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A Review on the Role of Fuzzy Logic in Hybrid Intelligent Systems

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Abstract. In this review the role of fuzzy logic (FL) in hybrid intelligent systems is discussed. We first review the papers in which fuzzy logic is used in conjunction with neural networks, as well as their application areas. Then, we review the papers in which fuzzy logic has been used in combination with evolutionary algorithms, and the corresponding application areas. We also review the papers in which fuzzy logic has been used in a hybrid way with optimization algorithms, as well as the application areas. Regarding FL, we consider the evolution that has been undergoing, where initially type-1 fuzzy logic was proposed and used, later type-2 was proposed and now more recently type-3 has been put forward. The evolution of FL has occurred due to the need of handling the higher uncertainty levels that real-world problems have. In this regard, we analyze the impact of this evolution on different types of hybrid intelligent systems.

Keywords. Type-3 fuzzy logic, neural networks, evolutionary algorithms, optimization algorithms.

1 Introduction

Hybrid intelligent systems have become a viable alternative for solving many real-world problems. Recently, the use of Soft Computing (SC) techniques in hybrid intelligent systems has become very popular due to the many advantages of SC techniques. In particular, three of the main areas of SC are: fuzzy systems (FSs), neural networks (NNs) and evolutionary algorithms (EAs). Fuzzy systems deal with the intrinsic uncertainty in solving problems with intelligent systems. Neural networks provide learning abilities to the intelligent systems. Evolutionary algorithms offer evolution and search abilities to the intelligent systems. A hybrid intelligent system (HIS) can be composed of two or more of these techniques, for example neuro-fuzzy systems combine the advantages of FSs (representing knowledge) with the learning abilities of NNs. Another case is evolutionary fuzzy systems in which EAs are used to optimize the design of a FS for a particular problem. In this paper, the goal is to study the role and impact of fuzzy logic (FL) when used to enhance the performance of neural networks, evolutionary algorithms and optimization algorithms (in general). For example, one recent trend has been to employ FSs for parameter adaptation in evolutionary and metaheuristic algorithms.

The contribution of this paper is providing an overview of the utilization of FL in HISs, meaning in which way FSs are used to enhance the performance of NNs and EAs. In addition, based on the review of existing papers in the literature, we can infer some relevant conclusions and envision future trends for the years to come. We can say that, to the moment, there is no similar review that has been done.

The review paper is structured as follows. Section 2 briefly reviews the evolution of FSs, since the original type-1 FSs were proposed by Zadeh [1-2] and later type-2 FSs were developed by Mendel [3], to finally Type-3 FSs theory [4-5] and applications [6-11]. Section 3 reviews the existing papers in which Fuzzy Logic (FL) is employed in conjunction with NNs. Section 4 summarizes the papers in the state of the art of FL used with evolutionary algorithms. Section 5 reviews the published papers in which FL is utilized in conjunction with optimization algorithms. Section 6 outlines a discussion of the results and envisions future trends for these areas. Finally, Section 7 outlines the conclusions.

2 Evolution of Fuzzy Logic and Systems

Since the emergence of the Fuzzy Sets, proposed by Zadeh [1], this kind of sets had evolved for handling more information, starting from vagueness to high level of uncertainty. This section summarizes the differences among types of Fuzzy Sets.

The definitions of Type-1, Type-2, and Type-3 Fuzzy Sets are formulated in a succinct way in (1), (2) and (3), respectively:

$$\mathrm{A}^{(1)} = \{(x, \mu_{\mathrm{A}}(x)) | \forall x \in [0,1]\}, \tag{1}$$

$$\mathrm{A}^{(2)} = \{((x,u), \mu_{\tilde{A}}(x,u)) | \forall u \in J_x \subseteq [0,1]\}, \tag{2}$$

$$\mathrm{A}^{(3)} = \left\{\left((x,u), \mu_{\mathrm{A}^{(3)}}(x,u,z_1)\right) \middle| \mathrm{x} \in \mathrm{X}, \mathrm{u} \in \mathrm{U} \subseteq [0,1], \quad \mathrm{z}_1 \in \mathrm{Z}_1 \subseteq [0,1]\right\}. \tag{3}$$

As we can note, in the original type-1 fuzzy sets only one membership function (MF) is used, but in type-2 there is a primary MF and a secondary MF [3], while type-3 introduces a tertiary MF [4]. Historically, this process has occurred due to the need of being able to cope with higher levels of uncertainty. These approaches are called Generalized Fuzzy Sets, and as can be noted, with the evolution of the Fuzzy Sets the definitions are more complex, handling vagueness, uncertainty and second order uncertainty, respectively. Additionally, there exist partial models of these Generalized Models called Interval Type-2 Fuzzy Sets (for simplifying the uncertainty management of Generalized Type-2 Fuzzy Sets) and Interval Type-3 (for simplifying the uncertainty management of Generalized Type-3 Fuzzy Sets). In the practical implementation of the generalized models, these interval approximations are used for approximating the generalized models by approaches, such as α-planes. For better understanding can be consulted the following reviews of the advances on Fuzzy Logic [12–13].

