, but rather supplement quantitative methodologies, by linking them to qualitative, experience-driven modeling. Fuzzy cognitive mapping

does not provide any real-value estimations [52]: FCM simulation is based on purely qualitative information and is therefore not intended for forming exact quantitative values [6], nor should it be perceived as such, but rather as a means of exploring which of the proposed policies or sets of policies are *believed* to perform better in the examined systems.

Using fuzzy cognitive maps for linking stakeholder input and quantitative modeling frameworks has been explored in the past [69], in the aim of enabling the quantification and integration of narrative storylines, i.e. participatory output, into the models. This approach assumes the need for the opposite sequence: after having determined a number of policy pathways that according to quantitative models results are sufficient to achieve the required transitions, FCMs can help select the optimal pathways, by utilizing expert knowledge and experience as to the feasibility and applicability of the different sets of policies. This is similar to the process Hobbs et al. [30] suggested undertaking in the Lake Erie Lakewide Management Plan project, following a fuzzy set theory approach, before considering the FCM alternative.

The proposed framework consists of the following steps, presented below:

- **Step 1.** Determining the group of stakeholders
- **Step 2.** Designing the cognitive map
- **Step 3.** Inferring causal relation weights
- **Step 4.** Exploring the time dimension
- **Step 5.** Quantifying concepts
- **Step 6.** Selecting configuration parameters
- **Step 7.** Running simulations

11.3.1 Determining the Group of Stakeholders

For the purpose of evaluating potential climate mitigation policy pathways within each country, experts from the following groups are to participate in the process:

- Government departments
- Private and public sector industries, associations and distributors
- Policy makers
- Research institutes
- Non-Governmental Organizations (NGOs) representing various societal groups, such as consumers and environmental protection activists
- Labor unions
- International organizations
- Electric utilities and regulators
- Media
- Communities and households

All country-specific stakeholders take part in the framework in the same way, responding to common surveys, questionnaires and workshops; however, they are nevertheless grouped into respective categories, in order to better assess the qualitative information they contribute.

11.3.2 Designing the Cognitive Map

This second step of the framework is the most challenging one. Normally, this step starts from scratch with experts being asked to either help the analysts design the map or draw the map themselves. Özesmi and Özesmi [51] discuss most of the existing ways in which cognitive maps can be obtained.

The most common way of doing that, in FCM literature, has been the use of questionnaire-oriented interviews or meetings, through which experts express their perceptions of concepts that are important with regard to the problem domain under examination. Roberts [57] explains that a list of variables is initially created and then refined, by selecting the most important ones to be included in the cognitive map. Isak et al. [32] present an analytical framework in which interviews can be conducted. Instead of separate interviews, collaborative determination of key concepts can be conducted, by organizing workshops [41].

Another commonly found process for visualizing expert input into maps has been that of experts directly drawing their cognitive maps. Özesmi [50], after enabling interviewees to express their views on the important variables of the system, had them draw lines with arrows bearing positive or negative signs between variables, showing causal increase or decrease respectively. A detailed description of an indicative framework for achieving this can be found in Özesmi and Özesmi [51], where stakeholders were guided along the whole procedure by using engaging questions. Papageorgiou and Kontogianni [52] too, after explaining the process of constructing fuzzy cognitive maps, asked each of their interviewees to draw their map.

Other methods include coding cognitive maps from implicit or explicit descriptions found in experts' narratives [77] and extracting cognitive maps from existing numerical measurements [60].

The proposed approach assumes that key concepts have been a priori determined, which however do not capture the whole picture nor include several uncertainties and insights that only experts are able to provide. Policies and transition drivers are identified in extensive case studies of the national systems of innovation [5, 58, 71] with regard to one or more sectors of interest and for each of the examined countries, while other key concepts can be extracted from the results of quantitative frameworks used for evaluating these policies onto the examined national and sectoral systems, as previously discussed. To complete the initial set of concepts, the most important risks and uncertainties, which are identified after a detailed literature review and prioritized using Multiple Criteria Decision Analysis methods, are added.

Given the large number of systems to be modeled, we select the first option presented: after determining the sets of policies to be examined, i.e. those that are able

to achieve the transitions to low carbon societies as per models results, as well as other key concepts, stakeholders are asked to provide their input during interviews. The research question that needs to be addressed at this stage is “*what does the informant perceive as important concepts in the problem domain, given the initial set of key concepts?*”. By following this approach, stakeholders’ opinions are taken into account in order to facilitate the development of the FCMs, while also minimizing their bias with regard to their suggestions [36]. Their liberty to add concepts is not limited but encouraged, as long as they include the predefined key concepts or, even better, are driven by the latter when listing their perceived concepts of significance. In countries where such an option exists, time-effective workshops are preferred.

