# A Review of Fuzzy Cognitive Maps Research During the Last Decade

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***Abstract*—This survey makes a review of the most recent applications and trends on fuzzy cognitive maps (FCMs) over the past decade. FCMs are inference networks, using cyclic digraphs, for knowledge representation and reasoning. Over the past decade, FCMs have gained considerable research interest and are widely used to analyze causal complex systems, which have originated from the combination of fuzzy logic and neural networks. FCMs have been applied in diverse application domains, such as computer science, engineering, environmental sciences, behavioral sciences, medicine, business, information systems, and information technology. Their dynamic characteristics and learning capabilities make them essential for a number of tasks such as modeling, analysis, decision making, forecast, etc. Overall, this paper summarizes the current state of knowledge of the topic of FCMs. It creates an understanding of the topic for the reader by discussing the findings presented in recent research papers. A survey on FCM studies concentrated on FCM applications on diverse scientific areas, where the FCMs emerged with a high degree of applicability, has also been done during the past ten years.**

***Index Terms*—Applications, fuzzy cognitive maps (FCMs), review, soft computing.**

## I. Introduction

THIS study presents a review of fuzzy cognitive maps (FCMs) that have emerged over the past decade. Dynamic capabilities and application characteristics of FCMs in diverse scientific areas have been attempted to be gathered. FCM represents a system in a form that corresponds closely to the way human beings perceive it. Experts of each scientific field are used to represent their knowledge through causal weighted digraphs. The developed model is understandable in an easy way, even by a nontechnical audience, since each parameter has a perceivable meaning [1], [2].

From an artificial intelligence point of view, FCMs are supervised learning fuzzy-neural systems, whereas increasingly, data are available to model the problem, and the system becomes better at adapting itself and reaching a solution. In a graphical form, the FCMs are typically signed fuzzy weighted digraphs, usually involving feedbacks, consisting of nodes and directed edges between them. The nodes represent descriptive behavioral concepts of the system, and the edges represent cause–effect relations between the concepts. In the context of FCM theory, the concept's fuzzy value (state) denotes the degree to which the fixed concept is active in the general system, usually bounded in a normalized range of [0, 1] or $[-1, +1]$. Furthermore, the weights of the edges show the degree of causal influence between the presynaptic and postsynaptic concepts, and they are usually assigned linguistically by experts [3]. They work by holding and representing cause and effect relationships.

According to Codara [4], FCMs can be used for several purposes, including four functions.

1) *Explanatory:* It is focused on reconstructing the premises behind the behavior of given agents, understanding the reasons for their decisions and for the actions they take and highlighting any distortions and limits in their representation of the situation.
2) *Prediction:* This function is based on predicting the future decisions and actions, or the reasons that a given agent will use to justify any new occurrences.
3) *Reflective:* This function helps decision makers to ponder over their representation of a given situation in order to ascertain its adequacy and possibly prompt the introduction of any necessary changes.
4) *Strategic:* The last function is based on generating a more accurate description of a complex situation.

In general terms, an FCM is built by mixing the current experience and knowledge regarding a system. This can be achieved by using a human experts' team to describe the system's structure and behavior in different conditions. FCM is a straightforward way to find which factor should be modified and how. In this sense, an FCM is a dynamic modeling technique in which the resolution of the system representation can be increased by applying further mapping [5], [6].

According to van Vliet *et al.* [7], the main motivations for using the FCM approach are the following: easy to build and parameterize, flexibility in representation (as more concepts/phenomena can be included and interact), easy to use, easily understandable/transparent to nontechnical experts, low time performing, handle complex issues related to knowledge elicitation and management, and handle dynamic effects due to the feedback structure of the modeled system.

Moreover, individual FCMs related to a specific domain can be mixed 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

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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], capturing the dynamic aspect of system behavior [14]. Thus, FCMs have gained considerable research interest and accepted as useful technique in many diverse scientific fields from knowledge modeling and decision making.

Anyway, conventional FCMs have several drawbacks. Several extensions have been proposed and more research is needed to overcome the following limitations of conventional FCMs.

1) FCM models lack time delay in the interactions between nodes.
2) Edges' weights are just linear.
3) FCMs cannot represent logical operators (AND, OR, NOT, and XOR) between ingoing nodes.
4) FCMs cannot model multimeaning (gray) environments.
5) It does not include a possible multistate (quantum) of the concepts.
6) It cannot handle more than one relationship between nodes.
7) Many real-world causal relations are neither symmetric nor monotonic as FCM model.
8) FCM dynamics is of first order, where the next state depends just on the previous one. FCM does not handle randomness associated with complex domains.

The main aim of this study is to give a trend on FCM research and a review on FCM applications over the past ten years. In addition, the methodological efforts and FCM extensions proposed by other researchers to enhance their applicability in different domains are described. It is difficult to present all the representative applications in each domain, as the number of FCM papers was extremely increased over the past three years. Thus, we attempt to figure out only some of the most representative works of eight main domains, during the past decade.

## II. Fuzzy Cognitive Maps and Applications

FCM is an efficient inference engine to model complex causal relationships easily, both qualitatively and quantitatively. Dickerson and Kosko used the FCM in a virtual world to model how sharks and fish hunt [15]. Parenthoen *et al.* [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, and so on. Aguilar was the first who tried to gather the FCM applications in different scientific domains until 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 to construct or enhance FCMs, as well as innovative applications of FCMs, emerged. It is pinpointed that the number of research papers in 2010 is almost the double the number of the research papers presented in 2006 (see Table I). A recent trial to gather and present the FCM applications, which has been used as a base for this extensive review work, was accomplished in [110].