It is noteworthy that the secondary MF in the case of the Generalized Type-3 membership degree is a Generalized Type-2 membership function. On the other hand, the secondary MF of the IT3 membership degree is an IT2 membership function.

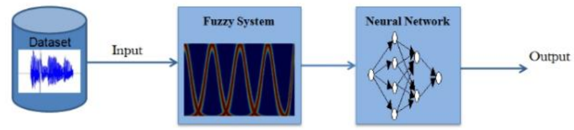

Fig. 1. A Hybrid fuzzy neural system

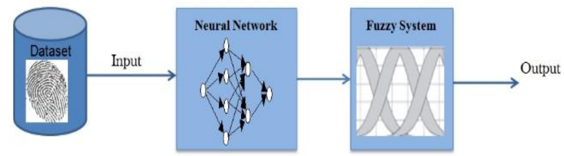

Fig. 2. A Hybrid neural fuzzy system

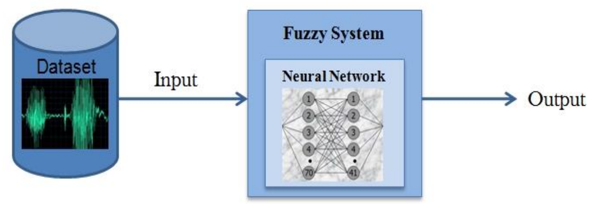

Fig. 3. A Hybrid adaptive neural fuzzy system

3 Fuzzy Logic in Neural Networks

In this section we describe and analyze the publications that have been done in the intersection of FL and NNs. We consider the documents in Scopus as the source for the search. As FL has evolved from the initial type-1 FL, to later type-2 and more recently type-3, we have accordingly organized this section into three subsections.

In general, we have noticed that hybrid fuzzy neural systems can arise from combining two separate modules of FL and neural networks, like in staged hybrid combination. Another case in when a fuzzy system is embedded in a neural system, like in the Adaptive Neuro-Fuzzy Inference System (ANFIS) approach. Other approaches are also possible, like when neuron activation is modeled with a fuzzy system. All these kinds of systems are considered in this study, as we are

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searching for all documents in Scopus, where the keywords "fuzzy neural networks" appear. The statistics and analysis for type-1, type-2 and type-3 are shown in the following subsections, respectively. We show in Figure 1 one possible hybrid approach in which data enters a fuzzy system for processing and later an NN processes the information to obtain a final output. Another choice (shown in Figure 2) is when first an NN is utilized and later a FS summarizes results to find the final output. Another option is when a FS is embedded into an NN to achieve obtaining a fuzzy system with learning abilities (Figure 3).

This section is divided in three parts that deal with type-1, type-2 and type-3 fuzzy neural networks, respectively. This order is historical, as type-1 was the first to be proposed and later type-2 and type-3 emerged, as more powerful fuzzy models. In this sense, the number of published papers is higher for type-1 and lower for type-3.

This section is divided in three parts that deal with type-1, type-2 and type-3 fuzzy NNs, respectively. This order is historical, as type-1 was the first to be proposed and later type-2 and type-3 emerged, as more powerful fuzzy models. In this sense, the number of published papers is higher for type-1 and lower for type-3.

3.1 Type-1 Fuzzy Logic in Neural Networks

We did search on the Scopus database for the documents with the words "fuzzy neural networks" and we did find more than 63303 documents. We can mention some interesting and representative works in this area that can be found in [14-21]. In Figure 4 we notice that the published documents per year, where an increasing trend is very clear. Figure 5 shows the published papers per year by source. Figure 6 shows the papers by authors (only top ten). Table 1 lists the top ten authors in this area.

3.2 Type-2 Fuzzy Logic in Neural Networks

We did search on the Scopus database for the documents with the words "type-2 fuzzy neural networks" and we did find more than 1264 documents. We can mention some interesting papers in this area, as a sample, which can be found in [22-31]. In Figure 7 we notice that the published documents per year, where an increasing trend is very clear. Figure 8 shows the papers by authors (only top ten). Figure 9 illustrates a dispersion diagram by author in this area. Figure 10 depicts a dispersion diagram by country in this area.

Table 1. List of the top Ten authors

	Author	Number of documents
1	Melin, P.	318
2	Pedrycz, W	311
3	Oh, S.K.	216
4	Castillo, O.	193
5	Kisi, O.	145
6	Lin, F.J.	135
7	Quek, C.	128
8	Lin, C.J.	124
9	Lin, C.T.	123
10	Lim, C.P.	103