After putting together a large list of concepts for a particular system, it is imperative that only a global and concise map be created. There exist various ways of refining concepts, by reducing their number to those that appear to be most critical. Lopolito et al. [45] pursued consensus over a compromise between the required preciseness and the unavoidable vagueness that the human language features as well as over the selection of the final set of concepts, during their discussion with stakeholders. Other scholars have taken advantage of structured communication methodologies in order to achieve consensus, such as the Delphi method [7]. Given the large number of different systems to be examined, our aim is to avoid a long, iterative process for each country and limit the stages of stakeholder engagement for the purpose of creating cognitive maps. To this end, the task of reducing the number of concepts is entirely up to the analysts. At first, all identified concepts are reviewed in case groups of two or more should be semantically merged and, then, the remaining concepts are prioritized by number of occurrences among stakeholders, so that concepts (including merged ones and their cumulative number of mentions) that rank at the bottom may be omitted.

Afterwards, a second round of stakeholder engagement revolves around the research question “*which of the other concepts does each concept affect, either positively or negatively?*”. Experts only need to specify which of the other concepts each concept has a causal relationship with; a structured way to achieve this is to enumerate all concepts and have experts note the numbers of variables of which each concept can be considered a cause, or ideally provide them with an empty adjacency matrix and have them fill it in.

After having obtained the adjacency matrix of this refined set of concepts, more techniques are available to the analysts for obtaining a final and concise cognitive map. A popular technique in the literature has been that of replacing subgraphs with a single concept, which is called condensation [27] or aggregation [51]. For example, Papageorgiou and Kontogianni [52] describe how they managed to cluster 52 variables into 26 high-level concepts. It should be noted that the goal is not to alter the derived model but rather simplify it and optimize its complexity; according to Özesmi and Özesmi [51], when the number of variables exceed the number 30 the map starts being counterproductive for gaining insights.

The whole process of designing the cognitive map can be viewed in Fig. 11.3.

At this point, it should be noted that, as far as receiver and ordinary variables are concerned, only concepts that feature a cause and/or effect relationship with the

