Journal of Informetrics 5 (2011) 146–166

Contents lists available at ScienceDirect

Journal of Informetrics

journal homepage: www.elsevier.com/locate/joi

An approach for detecting, quantifying, and visualizing the evolution of a research field: A practical application to the Fuzzy Sets Theory field

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ARTICLE INFO

Article history:
Received 26 April 2010
Received in revised form 3 October 2010
Accepted 6 October 2010

Keywords:
Science mapping
Co-word analysis
Bibliometric studies
Fuzzy Sets Theory
Thematic evolution
h-Index

ABSTRACT

This paper presents an approach to analyze the thematic evolution of a given research field. This approach combines performance analysis and science mapping for detecting and visualizing conceptual subdomains (particular themes or general thematic areas). It allows us to quantify and visualize the thematic evolution of a given research field. To do this, co-word analysis is used in a longitudinal framework in order to detect the different themes treated by the research field across the given time period. The performance analysis uses different bibliometric measures, including the h-index, with the purpose of measuring the impact of both the detected themes and thematic areas. The presented approach includes a visualization method for showing the thematic evolution of the studied field.

Then, as an example, the thematic evolution of the Fuzzy Sets Theory field is analyzed using the two most important journals in the topic: *Fuzzy Sets and Systems* and *IEEE Transactions on Fuzzy Systems*.

1. Introduction

Bibliometrics is usually used for the quantitative research assessment of academic output, and it is starting to be used for practice based research (for more information see Callon, Courtial, & Laville, 1991; Coulter, Monarch, & Konda, 1998; Henderson, Shurville, & Fernstrom, 2009; Ramos-Rodrguez & Ruz-Navarro, 2004; van Raan, 2005a). Concretely, bibliometrics is a set of methods used to study or measure texts and information, especially in big datasets. Many research fields use bibliometric methods to explore the impact of their field, the impact of a set of researchers, or the impact of a particular paper (Henderson et al., 2009; van Raan, 2005a).

In bibliometrics, there are two main procedures: performance analysis and science mapping (Noyons, Moed, & Luwel, 1999; van Raan, 2005a). Performance analysis aims at evaluating groups of scientific *actors* (countries, universities, departments, researchers) and the impact of their activity (Noyons, Moed, & van Raan, 1999; van Raan, 2005a) on the basis of bibliographic data. Science mapping aims at displaying the structural and dynamic aspects of scientific research (Börner, Chen, & Boyack, 2003; Noyons, Moed, & Luwel, 1999). A science map is used to represent the cognitive structure of a research field.

Various types of techniques have been developed to build a science map (Small, 2006), the most commonly used being documents co-citation (Small, 1973) and co-word analysis (Callon, Courtial, Turner, & Bauin, 1983). Moreover, different

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doi:10.1016/j.joi.2010.10.002

methods have been proposed to address the problem of delimiting a research field, and quantifying and visualizing the detected subfields by means of co-word or co-citation analysis (Börner et al., 2003; Callon et al., 1991; Chen, Ibekwe-SanJuan, & Hou, 2010; Coulter et al., 1998; Courtial & Michelet, 1994; Courtial, 1990; Kandylas, Upham, & Ungar, 2010; Leydesdorff & Rafols, 2009; Rip & Courtial, 1984; Small & Upham, 2009; Small, 1977, 2006; Upham & Small, 2010). The majority of these methods are mainly focused on measuring the performance of the scientific actors and little research has been carried out in order to measure the performance of given research fields in a conceptual way (specific themes or whole thematic areas). A performance analysis of specific themes or whole thematic areas can measure (quantitatively and qualitatively) the relative contribution of these themes and thematic areas to the whole research field, detecting the most prominent, productive, and highest-impact subfields.

The main aim of this paper is to present a general approach to analyze the thematic evolution of a given research field. This approach combines performance analysis and science mapping for detecting and visualizing conceptual subdomains (particular themes or general thematic areas). It also allows us to quantify and visualize the thematic evolution of the research field. To do this, co-word analysis is used in a longitudinal framework (Garfield, 1994). For a better interpretation of the results, strategic diagrams are used in order to categorize the detected themes. Furthermore, thematic areas are used to show conceptual evolution, proposing a visualization approach for graphically showing the thematic evolution of the studied field. Additionally, we develop a performance analysis using different basic bibliometric indicators (the number of published documents, the number of received citations, etc.,) and the h-index (Alonso, Cabrerizo, Herrera-Viedma, & Herrera, 2009; Cabrerizo, Alonso, Herrera-Viedma, & Herrera, 2010; Hirsch, 2005). As an example, the proposed approach is applied to analyze the thematic evolution of the Fuzzy Sets Theory (FST)[1] research field (Zadeh, 1965, 2008) by only considering the documents published in the two most important journals on the topic: *Fuzzy Sets and Systems* and *IEEE Transactions on Fuzzy Systems*.

This paper is organized as follows. Section 2 gives a brief overview of the science mapping and longitudinal studies. Section 3 introduces the approach to analyze the evolution of a research field. Section 4 uses the approach in order to analyze the FST research field. Finally, some conclusions are drawn in Section 5.

2. Science mapping and longitudinal studies

Science mapping or bibliometric mapping is a spatial representation of how disciplines, fields, specialities, and individual papers or authors are related to one another (Small, 1999). It is focused on monitoring a scientific field and delimiting research areas to determine its cognitive structure and its evolution (Noyons, Moed, & van Raan, 1999).

Various types of techniques have been developed to build a science map (Small, 2006), the most commonly used being documents co-citation and co-word analysis.

Co-citation analysis was proposed by Small (1973). This tool maps the structure of a research field through pairs of documents that are commonly cited together (Coulter et al., 1998). Co-citation has been used in the literature to delimit research areas (Small, 2006), discover knowledge communities (Kandylas et al., 2010), research fronts (Upham & Small, 2010) and invisible colleges (Noma, 1984), and also to study different research fields such as the absorptive capacity field (Calero-Medina & Noyons, 2008), the organic thin film transistors (Small & Upham, 2009), to analyze the Strategic Management Journal (Ramos-Rodrguez & Ruz-Navarro, 2004) or to study the marrow of science (Moya-Anegón et al., 2007), among other applications.

Co-word analysis was proposed by Callon et al. (1983) as a content analysis technique that is effective in mapping the strength of association between information items in textual data. It deals directly with sets of terms shared by documents, mapping the pertinent literature directly from the interactions of key terms. Co-word analysis has been used to analyze the interactions between basic and technological research (Callon et al., 1991), study the software engineering field (Coulter et al., 1998), the information research field (Ding, Chowdhury, & Foo, 2001), the scientific area of physical chemistry of surfactants (Bailón-Moreno, Jurado-Alameda, & Ruz-Baños, 2006), the Spanish FST field (López-Herrera et al., 2009), to study the hybridization of the FST field with other computational intelligence techniques (and fields) (López-Herrera, Cobo, Herrera-Viedma, & Herrera, 2010), among others applications.

At the end of the co-word or co-citation analysis, a set of clusters is returned which can be understood as conglomerates of different scientific aspects. In the case of co-citation analysis, the clusters represent groups of references that can be understood as the intellectual base of the different subfields. On the other hand, in the case of co-word analysis, the clusters represent groups of textual information that can be understood as semantic or conceptual groups of different topics treated by the research field. So, the detected clusters can be used with several purposes such as:

- To analyze their evolution through measuring continuance across consecutive subperiods.
- To quantify the research field by means of a performance analysis.

In some studies, co-citation and co-word analysis are used in a longitudinal framework (Garfield, 1994) in order to analyze and track the evolution of a research field along consecutive time periods. One of the first longitudinal studies was that carried

[1] The Fuzzy Sets Theory field was founded by Zadeh in 1965 (for more information see Zadeh, 1965, 2008).

out by Price and Gürsey (1975), in which the transience, continuance and discontinuity of the authors of academic documents were analyzed. There are different degrees of continuance that can be measured with various similarity measures. In this sense, the *Stability Index* (Braam, Moed, & van Raan, 1991; Small, 1977) has been used to measure continuance among clusters. The stability of individual items in two consecutive periods can also be measured through the Stability Index.

Although the co-citation and the co-word techniques are able to analyze the evolution of a research field by means of a longitudinal study, each one allows us to study a different evolution (Braam et al., 1991; van Raan, 2005a): while a longitudinal study based on co-word allows us to analyze the evolution of research topics, a longitudinal study based on co-citation allows us to analyze the continuity in the intellectual base.

A next step (Noyons, Moed, & Luwel, 1999; van Raan, 2005a) in bibliometrics is the integration of mapping and performance assessment in order to quantify a research field, its detected subfields (clusters) and its evolution. The performance analysis allows us to measure the importance of the research field and detected subfields, and to quantify the importance of different scientific actors (van Raan, 2005a, 2005b). Indeed, performance analysis allows us to track, predict and build predictive models of the growth and shrinking of a research field and its detected subfields (Kandylas et al., 2010; Small, 2003, 2006; Upham & Small, 2010).

Finally, we should point out that several visualization techniques have been proposed in the literature in order to provide a way of exploring and suggesting the interpretation of the results (Börner et al., 2003; Small, 2006):

- *Cluster string* (Small, 2006; Small & Upham, 2009; Upham & Small, 2010), *rolling clustering* (Kandylas et al., 2010) and *alluvial diagrams* (Rosvall & Bergstrom, 2010) have been used to show the evolution of detected clusters in successive time periods. Other authors proposed to layout the graph of a given time period taking into account previous and subsequent ones (Leydesdorff & Schank, 2008), or to pack synthesized temporal changes into a single graph (Chen, 2004; Chen et al., 2010).
- *Strategic diagrams* (Callon et al., 1991), *self-organizing maps* (Polanco, François, & Lamirel, 2001), *heliocentric maps* (Moya-Anegón et al., 2005), *geometrical models* (Skupin, 2009) and *thematic networks* (Bailón-Moreno, Jurado-Alameda, Ruiz-Banos, & Courtial, 2005; López-Herrera et al., 2009) have been proposed to show and layout the research field and its detected subfields.

3. An approach for analyzing a research field

In this section a general approach to carry out a complete analysis of the evolution of a specific research field is shown.