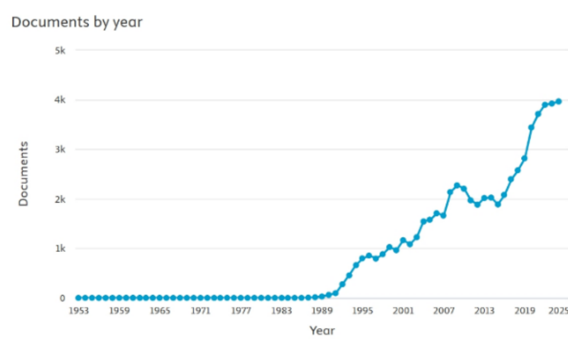

Fig. 4. Papers per year in fuzzy neural networks

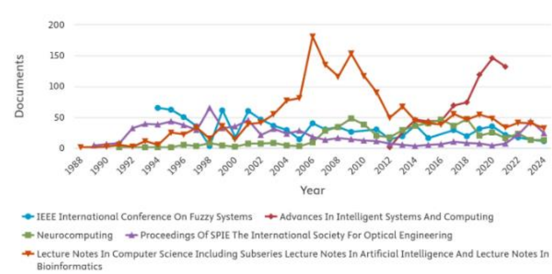

Fig. 5. Papers per year by source in fuzzy neural networks

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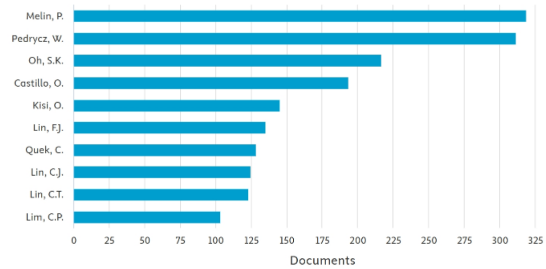

Fig. 6. Papers by author in fuzzy neural networks

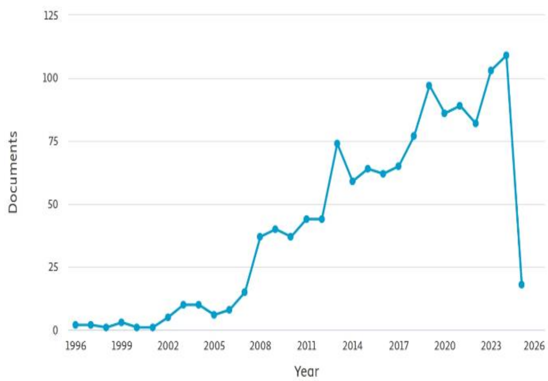

Fig. 7. Papers by author in fuzzy neural networks

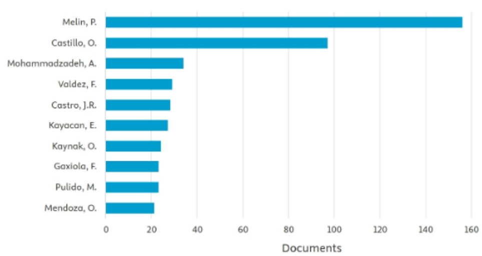

Fig. 8. Papers by author in type-2 fuzzy NNs

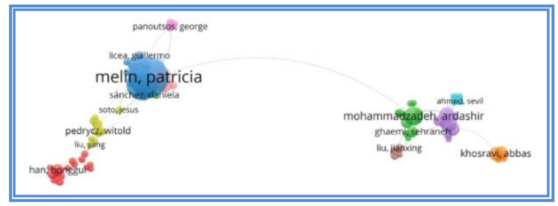

Fig. 9. Dispersion diagram by author in type-2 fuzzy NNs

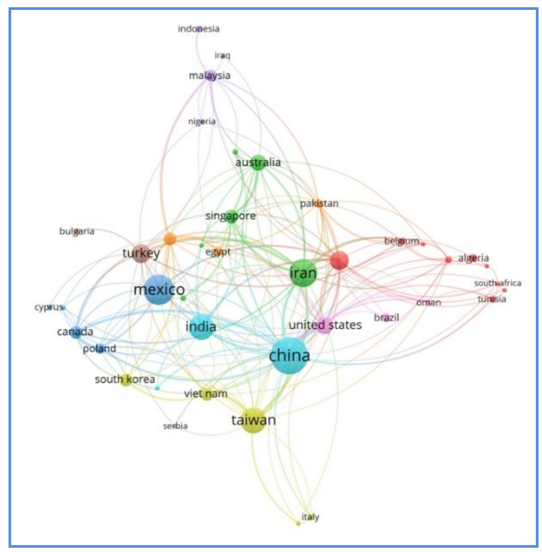

Fig. 10. Dispersion diagram by country in type-2 fuzzy NNs

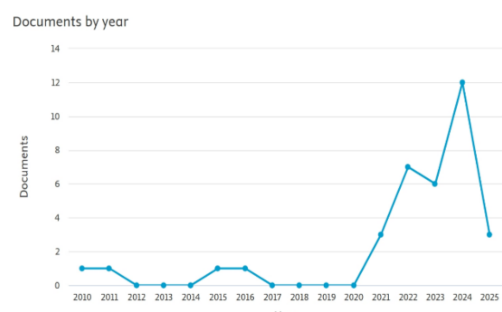

Fig. 11. Papers per year in type-3 fuzzy neural networks

3.3 Type-3 Fuzzy Logic in Neural Networks

We did search on the Scopus database for the documents with the words “type-3 fuzzy neural networks” and we did find only 35 documents due to the fact that type-3 is a relatively new concept. We can highlight some of the interesting works in this area in [32-38]. In Figure 11 we notice that the published documents per year, where an increasing trend is very clear. Figure 12 shows the