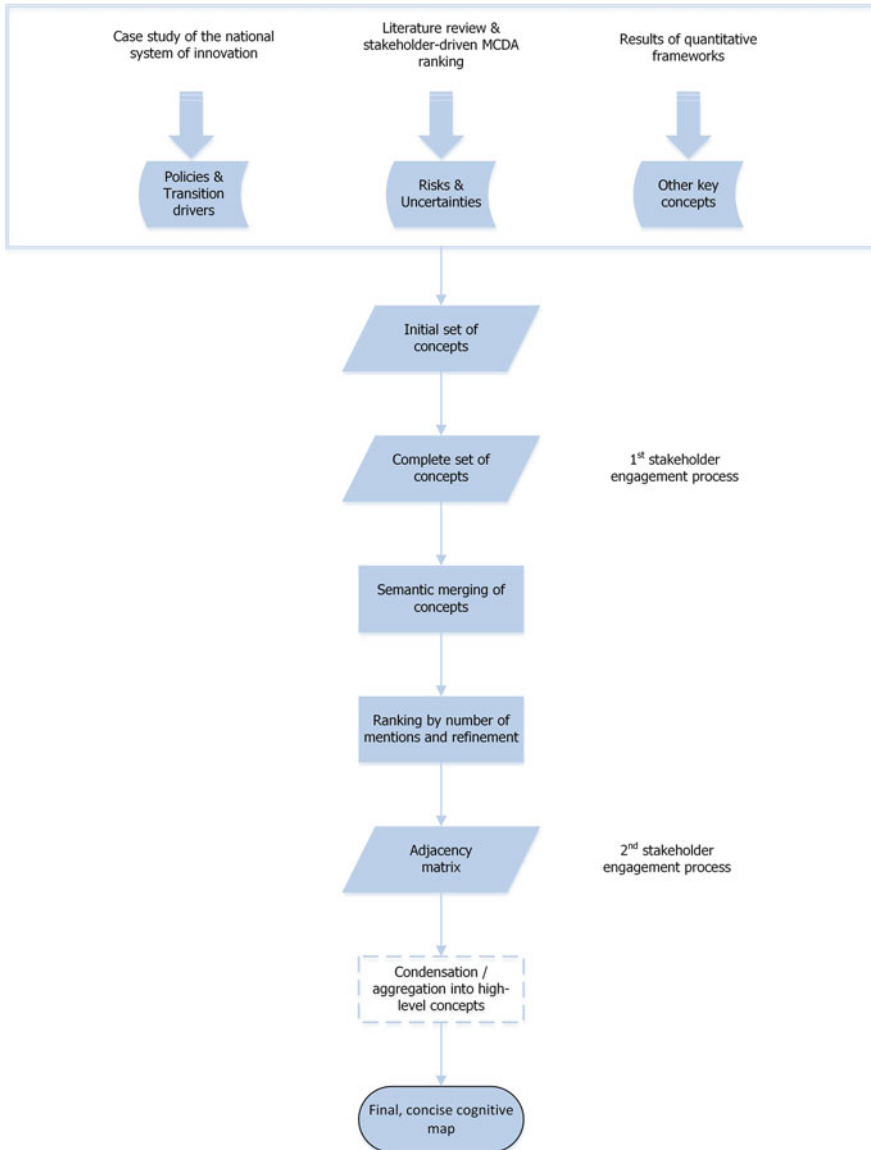


Fig. 11.3: Flow chart of Step 2 of the framework: designing the cognitive map

respective system should be included in the final map, while transmitter variables should exclusively be policies, as it is the policies’ effect on the system that we aim to explore. For example, although “population growth” is a concept that may have direct impact on a number of variables within a system, it should not be included in the map as the objective is to explore how the system reacts to certain policies every

time and draw comparisons, while “population growth” exists in every possible set of policies; however, if any concept of the system affects “population growth” in any way, then it should be included as well.

11.3.3 Inferring Causal Relation Weights

This stage calls for the third and final stakeholder engagement process which revolves around the research question “*given the cognitive map, as well as the national context, how strongly does each concept affect the others?*” and the purpose of which is to establish the grade of causality between concepts. In literature, these weights can be of binary form $\{0, 1\}$ depending on whether two concepts are directly related or not (e.g., [1]), take any value within the interval $[0, 1]$ (e.g., [7]), or take any value within the interval $[-1, 1]$ (e.g., [8]), which is also the case in our proposed framework. The sign expresses whether the causal concept has a positive or negative impact on the effect concept, and the value shows how much impact the former has on the latter.

There exist many different approaches for extracting the required information from experts. Özesmi and Özesmi [51], after having the stakeholders draw their own cognitive maps, asked their interviewees to directly assign numerical weights between -1 and $+1$ to the perceived interconnections. Papageorgiou and Kontogianni [52] proposed using if-then rules that infer a fuzzy linguistic variable from a given set of thirteen variables; alternatively, experts could directly assign fuzzy linguistic weights from the same set. In the same context, Lopolito et al. [45] used only three linguistic values for describing the grade of causality for the concept interconnections (namely weak, moderate and strong) and assigned these linguistic values to numerical weights: 0.33, 0.67 and 1, respectively. Other approaches include using structured communication techniques: for example, Biloslavo and Dolinšek [6] used an iterative approach with feedback based on the Delphi method [18] and the Multiple Criteria Decision Analysis method called Analytical Hierarchy Process [66] for calculating weights; Olazabal [48] used the Q-methodology [11] in order to support the whole stakeholder engagement process, including inferring weights. Last but not least, other researchers proposed iterative, penalization-based stakeholder engagement algorithms using a credibility factor [25].

Given the need to limit stakeholder engagement to the least possible number of stages, as dictated by the very large number of systems to be examined as well as the fact that this methodological framework presupposes the use of other models beforehand (Fig. 11.3), we propose that every stakeholder be free to choose among the 13 linguistic values of the following set [52]:

{negatively very very strong, negatively very strong, negatively strong, negatively medium, negatively weak, negatively very weak, zero, positively very weak, positively weak, positively medium, positively strong, positively very strong, positively very very strong}

These values, however, are directly assigned to the following numerical set:

$$\{-1, -0.83, -0.67, -0.5, -0.33, -0.17, 0, +0.17, +0.33, +0.5, +0.67, +0.83, +1\}$$

After individual weights have been inferred, all numerical values are aggregated using either the mean or the weighted mean of all weights for each causal relation; this depends on whether the analyst chooses to assign different weights to different stakeholders, as identified and grouped in Step 1 of the framework and based on the level and nature of expertise each stakeholder group has. For example, members of the media, consumers or community representatives are not as knowledgeable about every identified concept or policy as experts from research institutes or policy makers. For our purpose and given an appropriate sampling of experts, a mean value is considered adequate for aggregating causal relation weights. Finally, the weight matrix is filled in using the aggregated weight values.

