Exploring Brazilian Photovoltaic Solar Energy development scenarios using the Fuzzy Cognitive Map Wizard Tool

Konstantinos Papageorgiou
Dept. of Computer Science and Telecommunications, University of Thessaly, Papasiopoulou 2-4,
Lamia 35131,Greece
konpapageorgiou@uth.gr

Gustavo Carvalho
Faculty of Economics, Business Administration and Accounting University of Sao Paulo (USP)
São Paulo, Brazil
gustavocarvalho@usp.br

Elpiniki I. Papageorgiou,
Department of Energy Systems Faculty of Technology University of Thessaly, Geopolis Campus, 41500 Larissa, Greece,
Senior Member IEEE
elpinikipapageorgiou@uth.gr

Nikolaos I. Papandrianos
General Department University of Thessaly, 3rd Km Old National Road Lamia-Athens, 35100
Lamia, Greece,
npapandrianos@uth.gr

Márcio Mendonça
Electrical Academic Department (DAELE) Federal University of Technology – Parana (UTFPR)
Cornélio Procópio, Brazil
mendonca@utfpr.edu.br

George Stamoulis
Dept. of Electrical and Computer Engineering, University of Thessaly,
Volos 38221, Greece
georges@uth.gr

***Abstract*—Photovoltaic Solar Energy (PSE) sector has gained great attention during the last decades due to its significant role in the transition to sustainable energy systems. As a viable energy option, PSE has the potential to meet many of the challenges facing the world, along with the diminution of world's dependency to fossil fuels, greenhouse gas emissions reduction and global warming mitigation. In the case of Brazil, the adoption of photovoltaic solar energy is mainly driven by the shortages and several other barriers that are met in the Brazilian energy sector. The development of the Brazilian PSE is the main concern of this study, and authors focus on the investigation of certain factors and their influence on this main outcome with the use of Fuzzy Cognitive Maps (FCMs). FCM is a well-established methodology for scenario analysis and management in diverse domains, and is based on fuzzy logic and neural networks aspects. In this paper we report particularly on the application of a new web-based software tool, called "FCMWizard", which can model complex and dynamic systems, implement several hypotheses and run various scenarios, helping decision-makers and stakeholders with the policy-making and energy management process. In this context, a semi-quantitative model was designed, which comprises 10 key concepts and three plausible scenarios were further conducted. The findings of this study highlight the economic and political influence on the development of the PSE sector in Brazil.**

Keywords—Fuzzy Cognitive Maps, photovoltaic solar energy, FCMWizard, scenario analysis.

I. INTRODUCTION (*HEADING 1*)

Fuzzy cognitive maps (FCMs) constitute a methodology for addressing the main problem of modelling complex, dynamic systems [1]. FCM is a directed weighted graph that consists of nodes (concepts) that represent the behavior of a given system and structural relationships (connections) between these concepts that define the strength of influence of these concepts [2]. Their structure which resembles a graph, focuses on causal relations between concepts, while it captures and describes the system's behavior encapsulating and analyzing the accumulated knowledge and experiences of human experts on complex systems [3].

Due to their modelling and simulation capabilities, along with their ability to predict a system's behavior, FCMs have gained wide acceptance and popularity [2] during the last decades. A noteworthy characteristic is that they can promote learning since they can combine experts' knowledge and historical data to improve their performance on modelling and prediction, thus, overcome the subjectivity of experts' opinions [4], [5]. Moreover, FCMs were recently exploited for scenario planning, even though they were not introduced for such tasks [6]. A number of FCM-based scenarios have been explored in [7], [8] and [9] where the robustness of scenario planning was significantly enhanced.

Attention has also been given to the renewable energy sector over the last two decades, as it is considered a crucial domain in global power demand [10]. It needs particularly, to be well explored and studied through the design and modelling of all its main aspects. Concerning solar energy, a number of studies can be found in the literature [11]–[15]. Most of them deal with linear and non-linear models for solar energy and also other Artificial Intelligent (AI) techniques. Among them, a recent review paper presents an overview of research works related to the development of solar energy modeling techniques [14]. Also, the reviewing work in [15] refers to various modeling approaches, like those of fuzzy logic and artificial neural network (ANN), for solar irradiation and energy modelling.

Regarding linear and non-linear energy models, their main contribution is to define the correlation between solar energy and several meteorological parameters, such as sunshine duration, temperature and humidity [14], using simple linear and a third or fourth degree polynomial function, respectively [13], [15]. As regards AI techniques, mostly Artificial Neural Network (ANN) and fuzzy logic techniques have been explored to develop efficient solar energy modeling approaches [11], [16]–[19]. For example, ANN was used to predict the global solar radiation for various regions in Saudi Arabia [20], while a combination of ANN and fuzzy logic was used to estimate the solar radiation in several Spanish areas using satellite images and the cloud index [21]. In [19], solar

978-1-7281-6932-3/20/$31.00 ©2020 IEEE

global radiation values for month, day and hour period of time were estimated with the use of ANN-based models, while the data collected from 13 locations in India were used to train the model and test the predicted values. Furthermore, an ANN-based model was developed in [18] for Nigeria's solar energy potential forecasting. Geographical and meteorological data of 195 cities in Nigeria for 10 years were used for the training and testing the network. Finally, ANNs were used in [11] to predict solar energy potential in Turkey producing promising results.

As reported in the literature, fuzzy logic and ANN models work more efficiently in making predictions in solar energy related problems, compared to the regression models [14]. In particular, fuzzy logic seems to be more flexible to cope with ambiguities and fuzziness that are inherent in this application area [22], while it can handle uncertainty and model fuzziness when estimating solar radiation. Thus, they both are highly beneficial for modeling and decision making. Motivated from the aforementioned features of fuzzy logic and due to several limitations, like complexity and high uncertainty that these kinds of environmental problems exhibit, we investigate the performance of FCMs for modeling and decision making in the PSE sector.