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Table 2. List of the top Ten authors

	Author	Papers
1	Castillo, O	12
2	Melin, P	10
3	Mohammadzadeh, A.	8
4	Castro, J.R.	4
5	Pulido, M.	3
6	Arifin, M.S.	3
7	Elhaki, O.	2
8	Rathinasamy, S.	2
9	Shojaei, K.	2
10	Taghavifar, H.	2

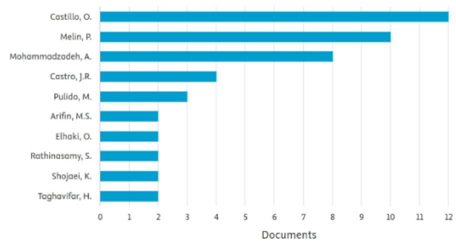

Fig. 12. Papers by author in type-3 fuzzy neural networks

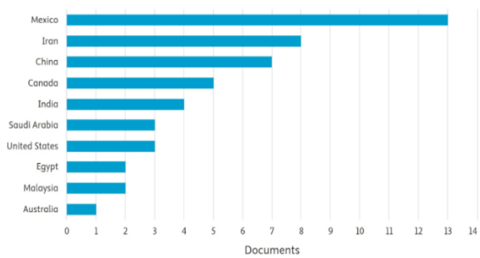

Fig. 13. Papers by country in type-3 fuzzy neural networks

papers by authors (only top ten). Table 2 lists the top ten authors in this area. Figures 13 and 14 depict the publications by country and affiliation, respectively.

4 Fuzzy Logic in Evolutionary Algorithms

We describe in this section the role that fuzzy logic has in enhancing evolutionary algorithms by providing its uncertainty handling capabilities. As was previously mentioned FL has evolved from the original type-1 to later type-2 and finally type-3 fuzzy logic. So, in the same way, the involvement of fuzzy logic for enhancing evolutionary algorithms have followed the same path [39-42]. Figure 15 illustrates one of the possible ways in which a fuzzy system could be used to enhance an evolutionary algorithm, which is by enabling parameter adaptation (in this case P1 and P2 are the parameters).

4.1 Type-1 Fuzzy Logic in Neural Networks

We first discuss the search in Scopus for publications with the keywords "Fuzzy Evolutionary Algorithms", which produces 7539 documents. Some examples of these papers are very recent [43-52]. Figure 16 illustrates the number of publications per year, which exhibit an increasing trend. Figure 17 shows the publications by author for this area, but only listing the top ten authors. Table 3 summarizes the number of documents of the top ten authors. Figure 18 exhibits the number of documents by affiliation.

Figure 19 illustrates the dispersion diagram of authors by documents in fuzzy evolutionary algorithms and Figure 20 exhibits the dispersion diagram with respect to citations of the papers. Both diagrams are similar, but there are some differences as in the diagram with respect to citations the authors with more citations can be distinguished by their bigger circles (as it is the case of Francisco Herrera from Spain, who looks bigger in the citation diagram).

4.2 Type-2 Fuzzy Logic in Evolutionary Algorithms

We now discuss the search in Scopus for publications with the keywords "Type-2 Fuzzy Evolutionary Algorithms", which produces only 203 documents, and some examples can be found in [53-68]. Figure 21 illustrates the number of publications per year, which exhibit an increasing trend. Figure 22 shows the publications by author for this area, but only listing the top ten authors. Figure 23 exhibits the number of documents by type of publication. Figure 24 illustrates the dispersion diagram of authors by documents in fuzzy evolutionary algorithms and Figure 25

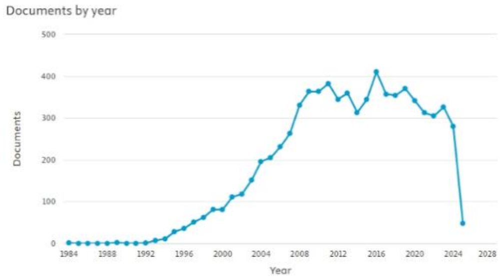

Fig. 16. Publications per year in fuzzy evolutionary algorithms

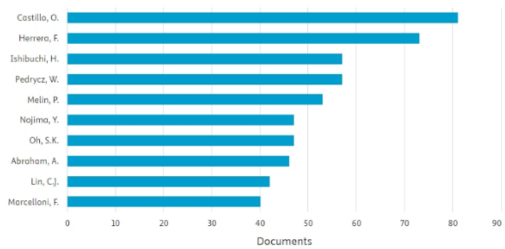

Fig. 17. Publications by author in fuzzy evolutionary algorithms

exhibits the dispersion diagram with respect to citations of the papers.

