Complexity Issues in Data-Driven Fuzzy Inference Systems: Systematic Literature Review[1]

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Abstract. The development of a data-driven fuzzy inference system (DataFIS) involves the automatic generation of membership functions and fuzzy if-then rules and choosing a particular defuzzification approach. The literature presents different techniques for automatic DataFIS development and highlights different challenges and issues of its automatic development because of its complexity. However, those complexity issues are not investigated sufficiently in a comprehensive way. Therefore, in this paper, we present a systematic literature review (SLR) of journal and conference papers on the topic of DataFIS *complexity issues*. We review 1 340 papers published between 1991 and 2019, systematize and classify them into categories according to the complexity issues. The results show that DataFIS complexity issues are classified as follows: computational complexity, fuzzy rules complexity, membership functions complexity, input data complexity, complexity of fuzzy rules interpretability, knowledge inferencing complexity and representation complexity, accuracy and interpretability complexity. The results of this study can help researchers and practitioners become familiar with existing DataFIS complexity issues, the extent of a particular complexity issue and to decide for future development.

Keywords: membership function, fuzzy inference system, issue, limitation, complexity

1 Introduction

Development of a data-driven fuzzy inference system (DataFIS) involves automatic generation of membership functions (MFs), which reflect what is known about linguistic variables in application domains, and fuzzy if-then rules, used for inferencing or

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assessment, and choosing a particular defuzzification approach to determine the output variables in interpretable and understandable way for the end-user.

The literature presents different techniques for automatic DataFIS development [1, 2, 3], and highlights different challenges and issues, because of its complexity, like the rule base (RB) complexity [4], data complexity [5], a number of linguistic terms [1, 6]. However, those complexity issues are not investigated sufficiently in a comprehensive way. In the analysed papers, authors have focused on a particular one or two issues separately, like computational complexity [2, 7], MF complexity [8, 9], fuzzy rules complexity [10, 11], etc. This lack of understanding of a general situation hampers progress in the field since academics are offering limited approach [12].

Therefore, the question arises – *What are the complexity issues in DataFIS*?

In order to answer the question raised, a systematic literature review (SLR) is presented in this paper. SLR has two purposes and contributions. It is used to determine, first, the possible set of complexity issues, and, second, the extent of a particular complexity issue in DataFIS area.

The rest of this paper is structured as follows. Section 2 introduces complexity in the context of DataFIS and explains the use of this concept in this paper. Section 3 presents the review methodology. Section 4 shows the obtained results of SLR. Section 5 discusses the results obtained in the paper. Finally, Section 6 concludes the paper.

2 Background and Related Work

DataFIS consists of four main components [1, 13, 14] (Fig. 1). *Data Collection and Pre-Processing* is responsible for crisp or linguistic stream collecting from one or multiple sources and its cleaning, organization and integration [15] for future data exploitation in the Fuzzification Mechanism. *Fuzzification Mechanism* transforms the data stream into MFs using fuzzy set theory. *Fuzzy Inference* uses MFs and applies a particular fuzzy reasoning mechanism to obtain a fuzzy output. *Knowledge base* is responsible for the definition and management of fuzzy rules, used by the Fuzzy Inference component for inferencing. *Output Processing* performs approximation, defuzzification and type reduction to convert the results of inferencing into output data (i.e., crisp or linguistic values), which should be understandable to a Stakeholder or a System.

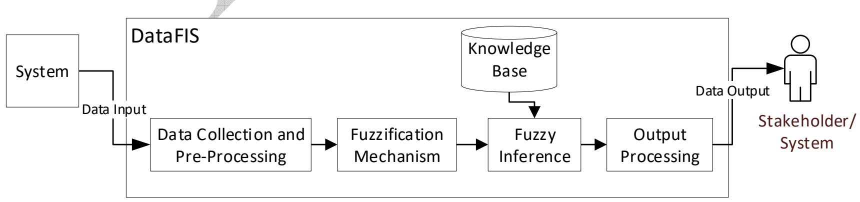

Fig. 1. The reference schema of a data-driven Fuzzy Inference System (DataFIS).