In this context, exploiting their advantageous capabilities of handling the uncertainty causality [23] and modelling complex systems with many parameters [2], FCMs have been successfully involved in the renewable energy domain. In the related literature, there are also several studies regarding the integration of FCMs in Energy sector dealing with management and decision-making tasks [6], [24], due to their ability to cope with inherent uncertainties in vast domains [25] and to model human reasoning processes [2]. Furthermore, the work in [26] focuses on the involvement of FCMs in management, forecasting and decision-making in Energy, whereas in [27], a FCM was utilized to model the electricity market, which is a complex and adaptive system. In the field of photovoltaic solar energy, the recent work in [28] examined through the exploration of FCMs, the impact that several uncertain elements could have on this field, in view of different exogenous socio-economic, political and technological factors.

Considering the aforementioned limitations and various specifications of the examined systems, there is a need of a powerful software module that would allow researchers to conduct simple tasks on FCM-based systems, like system development or even more complex ones, including learning and simulation processes. Casting a thorough look on the related literature, a variety of tools has been identified which provide different capabilities and include unique specifications. Among others are Mental Modeler [29], FCMapper [30], ESQAPE [31], FCM Expert [32], FCM-Analyst [33], JFCM [34], and FCM Designer [35]. Only MentalModeler [29] though, can implement scenario analysis and environmental modelling, by integrating different types of knowledge into environmental decision-making, as well as conducting scenarios to produce outcomes concerning certain strategic decisions.

Considering the reported capabilities of the aforementioned tools, there is a lack of a more user-friendly tool that could integrate advanced functionalities such as FCM model aggregation and training, using supervised and unsupervised algorithms. Noticing this gap, Papageorgiou E. and her team have developed a web-based tool, namely FCMwizard, (available at http://fcmwizard.com) [28], which offers users and the wider research community the ability to make use of these functionalities towards the implementation of their demanding cases. FCMWizard is under continuous development and the login credentials are available upon request from the authors.

In the examined case of Brazilian Photovoltaic Solar Energy Sector (PSE), the FCMWizard tool is employed for the exploration of relevant FCM-based scenarios. In particular, authors employ this software in this work to facilitate policy simulations and offer researchers and or stakeholders the flexibility to perform simulations for their models for successful management planning. As technological progress works for human development, energy demand increases, so as climate and environmental changes also increase [36]. This leads to the necessity of replacing fossil fuels with renewable energy sources, such as PSE.

We analyze the problem and conduct three relevant and possible scenarios using FCMWizard. In this way, the key variables, as well as the behavior of these variables are presented and further examined. Considering socio-political, environmental and technological uncertainties that affect the development of the Brazilian PSE to a great extent, scenario planning is a proper procedure for institutions that are immersed in this Photovoltaic Solar Energy sector for choosing the right strategic decisions.

This study is explicitly devoted to the following tasks: (i) to apply the quasi-qualitative method of Fuzzy Cognitive Mapping for modelling the complex Renewable Energy system through stakeholders' perceptions, and (ii) to perform an FCM-based simulation process by investigating various scenarios regarding the Brazilian PSE development with the use of the FCMWizard tool.

II. FUZZY COGNITIVE MAPS

FCM is an established methodology that inherits the features of fuzzy logic and neural networks. FCMs were first introduced by Kosko [1], and constitute a way to represent human knowledge and indicate the causality among concepts of systems, characterized by uncertainty and involve complex processes. They also serve as a promising tool for modelling and controlling dynamic decision systems. They are fuzzy diagrams that constitute a set of nodes (concepts) and arcs that represent causal links between concepts. These interconnections take fuzzy values within [0, 1] or [−1,+1] revealing the strength of influence between the concepts [37]. An FCM model with n nodes can be illustrated by an adjacency matrix W_{nxn}, whose elements w_{ij} take values in [−1,+1]. The most commonly used FCM inference rules are the following, (1)–(3):

$$\text{Kosko: } X_i^{(\kappa+1)} = f\left(\sum_{\substack{j=1 \\ j\neq i}}^{n} w_{ji} \times X_j^{\kappa}\right) \quad (1)$$

$$\text{Modified Kosko: } X_i^{(\kappa+1)} = f\left(X_i(t) + \sum_{\substack{j=1 \\ j\neq i}}^{n} X_j(t) \cdot w_{j,i}\right) \quad (2)$$

$$\text{Rescale: } X_i^{(\kappa+1)} = f\left((2 \times X_i^{\kappa} - 1) + \sum_{j=1, j\neq i}^{n} w_{ji} \times (2 \times X_j^{\kappa} - 1)\right) \quad (3)$$

where $X_i^{(\kappa+1)}$ is the value of concept C_i at simulation step $\kappa+1$, X_j^{κ} is the value of concept C_j at the simulation step κ, w_{ij} is the weight of the relation between concepts C_i and C_j, κ is the interaction index in every simulation step and $f(\cdot)$ is the threshold (activation) function applied to hold the values within [0, 1] or [−1, 1].

III. PSE in Brazil

A. Problem statement

The geographical location of Brazil which offers a great potential for solar energy utilization throughout the year [38], along with environmental concerns that regard air pollution, deforestation and greenhouse gas emissions [39], [40], have driven countries to take drastic actions and consider alternative sources for their electricity needs. Renewable energies have indeed attracted great attention recently, as a key to the problems caused by the unsustainable exploration of fossil fuels. Furthermore, the increase in the cost of energy produced in thermoelectric plants also leads to an urgent need for PSE investment in the Brazilian territory. Afterall, the reports in [41] and [42] indicate that Brazil attracts in a great extent, photovoltaic solar energy installation and by 2018, it should be among countries with the most eminent generation of solar energy.

On the other side, there is evidence of a wide range of barriers for the efficient distribution of PSE systems, including the high cost of their acquisition and their low conversion efficiency. It is up to the government to realize the dynamic of PSE development and impose certain policies that would boost the use of solar energy in an urban environment [43]. Moreover, a thorough planning and control by the experts could determine the future of the PES. Thus, scenario planning is a necessary step to be taken in this direction.

B. Model development

Following the definition of the PSE development problem in Brazil, as described above, the FCM development process is then explored for providing a quasi-quantitative model for scenario planning. The overall process consists of three steps. In the first step, authors define the list of the most important independent variables that have an impact on the dependent variable of the examined problem.

