



# A Survey on Genetic Fuzzy Systems

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## Abstract

Fuzzy Systems have shown their ability for solving a wide range of problems in different application domains. Genetic Algorithms are applied to provide the learning and adaptation capabilities for designing fuzzy systems, and this composition is called genetic fuzzy systems (GFSs). This paper reviews the field of GFSs consisting of the pioneer articles, the most cited papers, GFS milestones, recent research trends and, future outlooks. Additionally, there is paid attention to a short discussion on some critical considerations of recent developments and suggestions for potential future research directions.

## 1 Introduction

Genetic algorithms play a significant role as search techniques for handling complex spaces in many fields such as artificial intelligence, engineering, and robotics. Genetic algorithms are based on the underlying genetic processes in biological organisms and the natural evolution principles of populations.

Evolutionary Computation (EC) uses computational models of evolutionary processes as key elements in the design and implementation of computer-based problem-solving systems. Various evolutionary computational models, referred to as Evolutionary Algorithms (EAs), have been proposed and studied. In short, this paradigm covers several variations, such as Evolutionary Strategies, addressing continuous function optimization [1], Evolutionary Programming, generating finite-state automata that describe strategies or behavior [2], Genetic Algorithms, providing continuous and discrete function optimization and search [3, 4], and Genetic Programming, which evolve computer programs to solve problems [5].

Computational Intelligence techniques are concerned with complex engineering problems that are unsolvable, time-consuming, or difficult to solve using classical methods [6]. Therefore, methods such as Artificial Neural Networks (ANNs) [7], Fuzzy Logic [8], Genetic Algorithms (GAs) [3,

4], and Particle Swarm Optimization (PSO) have become popular research topics in recent years.

Fuzzy systems as a model structure in the form of Fuzzy Rule-Based Systems (FRBSs) are one of the most important applications of Fuzzy Set Theory. FRBSs that deal with ‘‘IF–THEN’’ rules with fuzzy antecedents and consequents, instead of classical ones, are considered extensions of classical rule-based systems. Their ability for control problems [9], modelling [10], classification or data mining [11–13] in many applications has been demonstrated in recent years. The key to success has been the ability of fuzzy systems to incorporate human expert knowledge or experience. In the 1990s, the lack of learning capabilities characterized most of the works in the field focused on fuzzy systems with added learning capabilities. Hybridization attempts in the Computational Intelligence community have been the most successful approaches, which include different techniques, such as neural and evolutionary, and provide fuzzy systems with learning and adaptation capabilities, as shown in Fig. 1.

Among these approaches, hybridization between Fuzzy Logic and GAs, known as Genetic Fuzzy Systems (GFSs) [14], has been very popular. Briefly, a GFS is a fuzzy system optimized by a learning process based on evolutionary computation using genetic algorithms and genetic programming [15].

The GA is a well-known and widely used global search technique with the ability to explore large and complex search spaces for suitable solutions that only require a performance measure. Defining an FRBS automatically can be regarded as an optimization or search problem. To incorporate a priori knowledge, GAs are very useful because of their generic code structures and independent

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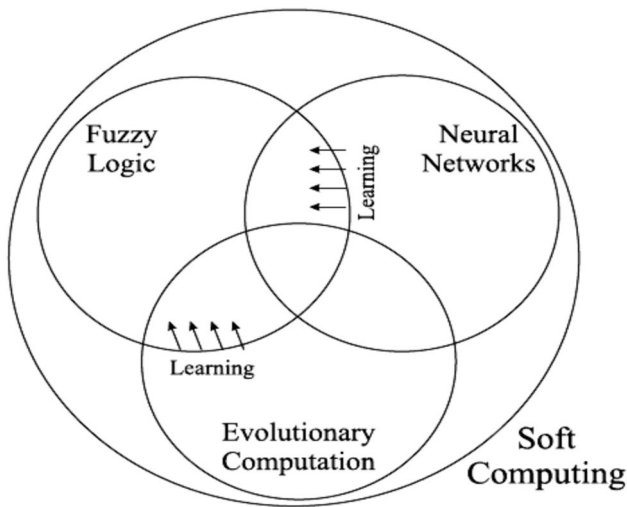


Fig. 1 Soft computing and learning in fuzzy systems

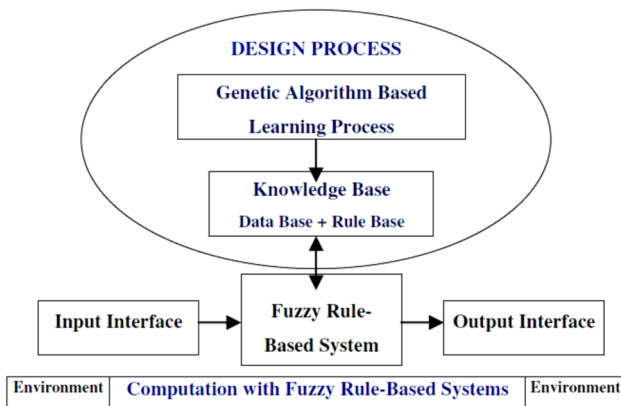


Fig. 2 Genetic fuzzy system

performance features. In FRBSs, a priori knowledge may be in the form of linguistic variables, fuzzy membership function parameters, fuzzy rules, number of rules, etc. These advantages have extended the use of GAs to the development of a wide range of approaches for designing FRBSs. Figure 2 illustrates this idea, where the genetic process learns or tunes the different components of an FRBS.

Because GAs provide a means to encode and evolve rule antecedent aggregation operators, different rule semantics, rule-based aggregation operators, and defuzzification methods, contrary to neural networks, clustering, rule induction, and many other machine learning approaches, they remain today as one of the fewest knowledge acquisition schemes available to design and optimize FRBSs with respect to design decisions, allowing decision makers to decide what components are fixed and which ones evolve according to the performance measures.

Genetic learning processes cover different levels of complexity according to the structural changes produced by the algorithm [16], from the simplest case of parameter optimization to the highest level of complexity in learning the rule set of a rule-based system. An analysis of the literature shows that the most prominent types of GFSs are Genetic Fuzzy Rule-Based Systems (GFRBSs) [14], whose genetic processes learn or tune different components of a FRBS. Figure 3 shows the concept of a system in which genetic design and fuzzy processing are two fundamental constituents. Inside GFRBSs, it is possible to distinguish between either parameter optimization or rule generation processes, that is, adaptation and learning. However, other types of GFSs have also been developed with successful results. These include genetic fuzzy neural networks and genetic fuzzy clustering algorithms [14, Chap. 10], which were not analyzed in this study.

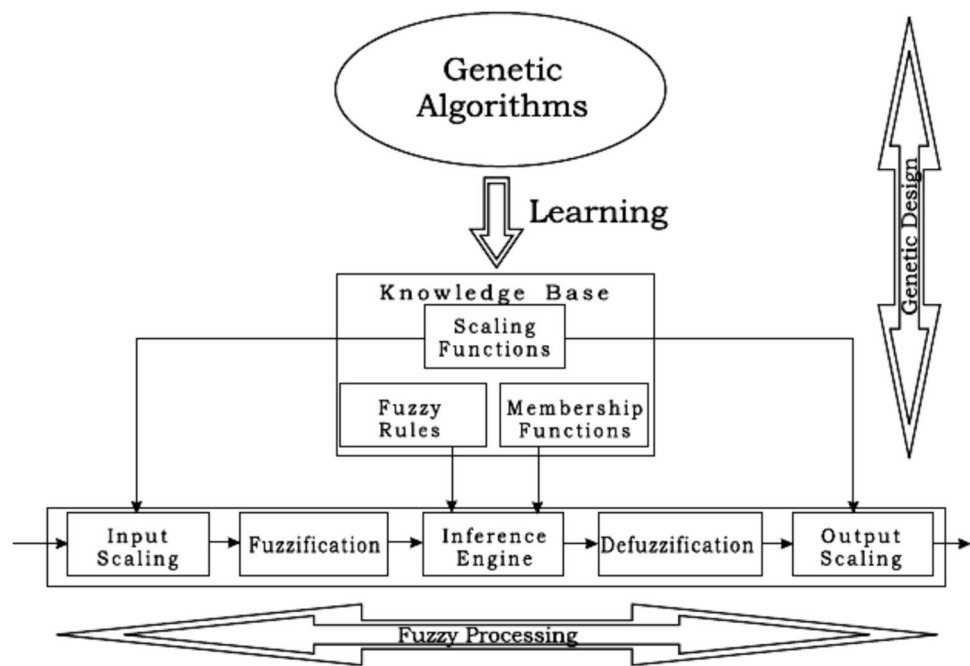
This paper briefly introduces GFSs, proposes a taxonomy focused on the FRBS components, and sketches a vision of some hot current trends and prospects of GFSs.

The paper is organized into eight sections as follows: Sect. 2 briefly augments GAs, Sect. 3 briefly introduces the GFS, and Sect. 4 presents categorizations of GFSs according to the FRBS components involved in the genetic learning process, taking into account which of them are encoded. An introduction to GFSs, paying attention to the pioneer GFS contributions, the GFSs visibility at ScienceDirect website, the most cited GFS papers at ISI Web of Science, and pointing out the milestones covered by existing books and special issues are presented in Sect. 5. Some current trends and critical considerations on recent developments and some suggestions for potential future research directions are presented in Sect. 7, respectively. Finally, concluding remarks are presented in Sect. 8.

## 2 Genetic Algorithms

Genetic algorithms (GAs) have achieved great success in solving search and optimization problems. The reason for a great part of this success is their ability to exploit the information accumulated about an initially unknown search space to bias subsequent searches into useful subspaces, that is, their adaptation. This is their key feature, particularly in large, complex, and poorly understood search spaces where classical search tools (enumerative, heuristic, ...) are inappropriate, offering a valid approach to problems that require efficient and effective search techniques.

GAs are general purpose search algorithms which use principles inspired by natural genetic populations to evolve solutions to problems [17, 18]. The basic idea is to maintain a population of chromosomes, which represent candidate solutions to a concrete problem that evolves over time

**Fig. 3** Genetic design and fuzzy processing

through a process of competition and controlled variation. Each chromosome in the population has an associated fitness to determine which chromosomes are used to form new chromosomes in the competition process, which is called selection. The new ones are created using genetic operators such as crossover and mutation.

A GA starts with a population of randomly generated chromosomes and advances toward better chromosomes by applying genetic operators modelled on the genetic processes occurring in nature. The population evolves in the form of natural selection. During successive iterations, called generations, chromosomes in the population are rated for their adaptation as solutions, and based on these evaluations, a new population of chromosomes is formed using a selection mechanism and specific genetic operators, such as crossover and mutation. An evaluation or fitness function ( $f$ ) must be devised to solve each problem. Given a particular chromosome as a possible solution, the fitness function returns a single numerical fitness, which is supposed to be proportional to the utility or adaptation of the solution represented by that chromosome.

Although there are many possible variants of the basic GA, the fundamental underlying mechanism consists of three operations:

1. Evaluation of individual fitness,
2. Formation of a gene pool (intermediate population) through selection mechanism, and
3. Recombination through crossover and mutation operators.

The basic principles of GAs were first rigorously laid down by Holland [79] and have been well described in many books, such as [17, 19]. It is generally accepted that the application of a GA to solve a problem must consider the following five components.

1. A genetic representation of solutions to the problem,
2. A way to create an initial population of solutions,
3. An evaluation function which gives the fitness of each chromosome,
4. Genetic operators that alter the genetic composition of offspring during reproduction, and
5. Values for the parameters used by the GA (population size, probabilities of applying genetic operators, etc).

## 2.1 Applications of GAs

GAs may successfully deal with a wide range of problem areas. The main reasons for this success are as follows:

- (1) GAs can solve hard problems quickly and reliably
- (2) GAs are easy to interface to existing simulations and models
- (3) GAs are extensible and
- (4) GAs are easy to hybridize.