The distinctive feature of DataFIS is that it is data-driven, i.e., MFs and fuzzy rules are generated from synthetic or real data streams automatically, but not defined by an expert. In DataFIS knowledge is represented through two levels [1]. First, in the *semantic level* knowledge is expressed as fuzzy sets and MFs. Second, in the *syntactic level* knowledge is represented in a form of fuzzy rules. This understanding of DataFIS and its complexity are used in this paper.

The concept of complexity in DataFIS can be viewed from different perspectives as the primary analysis shows. In [4], *the rule base (RB) complexity* is measured as the total number of conditions in the antecedents of the rules. Authors of [16] understand complexity as interpretability of RB, and interpretability of fuzzy partitions as integrity of the database (DB). A *data complexity* is measured in terms of the average number of patterns per variable (i.e., data density) for pattern recognition in [5].

A data-driven Fuzzy Inference System suffers from exponential complexity, which is manifested through a *number of linguistic terms* (number of subspaces on the universe of discourse of input variables) and a *number of input variables* [1]. Complexity is also measured by *counting the number of operations* [6] or *number of elements in RB* including the number of MFs, rules, premises, linguistic terms, etc. [1]. Selecting a small number of linguistic terms and the right linguistic terms is essential for *better interpretability*. Total number of parameters of the fuzzy RB is also a measure of interpretability. A system with less number of *parameters* is more interpretable and less complex [17]. In [1, 18], authors suggest reducing the exponential complexity of FIS be reducing the number of fuzzy (linguistic) terms or the number of fuzzy (linguistic) variables or both. According to [19], the *model interpretability* is measured in terms of complexity: "*Complexity is affected by the number of features used for generating the model: the lower the number of features, the lower the complexity*".

Summing up, the definition of system complexity depends on the complexity of its components. Therefore, in the next section we describe main components of a data-driven fuzzy inference system (DataFIS).

3 Review Methodology

3.1 Review method

The review methodology was developed and executed according to the guidelines and hints provided by [20, 21]. The structure of the methodology is adapted from [22] and presented in Table 1 as a review protocol [23].

Table 1. Review protocol.

Question Formulation
Question Focus: Membership function, development, generation, construction, issue, limit, complex, fuzzy inference system
Question (Q): "What are the complexity issues in DataFIS?"
Keywords and Synonyms: membership function, develop*, generat*, construct*, issue*, limit*, complex*
Effect: Description of different DataFIS development complexity issues; visualisation of statistics by diagrams, view integration**.**

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Field/Scope/Confines: Publications regarding MF and DataFIS issues.
Application: Computer Science (CS), Information Systems (IS), Software Engineering (SE)
Sources Selection
Studies Language: English.
Search string: (fuzzy) AND ("membership function*") AND ("develop*" OR "generat*" OR "construct*") AND ("issue*" OR "limit*" OR "complex*")
Sources list: Web of Science (WoS), https://apps.webofknowledge.com/ (see Section 3.2)
Studies Selection
Studies Inclusion Criteria (IC): **IC1:** Universally accepted relevant fundamental works on MF development, MF generation, MF construction, DataFIS and issues, limitations or complexity. **IC2:** Papers must be available to download. **Studies Exclusion Criteria (EC)**: **EC1:** Exclude papers, which contain relevant keywords, but MF and DataFIS issues, limitations or complexity are not the main topic of the paper. **EC2:** Exclude relevant sources that repeat ideas described in earlier works. **EC3:** Exclude papers, whose length is less than 8 pages, since such short papers can present only a general idea, but not describe overall approach. **EC4:** If there are several papers of the same authors with the similar abstract, i.e., one paper is an extension of another, the less extended (i.e., containing less pages) paper is excluded.
Studies Type Definition: Journal publications (research papers) and proceeding papers.
Procedures for Papers Selection (PPS): **PPS-1.** Run the search strings at the selected source → A primary set of papers is obtained. **PPS-2.** Extract the title, abstract and keywords of papers for the primary set. **PPS-3.** Evaluate a primary set of papers (the title, abstract and keywords) according to IC and EC → A secondary set of paper is obtained.
Selection execution: See Table 2.
Information Extraction
Information Inclusion and Exclusion Criteria Definition: The extracted information from papers must contain definition or analysis of the MF and DataFIS issues.
Synthesis of findings: The information extracted from the papers was tabulated and plotted to present basic information about the research process.