In the second step and for all the weighted interconnections between the variables of the investigated FCM model, participants are asked to assign values within the range 1–10, one (1) denoting the lowest strength and (10) the highest. A normalization process is then performed for coding the weights of each relationship within −1 and +1, so as the new values will fill the adjacency matrix [44]. In the third step, the depended variable of the examined problem is defined as decision concept. In our case which refers to the exploration of the Brazilian Solar Photovoltaic Energy Sector, the “development of PSE in Brazil” constitutes the dependent variable.

The design and development of the FCM model was performed by capturing knowledge, information and expertise from various researchers and specialists of the specific domain. The list of concepts which comprise the consolidated FCM, is depicted in Table I, including a short description of them. The corresponding 10-nodes FCM model that was produced from the participants is illustrated in Fig. 1, whereas, an adjacency matrix can be build containing the weights for all causal relationships between the participant concepts.

TABLE I. The Concepts Involved In The Consolidated FCM

Concept	*ID*	*Description*
Development of solar photovoltaic energy	C1	Potential growth of the PSE Sector in Brazil
Public knowledge of PSE	C2	Public awareness of the role and everyday use of PSE system in energy domain
Purchase cost	C3	The cost of products or services that are offered by suppliers.
Energy demand	C4	Consumption of energy by human activity for a set price in the market.
Government incentives	C5	Actions taken by the government to promote the PSE sector (tax exemptions, financing lines, demand creation).
Private sector involvement	C6	Private sector participation in energy projects of the government.
Energy dependence concerns	C7	Consideration of energy sources, supply and infrastructure dependence
Payback Period	C8	The period of time an investment reaches a break-even point.
Energy price	C9	The cost of energy in monetary terms.
Economic situation	C10	The state of the economy regarding the production of goods and services.

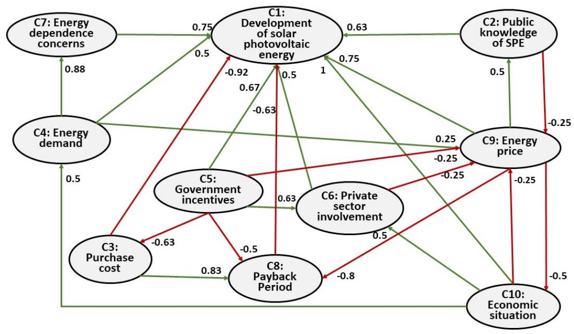


Fig. 1. 10-nodes FCM model produced by stakeholders

IV. Overview of the FCMWizard Tool

The objectives of the current research were achieved with the help of an online tool, namely FCMWizard, whose functionalities are presented in the current section. The modelling and simulation capabilities of this online software module will be presented through its application on the dynamic and complex system of the Brazilian renewable energy sector. As depicted in Fig. 2, the main menu of this tool includes among others, three fundamental modes for constructing an FCM, namely: (i) Expert mode, wherein users can manually develop a FCM for a real problem, (ii) Data-based Learning mode, that allows the FCM model automatic construction by utilizing the given data, and (iii) Merge mode, which combines different individual FCMs for the production of a collective FCM model, thus, generating aggregated system complexities.

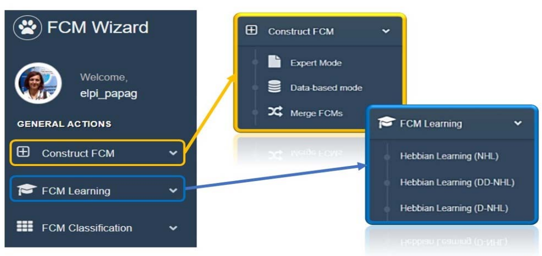


Fig. 2. a) FCMWizard Main menu, with FCM construction and FCM Learning modes

FCMWizard offers the option of FCM Learning in three modes (see Fig. 2): (i) Hebbian Learning (NHL): weights are fine-tuned by data, also considering that in each iteration all concepts are synchronously triggered and change their values. (ii) Data-driven Hebbian Learning (DD-NHL): an extended NHL method that uses historical data to regulate concepts' weights, and (iii) Differential Hebbian Learning (D-NHL): Concepts' weights are modified after their changes being correlated by this learning algorithm.

Next, the FCM Wizard tool is deployed to construct the FCM model for the given problem of the Brazilian PSE. The structural analysis along with the Hebbian-based Learning algorithm and the scenario analysis will be then presented and discussed, accompanied by the figures and tables, produced by the web-based tool.

A. *Expert-based construction / Modelling*

For the model development, users have the advantage of generating new concepts and causal relationships between them, with no need to know the mathematical foundations of the methodology and regardless the type of application domain. Selecting the "Expert Mode" under the main menu "Construct FCM", users can easily design an FCM model by adding new nodes (with the "+" button) and new directed lines that represent the causal relationships between nodes. The green direct line denotes a positive weight whereas the red inverse relationship denotes a negative weight.

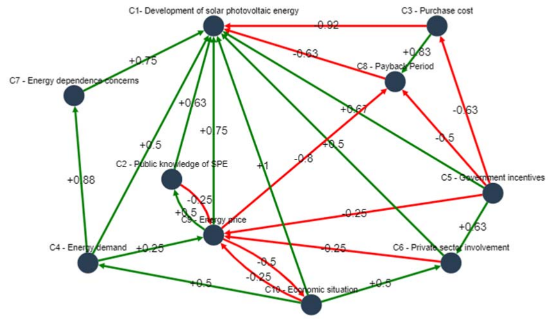
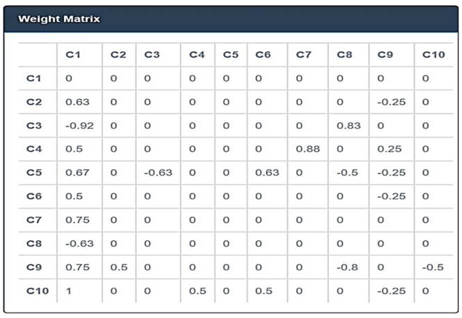


Fig. 3. FCMWizard model for PSE in Brazil.