11.3.4 Exploring the Time Dimension

A very weak point of Fuzzy Cognitive Mapping, as applied so far, has been that of appropriately defining and incorporating time [69]. The output of an FCM simulation can be used to assess how key factors play out after a number of iterations, when certain policies or sets of policies are at play, but this output cannot be directly translated into time. However, this can be overcome to some extent, by only including causal relations that are meaningful in the same time scale [38].

Hagiwara [26] was the first researcher to acknowledge the lack of the concept of time in FCMs, along with the need for conditional and non-linear causal relationships; he therefore proposed an extended FCM framework that is able to incorporate time delays, non-linear weights and conditional relations. However, this approach not only requires an extensive, time-consuming stakeholder engagement framework that assumes experts' knowledge and expertise is adequate for offering insight into all of the required information, but also significantly enhances the complexity of the FCM methodology.

In order to incorporate time relationships into Fuzzy Cognitive Mapping, Park and Kim [56] suggested collecting information on the time delay that every relationship between concepts features and then translating the original FCM into a fuzzy time cognitive map (FTCM) in which all causal relations apply in the same time unit. In order to achieve this, they proposed a framework that introduces dummy nodes between concepts and calculates the sign and value of individual weights that compose each original causal weight. Although this approach serves our purpose, in larger FCMs (such as the ones we anticipate to have to deal with, with regard to climate mitigation policies) there is significant increase in the FCM complexity and the visual outcome is hard to produce, supervise and gain insight from. This is partly why the proposed FTFCMs only incorporate time lags of two or three time units and no more, but this poses another limitation since causal relations may potentially feature larger delays.

Other approaches include the expression of the implicit time delay of every relation and the selection of a base time in Rule-Based Fuzzy Cognitive Maps [15]; the use of Fuzzy Time Cognitive Maps for analyzing trust dynamics in virtual enterprises [74]; the agent-based FCM methodological framework developed by Lee et al. [44], in an effort to better address the drawbacks identified by Hagiwara [26] and further analyzed by Schneider et al. [60], which was applied in industrial marketing planning; and a significantly more complex version of timed fuzzy cognitive maps that requires the determination of linguistically-expressed time-dependent weights [10].

In our approach, all causal relations are assumed to be yearly and stakeholders are asked to evaluate how many time units (i.e., years) it takes for each cause concept to have an impact on its effect concept(s). The research question that needs to be addressed at this stage is “*how long does it take for a change in each concept to have an effect on its adjacent concepts?*”. This process does not necessarily require an extra stakeholder engagement step, as it can be done in parallel with the weight inference stage (Step 3). After extracting this information, again an average value is calculated for each causal relation, as in Step 3.

Time lags are incorporated in the way new concept values are calculated, as described in Step 6. As discussed in Sect. 11.4, this approach does not provide different numerical results from what the FCM simulations would produce without integrating time lags, but offers new insight with regard to how soon each policy or set of policies can produce the calculated results.

This step concludes the stakeholder engagement process, which can be viewed in Fig. 11.4.

11.3.5 Quantifying Concepts

As explained in Sect. 11.2, all concept nodes are assigned a numerical value, which is usually within the interval $[0, 1]$ or $[-1, 1]$, depending on which threshold function is selected (Step 6). Certain researchers have proposed different approaches; for example, when suggesting an FCM-based approach for robust scenario planning with regard to wind energy development, Amer et al. [2] used concept values of binary form, i.e. $\{0, 1\}$, depending on whether a concept is clamped or not. Although such an approach could be applied for developing scenarios emerging from policies or sets of policies that greatly differ from one another, it would not allow for adequate comparisons in cases where policies have different effects on the same variables or where policies or sets of policies are clamped to a different extent among alternatives. In our approach, concepts are able to take values within the interval $[-1, 1]$, so as not to limit our methodology to a specific threshold function.

