Review Study on Fuzzy Cognitive Maps and Their Applications during the Last Decade

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Abstract. This survey work tries to review the most recent applications and trends on fuzzy cognitive maps (FCMs) at the last ten years. FCMs are inference networks, using cyclic directed graphs, for knowledge representation and reasoning. In the past decade, FCMs have gained considerable research interest and are widely used to analyze causal systems such as system control, decision making, management, risk analysis, text categorization, prediction etc. Some example application domains, such as engineering, social and political sciences, business, information technology, medicine and environment, where the FCMs emerged a considerable degree of applicability were selected Their dynamic characteristics and learning methodologies make them essential for modeling, analysis, prediction and decision making tasks as they improve the performance of these systems. A survey on FCM studies concentrated on FCM applications on diverse scientific fields is elaborated during the last decade.

Keywords: fuzzy cognitive maps, review, applications, styling, insert (key words).

1 Introduction

This study tries to gather the recent advances and trends on FCMs, their dynamic capabilities and application characteristics in diverse scientific areas. FCM represents a system in a form that corresponds closely to the way humans perceive it. Experts of each scientific area are used to express their knowledge by drawing weighted causal digraphs. The developed model is easily understandable, even by a non-technical audience and each parameter has a perceivable meaning [1,2].

In a graphical form, the FCMs are typically signed fuzzy weighted graphs, usually involving feedbacks, consisting of nodes and directed links connecting them. The nodes represent descriptive behavioral concepts of the system and the links represent cause-effect relations between the concepts. In the context of FCM theory, the fuzzy value of a concept denotes the degree in which the specific

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concept is active in the general system, usually bounded in a normalized range of [0, 1]. Furthermore, the weights of the system's interrelations reflect the degree of causal influence between two concepts and they are usually assigned linguistically by experts [3]. They work by capturing and representing cause and effect relationships.

According to Codara (1998) [4], FCMs can be used for various purposes, including:

- to reconstruct the premises behind the behavior of a given agent, to understand the reasons for their decisions and for the actions the take, highlighting any distortions and limits in their representation of the situation (explanatory function);
- to predict future decisions and actions, or the reasons that a given agent will use to justify any new occurrences (prediction function);
- to help decision-makers ponder over their representation of a given situation in order to ascertain its adequacy and possibly prompt the introduction of any necessary changes (reflective function);
- to generate a more accurate description of a difficult situation (strategic function).

Essentially, a Fuzzy Cognitive Map is developed by integrating the existing experience and knowledge regarding a system. This can be achieved by using a group of human experts to describe the system's structure and behavior in different conditions. With FCM it is usually easy to find which factor should be modified and how and by this sense, an FCM is a dynamic modeling tool in which the resolution of the system representation can be increased by applying further mapping [5,6]. As simple mathematical models, FCMs represent the structured causality knowledge for qualitative and quantitative inference. The resulting fuzzy model can be used to analyze, simulate, and test the influence of parameters and predict the behavior of the system.

The main reasons someone uses the FCM approach are [7]: easy of use, easy to construct and parameterize, flexibility in representation (as more concepts/phenomena can be added and interact), low time performing, easily understandable/transparent to non-experts and lay people [8], handle with complex issues related to knowledge elicitation and management, handle with dynamic effects due to the feedback structure of the modeled system.

Furthermore, individual FCMs pertaining to a particular domain can be combined mathematically [1,2]. This means that FCMs allow for different experts and/or stakeholder views to be incorporated [9], and can provide a useful mechanism for combining information drawn from many sources to create a rich body of knowledge [10-12]. Finally, vector-matrix operations allow an FCM to model dynamic systems [1,13], allowing for the dynamic aspect of system behaviour to be captured [14]. Thus, FCMs have gained considerable research interest and accepted as useful methodology in many diverse scientific areas from knowledge modeling and decision making.

This work presents a survey on FCMs applications and trends in diverse scientific areas during the last decade exploring some of the most representative for each application study. The main aim of this study is to give an outline on how the FCMs increase their applications and more methodological efforts made by other researchers to enhance their applicability in different domains. It is difficult to present all the representative applications in each domain, as the number of FCM papers was extremely increased the last three years. Thus, we attempt to figure out only some of the most representative works of each domain, during the last decade.