Weight Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
C1	0	0	0	0	0	0	0	0	0	0
C2	0.63	0	0	0	0	0	0	0	-0.25	0
C3	-0.92	0	0	0	0	0	0	0.83	0	0
C4	0.5	0	0	0	0	0	0.88	0	0.25	0
C5	0.67	0	-0.63	0	0	0.63	0	-0.5	-0.25	0
C6	0.5	0	0	0	0	0	0	0	-0.25	0
C7	0.75	0	0	0	0	0	0	0	0	0
C8	-0.63	0	0	0	0	0	0	0	0	0
C9	0.75	0.5	0	0	0	0	0	-0.8	0	-0.5
C10	1	0	0	0.5	0	0.5	0	0	-0.25	0

Fig. 4. Screenshot of weight matrix.

The model that was designed by the stakeholders as depicted in Fig. 1, is developed by FCMWizard and illustrated in Fig. 3. This FCM model can be also designed by the tool, only by properly importing the model's adjacency matrix. The produced weight matrix which is sited in the "weight matrix" tab of the tool is presented in Fig.4.

B. *Structural Analysis*

In order to describe certain specifications and different aspects of the behavior of the examined model, structural analysis is needed, as a necessary step for determining the dynamics of the system. The FCMWizard online module is designed to provide calculations over various graph theory indices, such as the total number of concepts and connections, connection to concept ratio, the type of variables (receiver, transmitter or ordinary), indegree, outdegree, degree centrality, betweenness centrality, closeness centrality, complexity ratio, density and hierarchy index (see Table II). Centrality is considered an index of importance for a concept. That is, a concept with a high degree of centrality plays an important role in the cognitive map [45]. Centrality is calculated by the sum of the corresponding absolute indegree and outdegree causal weights [46]. As observed from Table II, the concepts C1, C3, C4, C5, C8, C9 and C10 present higher degree of centrality than the other concepts, thus, having a significant role on the examined energy system.

Complexity, density and hierarchy index are among significant structural indices for analyzing the graphical structure of FCMs. In this model, they take values of 1.000, 0.2667 and 0.0907 respectively.

TABLE II. STRUCTURAL ANALYSIS INDICES

Concepts	***(Nodes) Graph indices***					
	Outdegree	***Indegree***	***Type***	***Degree of Centrality***	***Betweenness Centrality***	***Closeness Centrality***
C1	0	6.3	Receiver	6.3	29.6667	9
C2	0.9	0.5	Ordinary	1.4	0	5.5
C3	1.8	0.6	Ordinary	2.4	0	6
C4	1.6	0.5	Ordinary	2.1	2	6.5
C5	2.7	0	Transmitter	2.7	2.3333	7
C6	0.8	1.1	Ordinary	1.9	0.6667	6.5
C7	0.8	0.9	Ordinary	1.6	0	5.5
C8	0.6	2.1	Ordinary	2.8	0.6667	6.5
C9	2.5	1.3	Ordinary	3.8	10	8
C10	2.3	0.5	Ordinary	2.8	0.6667	6.5

From the constructed FCM model (Fig. 3) it emerges that the concepts: Public knowledge of SPE (C2), Energy demand (C4), Government incentives (C5), Private sector involvement (C6), Energy price (C9) and Economic situation (C10) have the most substantial number of connections. They are also directly and strongly connected to the objective concept C1 (development of solar photovoltaic energy). Hence, in terms of their degree of centrality and connectedness, concepts C2, C4, C5, C9 and C10 were chosen by the researchers to become the base of the scenarios since they can strongly affect the behavior of the system.

C. *Hebbian-based Learning*

The process of learning FCMs constitutes a means to update the initial knowledge of human experts and include any knowledge from historical data in the development of an FCM. Various algorithms have been proposed for FCM modelling, optimization prediction and decision support. Hebbian learning in FCMs constitutes the most efficient and well-known unsupervised method for learning FCMs [37]. The non-linear Hebbian learning emerges as one of the most used types of FCM learning for problems where experts' knowledge exists and no data are available for training the created models. The main aim of this algorithm is to find better interconnection weights than those provided by the experts. This algorithm is defined by (4):

$$W_{ij}^{(\kappa+1)} = \gamma W_{ij}^{(\kappa)} + n A_j^{(\kappa)} \left(A_i^{(\kappa)} - sign(W_{ij}^{(\kappa)}) A_j^{(\kappa)} W_{ij}^{(\kappa)} \right) \qquad (4)$$

where n and γ are learning parameters. Moreover, the usage of two cost functions, working as termination criteria of the learning procedure was a significant novel feature. The two cost functions should be defined following the problem constrains, as have been defined in [37].

FCMWizard includes the functionalities of Hebbian-based learning, so the users are able to define constraints of concepts and weights, before implementing the FCM learning process. The objective of the NHL learning algorithm is to define the interconnection weights that minimize the two cost functions, so the FCM model can reach a steady state.

D. *Scenario Analysis*

The ability of FCMWizard to perform "what-if" scenario analysis, allows users to simulate a FCM model by specifying the desired parameters for this task. The objective of this process is to determine the feasibility of scheduled simulations and anticipate contingent situations. In the case of the FCM model, various parameters need to be properly defined. These are: the initial stimulus state vector, the inference rule's type, the transfer function with its learning parameter along with the number of iterations or the convergence step. The provided tool also offer users the open/closed lock option, which can keep the value of a concept unchained throughout iterations, as being "clamped".

In what follows, a simulation example for the examined case, is presented, which is devoted to the investigation of the impact of concept C5-"Government incentives" on the other concepts and the examined system, as well. The first step of this process deals with the investigation of a baseline scenario, where all the initial values of concepts are zero. In the next step, a comparison between the results of the conducted scenarios and those of the baseline scenario is performed. The table with concepts' values produced in the baseline scenario for all iterations steps, is presented in Table III.