All these reasons may be summarized as only one reason: GAs are robust. GAs are more powerful in difficult environments where space is usually large, discontinuous, complex, and poorly understood. They are not guaranteed

to find the global optimum solution to a problem, but they are generally good at finding acceptable solutions to problems quickly. Therefore, during the last few years, GA applications have grown enormously in many fields.

### 3 Genetic Fuzzy Systems

The search capabilities and ability to incorporate a priori knowledge have extended the use of genetic algorithms in the development of a wide range of methods for designing fuzzy systems over the last few years. In a very broad sense, a Fuzzy System (FS) is a Fuzzy Logic-Based System, where Fuzzy Logic can be used either as the basis for the representation of different forms of system knowledge or to model the interactions and relationships among the system variables. FSs have proven to be an important tool for modelling complex systems, in which, due to the complexity or imprecision, classical tools are unsuccessful.

Many studies have explored the use of GAs in the design of fuzzy systems. These approaches called the general name of Genetic Fuzzy Systems (GFSs).

### 4 Categorization of Genetic Fuzzy Systems

Analyzing the design process of FRBSs as a search problem in the space of models, such as the space of rule sets, is a popular use of GAs for automatic learning of FRBSs, which can be done by means of the coding of the model in a chromosome.

To find an appropriate fuzzy model, it can be coded as a parameter structure and then the parameter values that optimize a specified fitness function can be found. Therefore, specifying the parts of the fuzzy system that should be optimized by GA is the first step in designing a GFS.

Thus, categorization of GFSs according to the different parts of the fuzzy systems coded by the genetic model can be presented first. Then, the different genetic learning coding approaches that can be found in the literature, according to the method of coding a Rule Base (RB) and the cooperation versus competition among chromosomes, connecting them with the mentioned taxonomy, are used.

GFS approaches can be divided into two sub-approaches: tuning and learning. Making a clear distinction between the tuning and learning sub-approaches is as difficult as defining the concept of learning itself. The first question is that if a previous Knowledge Base (KB), including Data Base (DB) and RB exists or not?

#### 4.1 Genetic Tuning

In the case of the KB, a genetic tuning process for ameliorating the FRBS performance by adjusting its parameters without altering the existing RB is applied.

One method to make an efficient FRBS when the RB has been derived is to improve the initial DB definition or the inference engine parameters. Figure 4 shows a representation of this type of tuning. According to the subtree under ‘‘genetic tuning’’ in Fig. 5, three tuning possibilities can be considered:

##### 4.1.1 Genetic Tuning of KB Parameters

In this tuning process, a posteriori is used to adjust the membership function parameters by considering the preliminary and derived RB. Nonetheless, the tuning process adjusts only the shapes of the membership functions, and not the number of linguistic terms in each fuzzy partition. The first classic proposal for tuning can be found in [20]. In [21], proposals were made by introducing linguistic modifiers for tuning the membership functions that are close to the inference engine adaptation. In this paper the use of linguistic hedges to perform slight modifications while maintaining good interpretability to adjust the components of the knowledge base without completely redefining it is proposed. This contribution introduces a genetic tuning process for jointly fitting the fuzzy rule symbolic representations and meaning of the involved membership functions. To alter the latter component, two different approaches that change the basic parameters and use nonlinear scaling factors have been proposed. As the experimental study shows, the good performance of our proposal mainly lies in the consideration of this tuning approach performed at two different levels of significance. The paper also analyzed the interaction of the proposed tuning method with a fuzzy rule-set reduction process. A good interpretability-accuracy trade-off was obtained by combining both processes with a sequential scheme: first, reducing the rule set and subsequently tuning the model.

##### 4.1.2 Genetic Adaptive Inference Systems

In this process, parameterized expressions in the Inference System, sometimes called Adaptive Inference Systems, are used to achieve higher cooperation among fuzzy rules that yield more accurate fuzzy models while maintaining linguistic rule interpretability. Some proposals focusing on regression and classification can be found in [17, 22, 23].

In [22] a study on the use of parameterized operators in the Inference System of linguistic fuzzy systems adapted by evolutionary algorithms to achieve better cooperation among fuzzy rules was presented. This approach produces a type of rule cooperation by means of an inference system, thereby

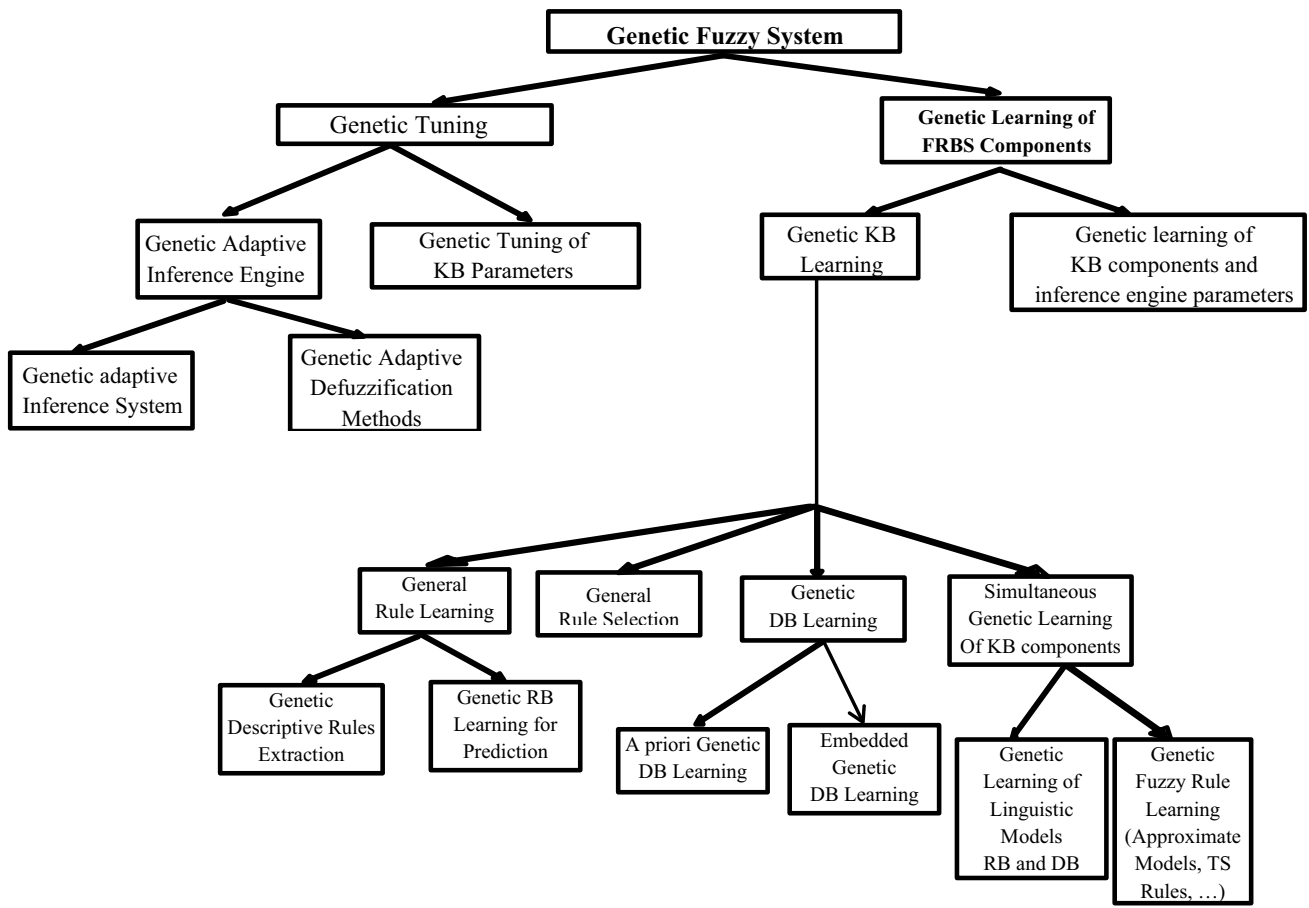


Fig. 4 GFS categorization

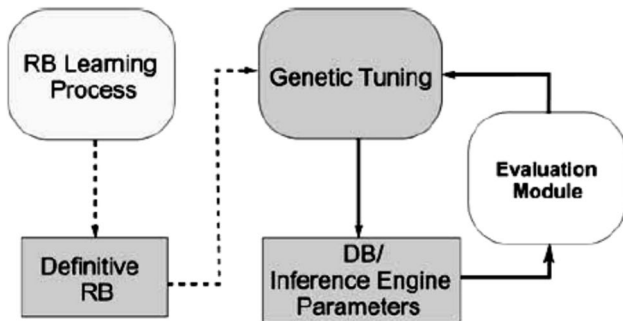


Fig. 5 Genetic tuning process

increasing the accuracy of the fuzzy system without losing its interpretability. Different alternatives for introducing parameters in the Inference System are studied, as well as their interpretation and how they affect the rest of the components of the fuzzy system.

In [23], a novel genetic algorithm framework for optimizing the strength of fuzzy inference operators concurrently with the tuning of membership functions for a given fuzzy classifier system was proposed. Each fuzzy system

was generated using two well-established decision tree algorithms: C4.5 and CHAID. (C4.5 is a classic decision tree algorithm developed by Ross Quinlan. It is used for decision tree induction, a popular machine learning technique for classification and regression tasks. C4.5 is known for its ability to handle both categorical and continuous attributes in the data set. It constructs a tree by recursively partitioning the data based on attributes to create a set of rules for decision making. C4.5 is widely used in data mining and machine learning applications due to its simplicity and effectiveness in generating interpretable models. CHAID stands for Chi-squared Automatic Interaction Detection. It is a decision tree algorithm used for data mining and predictive modelling. CHAID is a method that detects relationships between variables by analysing the significance of the association using chi-squared tests at each step of the tree building process. It is commonly used in market research, social science, and related fields to explore and uncover patterns in categorical data). This enables both classification and regression problems to be addressed within the framework. Each solution generated by the genetic algorithm will produce a set of fuzzy



membership functions and determines how strongly the inference is applied within each fuzzy rule. Several theoretically proven fuzzy inference techniques (T-norms) have been investigated in the context of both classification and regression problems. The proposed methodology is applied to several real-world datasets to determine the effects of the simultaneous tuning of membership functions and inference parameters on the accuracy and robustness of fuzzy classifiers.

In [17], a comparative study was presented that examined a number of T-norm and T-conorms and their application within Fuzzy Decision Trees. The methodology uses a Genetic Algorithm to tune the weights of T-norm operators and simultaneously optimize fuzzy membership functions in fuzzy trees. This study applied the methodology to two Fuzzy Decision Tree algorithms: Fuzzy Inference Algorithm (FIA) and Fuzzy CHAIDS [17]. FIA is a proven algorithm which generates optimized fuzzy decision trees from pre-generated crisp C4.5 trees. CHAID is an offshoot of Automatic Interaction Detection (AID) designed for a categorized dependent variable and is unique in its branching strategy and ability to classify numeric outcomes. Six T-norm models were investigated using five real-world datasets.

#### 4.1.3 Genetic Adaptive Defuzzification Methods

Owing to its good performance, efficiency, and straightforward implementation, applying the defuzzification function to every inferred rule fuzzy set (obtaining a characteristic value) and computing them using a weighted average operator has become the most practical technique. This approach proposes the possibility of using parameter-based average functions and adapts the defuzzification methods by using GAs that in [24]; a proposal of this method can be found. This paper proposes a design technique for an optimal Center Of Gravity (COG) defuzzifier using Lamarckian coadaptation of learning and evolution. The proposed COG defuzzifier is specified by various design parameters such as the centers, widths, and modifiers of the Membership Functions (MFs). The design parameters are adjusted with the Lamarckian co-adaptation of learning and evolution, where the learning performs a local search of the design parameters in an individual COG defuzzifier, but the evolution performs a global search of the design parameters among a population of various COG defuzzifiers. This co-adaptation scheme allows much faster evolution than the non-learning case and provides a higher possibility of finding an optimal solution owing to its wider searching capability. The approximation ability and control performance are compared with those of the conventional simplified COG defuzzifier in terms of the fuzzy logic controller approximation error and average tracing distance, respectively.