2 Fuzzy Cognitive Maps and Applications

FCM is an efficient inference engine for modeling complex causal relationships easily, both qualitatively and quantitatively. Dickerson and Kosko (1994) used the FCM in a virtual world to model how sharks and fish hunt [15]. Parenthoen and his colleagues [16] successfully used the FCM to model the intentions and movements of a sheep dog and sheep in a virtual world.

During the past decade, FCMs played a vital role in the applications of diverse scientific areas, such as social and political sciences, engineering, information technology, robotics, expert systems, medicine, education, prediction, environment etc. Aguilar (2005) was the first who tried to gather the FCM applications in different scientific domains till 2004 [17]. In his work, most of the FCM applications were referred: administrative sciences, information analysis, popular political developments, engineering and technology management, prediction, education, cooperative man–machines, decision making and support, environmental management etc. After 2004, a large number of research studies related to methodologies for constructing or enhancing FCMs as well as innovative applications of FCMs were emerged. It is pinpointed that the number of research papers at 2010 is almost the double of the research papers presented till 2004 (see Table 1). The recent applications are focused not only to the previous referred domains but to more others such as telecommunications, game theory, e-learning, virtual environments, ambient intelligence, collaborative systems. New methodologies engaged with dynamic construction of FCMs, learning procedures, fuzzy inference structures were explored to improve the performance of them.

In this work, we concentrate our effort on FCM research studies after 2000 and especially on the presentation of the main categories of them at the last ten years (2001 to 2010). In particular, we describe recent research studies after 2008 for most of the application domains.

From the number of FCM studies opposed in Table 1 (last access in scopus at 20 February 2011), it is observed that during the last decade (we consider the years 2000 till 2010), there is a large increase on the number of research papers related to FCMs.

Table 1 Research Studies of FCMs found in Scopus

Year	**Number of FCM-related studies from scopus**		
	Studies	***Journals & Book chapters***	***Conferences***
2000	18	8	10
2001	22	2	20
2002	7	4	3
2003	19	9	10
2004	53	15	38
2005	35	16	19
2006	50	11	39
2007	56	19	37
2008	81	21	60
2009	84	26	58
2010	(91+11 journals published in 2011) 102	50+11 Journals at 2011	41

Also, it is clearly shown that the last two years (2009-2010) the number of published papers in FCMs has been quadruple from the number of papers at the first years of decade (2000, 2001), and doubled from the papers published at 2004. Most of the research papers are related to FCMs applications and methodologies. 517 studies were accomplished during the past decade. A collection of papers with applications in various disciplines is presented in the book "Fuzzy Cognitive Maps: Advances in Theory, Methodologies, Applications and Tools edited by M. Glykas and prefaced by B. Kosko [6]. This is a significant index on FCM acceptability and applicability in research studies. Bar-chart in Figure 1 illustrates the FCM research studies for the last twenty years, including conference and journal papers, book chapters and technical reports, respectively for each year. It is clear from the chart that the FCMs have gained a considerable interest in research, which extremely increased during the last years. Furthermore, some types of typical problems solved by FCMs are modeling, prediction, interpreting, monitoring, decision making, classification, management. Paradigms of typical problems solved by FCMs are depicted in Table 2.