TABLE I
FCM Research Studies (Source: Scopus)

| Year | Number of FCM related Studies | | |
|---|---|---|---|
| | Studies | Journals & Book Chapters | Conference papers |
| 2000 | 15 | 8 | 7 |
| 2001 | 20 | 3 | 17 |
| 2002 | 7 | 3 | 4 |
| 2003 | 16 | 12 | 4 |
| 2004 | 45 | 18 | 27 |
| 2005 | 31 | 16 | 15 |
| 2006 | 44 | 17 | 27 |
| 2007 | 50 | 27 | 23 |
| 2008 | 74 | 25 | 49 |
| 2009 | 80 | 25 | 55 |
| 2010 | 89 | 33 | 56 |

### A. Fuzzy Cognitive Map Research Studies

The recent applications are focused not only on the previous referred domains, but also on more others such as telecommunications, game theory, e-learning, virtual environments, ambient intelligence (AmI), and collaborative systems. New methodologies engaged with dynamic construction of FCMs, learning procedures, and fuzzy inference structures were explored to improve the performance of them.

In this study, we concentrate our efforts on FCM research studies after 2000 and especially on the presentation of the main categories of them over the past ten years (2001–2010). Actually, we concentrate on the survey especially to describe recent research studies after 2007 for most of the application domains.

From the number of FCM studies apposed in Table I (last accessed in Scopus on May 3, 2011), it is observed that during the past decade (we considered the years 2000 to 2010), there is a large increase in the number of research papers that are related to FCMs.

In addition, it is clearly shown that over the past two years (2009–2010), the number of published papers in FCMs has been quadruple from the number of papers in the first years of decade (2000, 2001), and doubled from the papers published during 2004–2006. Most of the research papers are related to FCMs applications and methodologies. Four hundred and eighty-five studies were accomplished during the past decade.

A collection of papers with applications in various disciplines is presented in [6]. This is a significant index on FCM acceptability and applicability in research studies. Bar chart in Fig. 1 illustrates the FCM research studies during the past ten 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

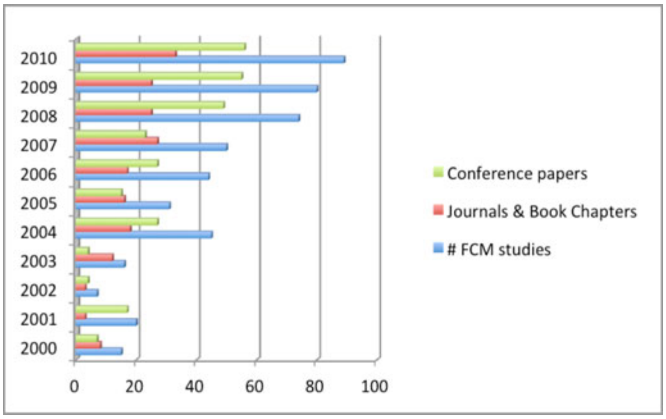


Fig. 1. FCM papers during the past ten years.

TABLE II
PARADIGMS OF TYPICAL PROBLEMS SOLVED BY FCMs

| Paradigm | Typical problems solved by FCMs<br>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 |

research interest, which extremely increased during the past years. Furthermore, some types of typical problems that are solved by FCMs are modeling, prediction, interpreting, monitoring, decision making, classification, management, etc. Paradigms of typical problems that are solved by FCMs are depicted in Table II.

## B. Fuzzy Cognitive Map Methodologies

In this section, a 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 is not powerful or robust enough to model a dynamic evolving virtual world. One more restriction is the usage of only simple monotonic and symmetric causal relations between concepts. However, 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, as described in the next section, are more than anything needed because of the feeble mathematical structure of FCMs and, mostly, the desire to assign advanced characteristics that are not met in other computational methodologies. Under this standpoint, some core issues are discussed and respective solutions are proposed in recent studies [18]–[25]; Pedrycz presented the synergy of granular computing and evolutionary optimization to design efficiently FCMs, through a theoretic analysis [18].

As another core task to design the FCMs, Song *et al.* 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. This mechanism 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 could be automatically built from data and, therefore, could be independent of the experts [28]. Next, Papageorgiou 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 to improve 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 algorithms, such as genetic algorithms (GAs), and the hybrid approaches composed of Hebbian-type and genetic algorithms were established to handle the task of FCM training [29]–[34]. These algorithms are the most efficient and widely used to train FCMs according to the existing literature, as has been described in a recent review study [112].

Furthermore, new trends in agent-based FCM systems architecture have emerged. The participation of agents in FCM process [86] intends to a noncentralized detection of FCM stable state and to a modification process using asynchronous calculations [95].

Stula developed an agent-based FCM to inject the concept of multiagent system (MAS) into the FCM and the different inference algorithms in each node, which enabled the simulation of systems with diverse behavior concepts [95]. Peña *et al.* proposed a framework for the design and development of ontology agents to manage rule-based FCMs [96]. This proposal takes into account the ontology agents and the FCMs represented by rule bases. Rodin *et al.* used MAS to simulate biological processes [97]. FCMs are integrated in cells to model Mitogen-activated protein kinases.

Miao *et al.* investigated a new type of FCM-based personalized recommendation agents called fuzzy cognitive agents [98]. They were designed to give personalized suggestions based on the user's current preferences, other user's common preferences, and expert's domain knowledge. Furthermore, Aguilar suggested an FCM-based approach to build supervision for MAS [99]. Acampora *et al.* developed an FCM-based emotional agent in an AmI environment [107].

## III. Fuzzy Cognitive Map Extensions

Several FCM extensions have been proposed during the past decade. Each one of them improves the conventional FCM, as initially suggested by Kosko, in different ways.