The construction of maps from bibliometric information (Garfield, 1994) is a technique used to show the different themes or topics treated by a scientific field in a given time. Different bibliometric information can be used in order to build a bibliometric map. Depending on the information used, different aspects of the research field can be studied. Co-word analysis and co-citation analysis are tools widely used to do this.

Whereas co-citation is used to analyze the structure of a scientific research field, co-word analysis is used to analyze the conceptual structure. That is, co-word analysis allows us to discover the main concepts treated by the field and it is a powerful technique for discovering and describing the interactions between different fields in scientific research. Although both techniques are useful for mapping science, the aim of our approach is to discover the conceptual evolution of a research field, and, therefore, co-word analysis is more suitable.

Formally, the methodological foundation of co-word analysis is the idea that the co-occurrence of key terms describes the content of the documents in a file (Callon et al., 1991). According to Krsul (1998) "*this technique illustrates associations between key words by constructing multiple networks that highlight associations between keywords, and where associations between networks are possible*" (p. 80). In this paper, these networks are associated to themes.

Each publication in the field can in turn be characterized by a sub-list of key terms which are like DNA fingerprints of these published articles (Börner et al., 2003). According to Börner et al. (2003) "*by matching keyword-based fingerprints, one can measure the similarity between a pair of publications. The more keywords two documents have in common, the more similar the two publications are, and the more likely they come from the same research field or research speciality at a higher level. Following the DNA metaphor, if two publications fingerprints' are similar enough, they are bound to come from the same species*" (p. 185).

With a list of the important keywords of the research field a graph can be built, where the keywords are the nodes, and the edges between them represent their relationships. Two nodes (keywords) are connected if they are presented in the same documents. We can add to each edge a weight representing how important the associated relationship in the whole corpus is (i.e., the set of documents belonging to the research field under study.)

As result of the co-word analysis, a set of detected themes is obtained for each subperiod studied. In order to represent the results in a visual way, different visualization techniques can be used. In the proposed approach the results are visualized by means of strategic diagrams and the conceptual evolution is shown through thematic areas.

To sum up, the stages carried out by our approach are:

1. To detect the themes treated by the research field by means of co-word analysis for each studied subperiod.
2. To layout in a low dimensional space the results of the first step (themes).

3. To analyze the evolution of the detected themes through the different subperiods studied, in order to detect the main general thematic areas of the research field, their origins and their inter-relationships.
4. To carry out a performance analysis of the different periods, themes and thematic areas, by means of quantitative and impact measures.

The following subsections describe each stage in more detail.

3.1. The process of detecting themes

The process of delimiting a research field (in both structural and conceptual ways) is usually split into several consecutive steps (Börner et al., 2003; Callon et al., 1991; Chen et al., 2010; Coulter et al., 1998; Courtial & Michelet, 1994; Courtial, 1990; Kandylas et al., 2010; Leydesdorff & Rafols, 2009; Rip & Courtial, 1984; Small & Upham, 2009; Small, 1977, 2006; Upham & Small, 2010). In our proposal, the process is divided into five steps: (1) collection of raw data, (2) selection of the type of item to analyze, (3) extraction of relevant information from the raw data, (4) calculation of similarities between items based on the extracted information and (5) use of a clustering algorithm to detect the themes. In what follows we discuss the way in which these steps are implemented:

The first step is to collect the raw data. So, for example, to analyze a scientific research field, the raw data is collected for all the published documents on the topic. In order to collect these published documents, bibliographic sources such as the ISI Web of Science[2] (ISIWoS), Scopus,[3] Google Scholar,[4] among others, must be used. To do this, a query including descriptive keywords in the topic must be built in order to collect as many documents as possible from the research field under study. Once the raw data has been collected, this can be divided into different partitions in order to analyze the evolution of the research field through the years. The different partitions are built selecting consecutive groups of years.

The second step consists of the selection of the type of item to analyze. As is pointed out in Börner et al. (2003), journals, papers, authors, and descriptive terms or words are most commonly selected as the type of item to analyze. In our case we use the keywords (authors keywords, journals keywords, indexing keywords such as ISIWoS' keywords Plus, or any combination of them) presented in the selected documents.

The third step in the process is the extraction of relevant information from the raw data collected in the first step. In this proposed approach, the relevant information consists of the co-occurrence frequencies of keywords. The co-occurrence frequency of two keywords is extracted from the corpus of documents by counting the number of documents in which the two keywords appear together.

The fourth step is based on the calculation of similarities between items based on the information extracted in the third step. Similarities between items are calculated based on frequencies of keywords' co-occurrences. Different similarity measures have been used in the literature, the most popular being Salton's Cosine and the Jaccard index. In van Eck and Waltman (2009) an analysis of well-known direct similarity measures was made, concluding that the most appropriate measure for normalizing co-occurrence frequencies is the *equivalence index* (Callon et al., 1991; Michelet, 1988). This measure is also known as *association strength* (Coulter et al., 1998; van Eck & Waltman, 2007), *proximity index* (Peters & van Raan, 1993; Rip & Courtial, 1984), or *probabilistic affinity index* (Zitt, Bassecoulard, & Okubo, 2000). The equivalence index, e_{ij} is defined as: $e_{ij} = c_{ij}^2/c_i c_j$, where c_{ij} is the number of documents in which two keywords i and j co-occur and c_i and c_j represent the number of documents in which each one appears. When the keywords always appear together, the equivalence index equals unity; when they are never associated, it equals zero.

The fifth step is based on a process of clustering to locate subgroups of keywords that are strongly linked to each other and which correspond to centers of interest or to research problems that are the object of significant investment by researchers (Callon et al., 1991). Different clustering algorithms can be used to create a partition of the keywords network or graph. Recently, some authors have prosed different clustering algorithms to carry out this task: *Streemer* (Kandylas et al., 2010), *spectral clustering* (Chen et al., 2010), *modularity maximization* (Chen & Redner, 2010) and a *bootstrap resampling* with a significance clustering (Rosvall & Bergstrom, 2010). The proposed approach allows us to use any clustering algorithm that performs with a similarity matrix and returns labelled groups. If the cluster algorithm does not give a label for each cluster, an automatic or manual post-process is required. As an example, we propose the use of the simple centers algorithm (Coulter et al., 1998). The simple centers algorithm is a simple and well-known algorithm in the context of co-word analysis, that has been used in many co-word studies (Bailón-Moreno et al., 2005, 2006; Coulter et al., 1998; Courtial, 1990; Courtial & Michelet, 1994; López-Herrera et al., 2009, 2010; He, 1999). Furthermore, the simple centers algorithm automatically returns labelled clusters, so a post-process to label the clusters is not needed.

As is described in Coulter et al. (1998), the simple centers algorithm uses two passes through the data to produce the desired networks. The first pass (Pass-1) constructs the networks depicting the strongest associations, and links added in this pass are called *internal links*. The second pass (Pass-2) adds to these networks links of weaker strengths that form associations

[2] An author is associated with the theme if he/she has published some document related to the theme.
[3] Other measures could be used such as citations.
[4] In order to get more information about this bibliometric index, visit the web site http://sci2s.ugr.es/hindex/.

between networks. The links added during the second pass are called *external links*. The pseudo-code of the simple centers algorithm contains the following steps (Coulter et al., 1998):

1. Select a minimum for the number of co-occurrences, c_{ij}, for keywords i and j, select maxima for the number of Pass-1 links, and select maxima for the total (Pass-1 and Pass-2) links;
2. Start Pass-1;
3. Generate the highest e_{ij} value from all possible keywords to begin a Pass-1 network;
4. From that link, form other links in a breadth-first manner until no more links are possible due to the co-occurrence minima or to Pass-1 link or node maxima. Remove all incorporated keywords from the list of subsequent available Pass-1 keywords;
5. Repeat steps 3 and 4 until all Pass-1 networks are formed; i.e., until no two remaining keyword pairs co-occur frequently enough to begin a network;
6. Start Pass-2;
7. Restore all Pass-1 keywords to the list of available keywords;
8. Start with the first Pass-1 network;
9. Generate all links to Pass-1 nodes in the current network to any Pass-1 nodes having at least the minimal co-occurrences in descending order of e_{ij} value; stop when no remaining keyword pairs meet the co-occurrence minima, or when the total link maxima is met. Do not remove any keyword from the available list;
10. Select the next succeeding Pass-1 network, and repeat step 9.

As was noted in (Coulter et al., 1998), two keywords that appear infrequently in the corpus but always appear together will have larger strength values than keywords that appear many times in the corpus almost always together. Hence, possibly irrelevant or weak associations may dominate the network. The simple centers algorithm solves this problem by using different parameters: minimum frequency and co-occurrence thresholds. Only the keyword pairs that exceed these thresholds are considered potential links while building networks during the first pass of the algorithm. On the other hand, the algorithm has two parameters to limit the size of the detected themes: the minimum and maximum size of the networks.

Although the simple centers algorithm has only four parameters, the detected themes are highly dependent on them. For this reason a process for tuning the parameters is needed. A group of experts in the research field under study is useful in order to carry out a feedback process to estimate the best parameter configuration that allows us to detect the main themes of the field.

Two measures can represent the detected networks: *Callon's centrality*, and *Callon's density*.

Callon's centrality, to be referred to as centrality henceforth, measures the degree of interaction of a network with other networks (Callon et al., 1991) and it can be defined as: $c = 10 \times \sum e_{kh}$, with k a keyword belonging to the theme and h a keyword belonging to other themes. Centrality measures the strength of external ties to other themes. We can understand this value as a measure of the importance of a theme in the development of the entire research field analyzed.

Callon's density, to be referred to as density henceforth, measures the internal strength of the network (Callon et al., 1991) and it can be defined as: $d = 100(\sum e_{ij}/w)$, with i and j keywords belonging to the theme and w the number of keywords in the theme. Density measures the strength of internal ties among all keywords describing the research theme. This value can be understood as a measure of the theme's development.