TABLE III. FCM ITERATIONS STEPS IN THE BASELINE SCENARIO

Concepts	*Iterations*								
	0	1	2	3	4	5	6	7	8
C1	0.5	0.893	0.956	0.965	0.966	0.966	0.966	0.966	0.966
C2	0.5	0.679	0.720	0.726	0.726	0.726	0.726	0.726	0.726
C3	0.5	0.546	0.538	0.532	0.529	0.529	0.528	0.528	0.528
C4	0.5	0.679	0.723	0.733	0.735	0.736	0.736	0.736	0.736
C5	0.5	0.622	0.651	0.657	0.657	0.659	0.659	0.659	0.659
C6	0.5	0.744	0.805	0.818	0.821	0.821	0.822	0.822	0.822
C7	0.5	0.719	0.789	0.806	0.810	0.811	0.811	0.811	0.811
C8	0.5	0.566	0.570	0.57	0.57	0.570	0.570	0.570	0.570
C9	0.5	0.531	0.512	0.501	0.497	0.496	0.496	0.496	0.496
C10	0.5	0.562	0.574	0.579	0.581	0.582	0.583	0.583	0.583

Let us now consider the concept "Government Incentives" (C5) for the considered PSE problem, and investigate how it affects the other concepts. In the scenario analysis, where this concept is "activated", users need to set up the tool by defining various parameters for the simulation process, such as the inference rule, the transformation function, the Lambda parameter and either the number of iterations or the convergence step. The screenshot in Fig. 5 illustrates the options offered by FCMWizard, concerning the parameters' configuration for the simulation process.

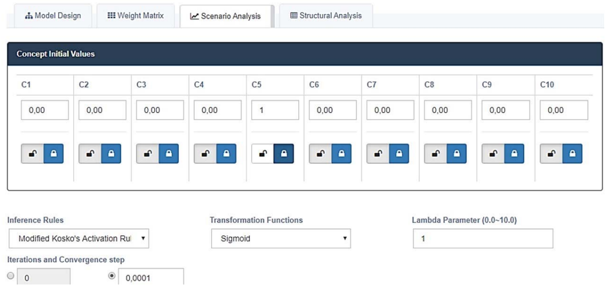


Fig. 5. Screenshot of the Scenario analysis mode by FCM Wizard.

The produced results of this scenario analysis example, in the form of tables and graphs, are depicted in Table IV and Fig. 6, and can reveal the variety of functionalities and capabilities of the FCMWizard tool.

TABLE IV. CONCEPTS' VALUES FOR THE EXAMINED SCENARIO

Concepts	*Iterations*								
	0	1	2	3	4	5	6	7	8
C1	0.661	0.946	0.973	0.976	0.976	0.976	0.976	0.976	0.976
C2	0.5	0.672	0.713	0.721	0.722	0.722	0.722	0.722	0.722
C3	0.347	0.429	0.450	0.455	0.456	0.457	0.457	0.457	0.457
C4	0.5	0.679	0.724	0.734	0.736	0.737	0.737	0.737	0.737
C5	1	1	1	1	1	1	1	1	1
C6	0.652	0.822	0.850	0.855	0.855	0.856	0.856	0.856	0.856
C7	0.5	0.719	0.789	0.806	0.810	0.811	0.811	0.812	0.812
C8	0.377	0.454	0.483	0.495	0.5	0.502	0.502	0.502	0.502
C9	0.438	0.475	0.469	0.466	0.465	0.464	0.464	0.464	0.464
C10	0.5	0.569	0.582	0.586	0.587	0.588	0.588	0.588	0.588

Fig. 6. Graphical plot of convergence performed by FCM Wizard

As observed in Table IV, the value of the examined concept C5 remains unchanged, while the final value of concept C1 in the examined scenario has changed compared to that of the Baseline scenario, after same number of iterations have been completed. Thus, it can be concluded that concept C5-"Government Incentives" affects the concept C1-"development of solar photovoltaic energy". Fig. 7 illustrates the deviations from the steady state (Baseline scenario) for all key concepts of the studied PSE problem.

From this exemplary scenario analysis, it is clearly observed that concept C5 has a negative effect on concepts C2, C3, C8 and C9, whereas a relatively minor positive influence can be seen on concepts C1, C4, C6 and C7.

Considering the processes conducted above, FCMWizard is emerged as an easy-to-use and powerful tool for designing FCM models and performing scenario analysis. It demonstrates key capabilities in modelling, analyzing and simulating complex systems with high uncertainty, providing policymakers with an advanced web-based software for strategic decision-making in various scientific domains. It should be underlined that FCMWizard is available to users upon a password request and is under continuous improvement.

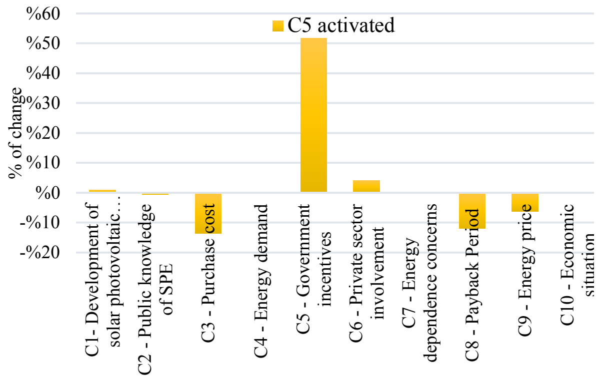


Fig. 7. Percentage of change for key concepts when concept C5 is activated.

V. Applying FCMWizard for Scenario Analysis

Scenario analysis is a necessary way to deeper understand the examined problem, in terms of investigating concepts' behavior and the relations among them. In particular, the input vector is multiplied with the adjacency matrix and afterwards, a squashing function (2) is applied in the output vector. The process of simulation is performed by "clamping" the initial value of certain key concepts each time. This outcome is compared against a baseline scenario, wherein the system reaches the steady state. The produced deviations of concepts' values are then analyzed by the Researchers who are able to interpret the impact of the key concepts on the system on a quantitative basis.

A. Scenario Development

During the scenario planning, authors identified 5 concepts among the ten key concepts selected for the FCM model construction (see Table I), as the most important, which could affect the behavior of the system (called decision concepts). The decision concepts C2, C4, C5, C9 and C10 were selected by the participants, because of their high values of centrality and in/out-degree, and due to their strong relation with the concept C1-"Development of PSE", which is the objective of this scenario planning.