A major issue that has never really been addressed or elucidated in the FCM literature is that of clarifying which of the concepts should be modeled as constants and which ones as variables. Since a Fuzzy Cognitive Map model is simulated over and over again using a particular threshold function and until it converges to a steady

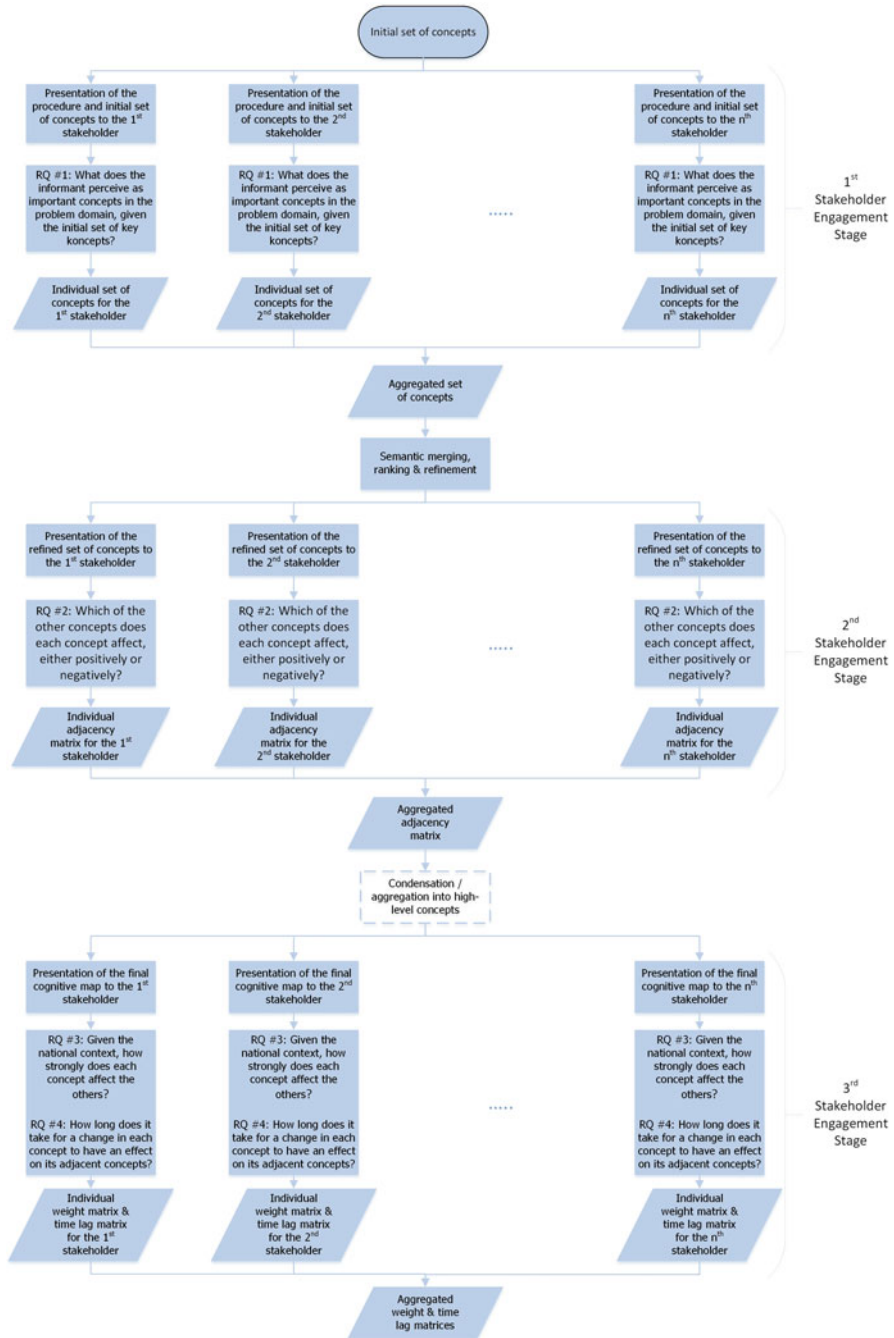


Fig. 11.4: The three stages of the proposed stakeholder engagement process

state vector, if all concepts were modeled as variables this final state vector would depend entirely on the FCM structure: set of concepts, adjacency matrix and weight matrix. In order for each simulation to depend on the initial state vector and thus be meaningful (given a fixed set of concepts, interconnections and weights), concepts that differentiate each alternative should be unaffected by the selected threshold function. As a result, policy (transmitter) concepts should be modeled as constants, while all other (ordinary and receiver) concepts should be modeled as variables.

Therefore, the initial state vector should be carefully selected for each alternative option considered and modeled. In most cases, different policies are examined and activated (i.e. 0 if unclamped and 1 if clamped) every time but this should not necessarily be the case; for example, Papageorgiou and Kontogianni [52] examined two different scenarios for future prospects and risks of the Black Sea marine environment, by attributing different, non-zero initial values to all concepts in each scenario.