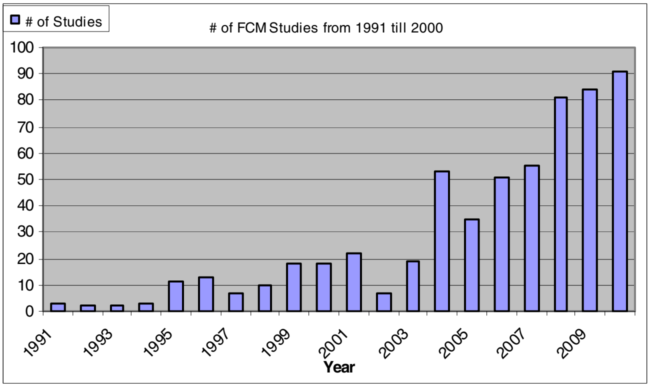

Fig. 1 FCM papers during the last twenty years

Table 2 Paradigms of typical problems solved by fcms

Paradigm	**Typical problems solved by FCMs** ***Description***
Control	Prediction interpreting, monitoring
Business	Planning, management, decision making, inference
medicine	Decision support, modeling, prediction, classification
robotics	Navigation, learning, prediction
environment	Knowledge representation, reasoning, stakeholders'analysis, policy making
Information technology	Modeling, analysis

2.1 FCM Methodologies

In this section, a very short review is attempted to present the FCM methodologies and theories, depicting the estimation of their causal weights, the design and development process, the inference process etc.

As a generic model, the FCM relies on several assumptions. For example, the concepts' activation values are updated simultaneously at the same rate, and the causalities among the concepts are always in effect. However, these assumptions might not always hold, and the FCM isn't powerful or robust enough to model a dynamic, evolving virtual world. One other restriction is that use only simple monotonic and symmetric causal relations between concepts. But many real world causal relations are neither symmetric nor monotonic.

To solve these and other shortcomings and thus to improve the performance of FCMs, several methodologies were explored. Extensions to the FCMs theory are more than anything needed because of the feeble mathematical structure of FCMs and mostly the desire to assign advanced characteristics not met in other computational methodologies. Under this standpoint, some core issues are discussed and respective solutions are proposed in recent studies [18-25]; Pedryez (2010) presented the synergy of granular computing and evolutionary optimization to design efficiently FCMs, through a theoretic analysis [18]. Salmeron (2010) proposed the case of fuzzy grey cognitive maps, based on grey system theory, which is a very effective theory for solving problems within environments with high uncertainty, under discrete small and incomplete data sets [19]. Next, Iakovidis and Papageorgiou (2011) introduced the intuitionistic fuzzy sets and reasoning to handle the experts' hesitancy for decision making [20]. Also, more extensions of FCMs have been proposed, such as Rule-based FCMs [21,22], temporal FCMs [23], evolutionary multilayered FCMs [24,25] etc.

A dynamic version of FCMs, namely Dynamic Cognitive Networks, and a transformation process of cognitive maps, were proposed by Miao et al. [5,26] in order to explore the dynamic nature of concepts and to determine the strength of the cause and the cause-effect relationships as much as the degree of influence. Also, Fuzzy Cognitive Networks (FCNs) proposed as an operational extension of FCMs [27] that always reach equilibrium points in their operations especially to control unknown plants.

As another core task to design the FCMs, Song and his colleagues (2010) proposed a fuzzy neural network to enhance the learning ability of FCMs so that the automatic determination of membership functions and quantification of causalities can be incorporated with the inference mechanism of conventional FCMs. They employed mutual subsethood to define and describe the causalities in FCMs. It provides more explicit interpretation for causalities in FCMs and makes the inference process easier to understand. In this manner, FCM models of the investigated systems can be automatically constructed from data, and therefore are independent of the experts [28]. Next, Papageorgiou (2011) proposed a new methodology to design augmented FCMs combining knowledge from experts and knowledge from different data sources in the form of fuzzy rules [12].

It is worth noting that another important methodology for improving the performance of FCMs is learning algorithms. Learning methodologies for FCMs have been developed in order to update the initial knowledge of human experts and/or include any knowledge from historical data to produce learned weight matrices. The adaptive Hebbian-based learning algorithms, the evolutionary-based such as genetic algorithms and the hybrid approaches composed of Hebbian type and genetic algorithm were established to handle the task of FCM training [29,30-33]. These algorithms are the most efficient and widely used for training FCMs according to the existing literature [29,34].

2.2 Example Application Areas

Some example application areas were selected to present the way FCMs were applied and depicted in what follows. In Figure 2, the number of research studies accomplished in each one of the most common application domains during the last decade is depicted. At 2010, 13 application studies of FCMs were emerged in business, 12 in engineering and control, 8 in information technology, 5 in medical domain, and 6 in environment and agriculture.