### *A. Rule-Based Fuzzy Cognitive Maps*

Carvalho and Tomé proposed rule-based fuzzy cognitive maps (RBFCM) as an evolution of FCMs including relations other than monotonic causality [35].

RBFCM are iterative fuzzy rule-based systems with fuzzy mechanisms to deal with feedback, including timing and new methods with uncertainty propagation. They defined several kinds of concept relations (causal, inference, alternatives, probabilistic, opposition, conjunction, and so on) to deal with the complexity of the dynamic qualitative systems. RBFCMs include a new fuzzy operation, i.e., fuzzy carry accumulation, which is a key to model the qualitative causal relations, i.e., fuzzy causal relations, while maintaining the FCM's versatility and simplicity. From a temporal point of view, RBFCMs exploit important concepts, such as implicit time and time delays, while they consider a novel important parameter called B-Time. B-Time represents the resolution of the simulation or, in other words, the highest level of temporal detail that a simulation can provide in the modeled system.

### *B. Fuzzy Grey Cognitive Maps*

Salmeron proposed the Fuzzy Grey Cognitive Maps (FGCM) as an FCM extension to deal with multiple (grey) meaning environments [19]. FGCM is based on Grey Systems Theory (GST) that has become a very effective mathematical theory to deal with problems within environments with high uncertainty, under discrete incomplete and small datasets.

An FGCM represents unstructured knowledge through causalities expressed in imprecise concepts and grey weighted relationships between them. Since FGCMs are hybrid methods mixing FCM and GST, each cause is measure by its grey intensity. A grey number is a number whose accurate value is unknown, but it is known that the range within the value is included.

FGCMs are a generalization of FCMs, since an FGCM with all the relations' intensities represented by white numbers would be an FCM. In that sense, FGCM represents the human intelligence better than FCM, because it faces unclear relations between factors and incomplete information better than FCM. In this sense, FGCM has several advantages over FCM.

Conventional FCMs measure the intensity of the causal relation between two concepts, and if no causal relation exists, its intensity is represented by zero in the adjacency matrix. FGCM measures not just the intensity of the causal relationships between factors or its absence between two concepts, but also represents the relations between any two concepts with (partial or completely) unknown intensity. Furthermore, FGCM are able to process the experts' uncertainty about their own judgments.

### *C. Intuitionistic Fuzzy Cognitive Maps*

Intuitionistic fuzzy cognitive maps (iFCM) have recently been developed by Iakovidis and Papageorgiou [20]. They introduced the intuitionistic fuzzy sets (IFS) and reasoning to handle the experts' hesitancy for decision making.

Conventional FCM does not take into account any cue regarding the credibility of the rule expressed by the expert in the FCM construction process. iFCM is an FCM-based decision-making model, enhanced through the intuitionistic reasoning so that it captures the degree of hesitancy in the relations defined by the experts between its concepts.

The experts describe the cause–effect relations among two concepts, not only by their mutual influence, but also by the degree to which the expert hesitates to express that influence.

Hesitancy is represented through IFS, improving knowledge elicitation. IFS generalize the fuzzy sets by treating membership as a fuzzy logical value rather than a single truth value. IFS are an extension of the notion of fuzzy sets. Their elements are featured by an additional degree, which is called degree of uncertainty.

### *D. Dynamical Cognitive Networks*

Dynamic cognitive network (DCN), which was proposed in [5], enables the definition of dynamic causal relationships between the FCM concepts, and it is able to handle complex dynamic causal systems. Theoretically, DCN can support a full set of time-related features. It is the first paper in the literature studying the two aspects of the causality separately, i.e., causes and effects. However, the DCN relies on the Laplacian framework to describe the causal relationships. The transformation between fuzzy knowledge and Laplacian functions imposes more modeling efforts to system designers. It is not easy for domain experts to model their cognitive knowledge by this way.

Each DCN concept can have its own value set, depending on how accurately it needs to be described in the network. It allows that DCNs describe the strength of causes and the degree of effects that are crucial to conducting relevant inferences. The DCN's edges establish dynamic causal relationships between concepts. Structurally, DCNs are scalable and more flexible than FCMs.

A DCN can be as simple as a cognitive map, i.e., an FCM, or as complex as a nonlinear dynamic system. DCNs take into account the three major causal inference factors: the strength of the cause, the strength of the causal relationship, and the degrees of the effect. It is also able to model dynamic cognitive processes. As a result, DCNs improve FCMs by quantifying the concepts and introducing nonlinear dynamic functions to the arcs [26]. Recently, a simplified DCN extending the modeling capability of an FCM has been proposed in [14], where the equivalence of the DCN and the FCM models has also been addressed.

### *E. Dynamic Random Fuzzy Cognitive Maps*

Aguilar proposed the dynamic random fuzzy cognitive maps (DRFCM) to model dynamic systems [100]. A conventional

FCM does not include a robust and dynamic inference mechanism; thus, this FCM lacks the temporal issue that is critical in many applications, as well as the statistical parameter estimates.

DRFCM improves the FCM approach by quantifying the probability of concepts' activation and including a nonlinear dynamic function to the inference process. The contribution of the DRFCM is focused on the dynamic causal relationships. The values of the edges are updated during the runtime of the FCM to adapt them to the new conditions. The quantitative concepts allow development of a feedback mechanism that is included in the causal model to update the edges. DRFCM can consider online adaptive procedures of the model like real-life problems.

### *F. Fuzzy Cognitive Networks*

Fuzzy cognitive network (FCN) was proposed by Kottas *et al.* as an operational extension of FCMs [27] that always reach equilibrium points. FCNs with continuous differentiable sigmoid-like functions having contractive or at least nonexpansive features can always converge to unique equilibrium points.