## 4.2 Genetic Learning

Learning the KB components (even by an adaptive inference engine) is the second case. It means involving the learning of KB components among other FRBS components.

The proposals according to these sub-approaches and the FRBS components involved in the genetic learning process were classified according to the categorization shown in Fig. 5.

In the following, the three main areas in the categorization i.e. genetic tuning, genetic KB learning, and genetic learning of KB components and inference engine parameters are analyzed. Also, some references for every approach are proposed.

### 4.2.1 Genetic KB Learning

The following four approaches can be found within the genetic learning of a KB, as shown in the second tree under “genetic KB learning.”

**4.2.1.1 Genetic Rule Learning** In this approach, a pre-defined DB is considered automatically by focusing on RB learning, and KB automatic learning from numerical information is performed. The usual way to define this DB involves choosing a number of linguistic terms for each linguistic variable (an odd number between three and nine, which is usually the same for all variables) and setting the values of the system parameters by a uniform distribution of the linguistic terms into the variable universe of discourse. This type of RB learning is illustrated graphically in Fig. 6. The pioneer proposal for this approach can be found in [25]. This study considered the application of a genetics-based learning algorithm to systems based on fuzzy logic. Fuzzy controllers are an attractive area for the application of fuzzy logic. A Fuzzy Logic Controller (FLC) is based on linguistic control strategies (or rules) that interface with real sensor

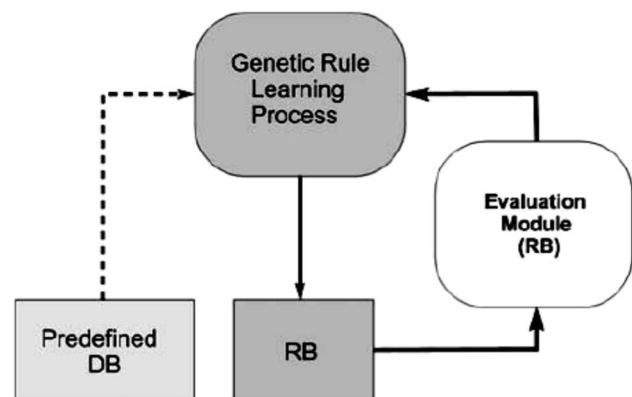


Fig. 6 Genetic rule learning process

and activator signals by using fuzzification and defuzzification algorithms. The discrete nature of fuzzy strategies makes them prime candidates for discovery using GAs. This approach is explored in this study.

On the other hand, we also find approaches that are focused on the extraction of some descriptive rules for data mining problems (association rules, subgroup discovery, ...) [26, 27].

In [26], a genetic fuzzy system for the data mining task of subgroup discovery was presented, the Subgroup Discovery Iterative Genetic Algorithm (SDIGA), which obtains fuzzy rules for subgroup discovery in a disjunctive normal form. This type of fuzzy rule allows us to represent knowledge about patterns of interest in an explanatory and understandable form that can be used by the expert.

In [27] first optimized fuzzy association rule mining was first optimized in terms of three important criteria: strength, interestingness, and comprehensibility. Subsequently, multi-objective Genetic Algorithm (GA)-based approaches for discovering these optimized rules are proposed. The optimization technique according to a given criterion may be one of two different forms. The first attempts to determine the appropriate fuzzy sets of quantitative attributes in a pre-specified rule, which is also called a certain rule. The second deals with determining both uncertain rules and their appropriate fuzzy sets.

**4.2.1.2 Genetic Rule Selection** In the case of having a large number of rules deduced via a data mining method with a large number of rules, we will have a large RB, and an excessive number of rules that understand the FRBS behavior makes it difficult. In such a fuzzy rule, different types of rules exist: irrelevant, redundant, erroneous, and conflicting rules, in which their coexistence with others perturbs the FRBS performance.

A genetic rule selection process can optimize the existing fuzzy rule set, as graphically shown in Fig. 7. The most classic and first contribution of this approach can be found in [28] and the first journal paper on multi-objective genetic rule selection in [29], in which various methods for constructing a compact fuzzy classification system consisting of a small number of linguistic classification rules were proposed. First, a rule selection problem of linguistic classification rules with two objectives—to maximize the number of correctly classified training patterns and to minimize the number of selected rules—is formulated. Next, three methods for finding a set of non-dominated solutions of the rule selection problem are proposed. These three methods are based on a single-objective genetic algorithm and also a method based on a multi-objective genetic algorithm for finding a set of non-dominated solutions is presented. Finally, a hybrid algorithm that combines a learning method for linguistic

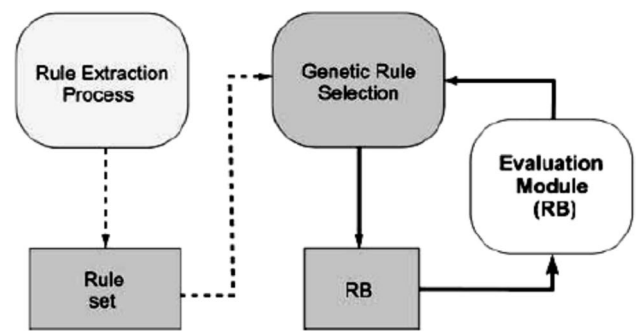


Fig. 7 Genetic rule selection process

classification rules with a multi-objective genetic algorithm is proposed.

In [21, 30], two recent proposals combined genetic tuning with rule selection to obtain a good rule set together with a tuned set of parameters. In [30], the application of Multi-Objective Genetic Algorithms to obtain Fuzzy Rule-Based Systems with a better trade-off between interpretability and accuracy in linguistic fuzzy modelling problems was proposed. To achieve this, a new post-processing method is presented that considers the selection of rules together with the tuning of membership functions to obtain solutions only in the Pareto zone with the highest accuracy, that is, containing solutions with the least number of possible rules, but still presenting high accuracy. This method is based on the well-known Strength Pareto Evolutionary Algorithm (SPEA2) algorithm [31], applying appropriate genetic operators and including some modifications to concentrate the search in the desired Pareto zone. SPEA is a multi-objective optimization algorithm that is used to solve optimization problems involving multiple conflicting objectives. SPEA uses the concept of Pareto dominance to evaluate the quality of solutions in the search space. The algorithm maintains a repository of non-dominated solutions known as the external archive, which represents the best trade-off solutions found so far. SPEA combines the concepts of evolution and strength calculation to guide the search towards the Pareto optimal front, where no solution can be improved in any objective without degrading another. SPEA is widely used in evolutionary multi-objective optimization and considered a robust algorithm for finding diverse and well-distributed Pareto optimal solutions. A schematic of the hybrid model proposed in [30] is shown in Fig. 8.

**4.2.1.3 Genetic DB Learning** This approach includes two different processes to derive both components, DB and RB. A DB generation process in order to learn the shape of the membership functions and other DB components such as the scaling functions, the granularity of the fuzzy partitions,

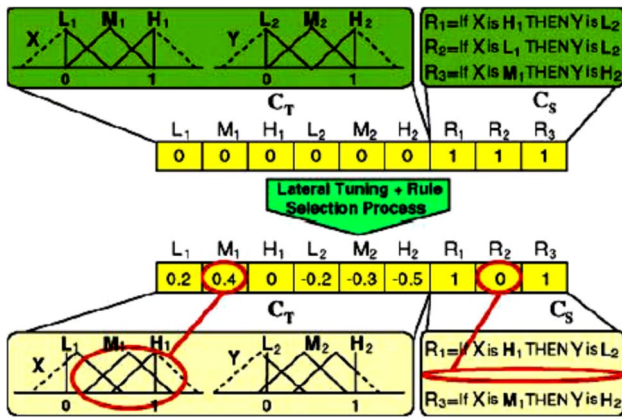


Fig. 8 Example of genetic lateral tuning and rule selection

etc. That can be used as a measure for evaluating the quality of the DB, named as ‘‘A priori genetic DB learning’’.

In the second method, each time a DB has been obtained by the DB definition process, the RB generation method is used to derive the rules, and some type of error measure is used to validate the whole KB obtained. Of course, this operation mode involves partitioning the KB learning problem. These two kinds of learning models are represented in Fig. 9, and in [32], a proposal following the embedded genetic DB learning can be found. In this paper, a new method is proposed to automatically learn the Knowledge Base (KB) by finding an appropriate Data Base (DB) by means of a genetic algorithm while using a simple generation method to derive the Rule Base (RB).

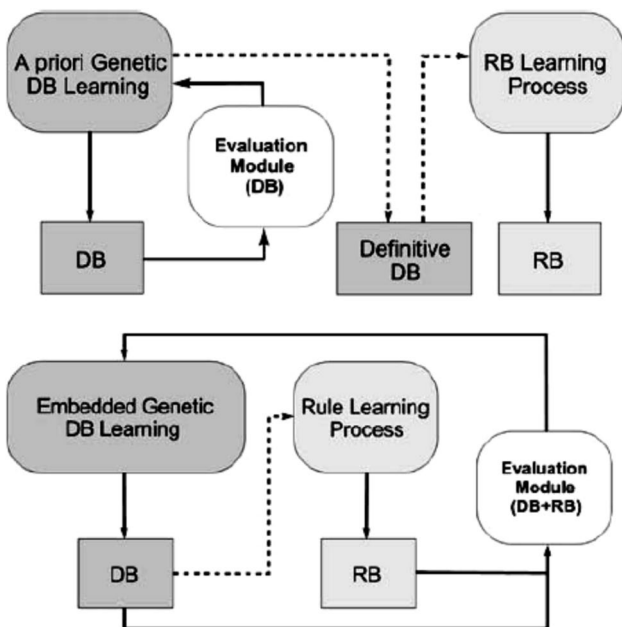


Fig. 9 Genetic DB learning (embedded and a priori)

The genetic process has learned the number of linguistic terms per variable and the membership function parameters that define their semantics, while a rule base generation method has learned the number of rules and their composition.

**4.2.1.4 Simultaneous Genetic Learning of KB Components** In the remaining approaches, learning the two components of the KB simultaneously was attempted, as depicted in Fig. 10. This approach has the advantage of generating better definitions but has the cost of dealing with a larger search space, which makes the learning process more difficult and slower. In [33], a contribution that is a reference for the simultaneous genetic KB learning process can be found. This study examined the applicability of GAs in the simultaneous design of membership functions and rule sets for fuzzy-logic controllers. Previous studies using genetic algorithms have focused on the development of rule sets or high-performance membership functions; however, the interdependence between these two components suggests that a simultaneous design procedure is a more appropriate methodology. When GA’s have been used to develop both, they have been done serially, for example, design the membership functions and then use them in the design of the rule set. However, this means that the membership functions were optimized for the initial rule set and not for the rule set designed subsequently. GAs are fully capable of creating complete fuzzy controllers, given the equations of motion of the system, eliminating the need for human input in the design loop. This new method was applied to two problems: a cart controller and a truck controller. Beyond the development of these controllers, the design of a robust controller for the cart problem and its ability to overcome faulty rules are also examined.