Table 2. Number of papers (Articles (A) or Proceedings Papers (PP)) for each PPS.

Years	**PPS-1**			**PPS-3**		
	A	PP	All	A	PP	All
1991-2019	864	476	1 340	78	23	101

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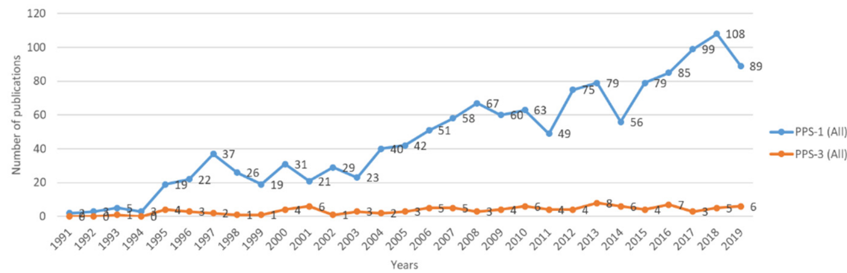

Fig. 2. Number of papers after PPS-1 and PPS-3.

In Fig. 2, the trend of the research on the topic is illustrated. The number of papers on fuzzy theory application to solve different complex domain problems has raised. This increase of papers can be attributed to technological development. However, the issues related to the usage of fuzzy theory are analyzed insufficiently. Issues related to the usage of fuzzy theory are analyzed more in <u>*A*</u> comparing to *PP* (Table 2).

3.2 Sources evaluation

The Web of Science (WoS) database was chosen for the analysis, since it covers a wider range of refined and not duplicating researches. WoS and Scopus databases are not overlapping only 12,2 % of documents in Engineering and Computer Science [114]. WoS has an Impact Factor (IF), which is calculated to assess the quality of publications and the level of scientific research in close fields of knowledge. Moreover, WoS presents an easy mechanism to export the search results in different formats, supported by various reference management software, like Mendeley[2], EndNote[3], etc., and bibliometric tools, like VOSviewer[4], CiteSpace[5], etc.

3.3 Threats to Validity

For the analysis, papers were chosen based on the searching strategy in Table 1. Validity of the results was performed applying the following measures. *Reading* the abstract and the title of the papers introduces a threat, because the abstract and the title allows excluding not relevant from the first glance papers [12]. Moreover, both authors of this paper have *assessed* the obtained results (primary and secondary sets of papers) independently and combined the results. Finally, to minimize the threat associated with inaccurate extraction of data, only papers describing complexity issues were selected.

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[2] https://www.mendeley.com/?interaction_required=true
[3] https://endnote.com/
[4] https://www.vosviewer.com/
[5] http://cluster.cis.drexel.edu/~cchen/citespace/

4 Results

The main results of our SLR are presented in Table 3. It consists of eleven columns, nine of which present the complexity issues found. They are as the following: References (R); Year of publication (Year); computational complexity (CC) (1) (i.e., the huge number of calculations in all DataFIS components); complexity of fuzzy rules (CFR) (2) (i.e., extraction, modification and optimization of fuzzy rules); complexity of MF (CMF) (3) (i.e., MF development, optimization, simplification); data complexity (DC) (4) (i.e., related to big data issues); complexity of fuzzy rules interpretability (CFRI) (5); complexity of inferencing (CI) (6); complexity of knowledge representation (CKR) (7) (i.e., development of MF and RB issues); accuracy (ACC) (8) (i.e., the ability to approximate the output of the system accurately); interpretability (I) (9) (i.e., ability to describe the behavior of the system in an interpretable way).