11.3.6 Selecting Configuration Parameters

One simulation driver function that has almost exclusively been used in FCM applications calculates the value of a concept at the end of an iteration as the sum of contributions of its causal concepts at the beginning of the iteration:

$$C_j^{(t)} = f \left(\sum_{i=1}^n C_i^{(t-1)} w_{ij} + C_j^{(t-1)} \right)$$

where $C_j^{(t)}$ is the value of concept j at the end of the iteration, $C_j^{(t-1)}$ is the value of concept j at the beginning of the iteration, $C_i^{(t-1)}$ is the value of concept i at the beginning of the iteration, and f is a threshold function.

Depending on the notion of auto-correlation that we will be using, the second term ($C_j^{(t-1)}$) can be omitted; functions of this form assuming no auto-correlation have been used in FCM literature. Of course, both functions can be considered identical, depending on whether the weight matrix includes auto-correlation: by assigning ones on the main diagonal of the weight matrix, i.e. $w_{ij} = 1$, then auto-correlation is implied and included in the first term and the second term should be omitted.

Stylios and Groumpos [65] proposed a slightly modified approach for calculating new concept values at the end of every iteration, by introducing two coefficients k_1 and k_2 , depending on how strongly auto-correlation affected each concept compared to the contribution of its causal concepts:

$$C_j^{(t)} = f \left(k_1^j \sum_{i=1}^n C_i^{(t-1)} w_{ij} + k_2^j C_j^{(t-1)} \right)$$

However, this approach too requires significantly more information from the stakeholder engagement process, since stakeholders should not only know but also be able to offer insight into the extent to which each and every single concept depends on its previous value compared to the contributions of its causes.

Another approach was introduced by Papageorgiou and Kontogianni [52], according to which limitations presented by the sigmoid threshold function, when initial values are 0 or 0.5 or the initial state cannot be efficiently described [54], can be addressed:

$$C_j^{(t)} = f \left(\sum_{i=1}^n \left(2C_i^{(t-1)} - 1 \right) w_{ij} + 2C_j^{(t-1)} - 1 \right)$$

Finally, Papaioannou et al. [55] suggested an interesting simulation driver function that, given a preliminary process of adjusting and greatly reducing weights depending on the number of iterations at which the system is expected to converge, requires no transformation function:

$$C_j^{(t)} = \sum_{i=1}^n \left(C_i^{(t-1)} - C_i^{(t-2)} \right) \frac{C_j^{(t-1)}}{C_i^{(t-2)}} w_{ij} + C_j^{(t-1)}$$

In the proposed framework, however, we will be using a different simulation driver function, based on the originally presented and most frequently used one, so as to incorporate the notion of time delays. This is done by multiplying the weight of a relation between causal node i and effect node j with the value of concept i at time t minus the time delay lag_{ij} of the respective impact:

$$C_j^{(t)} = f \left(\sum_{i=1}^n C_i^{(t-lag_{ij})} w_{ij} + C_j^{(t-1)} \right)$$

Finally, a threshold function must be selected and applied, in order to normalize new concept values within the interval $[-1, 1]$ at the end of every iteration. As in neural networks, there exist many different threshold functions, such as logistic, linear threshold or step functions [51]. However, the most frequently used threshold functions in the FCM literature are the sigmoid function and the hyperbolic tangent function.

When concept values can only be positive, i.e. belong to the interval $[0, 1]$, the bipolar sigmoid function ($\lambda > 0$) is usually used as a threshold function (e.g., [45]):

$$f(x) = \frac{1}{1 + e^{-\lambda x}}$$

If concept values can be negative as well, meaning that they can take values within the interval $[-1, 1]$, the hyperbolic tangent function can be used instead [25]:

$$f(x) = \tanh(x)$$

Having quantified concepts in the interval $[-1, 1]$, both threshold functions can be applied to our approach. The non-negative transformation of the sigmoid function allows for better understanding of concept activation levels [51]. Furthermore, given that it squashes values into a stricter interval, it usually converges faster than the hyperbolic tangent function. However, the latter allows for more realistic representation of the causal output and requires no calibration. For example, if the value of a certain concept can only decrease, the sigmoid function will still produce a positive outcome in the final state vector, which must then be compared to the inaction model in order to draw conclusions for a single scenario; of course, when dealing with a number of alternatives, comparisons between alternatives can still be drawn without comparing them to the inaction scenario, using the sigmoid function.