3.2. Visualizing themes and thematic networks

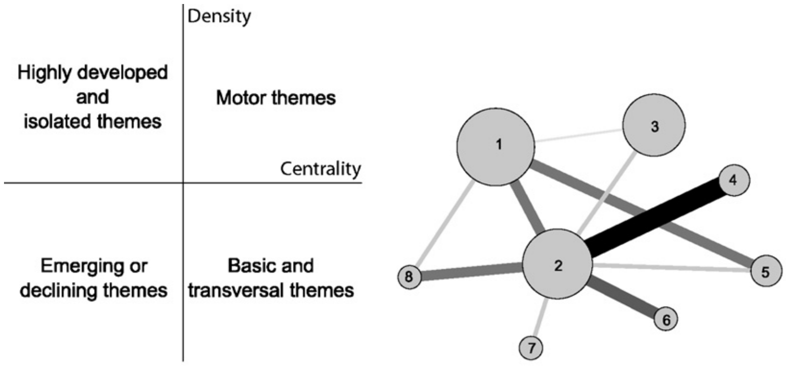
When co-word analysis is used for mapping science, clusters of keywords (and their interconnections) are obtained. These clusters are considered as *themes*.

Each research theme obtained in this process is characterized by two parameters ("density" and "centrality"). Both median and mean values for density and centrality can be used in classifying themes into four groups (Cahlik, 2000; Callon et al., 1991; Courtial & Michelet, 1994; Coulter et al., 1998; He, 1999). So a research field can be understood to be a set of research themes, mapped in a two-dimensional space.

A Strategic Diagram is a two-dimensional space built by plotting themes according to their centrality and density rank values (if we use median for classifying clusters) or values (if we use mean) along two axis, x-axis centrality, y-axis density. Strategic diagrams with rank values are used more commonly than ones with values, because of their legibility (Cahlik, 2000). As an example, in Fig. 1a a strategic diagram is presented.

We can find four kinds of themes (Cahlik, 2000; Callon et al., 1991; Courtial & Michelet, 1994; Coulter et al., 1998; He, 1999) according to the quadrant in which they are placed:

- Themes in the upper-right quadrant are both well developed and important for the structuring of a research field. They are known as the *motor-themes* of the specialty, given that they present strong centrality and high density. The placement of themes in this quadrant implies that they are related externally to concepts applicable to other themes that are conceptually closely related.
- Themes in the upper-left quadrant have well developed internal ties but unimportant external ties and so are of only marginal importance for the field. These themes are very specialized and peripheral in character.
- Themes in the lower-left quadrant are both weakly developed and marginal. The themes of this quadrant have low density and low centrality, mainly representing either emerging or disappearing themes.



a The strategic diagram. b An example of a the- matic network.

Fig. 1. The strategic diagram and thematic network.

- Themes in the lower-right quadrant are important for a research field but are not developed. So, this quadrant groups transversal and general, basic themes.

In a theme, the keywords and their interconnections draw a network graph, called a *thematic network*. Each thematic network is labelled using the name of the most significant keyword in the associated theme (usually identified by the most central keyword of the theme). An example of a thematic network is drawn in Fig. 1b. Here, several keywords are interconnected, where the volume of the spheres is proportional to the number of documents corresponding to each keyword, the thickness of the link between two spheres i and j is proportional to the equivalence index e_{ij}.

Together with the whole network of interconnected themes and keywords a second network is built, based on the documents linked to each thematic network. In this second network, documents with keywords associated with any detected thematic network are linked to it. So, two kinds of documents can be considered: *core documents* and *secondary documents*. Given a thematic network, a document is called a “core document” if it has at least two keywords presented in the thematic network. If a document has only one keyword associated with the thematic network, it is called a “secondary document”. Both core and secundary documents can belong to more than one thematic network.

Furthermore, the strategic diagrams can be enriched by adding a third dimension in order to show more information. So, for example, the themes can be represented as a sphere, its volume being proportional to different quantitative (or qualitative) data, for example: (i) the number of documents associated with the theme (core documents + secondary documents); (ii) the number of citations received of the documents associated with the theme; (iii) the number of authors[5] researching in the field of the theme.

3.3. Thematic areas: the evolution of themes

This subsection describes what the *thematic areas* are and how to detect and visualize them.

If the raw data is divided into different consecutive groups of years (i.e., subperiods), the evolution of the research field under study can be analyzed.

Let T^t be the set of detected themes of the subperiod t, with $U \in T^t$ representing each detected theme in the subperiod t. Let $V \in T^{t+1}$ be each detected theme in the next subperiod $t + 1$. It is said that there is a thematic evolution from theme U to theme V iff there are keywords presented in both associated thematic networks. So, V can be considered to be a theme evolved from U. Keywords $k \in U \cap V$ are considered to be a “thematic nexus” or “conceptual nexus”. Evolution bibliometric maps can be built by linking themes in T^t with themes in T^{t+1} through the “conceptual nexus”.

Thematic areas can be considered as a bipartite graph. A bipartite graph is a graph whose vertices can be divided into two disjoint sets U and V, and the edges can only connect elements from the set U to elements of the set V.

There will be an edge from themes in the subperiod t to themes in the subperiod $t + 1$ if there is a “thematic nexus” among them. In others word, if they have some elements in common.

The importance of a “thematic nexus” can be weighed by the elements that the two themes have in common. In our approach, the *Inclusion Index* is used to carry out this task:

$$\text{Inclusion Index} = \frac{\#(U \cap V)}{\min(\#U, \#V)}.$$

[5] The use of core and secondary documents implies that a document can belong to different themes, i.e., the sets of documents belonging to two themes are not disjoint.

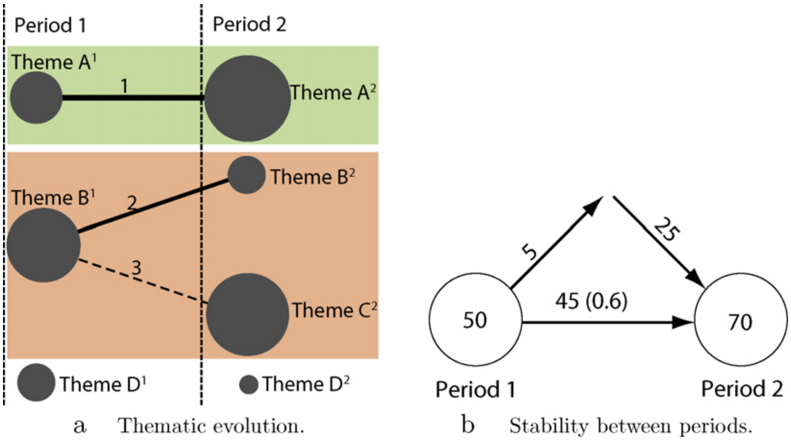


Fig. 2. Examples of evolution.

Although the weight of a thematic nexus can be measured with other similarity measures (e.g., the Jaccard index or Salton's cosine), the inclusion index has the advantage of being more useful to measure similar sets, in comparison to the Jaccard or cosine index, since it is not biased by the number of items as the latter are (Sternitzke & Bergmann, 2009). The inclusion index has also been used as an overlap measure in the field of information retrieval (van Eck & Waltman, 2009). Furthermore, the inclusion index will be equal to 1 if the keywords of the theme V are fully contained in the theme U. For these reasons and due to the fact that the weight of the thematic nexus is a good measure of the overlapping between themes, the inclusion index has been chosen.

So, a *thematic area* is defined as a group of evolved themes across different subperiods. Note that, depending on the interconnections among them, one theme could belong to a different *thematic area*, or could not come from any.

For example, suppose that we have two different subperiods (period 1 and period 2) under study, with three detected themes in the first one and four in the second (together with their associated thematic networks). In Fig. 2a an example of a thematic evolution bibliometric map is shown. The solid lines (lines 1 and 2) mean that the linked themes share the same name: both themes are labelled with the same keywords, or the label of one theme is part of the other theme (name of theme $\in$ {thematic nexuses}). A dotted line (line 3) means that the themes share elements that are not the name of the themes (name of theme $\notin$ {thematic nexuses}). The thickness of the edges is proportional to the inclusion index, and the volume of the spheres is proportional to the number of published documents associated with each theme.[6] The vertical lines separate the different subperiods.

In Fig. 2a we can observe two different thematic areas delimited by different color-shadows, one composed of themes *Theme* A^1 and *Theme* A^2, and the other composed of themes *Theme* B^1, *Theme* B^2 and *Theme* C^2. *Theme* D^1 is discontinued, and *Theme* D^2 is considered to be a new theme.

As the themes have an associated set of documents (core documents, or secondary documents, or core documents + secondary documents), the thematic areas could also have an associated collection of documents. In this case, the documents associated with each thematic area will be ascertained through the union of the documents associated with the set of themes belonging to each thematic area.

General overlapping between two consecutive subperiods can be measured through the Stability Index (Small, 1977) whose equation is similar to the Jaccard Index ($items_{ij}/items_i + items_j - items_{ij}$) for the case of two consecutive subperiods (Braam et al., 1991). General overlapping measures the number of shared keywords between successive subperiods. To show, in a graphical way, the "stability" across the different subperiods, a picture similar to that presented in Price and Gürsey (1975) is used.

Following the previous example, in Fig. 2b, the stability measures across the two consecutive periods is shown. The circles represent the periods and their number of associated keywords. The horizontal arrow represents the number of keywords shared by both periods and, in parentheses, the Similarity Index between them is shown. The upper-incoming arrow represents the number of new keywords in period 2, and the upper-outcoming arrow represents the keywords that are present in period 1 but not in period 2.

3.4. Performance analysis

In the previous subsections, the processes of detecting themes and thematic areas were described. The analysis can be further enriched by carrying out a performance analysis with different measures. These measures are divided into two

6 Other measures could be used such as citations.

categories: quantitative and qualitative ones. By means of quantitative measures the productivity of the detected themes and thematic areas is analyzed, whereas qualitative measures show the (supposed) quality based on the bibliometric impact of those themes and thematic areas.

- Quantitative measures: number of documents, authors, journals and countries.
- Qualitative or impact measures: number of received citations of the documents and bibliometric indices such as the h-index[7] (Alonso et al., 2009; Cabrerizo et al., 2010; Hirsch, 2005).

We should point out that both measures can be applied to different levels to help us to analyze the topics, themes, thematic areas, and different subperiods.

4. The research field of fuzzy sets theory

In this section the general approach described above is applied to analyze the research field of Fuzzy Sets Theory (FST) (Zadeh, 1965, 2008) using the publications that have appeared in the most important and prestigious journals of the topic: *Fuzzy Sets and Systems* and *IEEE Transactions on Fuzzy Systems*. The first one is the official publication of the International Fuzzy Systems Association (IFSA) and the second one is a publication of the IEEE Computational Intelligence Society for fuzzy systems. In comparison with other journals on FST, these present the highest IF, the highest number of publications and they are the oldest ones (see Table 1).