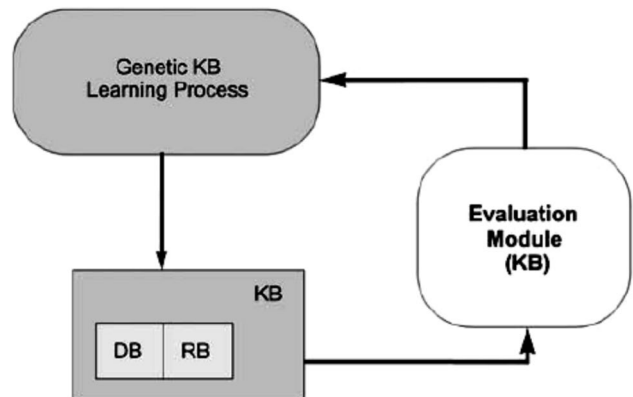


Fig. 10 Genetic KB learning process



### 4.2.2 Genetic Learning of KB Components and Inference Engine Parameters

A hybrid model between the adaptive inference engine and KB component learning is the last area of the GFSs categorization. Novel approaches attempt to find high cooperation between the inference engine via parameter adaptation and the learning of KB components, including both in a simultaneous learning process. In [34], a proposal to learn a linguistic RB and the parametric aggregation connectors of inference and defuzzification in a single step can be found. Figure 11 presents the coding scheme of the proposed model.

### 4.3 Genetic Learning: Rule Coding and Cooperation/Competition Evolutionary Process

Although GAs are not learning algorithms, they may offer a powerful and domain-independent search method for a variety of learning tasks, such that there has been a great deal of interest in using GAs for machine learning problems [35–37]. If machine learning methodology is based on the search for a good model inside the space of possible models, GAs offer a set of advantages for machine learning rather than global search algorithms because of their flexibility, such that the same GA can be used with different representations. Genetic learning processes cover different levels of complexity according to the structural changes produced by the algorithm, from the simplest case of parameter optimization to the highest level of complexity for learning the rule set of a rule-based system via the coding approach and the cooperation or competition between chromosomes.

When considering a rule-based system and focusing on learning rules, different genetic learning methods follow two approaches to encode rules within a population of individuals:

### 4.3.1 The “Chromosome = Rule Set” or Pittsburgh Approach:

In this approach, each individual represents a whole rule set [38]. Crossover serves to provide a new combination of rules and mutation provides new rules. In some cases, variable-length rule bases are used, employing modified genetic operators to handle variable-length and position-independent genomes.

In this case, a chromosome evolves a complete RB and competes among them during the evolutionary process. This model was initially proposed by Smith in 1980 [38]. Recent examples of this approach can be found in [37]. Genetic Algorithm for Building Inductive Learning (GABIL) is a proposal that follows this approach [39]. GABIL is an approach based on genetic algorithms used for inducing rule-based systems, particularly for learning Rule Bases (RB) and Knowledge Bases (KB) in Fuzzy Rule-Based Systems (FRBSs). In the context described, GABIL is utilized to evolve complete rule sets and compete among them during the evolutionary process to improve the performance of the fuzzy rule-based systems. GABIL follows a genetic algorithm paradigm to generate and optimize rule sets for decision-making tasks, taking into account the variable-length and position-independent genomes characteristic of rule-based systems.

This learning approach in two cases has been used: for learning Rule Bases (RB) and Knowledge Bases (KB) for Fuzzy Rule Based Systems (FRBSs).

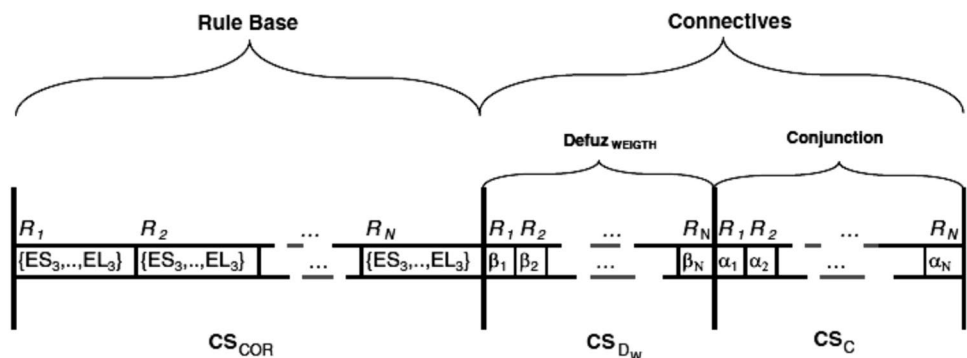
#### (a) Genetic Learning of RB

The Pittsburgh approach was applied to learn the rule bases in two different situations. The first situation refers to systems that use a complete rule base represented by a decision table or relational matrix. The second situation is that of FRBSs, in which the RB is represented using a list or set of fuzzy rules.

#### (a.1) Using a Complete RB

A tabular representation guarantees the completeness of the knowledge of the FRBS in the sense that the coverage of the input space (the Cartesian product of universes of

Fig. 11 Example of the coding scheme for learning an RB and the inference connective parameters



the input variables) is only related to the level of coverage of each input variable (the corresponding fuzzy partitions) and not to the rules.

**Decision tables.** A possible representation of the RB of an FS is the decision table. This is a classical representation used in various GFSs. A chromosome is obtained from the decision table by going row-wise and coding each output fuzzy set as an integer or any other type of label. It is possible to include the “no output” definition in a certain position, using a “null” label [25, 40].

**Relational matrices.** Occasionally, GAs are used to modify the fuzzy relational matrix (R) of a Fuzzy System with one input and output. The chromosome is obtained by concatenating the  $m \times n$  elements of R, where m and n are the numbers of fuzzy sets associated with the input and output variables, respectively. The elements of R that comprise the genes may be represented by binary codes [41] or real numbers.

#### (a.2) Using a Partial RB

Neither the relational nor tabular representations are adaptable to systems with more than two or three input variables because of the dimension of a complete RB for these situations. This stimulated the idea of working with a set of rules. In a set of rules, the absence of applicable rules for a certain input that is perfectly covered by fuzzy partitions of individual input variables is possible. As a counterpart to the loss of completeness, this representation allows the compression of several rules with identical outputs into a singular rule, which is an important issue as the dimension of the system grows.

There are many different methods for coding the rule base in this type of an evolutionary system. The code of the rule base is typically obtained by concatenating the rule codes.

**Rules of fixed length.** The first approach represents a rule with a code of fixed length and a position-dependent meaning. The code contains as many elements as the number of variables in the system. A possible content of these elements is a label pointing to a certain fuzzy set in the fuzzy partition of the variable or a binary string with a bit per fuzzy set in the fuzzy partition of the variable coding the presence or absence of the fuzzy set in the rule [42].

**Rules of variable length.** Codes with position independent meaning and based on pairs {*variable, membership function*} (the membership functions are described using a label) are used in [43].

#### (b) Genetic Learning of KB

The simultaneous use of the genetic material from the DB and RB of an FRBS has produced different and interesting results. The most general approach is the use of a set of parameterized membership functions and a list of fuzzy rules that are jointly coded to generate a chromosome and then applying a Pittsburgh-type GA to evolve a population of such chromosomes. This type of GFSs uses chromosomes

containing two sub-chromosomes that encode DB and RB separately, but not independently.

At this point, it is possible to maintain the same division that was stated when discussing genetic learning of RBs with a Pittsburgh approach: learning complete rule bases or partial rule bases.

#### (b.1) Using a Complete RB

In [44], the rule base is represented as a fuzzy relation matrix (R), and the GA modifies R, the fuzzy membership functions (triangular), or both simultaneously on a Fuzzy Logic Controller (FLC) with one input and one output variable. Each gene was a real number. When generating the optimal fuzzy relation matrix, this real number corresponds to a fuzzy relation degree with a value between 0 and 1. The genetic string is obtained by concatenating  $m \times n$  real numbers that constitute R. When finding the optimal rule base and fuzzy membership functions simultaneously, each chromosome allocates two sub-chromosomes: the genes of the rule base and the genes of the fuzzy membership functions. Both sub-chromosomes are treated as independent entities as far as crossover and mutation are concerned, but as a single entity, as far as reproduction is concerned.

A slightly different approach is to use a Takagi–Sugeno–Kang-type (TSK-type) [45] rule base, structuring its genetic code as if it came from the decision table. In this case, the contents of the code of a rule base are an ordered and complete list containing the consequences of all possible rules, where the antecedents are implicitly defined as a function of the position the consequent occupies in the list.

TSK refers to a type of fuzzy inference system commonly used in fuzzy logic and fuzzy modelling. The TSK fuzzy model is characterized by using a linear combination of input variables to determine the output variable. In a TSK-type rule base, the structure is typically organized like a decision table, where the genetic code represents the consequences of all possible rules and the antecedents are implicitly defined based on the positions of the consequents in the list. The TSK model consists of fuzzy membership functions to describe input variables and coefficients for the consequents in the linear combination that form the output variable.

The fuzzy membership functions constitute the first sub-chromosome, whereas the coefficients of the consequents for a TSK fuzzy model constitute the second sub-chromosome. One gene was used to code each coefficient of the TSK type in [46].

#### (b.2) Using a Partial RB

Liska and Melsheimer [47] used a rule base defined as a set of a fixed number of rules and coded each rule with integer numbers that define the membership function related to a certain input or output variable that is applied by the rule (membership functions for every variable are ordered). The systems use radial membership functions coded using two

real numbers (two genes). A genetic string was obtained by concatenating the two genes in each membership function.

There are many different methods for coding the rule base in this kind of evolutionary system. The code of the rule base is typically obtained by concatenating the rule codes. To represent a single rule, it is possible to use position-dependent code with as many elements as the number of variables in the system. Possible content in these elements is a label pointing to a certain fuzzy set in the fuzzy partition of the variable [48] or a binary string with a bit per fuzzy set in the fuzzy partition of the variable [49].

Using an approximation approach, [50, 51] includes the definition of membership functions in the rules, coding each rule through the corresponding set of membership functions.

### 4.3.2 The “Chromosome = Rule” Approach

In this approach, each individual codifies a single rule and the entire rule set is provided by combining several individuals in a population (rule cooperation) or via different evolutionary runs (rule competition). There are three generic proposals for this approach.

**4.3.2.1 The Michigan Approach** Using this approach, each individual encodes a single rule. These types of systems are typically called learning classifier systems. This model maintains the population of classifiers with credit assignment, rule discovery, and genetic operations applied at the individual rule level. These are rule-based message-passing systems that employ reinforcement learning and a GA to learn rules that guide their performance in a given environment. The GA is used to detect new rules that replace bad ones via competition between chromosomes in the evolutionary process. A complete description is provided in Ref. [52]. Reference [53] is a proposal for this approach in which the type of Cognitive System (CS) has four basic parts: (1) a set of interacting elementary productions, called classifiers, (2) a performance algorithm that directs the action of the system in the environment, (3) a simple learning algorithm that keeps a record of each classifier's success in bringing about rewards, and (4) a more complex learning algorithm, called the genetic algorithm, which modifies the set of classifiers so that variants of good classifiers persist and new, potentially better ones are created in a provably efficient manner. An interesting study of this topic can be found in [54]. This book [54] is a monograph on learning classifier systems, the main objective of which is to compare strength-based classifier systems with accuracy-based systems equipped with nine appendices and illustrated with many convincing examples. This text studies aspects of credit assignment in learning classifier systems, which combine evolutionary algorithms with reinforcement learning methods to address a range of tasks, from pattern classifi-

cation to stochastic control to the simulation of learning in animals. Credit assignment in classifier systems is complicated by two features: (1) their components are frequently modified by evolutionary search and (2) components tend to interact. Classifier systems are re-examined from first principles, and the result is primarily a formalization of learning in these systems and a body of theory relating types of classifier systems, learning tasks, and credit assignment pathologies. Most significantly, it is shown that both main approaches have difficulties with certain tasks, which the other type does not.

**4.3.2.2 The IRL (Iterative Rule Learning) Approach** In the Michigan model, each chromosome in the population represents a single rule; however, contrary to the Michigan model, only the best individual is considered to form part of the solution, discarding the remaining chromosomes in the population. Figure 12 presents a classifier system of the Michigan type. Therefore, in the iterative model, GA provides a partial solution to the learning problem. To obtain a set of rules that will be a true solution to the problem, the GA must be placed within an iterative scheme similar to the following:

1. A GA was used to obtain a rule for the system.
2. This rule was incorporated into the final set of rules.
3. Penalize this rule.
4. If the set of rules obtained thus far is adequate to be a solution to the problem, the system returns the set of rules as the solution. Otherwise, return to step 1.