4.3 Type-3 Fuzzy Logic in Evolutionary Algorithms

We now discuss the search in Scopus for publications with the keywords "Type-3 Fuzzy Evolutionary Algorithms", which produces only 3 documents, as type-3 is a very recent area of research [69-70]. Figure 26 shows the publications by author for this area, but only listing the top ten authors. Figure 27 exhibits the number of documents by type of publication. Other figures could not be drawn due to very low number of papers in this area (at the moment).

5 Fuzzy Logic in Optimization Algorithms

We describe in this section the role that fuzzy logic has in enhancing optimization algorithms by providing its uncertainty handling capabilities.

As was previously mentioned FL has evolved from the original type-1 to later type-2 and finally type-3 fuzzy logic. So, in the same way, the involvement of fuzzy logic for enhancing optimization algorithms have followed the same path [71-76]. Figure 28 illustrates one of the possible ways in which a fuzzy system could be used to enhance an optimization algorithm, which is by enabling parameter adaptation (in this case P1 and P2 are the parameters).

5.1 Type-1 Fuzzy Logic in Optimization Algorithms

We first discuss the search in Scopus for publications with the keywords "Fuzzy Optimization Algorithms", which produces 36323 documents. Some relevant papers in this area can be found in [77-88]. Figure 29 illustrates the number of publications per year, which exhibit an increasing trend. Figure 30 shows the publications by author for this area, but only listing the top ten authors. Table 4 summarizes the number of documents of the top ten authors. Figure 31 exhibits the number of documents per year by source. Figure 32 illustrates the dispersion diagram of authors by documents in fuzzy evolutionary algorithms and Figure 33 exhibits the dispersion diagram with respect to citations of the papers.

5.2 Type-2 Fuzzy Logic in Optimization Algorithms

We now discuss the search in Scopus for publications with the keywords "Type-2 Fuzzy Optimization Algorithms", which produces 1050 documents. A sample of this paper can be found in [89-100]. Figure 34 illustrates the number of publications per year, which exhibit an increasing trend. Figure 35 shows the publications by author for this area, but only listing the top ten authors. Figure 36 exhibits the number of documents by country. Figure 37 illustrates the dispersion diagram of authors by documents in fuzzy evolutionary algorithms and Figure 38 exhibits the dispersion diagram with respect to citations of the papers.

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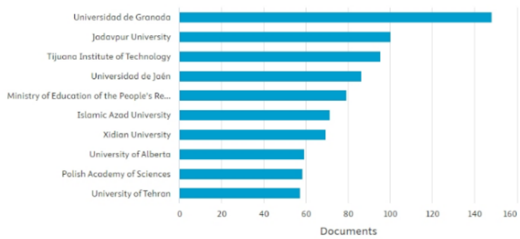

Fig. 18. Publications by affiliation in fuzzy evolutionary algorithms

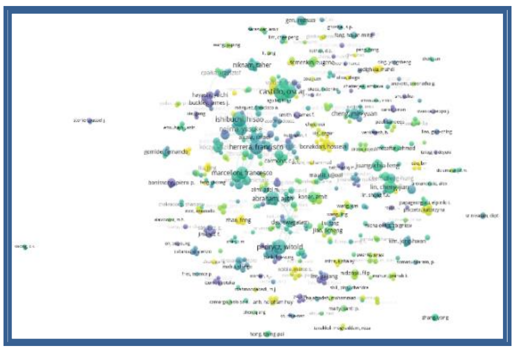

Fig. 19. Dispersion diagram of authors by documents in fuzzy evolutionary algorithms

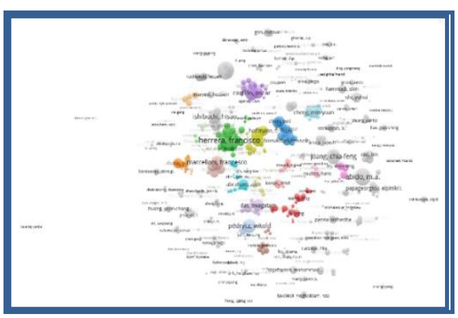

Fig. 20. Dispersion diagram of authors by citations in fuzzy evolutionary algorithms