11.3.7 Running Simulations

After the FCM model has been developed and all configuration parameters have been selected, simulations can begin for each country case study and respective sector; for every simulation and as discussed in Sect. 11.2, causal propagation takes place in every iteration until the system converges; this happens when no change occurs in any of the concept values after a certain point, the concept vector at which is called the final state vector.

11.4 Assessing Results

After having simulated the derived model for every possible policy strategy, comparisons between the final state vectors of the alternatives should be drawn in order to assess to what extent the desired transition has been promoted by activating each set of policies. The larger the value of the goal concept is at the end of the simulation, the better the selected policies are considered by the stakeholders. Of course, the analysts must define which of the concepts included in the FCM should be taken into account when comparing the various alternatives, as well as how important each of these concepts are. For example, Lopolito et al. [45] defined the concept representing the policy objective and distinguished five other concepts to negatively contribute to the alternative pathways' score, as equally undesired effects of the policies. Özemesi [50] proposed a different approach: different objectives were acknowledged for each of the stakeholder groups, leading to different conclusions for each group's perspective. On the other hand, when comparing scenarios with strict activation thresholds and values of binary form, all of the final state vector values are taken into account in order to produce sound narratives (e.g., [2]).

Other than the final state vector and given the integration of the time dimension into the proposed framework, another significant criterion to be taken into consideration when comparing the examined alternatives is how fast convergence has occurred.

As an example, simulations were run for the fuzzy cognitive map presented in Fig. 11.2, with and without time delays, and using the original weight matrix. When activating the first policy option, i.e. enhancing public information on the bio-refinery industry, all concept changes (including the desired transition) appear to slightly delay when very little time lag is introduced in certain interconnections, compared to a no-lag model (Fig. 11.5). It should be pointed out that the sigmoid threshold function was used.

In order to achieve a better understanding and more detailed examination of the time lags' effects, the same model was simulated using the hyperbolic tangent threshold function, using both of the options previously considered and adding a third one with a slightly increased time lag. The impact of both time delays on the goal concept, which is the development of the bio-refinery industry, can be viewed in Fig. 11.6.

Looking at both figures, it is safe to conclude that time delays do not alter the values of the final state vector, as produced without integrating time lags in the first place, but nevertheless offer new insight into how fast changes take place. As previously discussed, the final state vector depends solely on the FCM structure, including its concepts, interconnections and weights, as well as the initial values of the considered transmitter (policy) concepts. As a result, time delays introduced in the proposed manner cannot change the results, unless a certain delay is perceived to be so prolonged that the respective causal relation's impact is not observed before the system converges; this is a negative feature of the proposed approach that could potentially lead to false results, but which can easily be addressed by either comparing results with the respective no-lag model's results or introducing stricter convergence criteria, such as requiring zero numerical changes in the state vector for a number of iterations equal to the largest time lag included.

As expected, the observed delay had an impact on convergence as well: using the sigmoid threshold function and introducing low time lag resulted in a delay in the convergence by five iterations, while using the hyperbolic tangent function and introducing both the low time lag and a slightly higher one resulted in a delay in the convergence by four and six iterations respectively.

It should be noted, though, that iterations in a Fuzzy Cognitive Map simulation and real time units are not the same thing, and results should not be directly translated into time; this, however, can be partly overcome when causal relations are meaningful in the same time scale, as suggested by Kok [38]. In the same way that FCM results should not be used as real-value estimations [6, 52] but provide qualitative insight into the effectiveness of a set of policy strategies, the rate of causal propagation and eventually convergence too can provide qualitative insight into the rate of transition, without necessarily translating each simulation step into a time unit.

Given the need to limit global temperature increase within a strictly defined time frame in order to avoid the most significant and irreversible impacts, the introduction of the notion of time delays is of vital importance from a climate mitigation policy perspective.