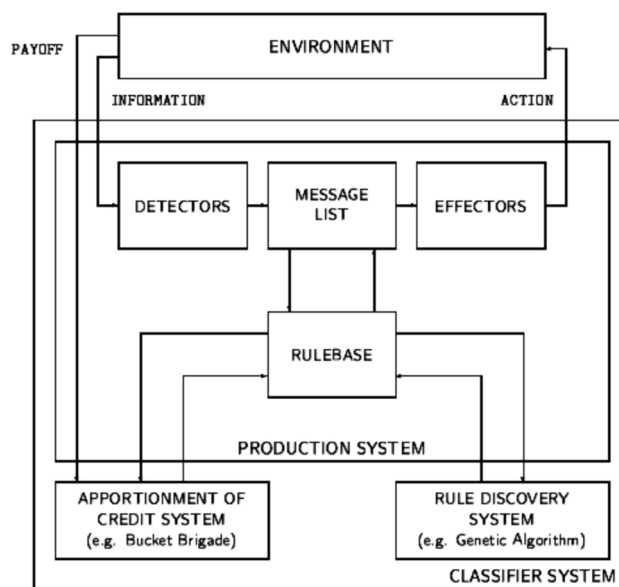


Fig. 12 A Classifier System of the Michigan Type

The main difference with respect to the Michigan approach is that the fitness of each chromosome is computed individually without considering cooperation with others. This substantially reduces the search space because only one rule is searched for in each iteration sequence.

Supervised Inductive Algorithm (SIA) [55] is a proposal that follows this approach. Reference [55] described a genetic learning system called SIA, which learns attribute-based rules from a set of pre-classified examples. Examples may be described using a variable number of attributes, which can be numeric or symbolic, and examples may belong to several classes. The SIA algorithm is somewhat similar to the Algorithm Quasi-optimal (AQ) ("AQ" is a rule learning algorithm developed by Ross Quinlan. The AQ algorithm is a symbolic rule induction system that learns rules from labelled examples. It aims to generalize from examples to create rules that classify new instances accurately. The algorithm uses a top-down approach, starting with a general rule and then specializing it to cover specific instances while minimizing errors. The AQ algorithm is widely known for its simplicity and effectiveness in generating understandable rules for decision-making tasks. In the context of the description provided, the "SIA" algorithm is compared to the AQ algorithm, suggesting similarities in their approach to supervised rule learning.) because it takes an example as a seed and generalizes it using a genetic process to find a rule maximizing a noise-tolerant rule evaluation criterion. The SIA approach to supervised rule learning significantly reduces the possible rule search space when compared to the genetic Michigan and Pitt approaches. SIA is comparable to AQ and decision tree algorithms for the two learning tasks. Furthermore, it was designed for a data analysis task in a large and complex justice domain.

**4.3.2.3 The GCCL (Genetic Cooperative-Competitive Learning) Approach** The complete population or a subset of it encodes the RB. In this model, the chromosomes compete and cooperate simultaneously. Competitive Gene-pool Inductive learning (COGIN) [56], Reproductive Genetic Algorithm Learning (REGAL) [57] and LOgic Grammar-based GENetic Programming system (LOGENPRO) [58] are examples of this representation.

In [56], COGIN is described, a GA-based inductive system that exploits the conventions of induction from examples to provide a framework that promotes the fundamental model-building objectives of predictive accuracy and model simplicity in order to effectively use genetic search in the context of extracting regularities from a dataset of examples to construct decision models. The predominant type of model is a classification rule (or set of rules), which maps a set of relevant environmental features into specific categories or values. Classifying loan risk based on borrower profiles, consumer choice from purchase data, or supply

levels based on operating conditions are all examples of this type of model-building task. Although current inductive approaches such as ID3 (ID3 (Iterative Dichotomiser 3) is a decision tree algorithm used for classification tasks. It operates by recursively partitioning the data based on features to create a tree structure where each internal node represents a decision based on a feature, and each leaf node represents a class label. ID3 builds the decision tree by selecting the best attribute at each step to split the data and create more homogeneous subsets. The algorithm aims to maximize information gain at each split to construct an effective classification model.) and CN2 (CN2 (ClassiNet version 2) is a rule-based inductive learning algorithm that focuses on constructing classification rules from data. It is known for its ability to generate comprehensible rule sets that accurately classify instances in a dataset. CN2 uses a separate-and-conquer strategy where it iteratively builds rules to cover subsets of the data. The algorithm aims to find the best rules for each class while ensuring generality and simplicity in the resulting model.) perform well on certain problems, their potential is limited by the incremental nature of their search. Genetic Algorithms (GA) have shown great promise on complex search domains, and hence suggest a means for overcoming these limitations. The novelty of COGIN lies in its use of training set coverage to simultaneously promote competition in various classification niches within the model and to constrain the overall model complexity.

Reference [57] describes REGAL, a distributed genetic-algorithm-based system designed for learning first-order logic concept descriptions from examples. The system is a hybrid of the Pittsburgh and Michigan approaches, as the population constitutes a redundant set of partial concept descriptions, each evolved separately. In order to increase effectiveness, REGAL is specifically tailored to the concept learning task; hence, REGAL is task-dependent, but, on the other hand, domain-independent. The system proved to be particularly robust with respect to parameter settings across a variety of application domains. REGAL is based on a selection operator called the Universal Suffrage operator, which allows the population to asymptotically converge, on average, to an equilibrium state, in which several species coexist. The system was presented in both serial and parallel versions, and a new distributed computational model was proposed and discussed.

Reference [58] describes a framework called Generic Genetic Programming (GGP), which integrates GP and ILP based on the formalism of logic grammars. A system in this framework, called The Logic grammar-based Genetic Programming system (LOGENPRO), is developed. This system has been tested for many problems related to knowledge discovery from databases. These experiments demonstrated that the proposed framework is powerful, flexible, and general. Experiments were performed to illustrate that



knowledge in different kinds of knowledge representation, such as logic programs and production rules, can be induced by LOGENPRO. The problem of inducing knowledge can be formulated as the search for a highly fit piece of knowledge in the space of all possible pieces of knowledge. The search space can be specified declaratively by the user in the framework. Moreover, formalism is sufficiently powerful to represent context-sensitive information and domain-dependent knowledge. This knowledge can be used to accelerate learning speed and/or improve the quality of the knowledge induced. LOGENPRO can emulate the effects of Strongly Type Genetic Programming (STGP) and ADFs simultaneously and effortlessly.

Different examples of these four genetic learning approaches (Pittsburgh, Michigan, IRL, and GCCL) for learning KB components can be found in literature. Two pioneer GFS proposals focused on the Pittsburgh [25] and Michigan [59] approaches. Multiple Objective Genetic Fuzzy Learning (MOGUL) [60–62] (MOGUL is a proposal that follows the Interactive Rule Learning (IRL) approach within the framework of Genetic Fuzzy Systems (GFSs). MOGUL focuses on simultaneously optimizing multiple conflicting objectives in the context of fuzzy rule base optimization. Through the use of evolutionary algorithms, MOGUL aims to evolve fuzzy rule bases that strike a balance between accuracy, interpretability, and other desired objectives.) and SLAVE [18] (SLAVE, on the other hand, is another proposal that also adopts the Interactive Rule Learning (IRL) approach within GFSs. The SLAVE system is designed to facilitate the interactive evolution and learning of fuzzy rule bases. It provides a framework where users can actively participate in the evolutionary process, guiding the optimization towards a solution that aligns with their preferences and domain knowledge. SLAVE emphasizes the role of human input and expertise in shaping the evolution of fuzzy systems to achieve more effective and interpretable models.) are two proposals that follow the IRL approach within the framework of GFSs. In [63, 64], we found two proposals based on the GCCL approach.

## 5 Genetic Fuzzy Systems Outlooks

This section presents a snapshot of the GFS status, stressing the following points:

- pioneer GFSs contributions, four contributions that mark the birth of GFSs in 1991,
- the GFSs visibility,
- the milestones that cover the books and journal special issues in the topic, and
- The most cited papers that can also mark milestones are important contributions to this topic.

### 5.1 Pioneer Papers: The Birth of GFSs in 1991

Below, we briefly describe the four pioneering papers that introduced the first genetic tuning and genetic RB learning proposals following the Michigan and Pittsburgh approaches:

- Karr's AI Expert paper (genetic tuning of DB) [20]. Pioneering work in genetic tuning has considered linguistic FRBSs. The DB definition is encoded in the chromosome, which contains concatenated parameters of the input and output fuzzy sets.
- Valenzuela-Rendon's ICGA91 paper (Linguistic RB Learning, Michigan approach) [59]. This proposal presents the first GFS based on the Michigan approach for learning RBs using DNF fuzzy rules. It employs a reward distribution scheme that requires knowledge of the correct action; thus, it must be considered a supervised learning algorithm. The authors later extended the original proposal to enable true reinforcement learning [65].
- Thrift's ICGA91 paper (Linguistic RB Learning, Pittsburgh Approach) [25]. This is a pioneering work on the Pittsburgh approach to learning RBs. This method works using a complete decision table that represents a special case of a crisp relation defined over the collections of fuzzy sets corresponding to the input and output variables. A chromosome is obtained from the decision table by going row-wise and coding each output fuzzy set as an integer, including a "null" label as a 0. Therefore, the GA employs integer coding.
- Pham and Karaboga's Journal of Systems Engineering (relational matrix-based FRBS learning) [41]. This is a significantly different approach that uses a fuzzy relation  $R$  instead of the classical crisp relation (decision table). The GA was used to modify the fuzzy relational matrix of a one-input, one-output fuzzy model. The chromosome is obtained by concatenating the  $M \cdot N$  elements of  $R$ , where  $M$  and  $N$  are the numbers of linguistic terms associated with the input and output variables, respectively. The elements of  $R$  are real numbers within the interval  $[0,1]$ .

After the publication of these four pioneer proposals, an increasing number of contributions can be found in the specialized literature with proposals that cover all the different areas of categorization, with a rich body of literature on this topic and with high visibility.