1) Political and Social Sciences

FCMs emerged as a technique for modeling political and strategic issues situations and supporting the decision-making process in view of an imminent crisis. The research group of Andreou et al. proposed the use of the genetically evolved certainty neuron fuzzy cognitive map (GECNFCM) as an extension of CNFCMs aiming at overcoming the main weaknesses of the latter, namely the recalculation of the weights corresponding to each concept every time a new strategy is adopted [35]. That novel technique combined CNFCMs with genetic algorithms (GAs), the advantage of which lies with their ability to offer the optimal solution without a problem-solving strategy, once the requirements are defined. Using a multiple scenario analysis the value of the hybrid technique was demonstrated in the context of a model that reflects the political and strategic complexity of the Cyprus issue, as well as the uncertainties involved in it. Later, the same research group [24,36], presented the evolutionary FCMs for crisis management of the political problem of Cyprus.

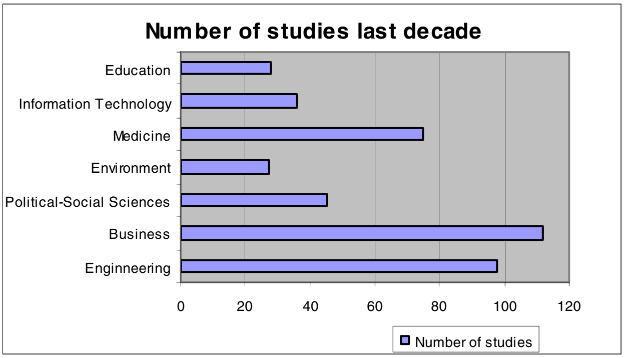

Fig. 2 Number of FCM studies during the last decade (approximately +/- 5 studies per category)

An Ambient Intelligence (AmI) system, integrating aspects of psychology and social sciences, can be considered as a distributed cognitive framework composed by a collection of intelligent entities capable of modifying their behaviors by taking into account the user's cognitive status in a given time. Acampora et al. (2007), introduced a novel methodology of AmI systems' design that exploits multi-agent paradigm and a novel extension of FCMs theory benefiting on the theory of Timed Automata in order to create a collection of dynamical intelligent agents that use cognitive computing to define actions' patterns able to maximize environmental parameters as, for instance, user's comfort or energy saving [37].

Carvalho (2010) in his recent study, discussed the structure, the semantics and the possible use of FCM as tools to model and simulate complex social, economic and political systems, while clarifying some issues that have been recurrent in published FCM papers [38].

2) Medicine

At the last decade, FCMs have found important applicability in medical diagnosis and decision support [12, 39-45. In medical domain and in particular for medical decision support tasks, FCM based decision methodologies include an integrated structure for treatment planning management in radiotherapy [39], a model for specific language impairment [40], models for bladder and brain tumor characterization [41], an approach for the pneumonia severity assessment [42], and a model for the management of urinary tract infections [43]. Stylios et al. proposed FCM architectures for decision support in medicine [44].

Papakostas et al. (2007) implemented FCMs for pattern recognition tasks [45]. Froelich and Deja, 2009, proposed an FCM approach for mining temporal medical data [46]. Rodin et al. (2009) developed a fuzzy influence graph to model cell behavior in systems biology through the intracellular biochemical pathway [47]. Next, this model can be integrated in agents representing cells. Results indicate that despite individual variations, the average behavior of MAPK pathway in a cells group is close to results obtained by ordinary differential equations. The model was applied in multiple myeloma cells signaling.

3) Engineering

In this domain, FCMs found a large number of applications, especially in control and prediction. Particularly, FCMs have been used to model and support a plant control system, to construct a system for failure modes and effect analysis, to fine tune fuzzy logic controllers, to model the supervisor of a control system etc. Stylios and Groumpos, [2004] investigated the FCM for modeling complex systems and controlling supervisory control systems [48]. Papageorgiou et al. implemented learning approaches based on non-linear Hebbian rule to train FCMs that model industrial process control problems [29].