Table 3. The secondary set of papers (1 – analyzed in the paper, 0 – not analyzed).

R	Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
[2, 3, 25]	2019	1	0	0	0	0	0	0	0	0
[8]		0	0	1	0	0	0	0	0	0
[24]		1	1	0	0	0	0	0	0	0
[26]		0	1	1	0	0	0	1	1	0
[27]	2018	0	0	1	0	0	0	0	0	0
[28, 29]		0	1	1	0	0	0	0	0	0
[30]		1	1	0	0	0	0	0	1	0
[7]		1	0	0	0	0	0	0	0	0
[1]	2017	0	1	1	0	0	0	0	0	1
[31, 19]		0	0	0	1	0	0	0	0	0
[32]		0	1	1	1	0	0	1	0	0
[33, 35, 36]	2016	1	0	0	0	0	0	0	0	0
[34, 10]		0	1	0	0	0	0	0	0	0
[37]		0	0	1	0	0	0	0	0	0
[9, 40]	2015	0	0	1	0	0	0	0	0	0
[38]		0	1	0	0	0	0	0	0	0
[39]		1	0	0	0	0	0	0	0	0
[41]	2014	0	0	1	0	0	0	0	0	0
[11]		0	1	0	0	0	0	0	0	0
[42]		0	1	1	0	0	0	1	0	0
[43]		0	1	0	0	1	0	0	0	0
[44]		0	0	0	1	0	0	0	0	0
[45]		1	0	0	0	0	0	0	0	0
[46]	2013	1	0	0	0	0	0	0	0	0
[48]		0	1	0	0	0	0	0	0	1
[49]		0	1	1	0	0	0	0	0	0
[50]		0	0	1	0	0	0	0	0	0
[51, 52, 53]		0	1	0	0	0	0	0	0	0
[54]	2012	1	0	0	0	0	0	1	0	0
[47]		1	1	0	0	0	0	0	0	0
[55]		0	0	0	1	0	0	0	0	0
[56]		1	0	0	0	0	0	0	0	0
[57]		0	1	0	0	0	0	0	0	0
[16]	2011	0	0	1	0	0	0	0	0	1
[58]		0	1	1	0	0	0	0	0	0

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R	Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
[59]		0	0	1	0	0	0	0	0	0
[60]		0	0	0	1	0	0	0	0	0
[61]	2010	0	0	1	0	0	0	1	0	0
[62, 4, 64]		0	1	1	0	0	0	0	0	0
[63]		0	1	0	0	0	0	0	0	0
[65]		0	0	1	0	0	0	0	0	0
[66]	2009	0	1	0	0	0	0	0	0	0
[67, 68, 69]		1	0	0	0	0	0	0	0	0
[70]	2008	0	1	0	0	0	1	0	0	0
[71]		1	0	0	0	0	0	0	0	0
[72]		0	1	0	0	0	0	0	0	0
[73]	2007	1	0	0	0	0	0	0	0	0
[74]		0	1	0	0	0	0	0	1	1
[75]		0	1	0	0	0	0	0	0	0
[76]		0	1	0	0	0	0	0	1	0
[77]		1	0	0	0	0	0	0	1	0
[78, 80, 81, 82]	2006	0	1	0	0	0	0	0	0	0
[79]		0	1	0	0	0	1	0	0	0
[83, 84]	2005	0	1	0	0	0	0	0	0	0
[85]		1	1	0	0	0	0	0	0	0
[86, 87]	2004	0	1	0	0	0	0	0	0	0
[88, 90]	2003	1	0	0	0	0	0	0	0	0
[89]		0	0	0	0	0	0	1	0	0
[91]	2002	0	1	0	0	0	0	0	0	0
[92, 95]	2001	0	1	0	0	0	0	1	0	0
[93]		1	1	0	0	0	0	1	0	0
[94]		0	1	0	0	1	0	0	0	0
[96]		0	0	0	0	0	0	1	0	0
[97]		0	0	0	0	0	0	0	1	0
[98]	2000	1	0	0	0	0	0	0	0	0
[99]		0	1	0	0	0	0	1	0	0
[100]		0	1	0	0	0	0	0	0	0
[101]		1	1	0	0	0	0	1	0	0
[102]	1999	0	1	0	1	0	0	0	0	0
[103]	1998	0	1	0	0	0	0	0	0	0
[104]	1997	1	0	0	0	0	0	0	0	0
[105]		1	1	0	0	0	0	0	0	0
[106]	1996	1	0	0	0	0	0	0	0	0
[107, 108]		0	1	0	0	0	0	0	0	0
[109, 111]	1995	0	0	0	0	0	0	1	0	0
[110]		0	0	1	0	0	0	0	0	0
[112]		0	1	0	0	0	0	0	0	0
[113]	1993	0	1	0	0	0	0	0	0	0