The journal FSS is the oldest (it started in 1978) and the ISIWoS includes their publications from the year 1980. IEEE-TFS started in 1993, and ISIWoS includes their publications from 1994.

We fix our study from 1978 to 2009. In Fig. 3 the distribution of documents (Article, Letter, Proceeding Paper and Review) per year is shown, where FSS contains 5724 documents and IEEE-TFS 1169 documents.

We retrieve the necessary data from the ISIWoS for the years included in it. For the remaining years the data are retrieved from Scopus (for the year 1993 of the journal IEEE-TFS), and from Science Direct[8] (for the years 1978 and 1979 of the journal FSS).

In this study the citations of the documents are also used; for this reason, the citations received will be considered up to January 15th 2010, the date when the data were downloaded. The citations that we take into account proceed from the ISIWoS.

The data are divided into five consecutive subperiods: 1978–1989, 1990–1994, 1995–1999, 2000–2004 and 2005–2009. In Fig. 4 the distributions of the published documents per period are shown.

In order to avoid the smooth of the data, the best option would be to choose periods spanning only one year. In the case of the FST research field, in a span of one year there are not enough data for a good performance of co-word analysis. For this reason, the years are grouped in subperiods of time. Additionally, although it is common to use periods of the same time span, we have fixed a first subperiod of twelve years (1978–1989). In this way, we provide a good input to the co-words analysis in order to detect the main themes. At the beginning of the FST field, we find few researchers and publications, and we observe that the fuzzy community tends to use an extremely low number of keywords in the publications (the average number of keywords per document was 1, indeed, there are 117 documents with less than two keywords). The first twelve years give us a good number of documents to be processed. We observe that in the next studied subperiod the FST research field begins to consolidate as a discipline. The time span of five years for the remaining subperiods is appropriate to provide a good input.

The co-word analysis is done with the software CoPalRed (CoPalRed, 2005; López-Herrera et al., 2009). CoPalRed is based on the simple center algorithm to detect the themes through different subperiods of years. The plotting of the themes in the strategic diagram, the drawing of the thematic networks and the detecting of thematic areas were made with specific ad hoc software.

As we said at the second step in Section 3.1, the keywords of the documents are used. Due to the data have been downloaded from the ISIWoS, the author keywords and the Keywords Plus of the documents are jointly used. A normalization process is carried out prior to this over the keywords, where the plural and singular forms of the keywords are joined. The acronyms are also joined with the respective keywords.

In order to measure the performance and quality of the detected themes and thematic areas, a quantitative and impact analysis is presented in each subperiod. To study the quantitative performance, the number of associated documents belonging to each theme and thematic area are analyzed. To study the quality and impact, the citations and h-index of each detected theme and thematic area are used.

In what follows we develop the visualizing of themes and thematic networks, the evolution of themes and the performance analysis.

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[7] In order to get more information about this bibliometric index, visit the web site http://sci2s.ugr.es/hindex/.

[8] http://www.sciencedirect.com/.

Table 1
Basic data on FST journals.

Journal	IF 2008	IF 2007	IF 2006	Total documents	Start year
IEEE TRANSACTIONS ON FUZZY SYSTEMS	3.624	2.137	1.803	1243	1993
FUZZY SETS AND SYSTEMS	1.833	1.373	1.181	6309	1978
INTERNATIONAL JOURNAL OF UNCERTAINTY FUZZINESS AND KNOWLEDGE-BASED SYSTEMS	1.000	0.376	0.406	756	1993
JOURNAL OF INTELLIGENT & FUZZY SYSTEMS	0.649	0.221	0.283	503	1993

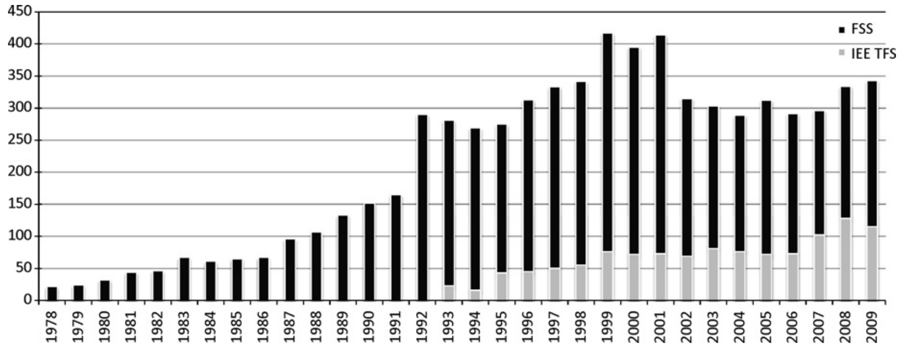


Fig. 3. Documents published in the FST research field from 1978 to 2009.

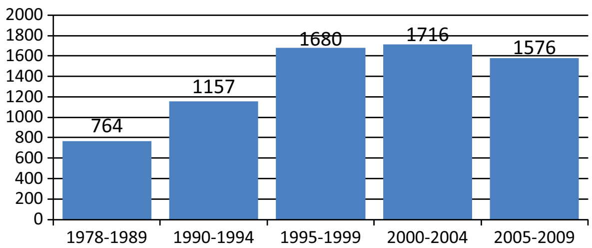


Fig. 4. Published documents per subperiod.

Table 2
Performance measures for the themes of the subperiod 1978–1989.

Theme name	Number of documents	Number of citations	Average of citations	h-Index
DECISION-MAKING	64	1131	17.67	14
FUZZY-CONTROL	54	1648	30.52	18
FUZZY-RELATIONAL-EQUATIONS	38	1229	32.34	19
FUZZY-TOPOLOGY	36	382	10.61	13
RELATIONS	21	1155	55.00	7
FUZZY-MAPPING	19	407	21.42	11
SUBGROUP	13	226	17.38	6

4.1. Visualization of themes of FST

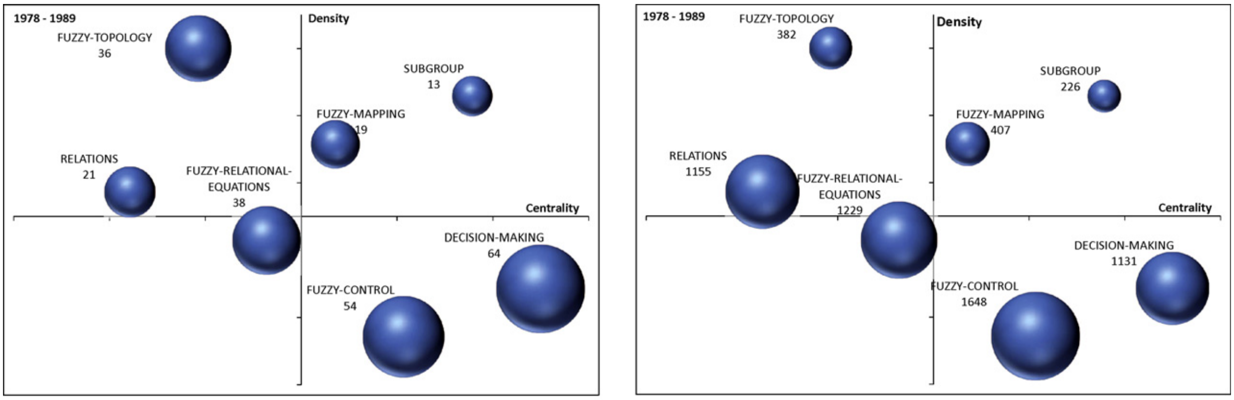
In order to analyze the most highlighted themes of the FST field for each subperiod, two kinds of strategic diagrams are built using the software CoPalRed (CoPalRed, 2005; López-Herrera et al., 2009): In the first one, the volume of the spheres is proportional to the number of published documents (core documents + secondary documents)[9] associated with each theme; and in the second one, the volume of spheres is proportional to the number of citations received for each theme.

In what follows we show the strategic diagrams of each subperiod and some tables containing some quantitative and impact measures to analyze each subperiod.

In the subperiod 1979–1989, the longest one, a total of 764 documents of the journal FSS are considered.

According to these strategic diagrams (Fig. 5) and quantitative measures (Table 2) we can observe that (i) the *motor-themes*, *SUBGROUP* and *FUZZY-MAPPING* received a few citations and did not have much impact (low h-index scores) later;

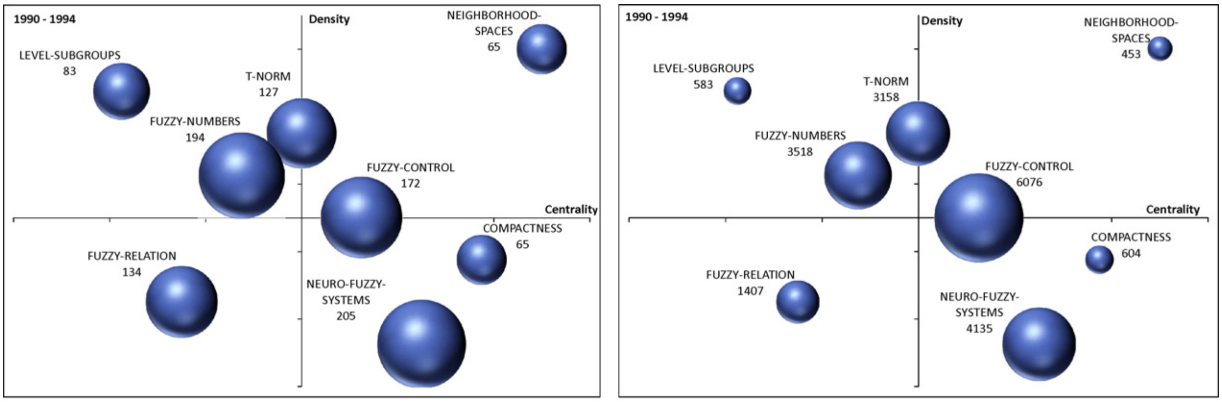
[9] The use of core and secondary documents implies that a document can belong to different themes, i.e., the sets of documents belonging to two themes are not disjoint.



a Strategic diagram based on the number of published documents.

b Strategic diagram based on citation.