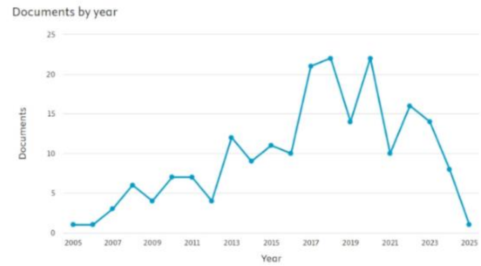

Fig. 21. Publications by author in fuzzy evolutionary algorithms

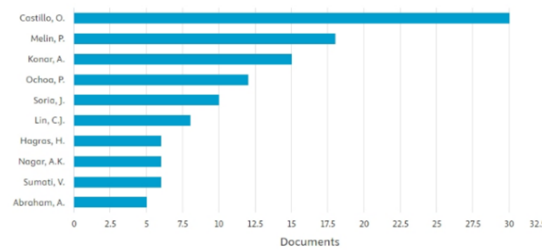

Fig. 22. Publications by author in fuzzy evolutionary algorithms

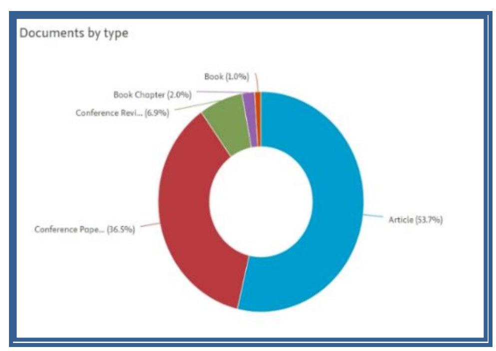

Fig. 23. Documents by publication type in type-2 fuzzy evolutionary algorithms

5.3 Type-3 Fuzzy Logic in Optimization Algorithms

We first discuss the search in Scopus for publications with the keywords "Type-3 Fuzzy Optimization Algorithms", which produces only 14 documents. Some of these papers can be found in [101-110]. Figure 39 illustrates the number of publications per year, which exhibit an increasing trend. Figure 40 shows the publications by author for this area, but only listing the top ten authors.

6 Discussion of Future Trends

n this section we describe the analysis of the data that was found from Scopus and also, we envision viable future trends for the role of FL in HISs.

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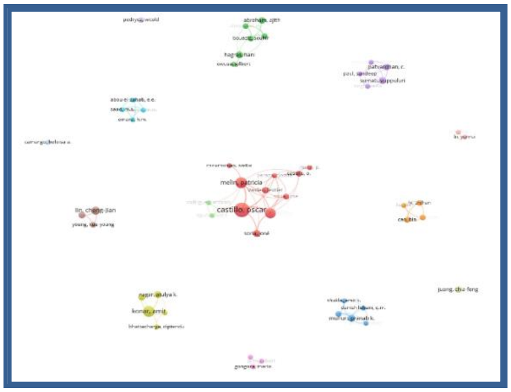

Fig. 24. Dispersion diagram by documents in type-2 fuzzy evolutionary algorithms

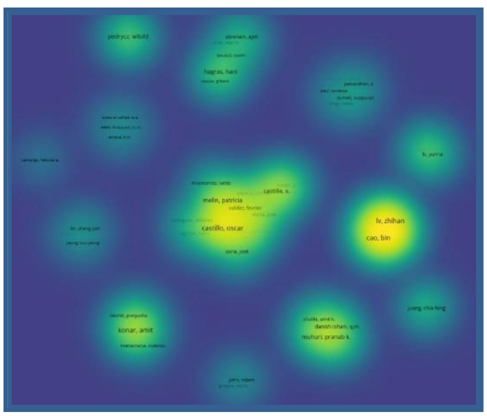

Fig. 25. Dispersion diagram by citations in type-2 fuzzy evolutionary algorithms

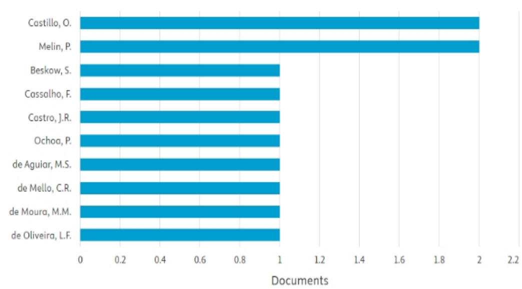

Fig. 26. Publications by author in type-3 fuzzy evolutionary algorithms

Based on the publications that have been produced over the years, we can state that most of the type-3 hybrid papers have been applied in control area, prediction and decision making.

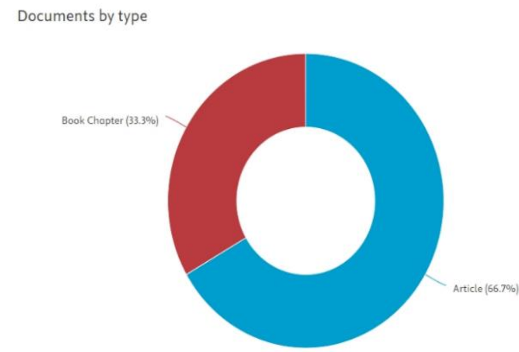

Fig. 27. Documents by publication type in type-3 fuzzy evolutionary algorithms

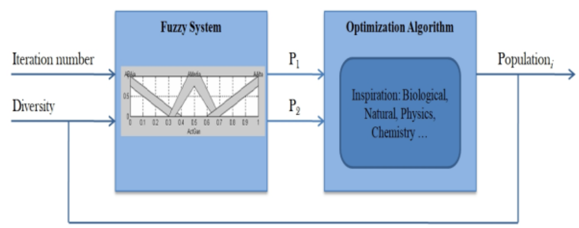

Fig. 28 Fuzzy parameter adaptation in an optimization algorithm

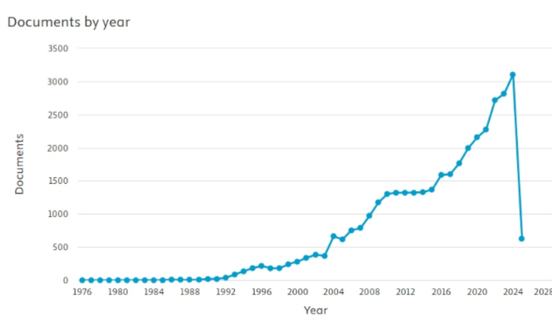

Fig. 29. Publications per year in fuzzy optimization algorithms

We are convinced that other areas will be undertaken in the near future, such as pattern recognition, clustering and intelligent agents. In addition, on the theoretical part, at the moment mostly the papers deal with interval type-3 FL