FCN initial graph depends on experts' judgment as FCM. However, the weighted relationships are estimated based on historical data from the physical system operation. Furthermore, FCNs are in continuous interaction with the system they control [43]. They improve conventional FCMs by introducing an updating mechanism that receives feedback from the real system and the storage of the acquired knowledge throughout the operation.

FCN is able to explore steady-state operational conditions of the described system and relate them with input values and its weight sets [59]. FCNs save the extracted knowledge in fuzzy rule-based databases, which can be used in the control actions. FCNs have successfully been applied to model a maximum power point tracker (MPPT) in order to improve energy conversion efficiency.

### *G. Evolutionary Fuzzy Cognitive Maps*

Cai *et al.* proposed evolutionary fuzzy cognitive maps (E-FCM) to simulate real-time variable states [36]. Their use was examined to model the dynamic and complex causal-related context variables.

E-FCM models every temporal state, which is named as *Evolving State* in the running process, as a collection of concept values. In E-FCM, the concept states evolve in real time, based on their internal states, external assignment, and even external causalities. Furthermore, the concepts update their internal states asynchronous with a small mutation probability.

Compared with FCM, E-FCM allows a different update time schedule for each concept, an asynchronous update of the concepts' values so that they can evolve in a dynamic and stochastic way. E-FCM enables the self-mutation of the context concepts as evolving behavior. Moreover, it involves the probabilistic causality among the variables, which reflects the real-world relationships among the different concepts.

### *H. Fuzzy Time Cognitive Maps*

Wei *et al.* [37] applies the fuzzy time cognitive maps (FTCM) proposed by Park and Kim [38]. FTCM is an FCM, including time in node's relationships. It models the delay of the one presynaptic node influenced over the postsynaptic. Each edge has two kinds of relative weights: the strength and the time lag determined by fuzzy linguistic values.

FTCM introduce dummy nodes for value preserving. In addition, it allows comparison of the results between the model dynamics of FTCM and FCM to analyze time delay effects on the system.

According with this proposal, FTCM can analyze systems behaviors according to lapse of time.

### *I. Fuzzy Rules incorporated in Fuzzy Cognitive Maps*

Song *et al.* proposed fuzzy rules incorporated with FCMs (FRI-FCM) as an FCM extension [39]. They claim that FCMs do not provide effective methods to determine the membership functions, which are critical to describe the dynamic behaviors of the modeled systems. Consequently, in the FCM literature, the interpretation of the inference result greatly depends on experts' knowledge.

Because of those drawbacks in the expression and architecture, FCMs suffer from that common limitation and cannot be applied in classification problems. To solve this problem, FRI-FCM translates the reasoning mechanism of conventional FCMs to a set of fuzzy IF–THEN rules. FRI-FCM inherits the representation of RBFCMs to represent the causality underlying the modeled systems.

FRI-FCM makes comprehensive use of the dimensional information underlying input vectors state and avoids inconvenient degrading of the activations of the respective fuzzy rules as the input dimensions increase [82]. The FRI-FCM better employs the mapping features provided by the rules' consequent components to approximate the desired output state values. The FRI-FCM partitions each output value into the consequent components; then, these are defuzzified by standard-volume-based centroid defuzzification operation. Finally, the FRI-FCM generates the numeric output value as a linear combination of the defuzzified consequent parts.

### *J. Belief-Degree-Distributed Fuzzy Cognitive Maps*

Ruan *et al.* developed belief-degree-distributed fuzzy cognitive maps (BDD-FCMs) [40]. It is not simple to assign linguistic terms for FCM nodes' relationships within complex problems, especially if the experts' judgment has to be done for the future forecasting. Experts have difficulties to decide the accurate linguistic term, as they are not absolutely sure about their own opinion. To overcome this issue, causal relationships of BDD-FCMs are expressed not by a single linguistic term but by a belief structure.

By using BDD-FCMs, causal edges are represented by belief structures which enable getting the edges' evaluations with distributions over the linguistic terms. Moreover, they propose a general methodology to build BDD-FCMs by directly using belief structures or other types of structures.

### *K. Rough Cognitive Maps*

Chunying *et al.* have proposed an FCM extension called rough cognitive maps (RCM) [105]. RCM is based on rough sets (RS) theory. RS is introduced to represent the diversity of the relations of concepts, the dynamic dependence between the relation measures and the state value of concepts, as well as the measures of uncertain causal relationships.

FCMs assume that the relation between the concepts is unique and reflected by a fixed fuzzy measure, usually established by experts. However, in the real world, the relations between a couple of concepts are used to be diverse and have corresponding properties. Thus, the RCM attempts to represent the comprehensive relationships between two concepts and to include a comprehensive weight to accomplish causal reasoning. Therefore, the simulating capability of FCM could be extended.

### *L. Time Automara-Based Fuzzy Cognitive Maps*

Acampora *et al.* developed a timed automata-based FCMs (TAFCM) to distribute emotional services in an AmI environment [107].

The timed automata theory enables FCMs to effectively cope with a double-layered temporal granularity extending the standard idea of B-Time that characterizes the iterative nature of cognitive inference engine. This model offers checking techniques to assess the cognitive and dynamic comportment of the framework being designed.

An FCM just represents a static view of a cognitive system. TAFCMs include a collection of operators that are able to transform a cognitive structure. These operators represent the basic operations on which constructing a cognitive/dynamic model. They try to change the cognitive configuration of a given agent's FCM, by following rules to add/remove concepts and causal relationships, and to magnify/reduce the strengths of causal relationships and the level of system concepts.