Recently, an integration of a cognitive map and a fuzzy inference engine was presented, as a cognitive–fuzzy model, targeting online fuzzy logic controller (FLC) design and self fine-tuning [49]. The proposed model was different than previous proposed FCMs in that it presents a hierarchical architecture in which the FCM process, available plant, and control objective data on represented knowledge to generate a complete FLC architecture and parameters description. Simulation results demonstrate model interpretability, which suggests that the model is scalable and offers robust capability to generate near optimal controller.

At 2010, Kottas et al. [27] presented basic theoretical results related to the existence and uniqueness of equilibrium points in FCN, the adaptive weight estimation based on system operation data, the fuzzy rule storage mechanism and the use of the entire framework to control unknown plants. The results are validated using well known control benchmarks. The same research team, at the same year, used FCN to construct a maximum power point tracker (MPPT), which may operate in cooperation with a fuzzy MPPT controller [50]. The proposed scheme outperforms other existing MPPT schemes of the literature giving very good maximum power operation of any PV array under different conditions such as changing insolation and temperature.

Beeson et al. (2010) proposed a factored approach to mobile robot map-building that handles qualitatively different types of uncertainty by combining the strengths of topological and metrical approaches [51]. This framework is based on a computational model of the human cognitive map and allows robust navigation and communication within several different spatial ontologies.

4) Business

In business, FCMs have found a great applicability. They can be used for product planning, for analysis and decision support. Some interested applications and worthy to be referred are illustrated. Jetter et al. (2006) used the concept of fuzzy front end for ideation, concept development and concept evaluation of new product development. This concept helped various problems managers who faced difficulty in early product development, as well as to systematic approaches to deal with them [52]. This approach helped in identification of market needs and technology potentials, detection and exploitation of idea sources, early stage assessment of ideas and product concepts, and successful management styles.

Yaman & Polat (2009) proposed the use of fuzzy cognitive maps (FCMs) as a technique for supporting the decision-making process in effect-based planning. With adequate consideration of the problem features and the constraints governing the method used, an FCM is developed to model effect-based operations (EBOs) [53]. In the mentioned study, the model was applied to an illustrative scenario involving military planning. Wei et al (2008) investigated the use of fuzzy cognitive time maps for modeling and evaluating trust dynamics in the virtual enterprises [54]. Bueno & Salmeron (2008) proposed a tool for fuzzy modeling Enterprise Resource Planning selection [55]. Salmeron (2009) proposed the augmented fuzzy cognitive maps for modeling LMS critical success factors [56].

Kim and his coworkers (2008) developed a hybrid qualitative and quantitative approach, using FCMs and GAs, to evaluate forward-backward analysis of RFID supply chain [57]. The research group of Trappey et al (2010) used FCMs to model and evaluates the performance of RFID-enabled reverse logistic operations [58]. Radio frequency identification (RFID) complying with the EPCglobal (2004) Network architecture, i.e., a hardware- and software-integrated cross-platform IT framework, is adopted to better enable data collection and transmission in reverse logistic management. Inference analysis using genetic algorithms contributes to the performance forecasting and decision support for improving reverse logistic efficiency [58]. The study provided a method to predict future logistic operation states and to construct a decision support model to manage system performance based on the forecast.

Büyüközkan et al. (2009) proposed a systematic way of analyzing collaborative planning, forecasting and replenishment (CPFR) supporting factors using FCM approach [59]. Through their study, it was verified the application of FCM where interrelated variables like decision variables and uncontrollable variables were used. Xirogiannis et al. (2010) addressed the problem of designing an “intelligent” decision support methodology tool to act as a back end to financial planning [60].

One of the challenges in Risk Analysis and Management (RAM) is identifying the relationships between risk factors and risks. Lazzerini et al. (2010), proposed Extended Fuzzy Cognitive Maps (E-FCMs) to analyze the relationships between risk factors and risks [61]. The main differences between E-FCMs and conventional FCMs are the following: E-FCMs have non-linear membership functions, conditional weights, and time delay weights. Therefore E-FCMs are suitable for risk analysis as all features of E-FCMs are more informative and can fit the needs of Risk Analysis. Particularly, the work explores the Software Project Management (SPM) and discusses risk analysis of SPM applying E-FCMs.