### 5.2 GFSs Visibility

In this section, the visibility of GFSs in the ScienceDirect website is explored. By the search of ("Genetic" and



“Fuzzy”) keywords in this science base, the following results were obtained:

The number of papers in each year is as follows and showed in Fig. 13:

The number of all journal papers in this field has been 57,393 papers that quotas of different journals are as follows and illustrated in Fig. 14:

Expert Systems with Applications (2718), Applied Soft Computing (2398), Information Sciences (1473),

Neurocomputing (1123), Energy (1017), Engineering Applications of Artificial Intelligence (1012), IFAC Proceedings Volumes (995), Computers & Industrial Engineering (962), Procedia Computer Science (954), International Journal of Electrical Power & Energy Systems (869), Journal of Cleaner Production (755), Fuzzy Sets and Systems (677), Knowledge-Based Systems (668), Renewable and Sustainable Energy Reviews (668), Applied Energy (617), Energy Conversion and Management (556), IFAC-Papers Online

### GFSs visibility in the ScienceDirect website

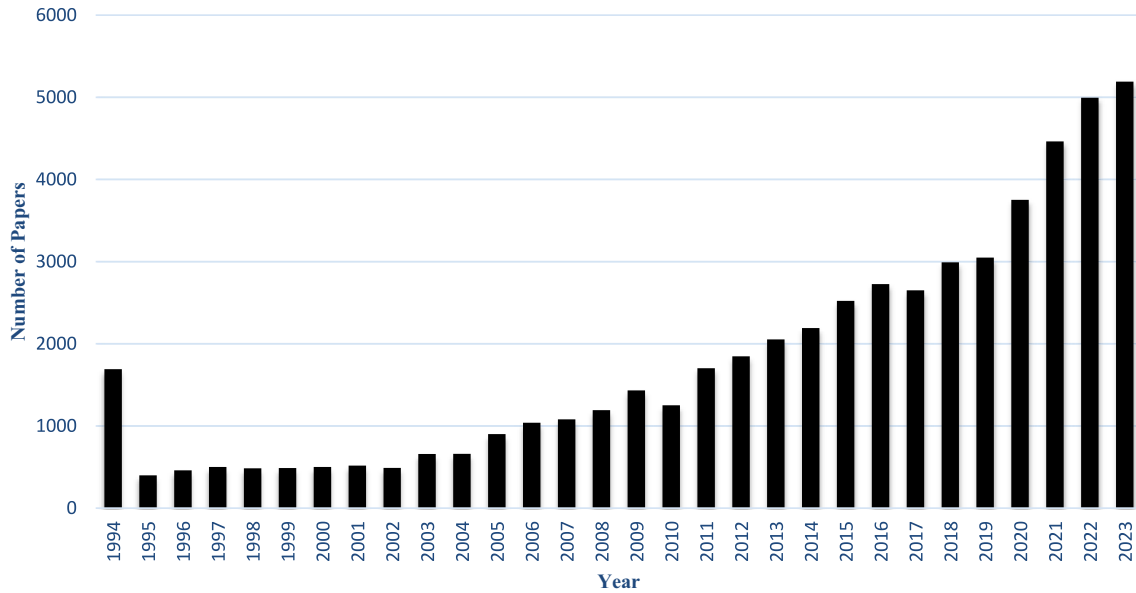


Fig. 13 Number of GFS paper in each year in ScienceDirect website

### The quotas of different journals in the GFS filed

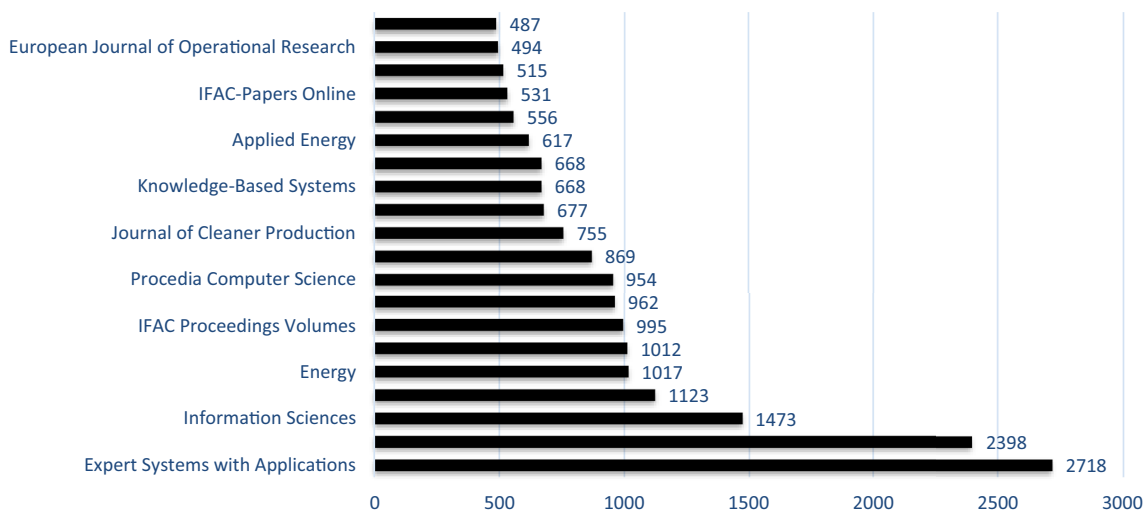


Fig. 14 The quotas of different journals

(531), Electric Power Systems Research (515), European Journal of Operational Research (494), Fuel and Energy Abstracts (487).

An increasing number of publications per year are observed that can allow us to say the field of GFSs has now reached a stage of maturity after the earliest papers published at 1991, and there are also many basic issues yet to be resolved and there is an active and vibrant worldwide community of researchers working on these issues.

By similar search of (“Genetic” and “Fuzzy”) keywords in IEEE website, the following results were obtained:

Since 1991 up to 2024: Conference Publications (7209), Journals & Magazines (1089), Books & eBooks (17), Early Access Articles (9).

The time extension of publications in IEEE is as follows:  
1991–2000:

Conference Publications (990), Journals & Magazines (121), Books & eBooks (1).

2001–2010:

Conference Publications (2870), Journals & Magazines (336), Books & eBooks (4), Early Access Articles (1).

2011–2020:

Conference Publications (2809), Journals & Magazines (425), Books & eBooks (7).

2021–2024:

Conference Publications (540), Journals & Magazines (206), Books & eBooks (5), Early Access Articles (8).

The authors with the most publication in IEEE, are brought in the following:

Ishibuchi, Hisao (73), Melin, Patricia (55), Pedrycz, Witold (52), Kubota, Naoyuki (49), Fukuda, Toshio (42), Castillo, Oscar Lopez (42), Hong, Tzung-Pei P. (38), Herrera, Francisco Guzmán (37), Nojima, Yusuke (35), Furuhashi, Takeshi (30), Juang, Chia-Feng (27), Chen, Chun-Hao (26), Bandyopadhyay, Sanghamitra (24), Lee, Chang-Shing (22), Castillo, Oscar (21), Maulik, Ujjwal (20), Mabu, Shingo (20), Hirasawa, Kotaro (19), Hagrass, Hani (19), Abraham, Ajith (19), Murata, Tadahiko (18).

And the publishers with the most publishing are: IEEE (8203), IET (55), BIAI (14), TUP (25), MIT Press (5), SGEPRI(4).

Also in these years, the number of IEEE conferences with this topic in different countries has been as:

China (914), Canada (232), USA (191), Singapore(148), Japan (147), India (147), Taiwan (107), Spain (82), UK (72), South Korea (67), Turkey (59), Hungary (58).

### 5.3 Some GFS Milestones: Books and Special Issues

The GFS milestones associated with the books and special issues published in the specialized literature are presented below:

- (1) A. Geyer-Schulz. Fuzzy rule-based expert systems and genetic machine learning. Physica–Verlag 1995 [66].

This is the first GFS book to focus on fuzzy classifier systems (Michigan approach) and RB learning with genetic programming. This book integrates fuzzy rule languages with genetic algorithms and classifier systems to obtain fuzzy rule-based expert systems with learning capabilities. The first part shows how the expressiveness of fuzzy-rule languages can be extended beyond fuzzy control. For syntax, context-free languages are used for semantic- and object-oriented systems. Several applications of these new fuzzy rule languages to qualitative models from various fields of business administration and management science are presented. The second part presents a new approach for the integration of fuzzy rule languages with genetic algorithms. For this purpose, a new class of genetic algorithms over context-free languages was developed and analyzed.

- (2) U. Bodenhofer. Tuning of fuzzy systems using genetic algorithms. na, 1996 [67].

This book focuses on the application of genetic algorithms to optimize and fine-tune fuzzy systems. The book provides a comprehensive exploration of how genetic algorithms can be effectively employed to enhance the performance and adaptability of fuzzy systems across various domains. Through practical examples and theoretical insights, Bodenhofer elucidates the process of tuning fuzzy systems using genetic algorithms, offering valuable guidance for researchers, engineers, and practitioners seeking to improve the efficiency of fuzzy systems through evolutionary computation techniques.

- (3) W. Pedrycz, Fuzzy Evolutionary Computation, Kluwer Academic Publishers, 1997 [68].

The main theme of this book is to highlight a synergistic effect that emerges between fuzzy sets and evolutionary computation, and to discuss and quantify the main advantages arising from this new symbiosis. The scope of the book is broad, ranging from the coverage of fundamental ideas in fuzzy sets and evolutionary computation through the inclusion of cutting-edge research to case studies. The focus is on the applied side of the fuzzy evolutionary calculations. Each contribution is systematic and thorough in its presentations and emphasizes the design of evolutionary schemes that embrace various sources of domain knowledge. This is an indispensable reference work for practitioners, engineers, and scientists interested in techniques of evolutionary computation in the context of fuzzy sets and/or global optimization, and will be useful for individuals actively pursuing research applications in both fuzzy sets and evolutionary computation.

- (4) O. Cordo'n, F. Herrera, F. Hoffmann, and L. Magdalena. *Genetic Fuzzy Systems. Evolutionary Tuning and Learning of Fuzzy Knowledge Bases*, World Scientific, 2001 [14].

This is the first general GFS book that covers the overall state of the art of GFSs. This book provides a comprehensive overview of genetic algorithms and fuzzy logic, focusing on the synergy between the two for building robust intelligent systems.

This book summarizes and analyzes the field of genetic fuzzy systems, paying special attention to genetic algorithms that adapt and learn the knowledge base of a fuzzy-rule-based system. It introduces the general concepts, foundations, and design principles of genetic fuzzy systems and covers the topic of the genetic tuning of fuzzy systems. It also introduces three fundamental approaches to genetic learning processes in fuzzy systems: Michigan, Pittsburgh, and iterative learning methods. Finally, it explores hybrid genetic fuzzy systems, such as genetic fuzzy clustering or genetic neuro-fuzzy systems, and describes several applications from different areas.

- (5) M. Sakawa. *Genetic Algorithms and Fuzzy Multiobjective Optimization* (Vol. 14). Springer Science & Business Media, 2012.

This book delves into the synergy between genetic algorithms and fuzzy logic in tackling multiobjective optimization challenges. This book explores the integration of genetic algorithms and fuzzy systems to address complex problems with multiple conflicting objectives. It provides insights into how these computational techniques can enhance the search for optimal solutions in real-world scenarios characterized by uncertainty and imprecision. The book serves as a comprehensive guide for researchers, practitioners, and students interested in the applications of genetic algorithms and fuzzy logic to multiobjective optimization problems.

- (6) N. Siddique, and H. Adeli. *Computational intelligence: synergies of fuzzy logic, neural networks and evolutionary computing*. John Wiley & Sons, 2013.

This book explores the interplay and collaborative potential of fuzzy logic, neural networks, and evolutionary computing within the realm of computational intelligence. The book delves into the theoretical underpinnings and practical applications of integrating these three powerful paradigms to address complex problems in diverse domains. Through a blend of foundational concepts, algorithms, and case studies, Siddique and Adeli demonstrate the enhanced problem-solving capabilities achievable by combining these computational techniques. This book is a valuable resource for researchers, practitioners, and students seeking to

harness the collective strength of fuzzy logic, neural networks, and evolutionary computing for innovative solutions and applications.

An important number of contributions that gave maturity to the topic are compiled in the following books compile:

- F. Herrera and J.L. Verdegay (eds.). *Genetic Algorithms and Soft Computing*. Physica-Verlag, 1996 [69].
- E. Sanchez, Shibata and L. Zadeh (eds.). *Genetic Algorithms and Fuzzy Logic Systems*. Soft Computing Perspectives. World Scientific, 1997 [70].
- W. Pedrycz (ed.). *Fuzzy Evolutionary Computation*. Kluwer Academic Publishers, 1997 [68].
- Y.Q. Zhang, and K. Abraham. *Compensatory genetic fuzzy neural networks and their applications*. Vol. 30. World Scientific, 1998 [71].
- E. Cox. *Fuzzy Modeling and Genetic Algorithms for Data Mining and Exploration*. Elsevier, 2005 [72].
- N. Siddique. *Intelligent control: a hybrid approach based on fuzzy logic, neural networks and genetic algorithms*. Vol. 517. Springer, 2013 [73].
- A. Tettamanzi, and T. Marco. *Soft computing: integrating evolutionary, neural, and fuzzy systems*. Springer Science & Business Media, 2013 [74].