Temporal distribution of nine complexity issues (CC (1), CFR (2), CMF (3), DC (4), CFRI (5), CI (6), CKR (7), ACC (8), I (9)) found in the papers included in the review, are given in Fig. 4. The size of the bubbles indicates the number of papers analyzing each complexity issue.

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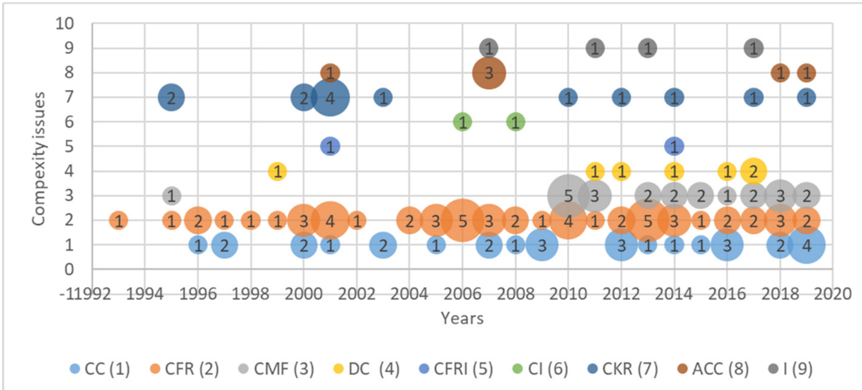

Fig. 3. Found complexity issues according to years.

5 Discussion and Conclusions

Finally, we can summarise the obtained results and answer to the research question "*What are the complexity issues in DataFIS?*". Based on Table 3, nine main issues are extracted from the analysed papers. Fig. 4 shows that the computational complexity (CC) (1) and complexity of fuzzy rules (CFR) (2) remained relevant throughout the analysed years (1991-2019). The complexity of MF (CMF) (3) issue becomes relevant since 2010. Such relevance of the issue can be explained by the growth of technologies that generate increasing amounts of data. Therefore, the need to develop MFs from large data strings that requires high computational power is raised. The data complexity (DC) (4) issue becomes relevant since 2011. Its relevance can be explained by the emergence of big data and unstructured data and their usage in DataFIS. The issues related to complexity of fuzzy rules interpretability (CFRI) (5), complexity of inferencing (CI) (6), accuracy (ACC) (8) and interpretability (I) (9) are weakly expressed directly because they are analysed in tandem with other issues.

The correlation analysis of complexity issues shows that in 67,33 % (68 papers of 101) of papers authors consider only one particular complexity issue. In 24,75 % (25) – two complexity issues, in 5,94 % (6) – three complexity issues, and in 1,98 % (2) – four complexity issues are analysed in tandem. Summing up, it shows that DataFIS complexity issue is characterized by complexity issues related to its components (see Section 2), but not separately. Therefore, the DataFIS complexity issue should be analysed as an ensemble of components complexity issues. In the future research, we are going to do the following: 1) to extend our SLR to several sources; 2) to offer a decision tree of complexity issue solutions existing in the literature now.

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