5) Production Systems

FCM can provide an interesting solution to the issue of assessing the factors which are considered to affect the operator’s reliability and can be investigated for human reliability in production systems [13]. Bertolini & Bevilacqua (2010) investigated the human reliability in production systems which act as an excellent means to study a production process and obtain useful indications on the consequences which can be determined by the variation of one or more variables in the system examined.

Lo Storto et al., (2010) presented a methodological framework to explore the cognitive processes implemented by members of a software development team to manage ambiguous situations at the stage of product requirements definition [62]. FCMs were used in the framework to elicit cognitive schemes and developed a measure of individual ambiguity tolerance. Moreover, FCMs were used to design game-based learning systems because it has the excellent ability of concept representation and reasoning [63]. A novel game-based learning model which includes a teacher submodel, a learner submodel and a set of learning mechanisms was established.

In computer vision, which is a new emerging area, there are demanding solutions for solving different problems. The data to be processed are bi-dimensional (2D) images captured from the tri-dimensional (3D) scene. The objects in 3D are generally composed of related parts that joined form the whole object. Fortunately, the relations in 3D are preserved in 2D. Hence, there are necessary ingredients to build a structure under the FCMs paradigm. FCMs have been satisfactorily used in several areas of computer vision including: pattern recognition, image change detection or stereo vision matching [64]. Pajares (2010) established a general framework of FCMs in the context of 2D images and described the performance of three applications in the three mentioned areas of computer vision.

6) Environment and Agriculture

FCMs were applied in ecology and environmental management for: modeling a generic shallow lake ecosystem by augmenting the individual cognitive maps [65], assessing local knowledge use in agroforestry management [66], modeling of interactions among sustainability components of an agro-ecosystem using local knowledge [67], predicting modeling a New Zealand dryland ecosystem to anticipate pest management outcomes [68], semi-quantitative scenario, with an example from Brazil [69]. Recently, van Vliet et al., (2010) used FCMs as a communication and learning tool for linking stakeholders and modelers in scenario studies [7]. In their recent work demonstrated the potential use of a highly participatory scenario development framework that involves a mix of qualitative, semi-quantitative and quantitative methods. Giordano, et al. (2010) proposed a methodology based on a FCM to support the elicitation and the analysis of stakeholders' perceptions of drought, and the analysis of potential conflicts [70]. The same year, Kafetzis et al. (2010) investigated two separate case studies concerned with water use and water use policy [71]. The documentation and analysis of such stakeholders' models will presumably offer insights into the use and limitations of local knowledge and management, while concurrently providing a current approach to developing appropriate strategies for process-oriented problem solving and decision making in an environmental pollution context.

In agricultrure, FCMs used to represent knowledge and assess cotton yield prediction in precision farming by connecting yield defining parameters with yield in Cotton Crop Production in Central Greece as a basis for a decision support system [72].

7) Information Technology (IT)

In information technology (IT) project management, a FCM-based methodology helps to success modeling. Current methodologies and tools used for identifying, classifying and evaluating the indicators of success in IT projects have several limitations. These could be overwhelmed by employing the FCMs for mapping success, modeling Critical Success Factors (CSFs) perceptions and the relations between them [8]. Rodriguez-Repiso et al (2007) demonstrated the applicability of the FCM methodology through a case study based on a new project idea, the Mobile Payment System (MPS) project, related to the fast evolving world of mobile telecommunications.

Xiangwei et al. (2009) analyzed and summarized common software's usability quality character system in order to find a software usability malfunction discovers and improve problems [73]. They used FCM to describe the software quality character relationship and give an integrated training arithmetic, syntax pruning arithmetic, semantic pruning arithmetic and quality relationship analysis arithmetic to the method.