Fig. 5. Strategic diagrams for the subperiod 1978–1989.



a Strategic diagram based on the number of published documents.

b Strategic diagram based on citation.

Fig. 6. Strategic diagrams for the subperiod 1990–1994.

(ii) the basic and transversal themes, *FUZZY-CONTROL* and *DECISION-MAKING*, received many citations and had a great impact later; (iii) a specific topic, *FUZZY-RELATIONAL-EQUATIONS* also had many citations and a great impact.

In this subperiod, we should point out that just 230 documents (about 30% of the documents published in those years) were associated with some theme. It is a consequence of the low number of keywords per document during this subperiod that makes co-word analysis and the association of documents with the themes difficult.

In the subperiod 1990–1994 a total of 1157 documents were published in the FST research field. Those years coincide with the starting point of the journal IEEE-TFS, so the documents of this subperiod belong to both journals.

According to Fig. 6 and Table 3 we can observe that (i) the *motor-theme NEIGHBORHOOD-SPACES* is not cited very often and presents the lowest impact; (ii) the basic themes *FUZZY-CONTROL* and *NEURO-FUZZY-SYSTEMS* are the most cited and they present the highest impact; (iii) two specific themes *FUZZY-NUMBERS* and *T-NORM* presented high citation scores and

Table 3
Performance measures for the themes of the subperiod 1990–1994.

Theme name	Number of documents	Number of citations	Average of citations	h-Index
NEURO-FUZZY-SYSTEMS	205	4135	20.17	34
FUZZY-NUMBERS	194	3518	18.13	31
FUZZY-CONTROL	172	6076	35.33	40
FUZZY-RELATION	134	1407	10.50	21
T-NORM	127	3158	24.87	30
LEVEL-SUBGROUPS	83	583	7.02	12
NEIGHBORHOOD-SPACES	65	453	6.97	8
COMPACTNESS	65	604	9.29	11

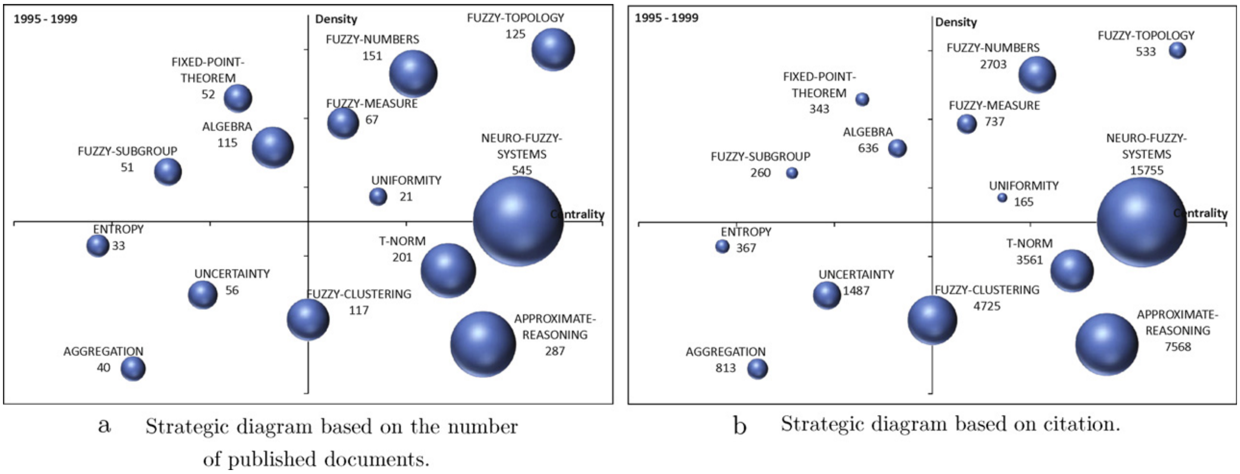


Fig. 7. Strategic diagrams for the subperiod 1995–1999.

impact. In this subperiod 67% of documents (774) are associated with some theme, which is due to the fact that in this subperiod we find more keywords describing the content of the documents.

In the next subperiod 1995–1999 we observe a higher number of themes as a consequence of the higher number of publications considered, 1680 documents. According to Fig. 7 and Table 4 we should point out that *motor-themes* and basic themes present the highest citations and impact scores.

In this subperiod 76% of documents (1281) were associated with some theme.

In the subperiod 2000–2004 (see Fig. 8 and Table 5) we also observe a high number of themes, but the density of themes in the quadrant of basic themes is notably higher than in previous subperiods. Similarly, in this case the basic themes and *motor-themes* are the most highly cited ones and present the highest impact and a high number of documents are associated with themes (81% of documents, i.e. 1383).

In the last studied subperiod (2005–2009), see Fig. 9 and Table 6, as with the previous subperiod, the basic themes and *motor-themes* are again the most highly cited and present the highest impact.

In this subperiod 84% of documents (1325) are associated with some theme.

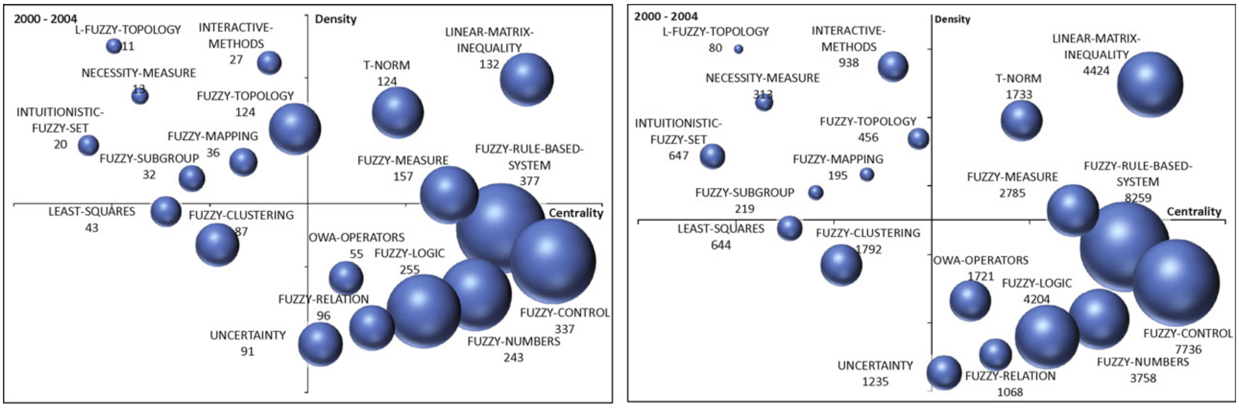
In general, we can observe that in all the studied subperiods, the basic and transversal themes achieved the highest citation scores and impacts. It is logical to think that themes which are considered to be more basic and transversal than others have more probability of getting attention and citations. This indicates that the identification of these themes is consistent.

4.2. Evolution of the FST themes

In this subsection, the thematic evolution of the FST research field is studied by means of thematic areas. Firstly, the evolution of the number of keywords and number of shared keywords in the different subperiods are analyzed. Then, the evolution of the themes is shown.

Table 4
Performance measures for the themes of the subperiod 1995–1999.

Theme name	Number of documents	Number of citations	Average of citations	h-Index
NEURO-FUZZY-SYSTEMS	545	15755	28.91	60
APPROXIMATE-REASONING	287	7568	26.37	45
T-NORM	201	3561	17.72	31
FUZZY-NUMBERS	151	2703	17.90	28
FUZZY-TOPOLOGY	125	533	4.26	11
FUZZY-CLUSTERING	117	4725	40.38	39
ALGEBRA	115	636	5.53	14
FUZZY-MEASURE	67	737	11.00	14
UNCERTAINTY	56	1487	26.55	20
FIXED-POINT-THEOREM	52	343	6.60	11
FUZZY-SUBGROUP	51	260	5.10	8
AGGREGATION	40	813	20.33	14
ENTROPY	33	367	11.12	10
UNIFORMITY	21	165	7.86	8



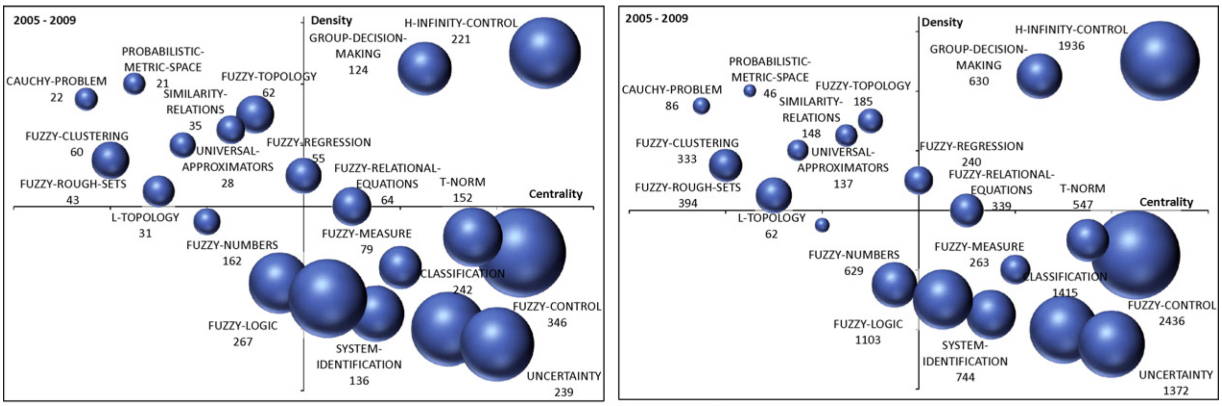
a Strategic diagram based on the number of published documents.

b Strategic diagram based on citation.

Fig. 8. Strategic diagrams for the subperiod 2000–2004.

Table 5
Performance measures for the themes of the subperiod 2000–2004.