In this context, feasible combinations of the selected decision concepts formed the following three scenarios: "Instability", "Disastrous" and "Economic Growth and High Consumption". The selected scenarios with their concepts are briefly presented in the following table.

TABLE V. The Key Concepts of Each Scenario

Scenarios	***Concepts***	
Scenario 1 (S1)	C9: Energy Price	
Scenario 2 (S2)	C2: Public Knowledge on PSE	C5: Government Incentives
Scenario 3 (S3)	C4: Energy Demand	C10: Economic Situation

- Scenario 1 (S1) examined the effects of energy price (C9) in financial terms.
- Scenario 2 (S2) investigated the effects of public knowledge on SPE (C2) in terms of general awareness of the role and significance of PSE, along with the government incentives (C5) in terms of taxation and financial grants, when environmental pollution is taken into consideration.
- Scenario 3 (S3) highlighted the effects of energy demand (C4) in terms of energy quantity along with economic situation (C10) in terms of country's financial capacity and GDP.

The "Instability" scenario is the first to investigate in the current analysis section and refers to the economic situation of Brazil in recent years. The economic crisis began in 2014 and become worse as it was accompanied by a political crisis too, causing an overall economic and political instability in the country. Along with unemployment which reached its peak in 2017, energy price has increased dramatically, too. In this direction, authors selected the concept "Energy price" as the most relevant to examine in this scenario, clamping its value to 1.

The "Disastrous" scenario was formed by authors due to various unpleasant events happening in the country, like electricity shortage, blackouts, and other environmental disasters, causing awkward situations to the government and the citizens of Brazil. In this case, thermoelectric plants needed to be activated regularly by the government which had to impose rationing due to the insufficient backup capacity. Therefore, this scenario examines the behavior of "Public knowledge on PSE" and "Government incentives" concepts and system's reaction.

In the third, "Economic Growth and High Consumption" scenario, there was an improvement in the economic situation of the country, and thus, the public felt more comfortable to consume more energy. However, the availability of energy did not keep pace with demand and so, energy became a scarce commodity. In this scenario, researchers investigate the degree that the concepts "Energy demand" and "Economic situation" affect the examined energy system.

B. Scenario Analysis for PV Solar Energy Sector

After the execution of the baseline scenario, scenario analysis continues with the simulations for the selected three scenarios (Table V). In particular, scenario 1 (S1) investigated the impact of the decision concept C9-"Energy price" on the examined system. Scenario 2 (S2) studied the behavior of the decision concepts C2-" Public Knowledge on PSE" and C5-" Government Incentives" as regards the system reaction, while Scenario 3 (S3) questioned how the increase of decision concepts C4-"Energy Demand" and C10-"Economic Situation" affect the examined system. All these concepts were clamped to 1. The results for scenario analysis are illustrated in Fig. 8 and Fig. 9 and are presented as deviations compared to the baseline scenario.

Fig. 8 gathers all the outcomes of all three scenarios, with respect to the percentage of change for each concept. Negative values mean that the concepts have negative acceleration, whereas positive values denote positive acceleration. The performed scenario analysis explores the impact of the decision concepts on the concept C1 which refers to the "Development of solar photovoltaic energy", and is the main objective of this project. Thus, we calculate the deviations for this concept (C1), after performing all three different scenarios. The results regarding the deviations of concept C1, compared to the initial state, after the three scenarios were performed, are depicted in Fig. 9.

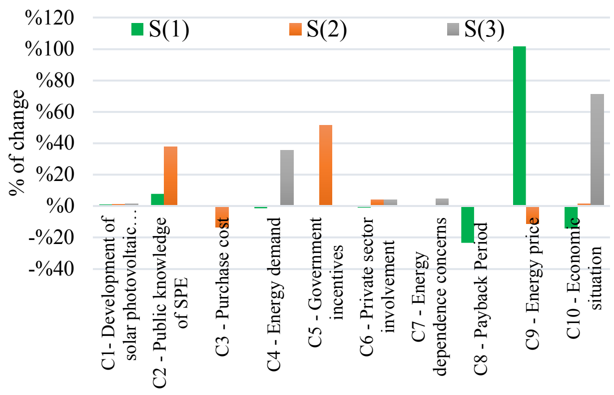


Fig. 8. Scenario Analysis graph that illustrates the deviations for all key concepts, compared to the initial steady-state.

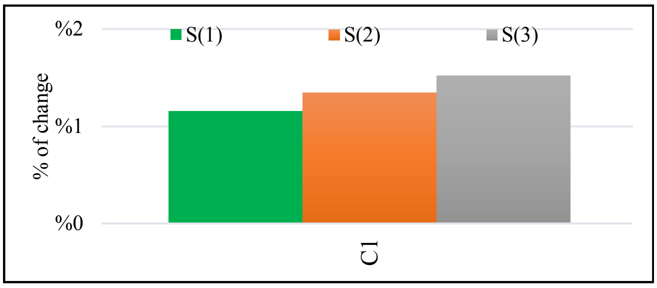


Fig. 9. Decision concept C1 percentage of change, compared to the initial steady-state (baseline scenario).

The overall observations that were drawn from Fig. 8 and Fig. 9 above, are summarized as follows:

- As regards the first scenario, decision concept C9 that refers to "Energy price", affected positively decision concept C2, whereas concepts C4, C6, C7, C8 and C10 were negatively affected.
- Considering the results of the second scenario (see Fig. 8), when decision concepts C2 and C5 increase, then concept C6 slightly increases and concepts C3 and C9 significantly decrease.
- The increase of decision concepts C4 and C10 (scenario S3) leads to a direct increase of key concepts C6 and C7 and a decrease of concept C2.
- All three scenarios have a significant positive impact on the main outcome of this study, decision concept C1 (see Fig. 9).

VI. Discussion & Conclusions

Considering the results reported in this study and depicted in the tables and figures above, certain observations rise for each one of the three performed scenarios. The outcomes of the first scenario (S1), revealed the need for alternative energy sources due to the increase of energy cost. Accordingly, a decrease in energy demand appeared, along with an increase in public awareness of the SPE. Furthermore, a reduction in the private sector involvement was observed, as private companies are unwilling to invest in a quite turbulent and disadvantageous market. This also led to an increase of purchase cost.