An interesting tool for FCM development was presented in [74] where the FCM is defined by concepts and relationships that can change during the execution time. Using the tool, someone can design a FCM, follow the evolution of a given FCM, change FCM defined previously, etc. Furfaro et al. (2010) presented a novel method for the identification and interpretation of sites that yield the highest potential of cryovolcanic activity in Titan and introduced the theory of FCMs for the analysis of remotely collected data in planetary exploration [75].

In telecommunications, FCMs applied for distributed wireless P2P networks [76]. Peer-to-peer (P2P) technologies have raised great research interest due to a number of successful applications in wired networks. Popular commercial applications such as Skype and Napster have attracted millions of users worldwide. A novel team-centric peer selection scheme based on FCMs, which simultaneously considers multiple selection criteria in wireless P2P networks, was proposed. The main influential factors and their complex relationships for peer selection in wireless P2P networks were investigated.

Table 3 FCM Applications at the first two months of 2011

Research works published in 2011	**FCM applications at the first two months of 2011**	
	Application area	***Problem solving***
Kannappan et al. [80]	medicine	Classification, prediction
Papageorgiou [12]	medicine	Knowledge representation, decision making
Beena, & Ganguli [79]	Structural damage detection	learning
Song et al. [78]	Business	Classification and prediction
Hanafizadeh, P., Aliehyaei, R. [81]	Soft system	Modeling, analysis
Iakovidis & Papageorgiou [20]	medicine	Decision making, reasoning
Lee, N., Bae, J.K., Koo, C. [82]	Sales assessment	reasoning
Chytas, P., Glykas, M., Valiris, G. [834]	Business	Planning, analysis
Jetter, A., Schweinfort, W. [84]	Solar energy	Modeling, policy scenarios
A. Baykasoglu, Z.D.U. Durmusoglu, V. Kaplanoglu, [71]	Industial process control	Learning, control

Moreover, the participation of agents in FCM process [77] intends to a non-centralized detection of FCM stable state and to a modification process using asynchronous calculations. Stula et al. (2010) developed an agent-based fuzzy cognitive map (ABFCM) for injecting the concept of multi-agent system (MAS) into the FCM and the different inference algorithms in each node enabled the simulation of systems with diverse behavior concepts.

Of course, it was difficult in this study to present all the innovative and useful applications performed by FCMs and their extensions. We attempted to figure out some of the most mentioned applications emerged in the literature and to give the recent research directions of FCMs.

3 FCM Applications at 2011

During the first two months of year 2011, ten journal papers on FCM applications and modeling in different scientific fields were emerged. Table 3 includes these studies with the related application areas. So, the FCM has gradually emerged as a powerful paradigm for knowledge representation and a simulation mechanism that is applicable to numerous research and application fields. For example, Song et al. (2011) proposed a fuzzy neural network to enhance the learning ability of FCMs and incorporated the inference mechanism of conventional FCMs with the determination of membership functions. The effectiveness of this approach lies in handling the prediction of time series [78]. Beena et al. (2011) developed a new algorithmic approach for structural damage detection based on the use of FCM and Hebbian-based learning [79] and Baykasoglu et al. (2011) proposed a new training algorithm for FCMs, the Extended Great Deluge Algorithm (EGDA) [71]. Hanafizadeh and Aliehyaei applied FCMs in soft system methodology [81], Lee et al applied FCMs to sales opportunity assessment [82], Chytas et al applied FCMs to address the problems of proactive balanced scorecards [83], and Jetter et al. applied FCMs for scenario planning of solar energy [84]. Kanappan et al. [80] and Papageorgiou [12,20] applied FCMs in medical domain for classification and decision making.

4 Conclusion

The Fuzzy Cognitive Map methodology has been proven through the literature a very useful approach and cognition tool to model and analyze complex dynamical systems. There is a considerable number of application studies of FCMs in different domains and the application of FCMs emerges a rapid continue. They are helpful to the decision-makers ponder over their representation of a given situation in order to ascertain its adequacy and possibly prompt the introduction of any necessary changes. It is a research challenge for applying FCMs in diverse scientific areas especially when efficient methods to quantify causalities, to adapt and learn FCMs, are proposed which might be handle with the complex tasks of each domain, thus to improve the FCM performance.

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