In the following, I provide a list of the journal special issues devoted to GFSs, including important contributions to all topics of GFSs:

- F. Herrera. Special Issue on Genetic Fuzzy Systems for Control and Robotics. *International Journal of Approximate Reasoning*, Vol 17, No 4, November 1997 [75].
- F. Herrera and L. Magdalena. Special Issue on Genetic Fuzzy Systems. *International Journal of Intelligent Systems*, Vol 13, No 10–11, October–November 1998 [76].
- O. Cordo'n, F. Herrera, F. Hoffmann and L. Magdalena. Special Issue on Recent Advances in Genetic Fuzzy System. *Information Sciences*, Vol 136, No 1–4, August 2001 [77].
- B. Carse, A.G. Pipe, I. Renners, A. Grauel, A.F. Gómez-Skarmeta, F. Jiménez, G. Sánchez, O. Cordón, F. Herrera, F.A. Gomide, I. Walter. Current issues and future directions in evolutionary fuzzy systems research. *InEUSFLAT Conf.* 2003 [78].
- O. Cordo'n, F. Gomide, F. Herrera, F. Hoffmann, L. Magdalena. Special Issue on Genetic Fuzzy Systems. *Fuzzy Sets and Systems*, Vol 141, No 1, January 2004 [79].
- J. Casillas, M.J. del Jesus, F. Herrera, R. Pe' rez, P. Villar. Special Issue on Genetic Fuzzy Systems and the Interpretability-Accuracy Trade-off. *International Jour-*

- nal of Approximate Reasoning. Vol 44, No 1, February 2007 [80].
- O. Cordon, R. Alcalá, J. Alcalá-Fdez, I. Rojas. Genetic Fuzzy Systems. Special Section on Genetic Fuzzy Systems: What's Next?. IEEE Transactions on Fuzzy Systems. Vol 15, No 4, August 2007 [81].
  - B. Carse, A.G. Pipe. Special Issue on Genetic Fuzzy Systems. International Journal of Intelligent Systems. Vol 22, No 9, September 2007 [82].
  - F. Herrera. Genetic fuzzy systems: taxonomy, current research trends and prospects. Evolutionary Intelligence. Vol 1, pp. 27–46, March 2008 [83].
  - R. Alcalá, and N. Yusuke. "Special issue on genetic fuzzy systems: new advances." Evolutionary Intelligence. Vol 2, pp. 1–3, 2009 [84].
  - J. Casillas, B. Carse. Special issue on "Genetic Fuzzy Systems: Recent Developments and Future Directions". Soft Computing. Vol 13, pp.417–8, March 2009 [85].
  - Y. Nojima, R. Alcalá, H. Ishibuchi, F. Herrera. Special issue on evolutionary fuzzy systems. Soft Computing. Vol 15, pp. 2299–2301, December 2011 [86].
  - R. Alcalá, Y. Nojima, H. Ishibuchi, F. Herrera. Special issue on evolutionary fuzzy systems. International Journal of Computational Intelligence Systems. Vol 5, No 2, pp. 209–211, April 2012 [87].
  - T. Latinovic, M. Rogic, M. Djurdjevic. Adaptive genetic fuzzy systems in industry: current framework and new trends. In19 International DAAAM Symposium "Intelligent Manufacturing & Automation" 2015 [88].
  - A. Fernandez, V. Lopez, M.J. del Jesus, F. Herrera. Revisiting evolutionary fuzzy systems: Taxonomy, applications, new trends and challenges. Knowledge-Based Systems. Vol 80, pp. 109–121, May 2015 [89].
  - H. Ishibuchi, Y. Nojima. Multiobjective Genetic Fuzzy Systems. Springer handbook of computational intelligence. 2015 [90].
  - C.W. Tao, C.C. Chuang, H.C. Huang. Editorial message: Special issue on advances in evolutionary fuzzy systems. International Journal of Fuzzy Systems. 2016 [91].
  - A. Fernandez, F. Herrera, O. Cordon, M.J. del Jesus, F. Marcelloni. Evolutionary fuzzy systems for explainable artificial intelligence: Why, when, what for, and where to?. IEEE Computational intelligence magazine. 2019 [92].
  - P.K. Dwivedi, S.P. Tripathi. A Review of Multi-Objective Evolutionary Based Fuzzy Classifiers. Recent Advances in Computer Science and Communications (Formerly: Recent Patents on Computer Science). 2020 [93].
  - A. Yusupbekov, S. Gulyamov, K. Turaev. Optimization of the rules base of genetic fuzzy systems. InCEUR Workshop Proceedings 2021 [94].

### 5.3.1 Abstract on Key Contributions from Referenced Papers

The collection of papers that we could find on these special issues give us a historical tour on the different stages we can find in the evolution of GFSs research:

- (1) Exploration of Genetic Learning Approaches (1997, 1998, 2003):
  - The initial special issues focused on utilizing genetic learning approaches such as Michigan, IRL, and Pittsburgh to learn KB components in Genetic Fuzzy Systems (GFSs) for control, robotics, and intelligent systems applications.
  - Emphasizing the importance of genetic algorithms in evolving fuzzy systems, these papers laid the foundation for innovative applications and methodologies in genetic fuzzy systems research.
- (2) Advancements in GFS Models and Branches (2001, 2003, 2004):
  - The subsequent special issues introduced advancements in genetic fuzzy systems by exploring new branches like genetic rule selection, multi-objective genetic algorithms, hierarchical genetic systems, and co-evolutionary genetic fuzzy systems.
  - The collective contributions highlighted novel methodologies for learning fuzzy systems, addressing high-dimensional problems and incorporating domain knowledge for improved performance.
- (3) **(3) Focus on Evolutionary Learning Directions (2007, 2012, 2021):**
  - Special issues delved into various evolutionary learning directions within Genetic Fuzzy Systems, encompassing multi-objective evolutionary learning, boosting techniques, and adaptive inference systems.
  - Addressing the interpretability-accuracy trade-off, incremental evolutionary learning strategies, and optimization of rule bases, these papers paved the way for advancements in evolutionary fuzzy systems research.
  - The last three special issues, published in 2007, emphasize three different directions. Carse and Pipe's special issue collect papers focused in the mentioned areas (multi-objective evolutionary learning, boosting and evolutionary learning, ...) and stress some new ones such as evolutionary adaptive inference systems. Casillas et al.'s special issue is focused on the trade-off between interpretability

and accuracy, collecting four papers that proposed different GFSs for tackling this problem. Cordo'n et al.'s special issue focuses its attention on novel GFS proposals under the title "What's Next?", collecting highly innovative GFS proposals that can mark new research trends. The four collected papers are focused on: a new Michigan approach for learning RBs based on XCS [95], GFSs for imprecisely observed data (low quality data) [96], incremental evolutionary learning of TS-fuzzy systems [97], and evolutionary fuzzy rule induction for subgroup discovery [26].

(4) Review and Future Trends in GFS Research (2008, 2019, 2020):

- Review papers and future trend analyses provided valuable insights into the evolution of Genetic Fuzzy Systems, taxonomy refinements, and emerging research directions.
- These publications underscored the significance of categorization frameworks, multi-objective evolutionary approaches, and applications of evolutionary fuzzy systems for explainable artificial intelligence.

(5) Latest Developments, Innovations and Challenges (2009, 2015, 2021):

- Recent publications highlighted innovative proposals, emerging trends, and challenges in Genetic Fuzzy Systems research, emphasizing the optimization of rule bases, taxonomy enhancements, and industry applications.
- By addressing novel methodologies, applications in industry contexts, and future research challenges, these papers contributed to the ongoing evolution and diversification of the field of Genetic Fuzzy Systems.

#### 5.4 The Most Cited Papers at the ISI Web of Science

The search on the ISI Web of Science allows us to get the most cited papers that can provide a picture on the important contributions on the topic that are representative approaches of different categorization areas. Following, we shortly describe them, paying attention to the associated area of the categorization and the used learning approach.

(1) Selecting Fuzzy If–Then Rules for Classification Problems Using Genetic Algorithms (IEEE Transactions on Fuzzy Systems, 525 cites, 1995) [28].

The proposed algorithm was based on a simple GA with binary coding representing whether a rule should

be selected or not from an initial set of candidate rules (obtained from a predefined DB by applying a simple data-driven method). The problem was formulated as a combinatorial optimization problem with two objectives considered by a weighted fitness function: to maximize the number of correctly classified patterns and to minimize the number of rules. This contribution is the most classic contribution for genetic rule selection and one of the departure points for studies in the trade-off between interpretability and accuracy.

(2) Ten years of genetic fuzzy systems: current framework and new trends (Fuzzy Sets and Systems, 524 cites, 2004) [16].

The objective of this paper is to provide an account of genetic fuzzy systems, with special attention to genetic fuzzy rule-based systems. After a brief introduction to models and applications of genetic fuzzy systems, the field is overviewed, new trends are identified, a critical evaluation of genetic fuzzy systems for fuzzy knowledge extraction is elaborated, and open questions that remain to be addressed in the future are raised. The paper also includes some of the key references required to quickly access implementation details of genetic fuzzy systems.

(3) Simultaneous Design of Membership Functions and Rule Sets for Fuzzy Controllers Using Genetic Algorithms (IEEE Transactions on Fuzzy Systems, 448 cites, 1995) [33].

Authors proposed the use of GAs to learn a complete KB for control problems, determining both membership functions and RB together in order to address their co-dependency (KB learning). They considered the simple GA for a Pittsburgh approach, with integer coding for rule consequents (similar to Thrift's proposal) and integer coding for membership function support amplitude (five different amplitude values) in the same chromosome. This contribution is a reference in the topic as a classic Pittsburgh approach for genetic KB learning.

(4) A TSK-type recurrent fuzzy network for dynamic systems processing by neural network and genetic algorithms (IEEE Transactions on Fuzzy Systems, 365 cites, 2002) [98].

This study presents a novel structure called TSK-type Recurrent Fuzzy Network (TRFN) that adapts to different learning environments using neural networks or genetic algorithms. TRFN employs recurrent fuzzy if-then rules with TSK-type consequences, feeding internal variables back to input and output layers for memory and learning enhancement. TRFN is tailored for supervised learning (TRFN-S) with neural networks and genetic learning (TRFN-G) for scenarios like reinforcement learning. TRFN-S features



compact size and high accuracy, while TRFN-G optimizes parameters using genetic algorithms. Comparative tests show TRFN's efficiency in dynamic system identification and control. TRFN outperforms other recurrent network models, highlighting its superior learning capabilities.

- (5) GA-fuzzy modeling and classification: Complexity and performance (IEEE Transactions on Fuzzy Systems, 360 cites, 2000) [99].

A two-step approach was proposed for function approximation, dynamic systems modelling and data classification problems by learning approximate TS-rules. First, fuzzy clustering was applied to obtain a compact initial KB. Then this model is optimized by a real-coded GA subjected to constraints in order to maintain the semantic properties of the rules. Each chromosome represents the parameters defining each fuzzy model (membership functions of the antecedents and coefficients of the consequents), thus performing a tuning of the initial model. This approach was also combined with an iterative similarity-driven rule base simplification algorithm as an intermediate stage between KB generation and parameter optimization. This is an important contribution that uses GAs for tuning inside a hybrid method, trying to get a more interpretable approximate TS model.

- (6) Performance evaluation of fuzzy classifier systems for multidimensional pattern classification problems (IEEE Transactions on Systems Man And Cybernetics Part B-Cybernetics, 350 cites, 1999) [63].