Table 4. Top ten authors by number of documents

Author	Documents
Castillo, O.	366
Pedrycz, W.	226
Melin, P.	217
Oh, S.K.	156
Valdez, F.	134
Soria, J.	83
Niknam, T.	75
Abraham, A.	67
Panda, S.	66
Gen, M.	61

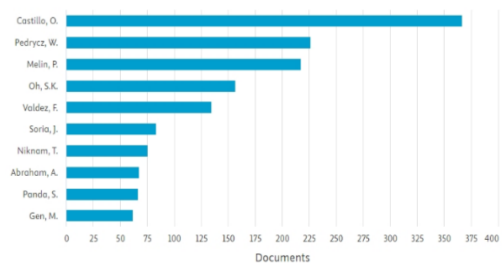

Fig. 30. Top ten authors in fuzzy optimization algorithms

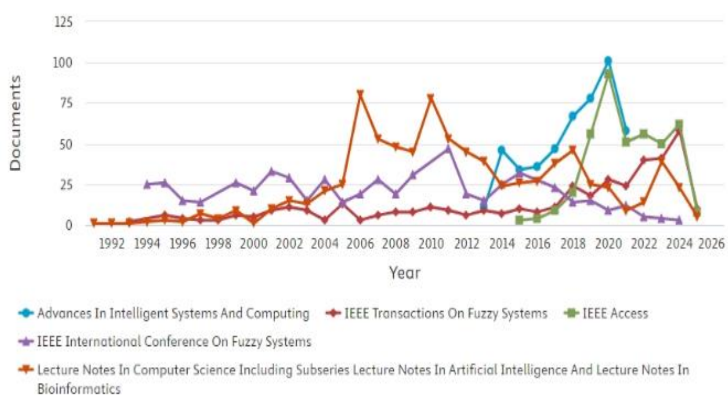

Fig. 31. Number of documents per year by source

(meaning the tertiary membership function is fixed to a value of one), but we envision that generalized type-3 would be achieved in the near future, allowing obtaining even better results for many complex real-world problems.

Finally, there is also possible theoretical work on type-n FL, which could also enable even more remarkable results in the future.

7 Conclusions

In this review the role of fuzzy logic in HISs has been analyzed and discussed. We first reviewed the papers in which FL is used in conjunction with NNs, as well as their application areas. Then, we reviewed the papers in which FL has been used in

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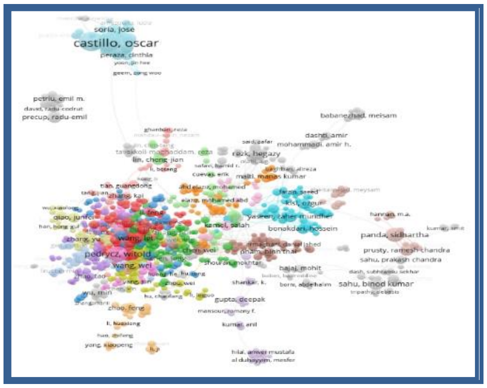