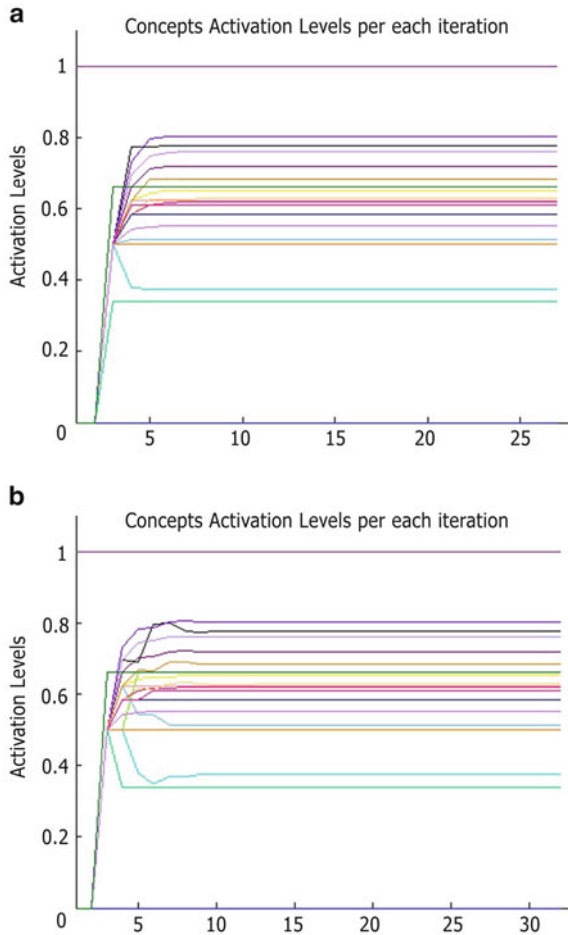


Fig. 11.5: Concept activation levels of the example FCM, using the sigmoid threshold function, (a) without time lag and (b) with slight time lag

11.5 Conclusions

The proposed methodological framework for selecting effective climate policies for low carbon transitions is based on the Fuzzy Cognitive Mapping method, and builds on the output of previously run quantitative models, an extensive literature review of potential risks and uncertainties, as well as country case studies of technological innovation systems, as part of a complete, analytical framework for developing robust transition pathways. This chapter, therefore, aims to present an innovative approach that takes advantage of the qualitative insight that Fuzzy Cognitive Maps can offer, suggesting however that the FCM technique cannot stand on its own when exploring alternative climate policy strategies but rather supplement existing quantitative methodologies, by linking them to experience-driven modeling.

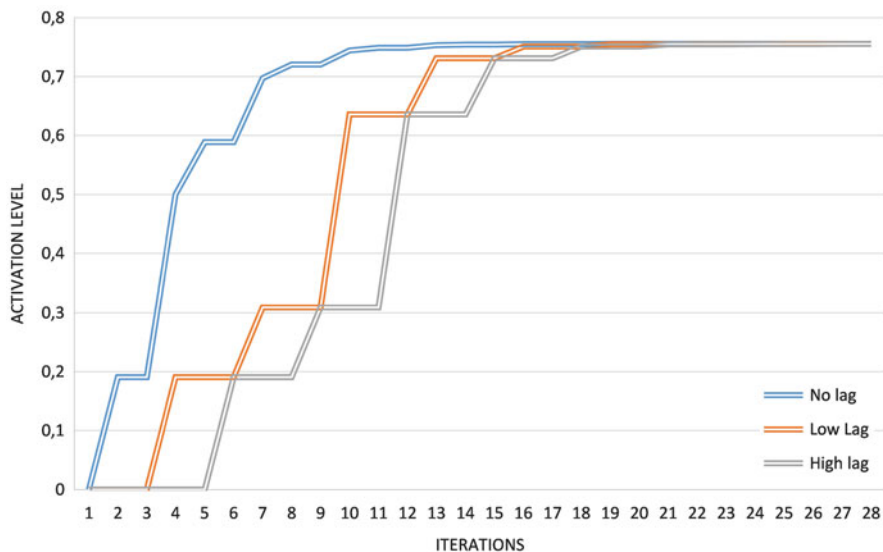


Fig. 11.6: Value increase in the goal concept, due to various time delays, using the hyperbolic tangent threshold function

Another key aspect of the presented approach lies in the simplification of the FCM model construction, from the experts’ perspective. Although the required qualitative input is extended in order to include time-related issues, stakeholder engagement is limited to a clearly-defined and structured three-stage process. In this direction, extensive literature review on the various approaches of stakeholder engagement in fuzzy cognitive maps has been conducted, and specific research questions and steps have been determined, so as to reduce the method’s complexity while at the same time not compromising the added value of the derived conclusions.

Last but not least, the proposed method introduces an ill-defined aspect of FCMs, which is the notion of time. By including causal relationship impacts that are defined in the same time unit, to the extent experts can offer such knowledge, and integrating potential time delays of these impacts into the model, the fuzzy cognitive maps of the examined systems become more dynamic, and new insight can be explored and gained with regard to each considered alternative, in an attempt to enhance the robustness of the resulting climate policy strategies.

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