Once those TAFCMs have been defined, a more accurately definition of cognitive agent, cognitive space and emotion-aware AmI is provided.

## IV. Fuzzy Cognitive Map Convergence and Stability Issues

FCM can be considered as a system dynamics method, especially because of its focus on feedback loops. Therefore, FCM nodes' state is changing along the iteration process.

FCMs use the edge's weight and a nonlinear activation function to model complex relations between a couple of concepts. Usually, two kinds of activation functions are used in FCM dynamics [41]: unipolar sigmoid and hyperbolic tangent. Both activation functions include a lambda parameter to define function slope (degree of fuzzification). Its value must be established by the FCM designer. For high values of lambda parameter, the sigmoid approximates a discrete function, and for lower values of lambda, the sigmoid approximates a linear function, while values of lambda closer to 5 generate a balanced degree of fuzzification [41].

When FCM converges, the stability is reached. The FCM reaches either one of three states. It converges to a fixed pattern of node state values, the so-called hidden pattern or fixed-point attractor. Otherwise, the state could keep cycling between several states, known as a limit cycle. A third option would be a chaotic attractor using a continuous function. This occurs when, instead of stabilizing, the FCMs generate different state values for each cycle.

Anyway, the stability issues of dynamic systems, such as FCMs, are always present. Carvalho and Tomé claim that since FCMs model concepts as simple neurons, and relations as simple edges between a couple of neurons, the modeling of relations in FCMs is gravely damaged [42]. In this sense, the stability analysis of an FCM, modeling a complex system, is probably so distant from the real-world system. It would not be a drawback if the system is evolving in the short-term range. Unfortunately, stability analysis usually implies a long-term evolution. Then, each minor divergence between the FCM model and the real-world modeled system grows up, when the number of iterations increases. For that reason, the results of the long-term systems evolution are usually unfit.

Analytic methods to reach stability solutions, such as Lyapunov function analysis, are so worthy and widespread. Kosko [1], [15] approached the problem of finding an analytic method to provide a faster answer to the problem of system stability analysis in FCM using Lyapunov functions and concluded that despite being adapted to the study of stability in feedback standard additive models, which share some of FCM characteristics, one cannot extend such conclusions to FCM (according to Kosko, because of the large number of feedback links involved in FCM [6], [15]).

It is well known that when the edges' weights accomplish determined conditions, related to the FCM size and the slope of the sigmoid applied, the concept state will converge to a unique solution regardless their initial values [43], [113]. When those specific conditions are present, the concepts' convergence is just related to the adjacency matrix.

Boutalis *et al.* proposed an adaptive estimation algorithm for the weights' estimation to a new equilibrium point and they gave proofs for its stability and convergence properties [43]. That algorithm considers the convergence issues and incorporates them in the parameter projection schemes.

## V. Application-Domain Areas

Some example application areas were selected to present the way FCMs were applied and depicted in what follows. In Fig. 2, the number of research studies accomplished in each one of the most common application domains, such as environment, medicine, engineering, business and management, mathematics, computer science, and others, during the past decade is depicted. In 2010, 15 application studies of FCMs emerged in business and management, 23 in engineering and control, 67 in computer science, and two in the medical domain.

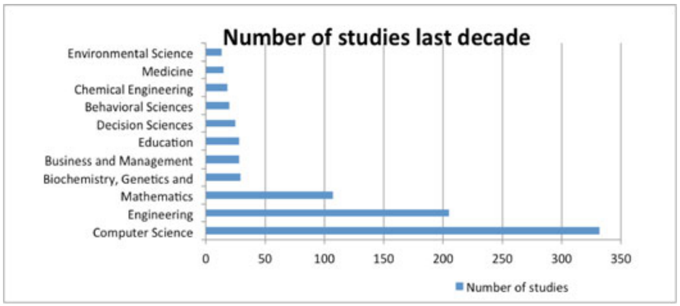


Fig. 2. Number of FCM studies during the past decade.

## A. Behavioral Sciences

FCMs emerged as a technique to model social, 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 (CNFCM) as an extension of CNFCMs aiming to overcome the main weaknesses of the latter, namely the recalculation of the weights corresponding to each concept every time a new strategy is adopted [44]. That novel technique combined CNFCMs with 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], [45] presented the evolutionary FCMs for crisis management of the political problem of Cyprus.

An AmI system, integrating aspects of psychology and social sciences, can be considered as a distributed cognitive framework composed of 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.* introduced a novel methodology of AmI systems' design that exploits a multiagent paradigm and a novel extension of FCMs theory benefiting from the theory of timed automata in order to create a collection of dynamical intelligent agents that use cognitive computing to define actions' patterns that are able to maximize environmental parameters as, for instance, user's comfort or energy saving [46].

Carvalho in his recent study has 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 [47].

## B. Medicine

Over the past decade, FCMs have found important applicability in medical diagnosis and decision support [12], [48]–[54]. 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 [48], a model for specific language impairment [49], models for bladder and brain tumor characterization [50], an approach for the pneumonia severity assessment [51], and a model for the management of urinary tract infections [52]. Stylos and Georgopoulos proposed FCM architectures for decision support in medicine [53].

Papakostas *et al.* implemented FCMs for pattern recognition tasks [54]. Froelich and Wakulicz-Deja proposed an FCM approach for mining temporal medical data [55]. Rodin *et al.* developed a fuzzy influence graph to model cell behavior in systems biology through the intracellular biochemical pathway [56]. 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.