The findings of the second scenario (S2) are discussed below. The initiatives and programs that the Brazilian government worked on for the sake of the PSE growth, along with people's ecological awareness on PSE, resulted in the decrease of energy demand, part of which migrated to the PSE field. Moreover, a decrease in electricity price was noticed, as well as in the purchase cost.

In response to the third scenario (S3), where economic growth and high consumption are considered, high energy demand is possible to generate a noteworthy increase in private sector contribution and to raise energy dependence concerns.

Acknowledgment

The authors would like to acknowledge the beneficial contribution of the researchers and specialists in solar photovoltaic energy of University of Brasília (UNB) and University of São Paulo (USP). Moreover, we would like to thank the experts from the Brazilian Solar Energy Association (professionals) and the National Electric Energy Agency (government), whose valuable knowledge, expertise and comments have enhanced the strength and significance of our work.

References

[1] B. Kosko, "Fuzzy cognitive maps," *International Journal of Man Machine Studies*, vol. 24, no. 1, pp. 65–75, 1986.

[2] E. I. Papageorgiou, "Learning algorithms for fuzzy cognitive maps: a review study," *IEEE Trans Syst Man Cybern C*, vol. 42, no. 2, pp. 150–163, 2012.

[3] P. P. Groumpos, "Fuzzy Cognitive Maps: Basic Theories and Their application to Complex Systems," in *Fuzzy Cognitive Maps: Advances in Theory, Methodologies, Tools and Applications*, Springer, 2010, pp. 1–22.

[4] E. I. Papageorgiou, "A new methodology for decisions in medical informatics using fuzzy cognitive maps based on fuzzy rule-extraction techniques," *Appl. Soft Comput*, vol. 11, pp. 500–513, 2011, doi: doi:10.1016/j.asoc.2009.12.010.

[5] J. L. Salmeron, "Supporting decision makers with fuzzy cognitive maps," *Res. Technol. Manage*, vol. 52, no. 3, pp. 53–59, 2009.

[6] M. Amer, A. Jetter, and T. Daim, "Development of fuzzy cognitive map (FCMs)-based scenarios for wind energy," *International Journal of Energy Sector Management*, vol. 5, no. 4, pp. 564–584, 2011, doi: 10.1108/17506221111186378.

[7] K. Kok, "The potential of Fuzzy Cognitive Maps for semi-quantitative scenario development, with an example from Brazil," *Global Environmental Change*, vol. 19, no. 1, pp. 122–133, 2009, doi: 10.1016/j.gloenvcha.2008.08.003.

[8] M. Van Vliet, K. Kok, and T. Veldkamp, "Linking stakeholders and modelers in scenario studies: the use of Fuzzy Cognitive Maps as a communication and learning tool," *Futures*, vol. 42, no. 1, pp. 1–14, 2010, doi: DOI:/10.1016/j.futures.2009.08.005 59.

[9] A. Jetter and W. Schweinfort, "Building scenarios with Fuzzy Cognitive Maps: An exploratory study of solar energy," *Futures*, vol. 43, no. 1, pp. 52–66, 2011, doi: 10.1016/j.futures.2010.05.002.

[10] I. E. Karagiannis and P. P. Groumpos, "Modeling and analysis of a hybrid-energy system using fuzzy cognitive maps," presented at the 21st Mediterranean Conference on Control and Automation, Chania, 2013, pp. 257–264, doi: 10.1109/MED.2013.6608731.

[11] A. Sözen, E. Arcaklıoğlu, M. Özalp, and N. Çağlar, "Forecasting based on neural network approach of solar potential in Turkey," *Renewable Energy*, vol. 30, no. 7, pp. 1075–1090, 2005, doi: https://doi.org/10.1016/j.renene.2004.09.020.

[12] H. T. C. Pedro and C. F. M. Coimbra, "Assessment of forecasting techniques for solar power production with no

exogenous inputs," *Solar Energy*, vol. 86, no. 7, pp. 2017–2028, Jul. 2012, doi: 10.1016/j.solener.2012.04.004.

[13] J. Sargunam and S. Iniyan, "A review of energy models," *Renewable and Sustainable Energy Reviews*, vol. 10, pp. 281–311, 2006, doi: 10.1016/j.rser.2004.09.004.

[14] T. Khatib, A. Mohamed, and K. Sopian, "A review of solar energy modeling techniques," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 5, pp. 2864–2869, 2012, doi: https://doi.org/10.1016/j.rser.2012.01.064.

[15] Z. Sen, *Solar Energy Fundamentals and Modeling Techniques*, 1st ed. London: Springer-Verlag London, 2008.

[16] J. C. Lam, K. K. W. Wan, and L. Yang, "Solar radiation modelling using ANNs for different climates in China," *Energy Conversion and Management*, vol. 49, no. 5, pp. 1080–1090, 2008, doi: https://doi.org/10.1016/j.enconman.2007.09.021.

[17] T. Khatib, A. Mohamed, K. Sopian, and M. Mahmoud, "Solar Energy Prediction for Malaysia Using Artificial Neural Networks," *International Journal of Photoenergy*, vol. 2012, p. 419504, Jun. 2012, doi: 10.1155/2012/419504.

[18] D. Fadare, "Modelling of solar energy potential in Nigeria using an artificial neural network model," *Applied Energy*, vol. 86, pp. 1410–1422, Sep. 2009, doi: 10.1016/j.apenergy.2008.12.005.

[19] K. S. Reddy and M. Ranjan, "Solar resource estimation using artificial neural networks and comparison with other correlation models," *Energy Conversion and Management*, vol. 44, no. 15, pp. 2519–2530, Sep. 2003, doi: 10.1016/S0196-8904(03)00009-8.

[20] M. Mohandes, S. Rehman, and T. O. Halawani, "Estimation of global solar radiation using artificial neural networks," *Renewable Energy*, vol. 14, no. 1, pp. 179–184, 1998.