Theme name	Number of documents	Number of citations	Average of citations	h-Index
FUZZY-RULE-BASED-SYSTEM	377	8259	21.91	43
FUZZY-CONTROL	337	7736	22.96	46
FUZZY-LOGIC	255	4204	16.49	31
FUZZY-NUMBERS	243	3758	15.47	31
FUZZY-MEASURE	157	2785	17.74	24
LINEAR-MATRIX-INEQUALITY	132	4424	33.52	34
FUZZY-TOPOLOGY	124	456	3.68	9
T-NORM	124	1733	13.98	22
FUZZY-RELATION	96	1068	11.13	18
UNCERTAINTY	91	1235	13.57	20
FUZZY-CLUSTERING	87	1792	20.60	23
OWA-OPERATORS	55	1721	31.29	23
LEAST-SQUARES	43	644	14.98	16
FUZZY-MAPPING	36	195	5.42	9
FUZZY-SUBGROUP	32	219	6.84	9
INTERACTIVE-METHODS	27	938	34.74	12
INTUITIONISTIC-FUZZY-SET	20	647	32.35	13
NECESSITY-MEASURE	13	313	24.08	6
L-FUZZY-TOPOLOGY	11	80	7.27	5



a Strategic diagram based on the number of published documents.

b Strategic diagram based on citation.

Fig. 9. Strategic diagrams for the subperiod 2005–2009.

Table 6
Performance measures for the themes of the subperiod 2004–2009.

Theme name	Number of documents	Number of citations	Average of citations	h-Index
FUZZY-CONTROL	346	2436	7.04	23
FUZZY-LOGIC	267	1103	4.13	16
CLASSIFICATION	242	1415	5.85	18
UNCERTAINTY	239	1372	5.74	18
H-INFINITY-CONTROL	221	1936	8.76	24
FUZZY-NUMBERS	162	629	3.88	12
T-NORM	152	547	3.60	11
SYSTEM-IDENTIFICATION	136	744	5.47	14
GROUP-DECISION-MAKING	124	630	5.08	13
FUZZY-MEASURE	79	263	3.33	8
FUZZY-RELATIONAL-EQUATIONS	64	339	5.30	9
FUZZY-TOPOLOGY	62	185	2.98	6
FUZZY-CLUSTERING	60	333	5.55	11
FUZZY-REGRESSION	55	240	4.36	9
FUZZY-ROUGH-SETS	43	394	9.16	10
SIMILARITY-RELATIONS	35	148	4.23	8
L-TOPOLOGY	31	62	2.00	4
UNIVERSAL-APPROXIMATORS	28	137	4.89	7
CAUCHY-PROBLEM	22	86	3.91	5
PROBABILISTIC-METRIC-SPACE	21	46	2.19	4

In each subperiod the keywords are not the same, in a lexicographic sense or in number. That is, the FST terminology evolves through the time period using different keywords to describe the content of the documents. New topics with their associated keywords appear and others disappear. On the other hand, there is a subset of keywords that have remained unchanged during consecutive subperiods and a subset of keywords that has only been used in some subperiods. For example, the keywords *fuzzy-control*, *fuzzy-topology* and *neuro-fuzzy-systems* appear in all of the studied subperiods. By contrast, the keyword *multi-valued-logic* only appears in the first studied subperiod (1978–1989).

Following the philosophy of Price and Gürsey (1975), in Fig. 10 the keywords' evolution is shown. The circles represent each subperiod, and the number of keywords of the subperiod is represented inside. The arrows between consecutive subperiods represent the number of keywords shared between them and, in parentheses the Similarity Index (overlap fraction) is shown. The upper-incoming arrows represent the number of new keywords of the subperiod, and finally, the upper-outcoming arrows represent the keywords that are not present (i.e., discontinued) in the next subperiod. For example, in the third studied subperiod (1995–1999) there are 3782 keywords, of which 1176 keywords remain in the next studied subperiod (2000–2004). The remainder of the keywords, 2606, are not kept in the next subperiod. The similarity index between the third and fourth subperiod is 0.53.

The number of keywords is incremented drastically along the time period; in fact, in the last subperiod we find six times more than in the first one. Similarly, the number of shared keywords between successive subperiods grew (from 453 between the first and second subperiod, to 1328 between the fourth and fifth subperiod), in fact, the similarity index grew across the subperiods (from 0.25 between the first and second subperiod, to 0.55 between the fourth and fifth subperiod). This means that the FST community consolidates its terminology. On the other hand, the number of new and transient keywords is high, so there is a big quantity of transversal keywords that are only used in one subperiod and no more times. For example, in the fourth subperiod (2000–2004) there are 3200 transient keywords from a total of 3352 new keywords.

Once the keywords' evolution has been analyzed, we study the thematic evolution of the research FST field through the thematic areas.

In Fig. 11 the thematic evolution of the FST research field is shown. As mentioned before, the solid lines mean that the linked themes share the name: both themes have the same name, or the name of one of the themes is part of the other theme. A dotted line means that the themes share elements that are not the name of the theme. The thickness of the edge is proportional to the inclusion index, and the volume of the spheres is proportional to the number of published documents of each theme.

Although the graph of Fig. 11 is very dense (the themes are very interconnected) the different thematic areas can be detected. In Fig. 11 the different colour-shadows group the themes which belong to the same thematic area. There are themes that have more than one shadow, which implies that the theme belongs to more than one thematic area. On the

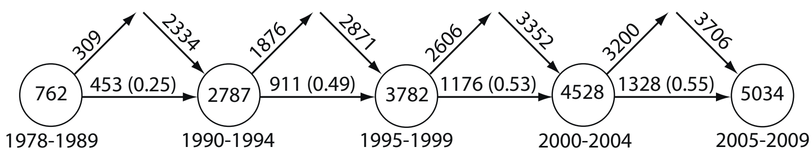


Fig. 10. Overlap fractions (incoming and outcoming keywords between successive subperiods).

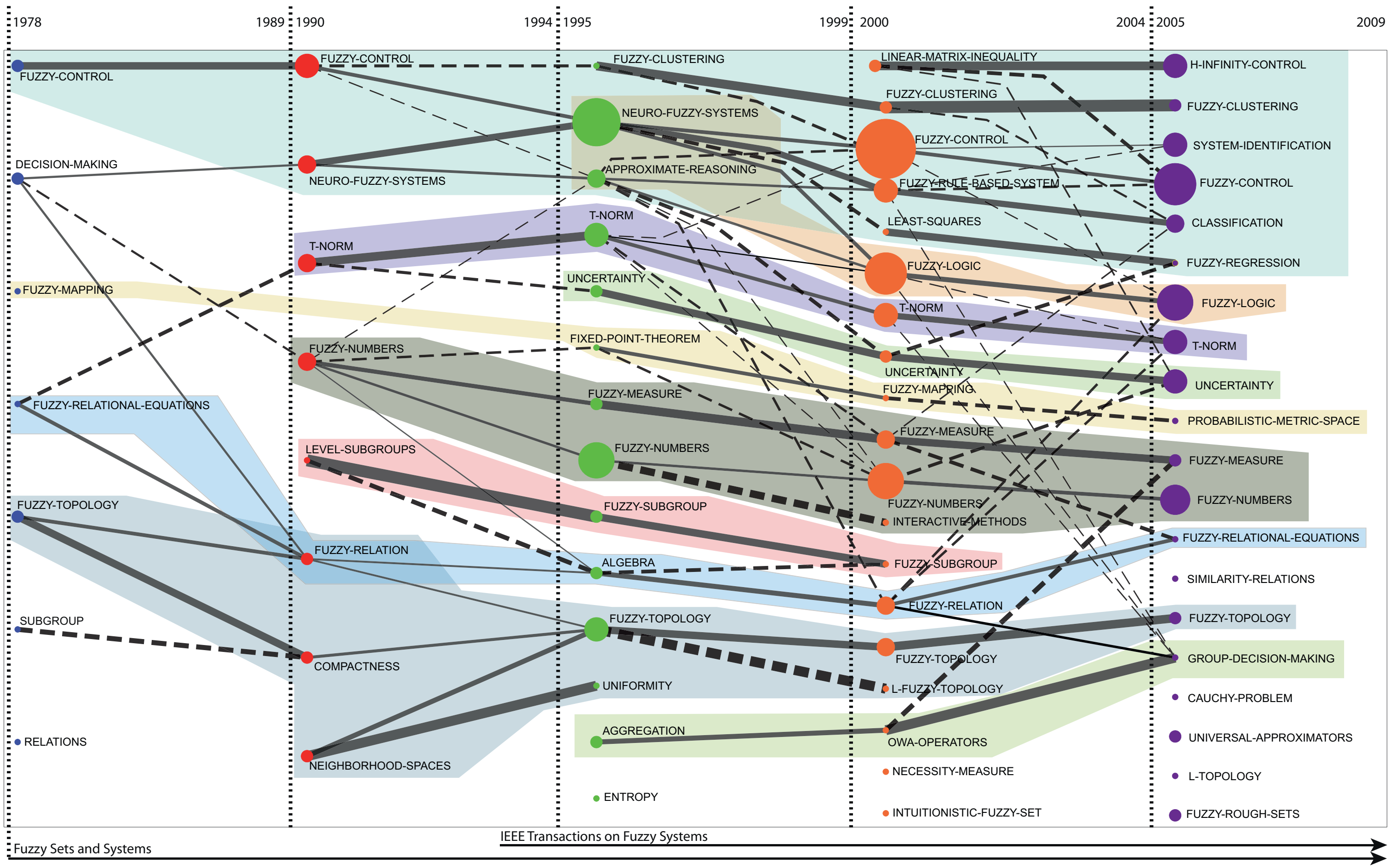


Fig. 11. Thematic evolution of the FST research field (1978–2009).

Table 7
Quantitative and impact data for the detected thematic areas (1978–2009).

Theme name	Number of documents	Number of citations	Average of citations	h-Index
FUZZY-CONTROL	2461	49,726	20.21	92
FUZZY-LOGIC	1217	24,477	20.11	69
FUZZY-NUMBER	1008	13,896	13.79	50
T-NORM	604	8999	14.90	44
FUZZY-TOPOLOGY	581	3678	6.33	28
FUZZY-RELATION	447	4679	10.47	33
UNCERTAINTY	386	4094	10.61	29
GROUP-DECISION-MAKING	219	3164	14.45	29
FUZZY-SUBGROUP	166	1062	6.40	16
FUZZY-MAPPING	128	991	7.74	16

other hand, there are themes that do not have a shadow, which implies that these themes do not belong to any thematic area. In Table 7 we identify the main thematic areas and show their respective global quantitative and impact measures.