## C. 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 (FLCs), to model the supervisor of a control system, etc. Stylios and Groumpos investigated the FCM to model complex systems and control supervisory control systems [57]. Papageorgiou *et al.* implemented learning approaches based on nonlinear Hebbian rule to train FCMs that model industrial process control problems [29].

Recently, an integration of a cognitive map and a fuzzy inference engine has been presented as a cognitive fuzzy model, targeting online FLC design and self-fine-tuning [58]. The proposed model was different from the previously proposed FCMs in that it presents a hierarchical architecture in which the FCM process, available plant, and control objective data on represented knowledge generate a complete FLC architecture and parameter description. Simulation results demonstrate model interpretability, which suggests that the model is scalable and offers robust capability to generate near-optimal controller.

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 an MPPT, which may operate in cooperation with a fuzzy MPPT controller [59]. The proposed scheme outperforms other existing MPPT schemes of the literature giving very good maximum power operation of any photovoltaic array under different conditions, such as changing insolation and temperature. In [114] and [115], the modeling and the control, respectively, of a waste–water treatment plant based on FCNs was regarded.

Beeson *et al.* 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 [60]. This framework is based on a computational model of the human cognitive map and allows robust navigation and communication within several different spatial ontologies.

Lu *et al.* applied an FCM-based control method on district heating network [111]. This work proposed a methodology to establish the FCM model of controlled object-based least squares and historical data. They also proposed learning rules to make FCM imitate human reasoning capability to realize control of the complex industrial process. They used the proposal to realize even heat supply within a district heating network model. Vaščák and Hirota designed an integrated FCM-based decision-making system for robot soccer [108]. This paper describes an innovative FCM-based design for kicking decisions.

Furfaro *et al.* 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 [84].

### D. Business and Management

In business and management, FCMs have found a great applicability. They were used for product planning, analysis, and decision support. Some interested applications that are worth referring to are illustrated. Jetter 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 [61]. This approach attempts to help 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 and Polat proposed the use of FCMs as a technique to support 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 [62]. In the mentioned study, the model was applied to an illustrative scenario involving military planning. Wei *et al.* investigated the use of fuzzy cognitive time maps to model and evaluate trust dynamics in the virtual enterprises [63].

Kim *et al.* developed a hybrid qualitative and quantitative approach, using FCMs and GAs, to evaluate forward–backward analysis of radio frequency identification (RFID) supply chain [64]. The research group of Trappey *et al.* used FCMs to model and evaluates the performance of RFID-enabled reverse logistic operations [65]. RFID complying with the EPCglobal 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 GAs contributes to the performance forecasting and decision support to improve reverse logistic efficiency [65]. 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.

Baykasoglu *et al.* proposed a systematic way of analyzing collaborative planning, forecasting, and replenishment supporting factors using FCM approach [66]. Through their study, it was verified the application of FCM where interrelated variables, such as decision variables and uncontrollable variables, were used. Xirogiannis *et al.* addressed the problem of designing an "intelligent" decision support methodology tool to act as a back end to financial planning [67].

One of the challenges in risk analysis and management is identifying the relationships between risk factors and risks. Lazzerini and Lusine proposed extended fuzzy cognitive maps (eFCM) to analyze the relationships between risk factors and risks [68]. The main differences between E-FCMs and conventional FCMs are the following: E-FCMs have nonlinear 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.

Chytas *et al.* have developed a methodology for proactive balanced scorecard development [91]. Their proposal addresses the problems of the balanced scorecard by utilizing FCMs. By using FCMs, the proposed methodology generates a dynamic network of interconnected key performance indicators (KPIs), simulates each KPI with imprecise relationships, and quantifies the impact of each KPI to other KPIs in order to adjust the performance goals.

### E. 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. Bertolini and Bevilacqua [13] 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 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 [69]. 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 [70]. 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 to solve different problems. The data to be processed are 2-D images captured from the 3-D scene. The objects in 3-D are generally composed of related parts that joined to form the whole object. Fortunately, the relations in 3-D are preserved in 2-D. Hence, there are necessary ingredients to build a structure under the FCMs paradigm. FCMs have satisfactorily been used in several areas of computer vision including pattern recognition, image change detection, or stereovision matching. Pajares [71] established a general framework of FCMs in the context of 2-D images and described the performance of three applications in the three mentioned areas of computer vision.

### F. Environment and Agriculture

FCMs were applied in ecology and environmental management to model a generic shallow lake ecosystem by augmenting the individual cognitive maps [72], assess local knowledge use in agroforestry management [73], model the interactions among sustainability components of an agro-ecosystem using local knowledge [74], predict modeling a New Zealand dryland ecosystem to anticipate pest management outcomes [75], i.e., a semiquantitative scenario, with an example from Brazil [76]. Recently, van Vliet *et al.* have used FCMs as a communication and learning tool for linking stakeholders and modelers in scenario studies [7]. Their recent work demonstrated the potential use of a highly participatory scenario development framework that involves a mix of qualitative, semiquantitative, and quantitative methods.

Giordano and Vurro proposed a methodology based on an FCM to support the elicitation and the analysis of stakeholders' perceptions of drought, and the analysis of potential conflicts [77].

In the same year, Kafetzis *et al.* investigated two separate case studies concerned with water use and water use policy [78]. 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 agriculture, FCMs are 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 [79].

### G. Information Systems and Information Technology

In Information Systems and Information Technology (IS/IT) project management, an FCM-based methodology helps to success modeling. Current methodologies and tools that are used to identify, classify, and evaluate the indicators of success in IS/IT projects have several limitations. These could be overwhelmed by employing the FCMs for mapping success, modeling critical success factor (CSF) perceptions and the relations between them. Rodriguez-Repiso *et al.* [8] demonstrated the applicability of the FCM methodology through a case study based on a new project idea, i.e., the mobile payment system project, related to the fast evolving world of mobile telecommunications. Bueno and Salmeron proposed an FCM-based model for fuzzy modeling an enterprise resource planning selection [80]. Salmeron proposed the augmented FCM to model learning management system (LMS) CSFs [81].