Fig. 32. Dispersion diagram by documents in fuzzy optimization algorithms

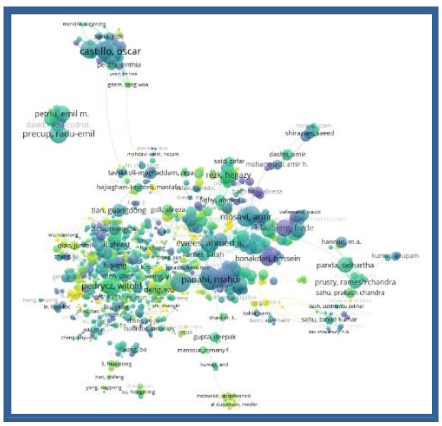

Fig. 33. Dispersion diagram by citations in fuzzy optimization algorithms

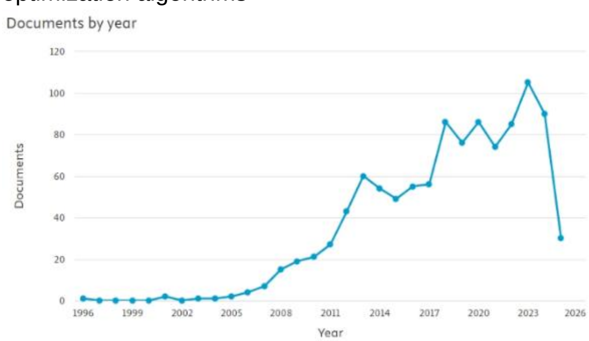

Fig. 34. Publications per year in fuzzy optimization algorithms

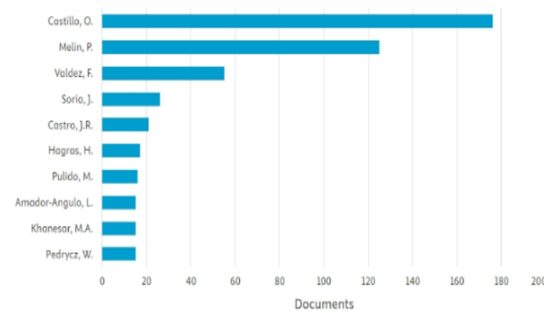

Fig. 35. Top ten authors in type-2 fuzzy optimization algorithms

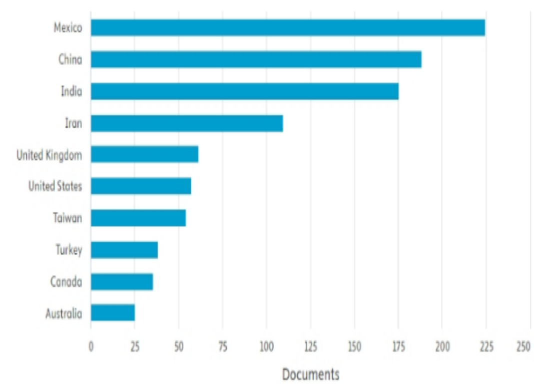

Fig. 36. Number of publications by country in type-2 fuzzy optimization algorithms

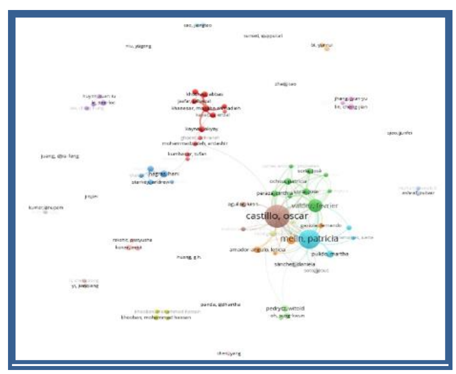

Fig. 37. Dispersion diagram by documents in type-2 fuzzy optimization algorithms

combination with evolutionary algorithms, and the corresponding application areas.

We also reviewed the papers in which FL has been used in a hybrid way with optimization algorithms, as well as the application areas. Regarding FL, we consider the evolution that has been undergoing, where initially type-1 fuzzy logic was proposed and used, later type-2 was proposed

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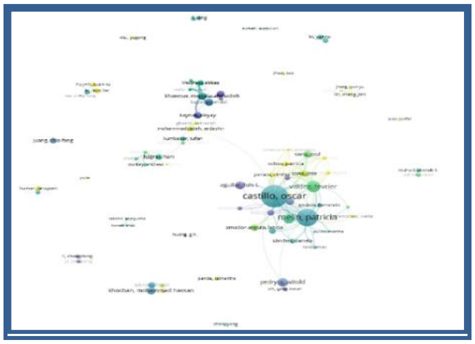

Fig. 38. Dispersion diagram by citations in type-2 fuzzy optimization algorithms

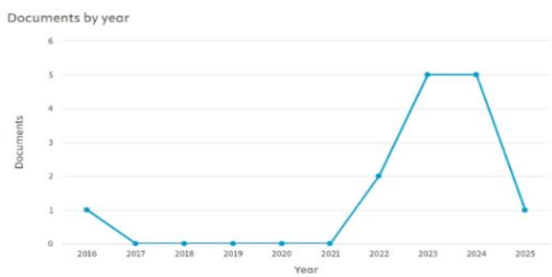

Fig. 39. Publications per year in type-3 fuzzy optimization algorithms

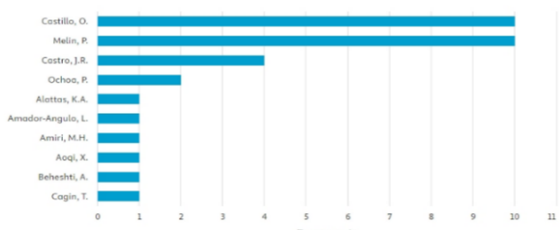

Fig. 40. Top ten authors in type-3 fuzzy optimization algorithms

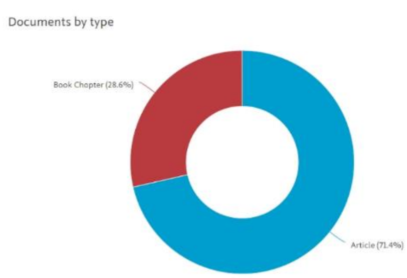

Fig. 41. Documents by publication type in type-3 fuzzy optimization algorithms

and now more recently type-3 has been put forward. The evolution of fuzzy logic has occurred do to need of handling the higher uncertainty levels that real-world problems required. In this regard, we analyze the impact of this evolution on different types of hybrid intelligent systems.

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