[21] L. F. Zarzalejo, L. Ramirez, and J. Polo, "Artificial intelligence techniques applied to hourly global irradiance estimation from satellite-derived cloud index," *Energy*, vol. 30, no. 9, pp. 1685–1697, 2005, doi: 10.1016/j.energy.2004.04.

[22] Z. Sen, "Fuzzy algorithm for estimation of solar irradiation from sunshine duration," *Solar Energy*, vol. 63, no. 1, pp. 39–49, 1998.

[23] S. Huang, S. Lo, and Y. Lin, "Application of a fuzzy cognitive map based on a structural equation model for the identification of limitations to the development of wind power," *Energ Policy*, vol. 63, pp. 851–861, 2013.

[24] G. Ziv, E. Watson, D. Young, D. Howard C., S. T. Larcom, and A. J. Tanentzap, "The potential impact of Brexit on the energy, water and food nexus in the UK: a fuzzy cognitive mapping approach," *Appl Energy*, vol. 210, pp. 487–98, 2018.

[25] P. J. Schoemaker, "Scenario planning: a tool for strategic thinking," *Sloan Manag Rev*, vol. 36, pp. 25–50, 1995.

[26] A. Azadeh, M. Saberi, A. Gitiforouz, and Z. Saberi, "A hybrid simulation adaptive-network-based fuzzy inference system for improvement of electricity consumption estimation,"," *Expert Systems with Applications*, vol. 36, pp. 11108–11117, 2009.

[27] D. Borrie and C. S. Ozveren, "The electric power market in the United Kingdom: Simulation with adaptive intelligent agents and the use of fuzzy cognitive maps as an inference engine," presented at the 39th International universities power engineering conference, UPEC, 2004, vol. 3, pp. 1150–1154.

[28] M. Alipour, R. Hafezi, E. I. Papageorgiou, M. Hafezi, and M. Alipour, "Characteristics and scenarios of solar energy development in Iran: Fuzzy cognitive map-based approach," *Renewable and Sustainable Energy Reviews*, vol. 116, 2019.

[29] S. A. Gray, S. Gray, L. J. Cox, and S. Henly-Shepard, "Mental modeler: a fuzzy-logic cognitive mapping modeling tool for adaptive environmental management," presented at the 46th Hawaii international conference on system sciences, Hawaii, 2013, pp. 965–73.

[30] M. Bachhofer and M. Wildenberg, "FCMappers – disconnecting the missing link," *FCMappers-Disconnecting the missing link*, Feb. 10, 2019. http://www.fcmappers.net/joomla/ (accessed Feb. 10, 2020).

[31] A. Nikas, E. Ntanos, and H. Doukas, "A semi-quantitative modelling application for assessing energy efficiency strategies," *Appl Soft Comput*, vol. 76, pp. 140–55, 2019.

[32] G. Napoles, M. Leon, I. Grau, and K. Vanhoof, "Fuzzy cognitive maps tool for scenario analysis and pattern classification," presented at the 29th international conference on tools with artificial intelligence (ICTAI), 2017, pp. 644–51.

[33] M. Margaritis, C. Stylios, and P. P. Groumpos, "Fuzzy cognitive map software," presented at the 10th international conference on software Telecommunications and Computer Networks SoftCom, 2002, pp. 8–11.

[34] D. De Franciscis, "JFCM: a java library for FuzzyCognitive maps," in *Fuzzy cognitive maps for applied sciences and engineering*, Springer, 2014, pp. 199–220.

[35] M. Glykas, *Fuzzy cognitive maps: advances in theory, methodologies, tools and applications*. Springer, 2010.

[36] A. Ferreira *et al.*, "Economic overview of the use and production of photovoltaic solar energy in brazil," *Renewable and Sustainable Energy Reviews*, vol. 81, pp. 181–191, 2018, doi: /10.1016/j.rser.2017.06.102.

[37] E. I. Papageorgiou and J. L. Salmeron, "Methods and Algorithms for Fuzzy Cognitive Map-based Modeling," *Fuzzy Cognitive Maps for Applied Sciences and Engineering*, 2014.

[38] F. R. Martins, E. B. Pereira, and S. L. Abreu, "Satellite-derived solar resource maps for Brazil under SWERA project," *Solar Energy*, vol. 81, pp. 517–528, 2007.

[39] B. C. Rocha, P. P. F. V. Ferreira, D. H. N. Dias, and B. S. M. C. Borba, "Economic evaluation of photovoltaic microgenaration in the Southeast region of Brazil," presented at the SBSE, 2018 - 7th Brazilian Electrical Systems Symposium, 2018, pp. 1–6.

[40] A. M. Lenz *et al.*, "Evaluation of three systems of solar thermal panel using low cost material, tested in Brazil," *Journal of Cleaner Production*, vol. 167, pp. 201–207, 2017.

[41] B. Warren, *Renewable Energy Country Attractiveness Index (RECAI)*. London, U.K.: Ernst Young, 2015.

[42] Ministério de Minas e Energia (MME), "Energia solar no Brasil e no mundo," *Núcleo de Estudos Estratégicos de Energia,* Jul. 20, 2016. http://gesel.ie.ufrj.br/app/webroot/files/IFES/BV/mme68.pdf (accessed Oct. 02, 2020).

[43] A. F. Paulo and G. S. Porto, "Evolution of collaborative networks of solar energy applied technologies," *Journal of Cleaner Production*, vol. 204, pp. 310–320, 2018.

[44] R. G. Brown, *Smoothing, Forecasting and Prediction of Discrete Time Series*. Englewood Cliffs, NJ.: Prentice-Hall, 1963.

[45] E. I. Papageorgiou, K. Papageorgiou, Z. Dikopoulou, and A. Mouhrir, "A web-based tool for Fuzzy Cognitive Map Modeling," presented at the 9th International Congress on Environmental Modelling and Software. (iEMSs), Fort Collins, CO., 2018.

[46] S. R. J. Gray *et al.*, "Are coastal managers detecting the problem? Assessing stakeholder perception of climate vulnerability using Fuzzy Cognitive Mapping," *Ocean & Coastal Management*, vol. 94, pp. 74–89, 2014.