Lai *et al.* analyzed and summarized common software's usability quality character system in order to find a software usability malfunction discovers and improve problems [82]. 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 [83], where the FCM is defined by concepts and relationships that can change during the execution time. Using the tool, someone can design an FCM, follow the evolution of a given one, change FCM defined previously, etc.

### H. Telecommunications

In telecommunications, FCMs are applied for distributed wireless peer-to-peer (P2P) networks [85]. 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.

### I. Education

Laureano-Cruces used FCM to evaluate the teaching–learning process [103]. FCMs control the diagnostic process in an intelligent learning system. This proposal is based on a multinodal perspective, a holistic and complete approach (knowledge, abilities, attitudes, values). It uses the cognitive components from the expert and the learner, prioritizing the use of cognitive strategies to activate the mental processes within the learning process. They claim that an advantage of its proposal is the ability to include the experts' knowledge by taking advantage of the conceptual graph, thus avoiding the symbolic representation of behavioral reasoning based on rules. In addition, the FCM allows a faster control of the different states of the environment.

Pacheco *et al.* apply FCM to engineering education assessment [104]. FCM put together the different aspects of a complex environment considering each issue involved, by means of a graphical and mathematical representation. The proposed model can be applied to any course, a group of them, a whole educational institution program, an academic department, or even to other processes that need to model uncertainty.

Hossain and Brooks used FCM to model educational software at U.K. secondary schools [101]. They model the stakeholders' perceptions about that kind of software. The FCM approach was developed in three stages. The first one is focused with the building of individual FCMs based on the empirical data from the fully structured interviews with each participant.. The second stage was the aggregation of the individual FCMs to get an augmented FCM model. The third stage involved making improvements to the augmented FCM. This was based on findings from the semistructured interviews. The "documentary coding method" and content analysis were used to analyze the empirical data. It was useful to identificate further interrelationships between factors.

Salmeron proposed to build an augmented FCM-based to model CSFs in LMS [81]. LMS are web-based software packages that enable the management and delivery of learning content and resources to students. LMS selection is a complex process. This proposal, according with an expert panel, specified ten LMS CSFs categories that can help decision makers to efficiently and effectively choose e-learning technologies.

Luo *et al.* designed a game-based learning system based on FCMs. Since FCM cannot get new knowledge from existing data, Hebbian learning rule is utilized to solve the problem and the concept of unbalance degree is used to enhance the game-based learning ability. As a result, the improved FCM has the ability of self-learning from both existing data and prior knowledge and is more suitable for a game-based learning system. The teacher submodel has the standard answers which can be deduced from the improved FCM. The learner submodel is built and adjusted according to the teacher's FCM, which reflects the learner's learning process. The learning mechanisms compute the difference between the outputs of the teacher submodel and the learner submodel, and control the whole game learning process according to the difference. An automobile driving learning system is developed to prove the effectiveness of the proposed model. Extensive experimental results demonstrate our model validity in terms of controlling the learning process and the guiding learners learning.

Cai *et al.* developed the E-FCM, and it was applied to a serious game for science learning [36]. This serious game helps students learn about different diseases by exploring in a virtual world. The game was implemented with torque game engine to test the proposal approach for virtual world modeling in terms of three key aspects. Immersion is the user's feeling of involvement. The E-FCM shows the evolution of the states in real time. This is critical as a simulation tool to model real time characters and contexts.

Georgiou and Botsios applied FCM to learning style recognition [102]. They proposed a three-layer FCM schema to allow experienced educators or cognitive psychology to tune up the system's parameters to adjust the accuracy of the learning style recognition. The inner layer is composed of the learning styles, the middle one the learning activity factors, and the outer layer the 48 statements of the learning style inventory. FCM emerged as a worthy tool for learning style recognition, since it can handle the uncertainty and fuzziness of a learning style diagnosis in an efficient way.

Chunying *et al.* proposed RCM as an FCM extension to model the whole set of relations between two concepts in real world. It pretends to improve the simulation capabilities of the FCM [105]. Altay and Kayakutu apply FCM to factor reduction in a decision-making environment [106]. An excess number of criteria is a critical issue within decision making and/or evaluations in terms of complexity and computational time. Decreasing the number of factors in exchange for a negligible amount of knowledge can discharge to the decision maker yet does not impact the quality of the final decision. FCM-based factor prioritization was applied to large companies and the results are compared with the choices of small- and medium-size enterprises.

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.

Moreover, some FCM drawbacks on these major applications could be assigned. Knowledge on the behavior of a complex system modeled by FCMs is rather subjective. FCM construction methodologies usually rely on experts' knowledge on problems' model and behavior. FCM models are strongly dependent on experts' beliefs and judgment. Most experts have different points of view and use different scales to evaluate the problems. A number of experts are required to ensure objective and globally valid results, as the opinion of one expert is never 100% accurate and always contains some level of subjectivity. In addition, all the experts have not the same expertise, and it could be needed to assign a credibility weight to each one, but it is not an accurate process. Furthermore, FCM models developed by experts could be so complex to develop for large problems involving a huge number of concepts.