Then, analyzing Fig. 11 and Table 7 we should point out the following:

- If we observe the development of the FST research field according to its grouped thematic areas and themes, we can conclude that the FST field presents great cohesion, given that the most identified themes are grouped in some thematic area and originate from a theme identified in a previous subperiod. Furthermore, when we find some theme that is not in a thematic area, this is because (i) the theme is very recent and could be considered as the beginning of a new thematic area, for example as happens with the themes *INTUITIONISTIC-FUZZY-SET* or *FUZZY-ROUGH-SET* in the fourth and fifth subperiod, respectively; or (ii) the theme is connected with many thematic areas (it is a basic theme) and it is difficult to categorize it, for example, as happens with the theme *DECISION-MAKING* in the first subperiod; or (iii) the theme is not well described by keywords and it is not possible to detect its connections with others, for example, as happens with the theme *RELATIONS* in the first subperiod.
- Most thematic areas evolve in a continuous and compact way from their beginning until the last studied subperiod (2005–2009), i.e., there are no gaps in their evolution. This means that they attract the fuzzy community members' interest in all analyzed subperiods. An exception is in the case of the thematic area *FUZZY-SUBGROUP*, which disappears after the fourth subperiod.
- Regarding the evolution of the number of documents, looking at the volume of the spheres, most thematic areas evolve in an increasing way; that is, in each subperiod the number of documents increases in respect to the previous one. Therefore, we detect an increasing interest in the fuzzy community for these thematic areas represented by a progressive growth in work on them. Again, the evolution of the thematic area *FUZZY-SUBGROUP* does not present this behaviour and neither does the thematic area *FUZZY-MAPPING*.
- Regarding the evolution of the number of themes we find that there is only one thematic area that evolves in an increasing way, i.e, *FUZZY-CONTROL* (see its evolution in detail in Fig. 12). This thematic area is the origin of another important thematic area *FUZZY-LOGIC*. The remainder evolve in a constant way such as *T-NORM* (see its evolution in detail in Fig. 14a) or *GROUP-DECISION-MAKING* (see Fig. 14b), or in a decreasing way such as *FUZZY-LOGIC* (see its evolution in detail in Fig. 13).
- Furthermore, we should point out that there are only three thematic areas that are present or contain themes in all of the studied subperiods: *FUZZY-CONTROL*, *FUZZY-TOPOLOGY* and *FUZZY-RELATION*. Therefore, we can affirm that these three thematic areas have maintained the fuzzy community's interest in all the studied subperiods, but clearly, according to Table 7, the thematic area that is increasing in respect to the number of themes, *FUZZY-CONTROL*, presents the best quality indicators.
- Regarding the thematic composition of each thematic area we find that there are:
  - Two solid thematic areas according to their thematic composition; that is, they are composed of motor or basic themes in all subperiods: *FUZZY-CONTROL*, *T-NORM*.
  - Two important thematic areas that show exhaustion signs; that is, they are composed of motor or basic themes in most subperiods but in the last one they present disappearing themes such as *FUZZY-LOGIC* and *FUZZY-NUMBERS*.
  - Two specific or peripheral thematic areas composed of peripheral themes in all subperiods: *FUZZY-SUBGROUP* and *FUZZY-MAPPING*.
  - Two ascending thematic areas; that is, initially they present specific themes and in the last subperiod (2005–2009) they begin to consolidate with motor and basic themes: *FUZZY-RELATIONS*, *UNCERTAINTY* and *GROUP-DECISION-MAKING*.
  - There is also one descending thematic area, *FUZZY-TOPOLOGY*.
- In short, we should point out the following:
  1. *FUZZY-CONTROL* is the most important thematic area in the FST research field, which presents the best evolution behavior and the best quality indicators according to Table 7.
  2. *T-NORM* is another important and basic thematic area in the FST research field, which presents a solid evolution and good impact indicators (h-index = 44) according to Table 7.

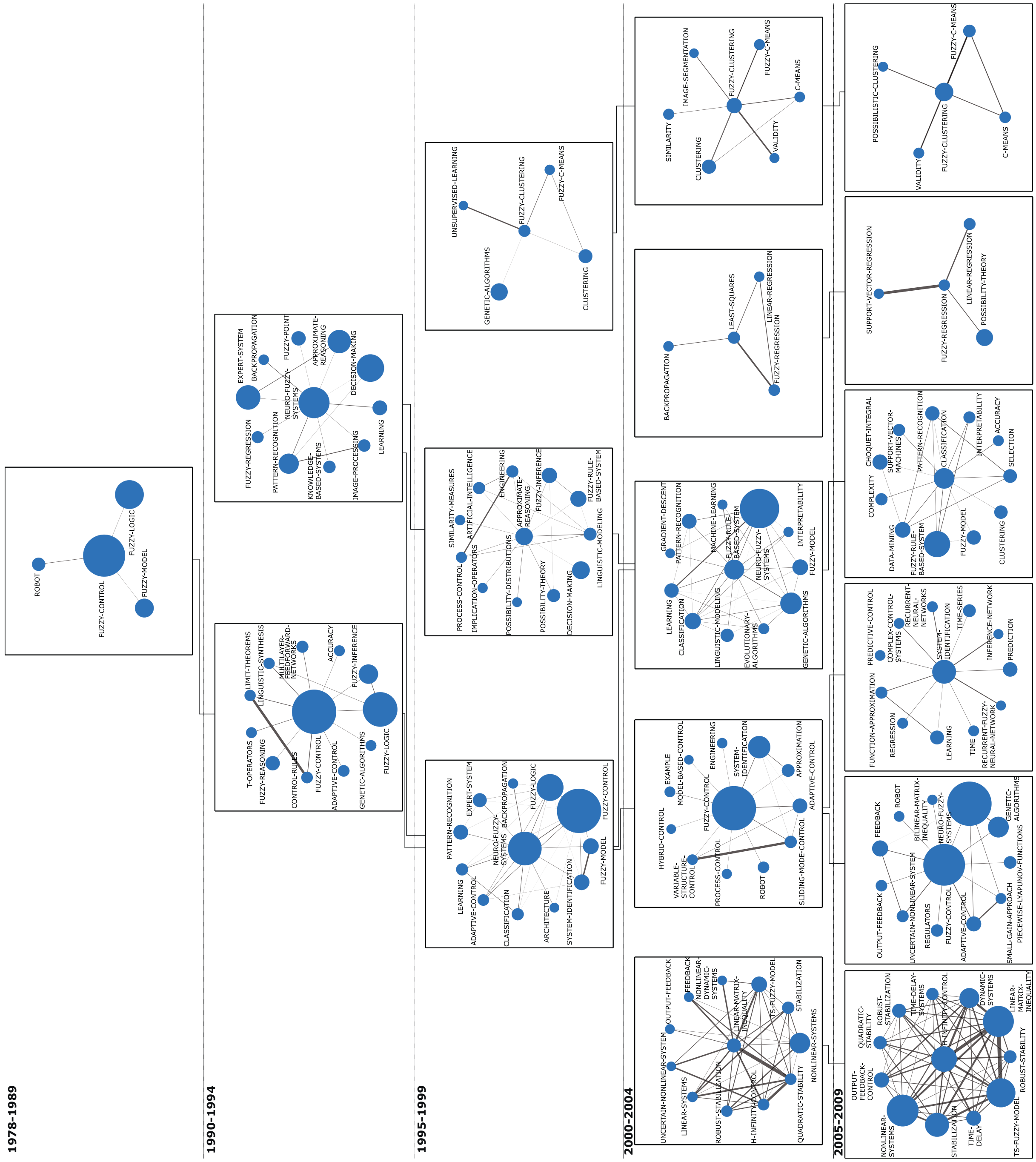


Fig. 12. The FUZZY-CONTROL thematic area (1978–2009).