On the other hand, FCM designers must select the activation function slope value. That value depends widely on the experts' preferences and the problem complexity. In this context, the number of iterations and the steady vector will be conditioned by the value used. The applied FCMs usually use simple monotonic and symmetric causal relations between concepts which are not correct in real-world causal relations. Moreover, FCM does not handle the whole uncertainty inherent in complex domains by assessing the nodes and edges with discrete values. FCM would need measures about the associated uncertainty in weights and concepts. More research seems to be useful in FCM extensions which add uncertainty measures.

## VI. Fuzzy Cognitive Map Applications in 2011

In 2011, 86 research works (33 published journal papers, 11 articles in press, and 42 conference papers) were published in Scopus from several research teams related to FCMs applied in diverse scientific domains and FCM theories and extensions. Because of the large number of these research works, we selected to present only the research articles presented in Scopus at the first two months of 2011. During the first two months of 2011, eight journal papers (published) and six articles in press on FCM modeling, analysis, and applications in different scientific fields were emerged. Table III includes these example studies with the related application areas. Therefore, 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.

Song *et al.* 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 [28]. Beena and Ganguli developed a new algorithmic approach for structural damage detection based on the use of FCM and Hebbian-based learning [87], and Baykasoglu *et al.* proposed a new training algorithm for FCMs: the extended great deluge algorithm [88].

Hanafizadeh and Aliehyaei applied FCMs in soft system methodology [89], Lee *et al.* applied FCMs to sales opportunity

TABLE III
FCM RESEARCH IN THE BEGINNING OF 2011

| **Research Works** (at the first two months of 2011)-*presented at scopus* | **FCM Area** | |
|---|---|---|
| | **Application Domain** | **Problem Solving** |
| Kannappan et al. [93] | Medicine | Classification, prediction |
| Jetter and Schweinfort [95] | Solar energy | Modeling, policy scenarios |
| Baykasoglu, et al. [88] | Industial process control | Learning, control |
| Beena, and Ganguli [87] | Structural damage detection | Learning |
| Song et al. [28] | Business | Classification and prediction |
| Hanafizadeh, and Aliehyaei [89] | Information Technology | Modeling, analysis |
| Lee et al. [90] | Sales assessment | Reasoning |
| Papageorgiou [12] | Medicine | Knowledge representation, decision making |
| Iakovidis and Papageorgiou [20] | Medicine | Decision making, reasoning |
| Chytas et al. [91] | Business | Planning, analysis |
| Salmeron and Lopez [94] | Information Technology | Knowledge representation, decision making |
| Acampora et al. [107] | Ambient Intelligence | Emotional service-oriented architecture |
| Vaščák and Hirota [108] | Engineering | Decision making, reasoning |
| Papageorgiou et al [109] | Agriculture | Classification, prediction |

assessment [90], Chytas *et al.* applied FCMs to address the problems of proactive balanced scorecards [91], and Jetter and Schweinfort investigated FCMs for scenario planning of solar energy presenting a methodology to help scenario planners to integrate the qualitative and partial knowledge of multiple experts and overcome information processing limitations of FCM [92].

Arthi *et al.* [93], Papageorgiou [12], and Iakovidis and Papageorgiou [20] applied FCMs in medical domain for classification and medical decision making. Salmeron and Lopez applied augmented FCMs in enterprise resource planning software maintenance risks impact forecasting [94]. Acampora *et al.* proposed TAFCMs to distribute emotional services in an AmI environment [107]. Vaščák and Hirota exploited a designation of an integrated FCM-based decision-making system for robot soccer [108]. Papageorgiou *et al.* applied FCMs to precision agriculture for yield prediction [109].

## VII. CONCLUSION

FCM technique has been widely proven through the literature as a very useful one to model and analyze complex dynamical systems. It is an easy-to-use cognition tool which can represent the knowledge and reasoning in it efficiently.

This study has presented a survey on FCMs applications and trends in diverse scientific fields during the past decade exploring some of the most representative works for each application study. There is a considerable number of application studies of FCMs in different domains, extensions of FCMs, or generalizations. The FCM applications are speedily growing up. FCMs are helpful as decision makers ponder their representation of a given problem in order to ascertain its adequacy and possibly prompt the launch of any necessary changes.

It is a research challenge to apply the FCMs approach in different scientific fields, especially when efficient methods to quantify causalities and to adapt and learn FCMs are proposed which might be handle with the complex tasks of each domain, thus improving FCM performance.

Research on FCM theory, as well as the number of applications and the heterogeneity of them, are quite promising. We hope that in the future, more FCM research will be done.

As a critical overview, FCM community trends spread out FCM research in a lot of extensions. It is a weak point because lesser efforts are focused on FCM. More research is needed on learning, automatic construction, knowledge representation, and so on. The new theoretical contributions could be included in current or emerging extensions as well. Regarding the application domains, most of them are proofs of concept. A permanent effort would be needed in each domain for a fitter to adjust the FCM technique in each domain. In this sense, there are several trends on FCM theory and applications.

1) *Theory:* A lot of works analyze FCM dynamics, but little research has been done on FCM static analysis. Indeed, fewer works focus on both kind of analysis at the same time. We consider that it could enrich the FCM outlet.
2) *Learning:* Automatic learning in FCMs is used to focus on weights adjustment. More research is needed on automatic construction. It would make FCMs less expert dependent.
3) *Extensions:* The current extensions are usually designed to solve three FCM drawbacks, uncertainty modeling (FGCM, iFCM, BDD-FCM, and RCM), dynamics issues (DCN, DRFCM, FCM, E-FCM, FTCM, and TQFCM), and rule-based knowledge representation (RBFCM and FRI-FCM). The extensions of conventional FCM seem to be a useful trend to overcome FCM limitations.
4) *Application domains:* The main domains where FCM are applied are medicine, business, information technology, industrial processes and control, engineering, environment, and agriculture.

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