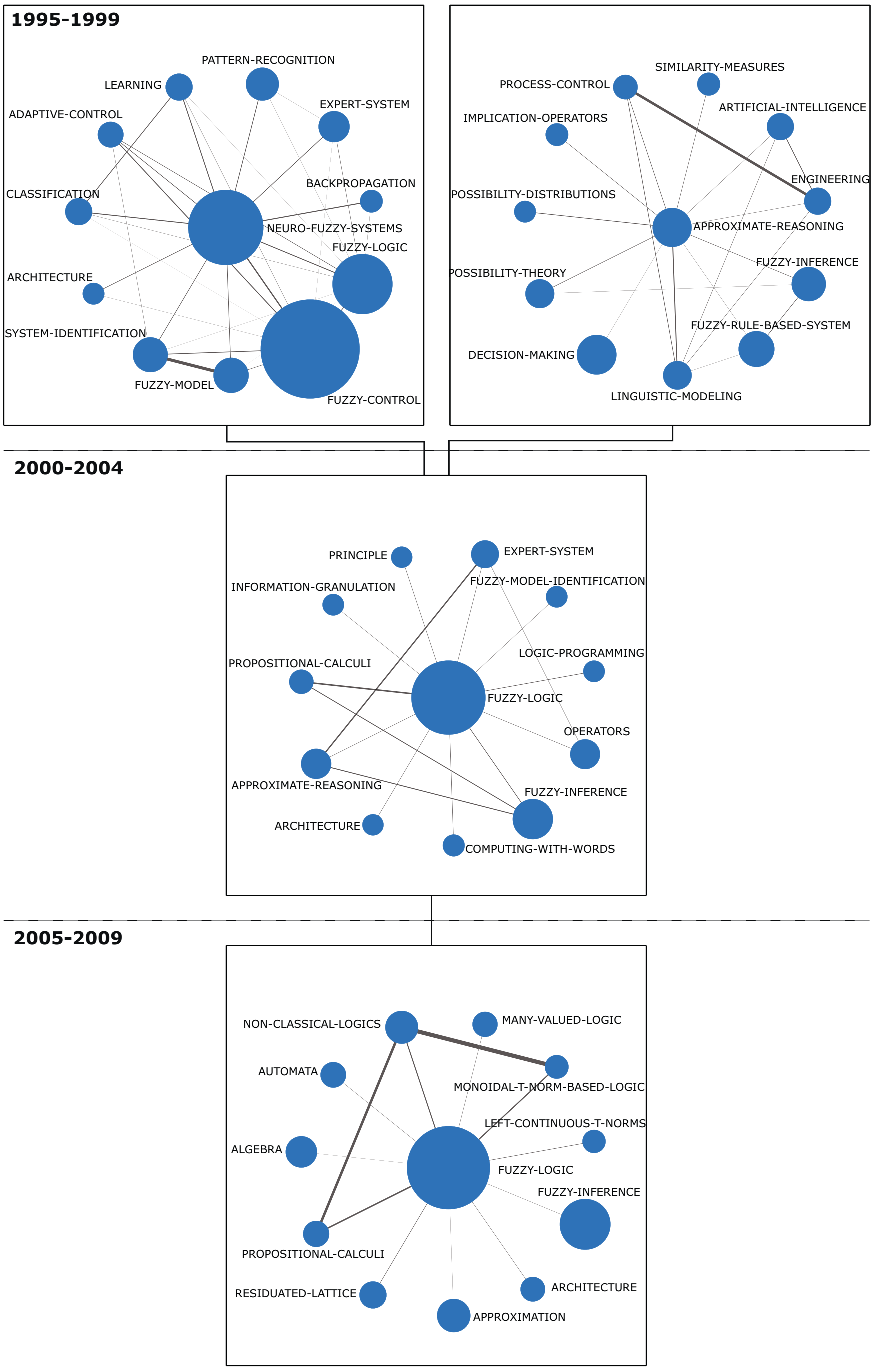
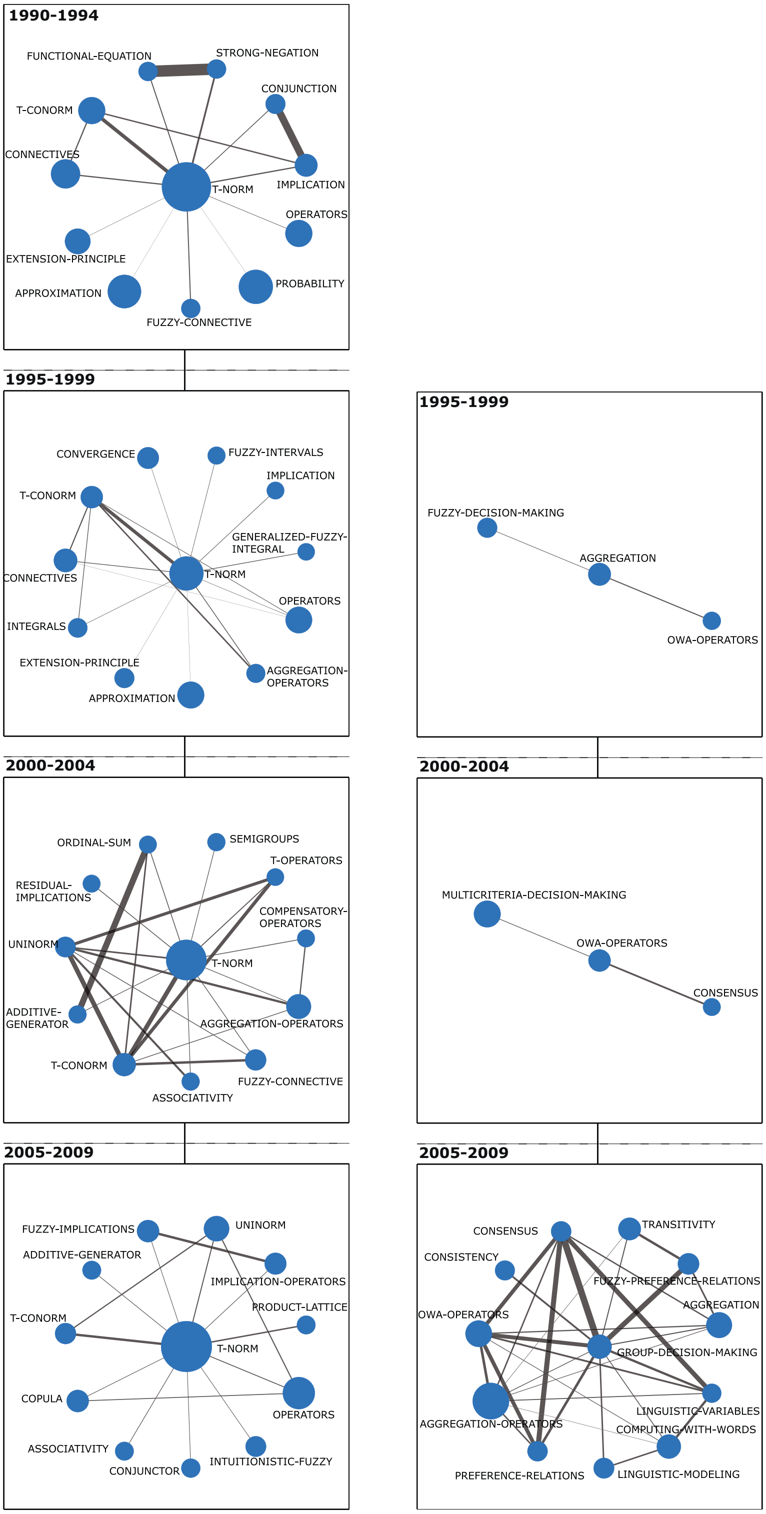


Fig. 13. The FUZZY-LOGIC thematic area (1978–2009).

3. *FUZZY LOGIC* and *FUZZY-NUMBERS* are also important thematic areas in the FST research field, with good impact indicators (h-index = 69 and h-index = 50, respectively), but that now present exhaustion signs.
4. *FUZZY-RELATIONS*, *UNCERTAINTY* and *GROUP-DECISION-MAKING* are three ascending thematic areas which present good impact indicators, h-index = 33, h-index = 29, h-index = 29, respectively.
5. *FUZZY TOPOLOGY* is not an important thematic area and presents a descending behavior with low impact indicators, i.e., h-index = 28, although it has been present in all studied subperiods.
6. *FUZZY-SUBGROUP* and *FUZZY-MAPPING* are the peripheral thematic areas which present the lowest impact indicators according to Table 7.



a T-NORM thematic area. b GROUP-DECISION-MAKING thematic area.

Fig. 14. T-NORM and GROUP-DECISION-MAKING thematic areas (1978–2009).

7. We identify two themes that could be the origin of new thematic areas, *INTUITIONISTIC-FUZZY-SETS* and *FUZZY-ROUGH-SETS*.

Between 1978 and 2009, the whole FST research field achieved an h-index of 115. Not all thematic areas contributed equally, some of them have provided a greater number of highly cited documents. Concretely, 60 of the documents of the *FUZZY-CONTROL* thematic area belong to the core papers of the global h-index, so half of the highly cited papers of the FST research field belong to this thematic area. Other important thematic areas were *FUZZY-LOGIC* and *FUZZY-NUMBER* which contributed 31 and 11 highly cited documents, respectively. The remaining thematic areas contributed less than 10 highly cited documents, i.e., the *GROUP-DECISION-MAKING* thematic area contributed 3 highly cited documents. Indeed, the thematic areas *FUZZY-MAPPING* and *FUZZY-SUBGROUP* did not contribute any published documents. This last point confirms that the subfields associated with specialized and peripheral themes are well identified by our approach (Fig. 14).

It is necessary to say that since a document can belong to different themes (we have used the core documents + secondary documents) and a theme can belong to different thematic areas, the sets of documents belonging to each thematic network are not disjoint. So, a core paper of the h-index can be repeated in several thematic areas. Furthermore, it is possible that a highly cited document does not belong to any thematic area.

4.3. What does the analysis of FST indicate?

As a consequence of the application of our approach to the FST research field we should point out some aspects:

1. Technical aspects related to our analysis approach:
   - This approach combines different bibliometric tools to analyze the evolution of the cognitive structure of a research field, allowing us to discover important knowledge related to its themes and thematic areas. In such a way, as was pointed out in Section 4.1, we discover that our approach adequately identifies the FST basic themes in each subperiod, because they achieve the highest citation scores and impacts. Additionally, as was shown in Section 4.2, we are able to identify thematic areas (see Table 7) and show their evolutionary behaviour, as with *FUZZY-CONTROL* whose evolution is increasing or *FUZZY-LOGIC* whose evolution is decreasing.
   - This approach is supported by different visualization tools that allow us to easily detect the themes and thematic areas and to understand their evolution, importance and likely future tendencies. For example, we show the evolution of the FST research field in Fig. 11 and we identify that *FUZZY-CONTROL* is the most important thematic area with the highest impact, as is shown in Table 7. We have also concluded that *FUZZY-ROUGH-SETS* seems to be the origin of a new thematic area.
   - This approach is completed by incorporating a more elaborated bibliometric index, i.e., the h-index, which allows us to better analyze the quality or impact of the themes and thematic areas. In our FST analysis, as is shown in Sections 4.1 and 4.2 we use the h-index to evaluate the impact of themes and thematic areas.
2. *Application aspects related to the research field:* The application of our approach to analyze the evolution of the FST research field has been shown to be very effective, allowing us to analyze it and discover information easily in each one of the studied subperiods and from a global point of view. Furthermore, many of the obtained results can be followed easily by any user by means of the visualization tools that support them.

5. Concluding remarks

A general approach to analyze and visualize a research field has been proposed. Co-word analysis is the technique used in order to create a bibliometric map. Strategic diagrams and thematic areas are used to study the thematic evolution of a research field. Finally, the performed analysis shows the impact of the research field (including detected themes and thematic areas) by means of quantitative and impact measures such as the h-index.

As an example, this approach has been tested by analyzing the thematic evolution of the FST research field using the papers published by the two most important journals: *Fuzzy Sets and Systems* and *IEEE Transactions on Fuzzy Systems*.

Finally, we can conclude that a strong correlation has been observed between the themes with high centrality (right quadrants) and the number of received citations, as shown in Figs. 5b, 6b, 7b, 8b and 9b. This correlation indicates to us that the proposed approach is very suitable for use as an analysis tool of a given general research field.

Acknowledgments

This work has been developed with the financing of FEDER funds in FUZZYLING project (TIN2007-61079), FUZZYLING-II project (TIN2010-17876), PETRI project (PET2007-0460), project of Ministry of Public Works (90/07) and Excellence Andalusian Project (TIC5299).

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