The authors investigate the effectiveness of a genetic fuzzy machine learning approach for addressing multidimensional pattern classification issues involving continuous attributes. In their methodology, each individual fuzzy if-then rule is managed separately, with a corresponding fitness value assigned to define a classifier system. The paper outlines the fundamentals of fuzzy if-then rules and fuzzy reasoning applicable to pattern classification tasks. Furthermore, a genetic machine learning technique is introduced with the ability to automatically produce fuzzy if-then rules from numerical data sets. By utilizing linguistic values alongside fixed membership functions in antecedent fuzzy sets, an easy linguistic interpretation of each fuzzy rule is established. The fixed membership functions simplify the implementation process of their method into a computer program. The primary distinguishing factors of their method lie in its simplicity of implementation and the linguistic clarity provided by the generated fuzzy if-then rules. The authors evaluate the performance of their approach through computer simulations on various benchmark problems. Despite the absence of a membership function tun-

ing mechanism, their method demonstrates notable efficacy when compared to alternative classification methodologies such as non-fuzzy machine learning tactics and neural networks.

- (7) Fuzzy rule selection by multi-objective genetic local search algorithms and rule evaluation measures in data mining (Fuzzy Sets and Systems, 307 cites, 2004) [101].

This paper illustrates a method for selecting a small set of uncomplicated fuzzy if-then rules to address pattern classification problems involving numerous continuous attributes. The methodology follows a two-phase approach: initial generation of candidate rules through rule evaluation metrics in data mining, followed by rule selection using multi-objective evolutionary algorithms. Initially, candidate fuzzy if-then rules are derived from numerical data and screened based on two rule evaluation metrics (confidence and support) in data mining. Subsequently, a limited number of fuzzy if-then rules are chosen from the pre-screened candidate pool using multi-objective evolutionary algorithms. In the rule selection process, three objectives are considered: maximizing classification accuracy, minimizing the number of selected rules, and minimizing total rule length. Thus, the role of multi-objective evolutionary algorithms is to identify multiple non-dominant rule sets concerning these objectives. The primary contribution of this work is introducing the concept of utilizing two rule evaluation metrics as pre-screening criteria for selecting fuzzy rules. By generating a specified number of candidate rules from numerical data for high-dimensional pattern classification problems, the paper demonstrates through computer simulations that this pre-screening enhances the efficiency of fuzzy rule selection. Additionally, the study expands on the previous work by transforming a multi-objective genetic algorithm (MOGA) into a multi-objective genetic local search (MOGLS) algorithm, where a local search procedure fine-tunes the selection (inclusion or exclusion) of each candidate rule. Furthermore, the integration of a learning algorithm for rule weights (certainty factors) with the MOGLS algorithm presents another advancement in fuzzy rule selection methodology.

- (8) Single-objective and two-objective genetic algorithms for selecting linguistic rules for pattern classification problems (Fuzzy Sets and Systems, 268 cites, 1997) [29].

This paper introduces several techniques for developing a concise fuzzy classification system comprising a limited number of linguistic classification rules. Initially, the authors define a rule selection challenge concerning linguistic classification rules with the

dual objectives of maximizing correctly classified training patterns and minimizing the chosen rule count. Subsequently, three approaches for identifying a collection of non-dominant solutions to the rule selection problem are presented, all centered around a single-objective genetic algorithm. Additionally, a multi-objective genetic algorithm-based method is proposed to find a set of non-dominant solutions. The effectiveness of these proposed methodologies is assessed through their application to the renowned iris dataset. Furthermore, a hybrid algorithm is proposed by amalgamating a learning technique for linguistic classification rules with the multi-objective genetic algorithm. Through computer simulations on the iris dataset, the superior performance of the hybrid algorithm is showcased.

- (9) Optimization of interval type-2 fuzzy logic controllers for a perturbed autonomous wheeled mobile robot using genetic algorithms (Information Sciences, 265 cites, 2009) [102].

In this paper a tracking controller for the dynamic model of a unicycle mobile robot by integrating a kinematic and a torque controller based on type-2 fuzzy logic theory and genetic algorithms were described. Computer simulations are presented confirming the performance of the tracking controller and its application to different navigation problems.

- (10) Combining a fuzzy optimal model with a genetic algorithm to solve multi-objective rainfall-runoff model calibration (Journal of Hydrology, 252 cites, 2002) [103].

A novel automatic calibration approach for the widely utilized Xinanjiang model in China is outlined in the paper. The calibration process involves two primary components: calibration of water balance parameters and calibration of runoff routing parameters. The former is accomplished using a straightforward genetic algorithm (GA), while the latter employs a new method that integrates a fuzzy optimal model (FOM) with a GA to address the multiple objective runoff routing parameter calibration issue. The GA utilized in this context with multiple objectives is essentially similar to a standard GA, with the exception of incorporating specific fitness criteria involving the membership degree of alternatives obtained by FOM within a limited set of alternatives and multiple objectives. The parameter calibration scheme focuses on optimizing three key objectives: (1) peak discharge, (2) peak time, and (3) total runoff volume. To calibrate the model parameters, historical flood data from 34 events spanning 12 years at the Shuangpai Reservoir are utilized, while flood data from the most recent 2 years are employed to validate these

parameters. The findings of this research and its practical application demonstrate that the amalgamation of GAs and the FOM in a hybrid methodology not only effectively leverages the essential flood characteristics but also proves to be efficient and robust in performance.

- (11) Integration of genetic fuzzy systems and artificial neural networks for stock price forecasting (Knowledge-based Systems, 245 cites, 2010) [104].

Forecasting stock market movements is acknowledged as a demanding task within the realm of financial time-series prediction. The key to successful stock market prediction lies in achieving optimal outcomes by utilizing minimal input data and a simplified stock market model. This study introduces an integrated methodology that leverages genetic fuzzy systems (GFS) and artificial neural networks (ANN) to develop an expert system for forecasting stock prices. Initially, stepwise regression analysis (SRA) is employed to identify the factors with the most significant influence on stock prices. Subsequently, the raw data is partitioned into  $k$  clusters using self-organizing map (SOM) neural networks. Finally, each cluster is input into distinct GFS models capable of rule extraction and data tuning. The effectiveness of the proposed approach is assessed by applying it to stock price data obtained from the IT and Airlines sectors, and comparing the results with previous stock price forecasting methods using mean absolute percentage error (MAPE). The findings indicate that the proposed approach surpasses the performance of prior methods, establishing itself as a viable tool for addressing stock price forecasting challenges.

- (12) A historical review of evolutionary learning methods for Mamdani-type fuzzy rule-based systems: Designing interpretable genetic fuzzy systems (International Journal of Approximate Reasoning, 244 cites, 2011) [105].

The balancing act between interpretability and accuracy is a fundamental aspect of utilizing fuzzy systems. The quest for precise yet easily understandable fuzzy systems has been pivotal in the foundational concepts and system identification methodologies introduced by Zadeh and Mamdani [106]. With the progression towards soft computing, there was a shift towards prioritizing accuracy in fuzzy model construction, leading to fuzzy systems resembling black-box models like neural networks. Fortunately, the scientific community focused on fuzzy modeling has circled back to the roots, emphasizing design approaches that address the interpretability-accuracy dilemma. Genetic fuzzy systems have gained significant traction due to their inherent adaptability and the

## The time extension of publications in IEEE

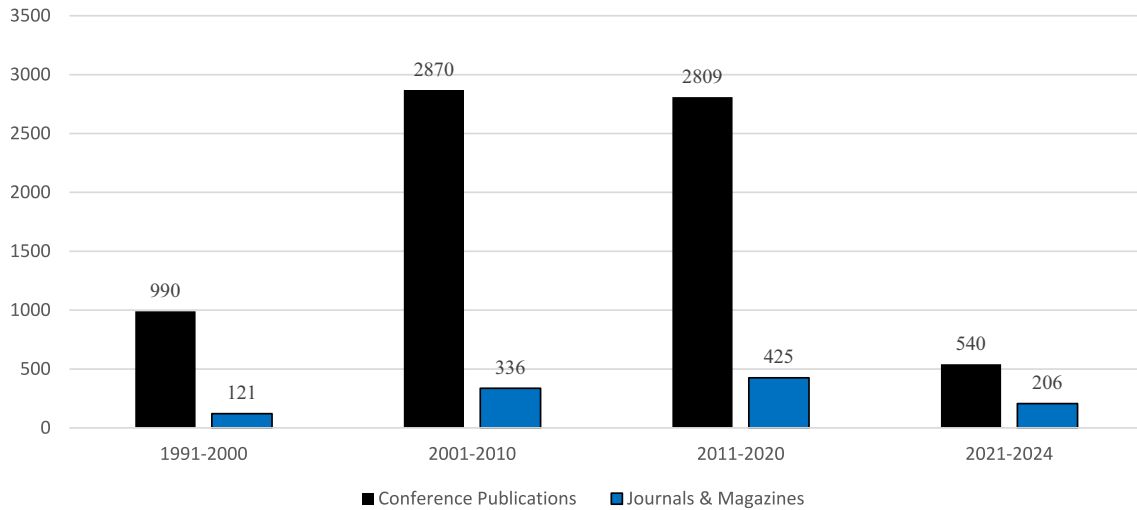


Fig. 15 The time extension of publications in IEEE

ability to simultaneously consider various optimization criteria. This study presents an overview of the prominent genetic fuzzy systems based on Mamdani-type fuzzy rule-based systems, aimed at generating interpretable linguistic fuzzy models with high accuracy.

- (13) Tuning fuzzy-logic controllers by genetic algorithms (International Journal of Approximate Reasoning, 226 cites, 1995) [107].

Authors proposed a tuning method for obtaining high-performance fuzzy control rules by means of GAs. The tuning method locally fits the membership functions of the fuzzy rules dealing with the parameters of the membership functions. A chromosome represents the parameters of the membership functions used by each rule in the initial KB, the chromosome represents the concatenated rule parameters. This is the first proposal for getting an approximate FRBS via tuning associated to the rules.

## 6 Some Research Trends in GFSs

This section is introduced some current trends that have focused the attention of researchers in the last few years and discussed some critical considerations on the publications in the topic at the present.

### 6.1 Discussing Some Trends in the Past Few Years

In this subsection, from the abundant GFSs literature published, we focus our attention into the following current

trends that are of high interest at the present and show considerable potential in the near future.

1. Multi-objective genetic learning of FRBSs: interpretability-precision trade-off.
2. GA-based techniques for mining fuzzy association rules and novel data mining approaches.
3. Learning genetic models based on low quality data (noise data and vague data).
4. Genetic learning of fuzzy partitions and context adaptation.
5. Genetic adaptation of inference engine components.
6. Revisiting the Michigan-style GFSs.

#### 6.1.1 Evolutionary Multi-objective Learning of FRBSs: Interpretability-Precision Trade-Off

Obtaining high degrees of interpretability and accuracy is a contradictory aim; in practice, one of the two properties prevails over the other. Nevertheless, a new tendency in the fuzzy modelling scientific community that seeks a good balance between interpretability and accuracy is increasing in importance. The improvement of the interpretability of rule-based systems is a central issue in recent research, where not only the accuracy but also the compacting and interpretability of the obtained rules are receiving attention [108, 109].

In multi-objective GFSs, it is desirable to design genetic learning algorithms in which the learning mechanism finds an appropriate balance between interpretability and accuracy. We consider objectives based on accuracy, and objectives that include different complexity/interpretability measures. Figure 15 from [110] illustrates this concept, where

each ellipsoid denotes a fuzzy system. A large number of nondominated fuzzy systems exist along the accuracy–complexity trade-off curve.

There exists an important number of contributions focused on this topic:

- A. Multi-objective genetic fuzzy rule selection [29, 101].
- B. Multi-objective genetic RB learning [111–114].
- C. Multi-objective genetic data mining [27, 115].
- D. Multi-objective genetic tuning [116].

, ...

In the following, a wide range of related studies to multi-objective genetic fuzzy systems in various research areas is briefly reviewed. Of course, it is far from exhaustive. See [117] for multi-objective approaches in machine learning, and see [118] for multi-objective data mining.

#### A. Multi-objective Genetic Fuzzy Rule Selection

Two-objective genetic fuzzy rule selection for the design of fuzzy classifiers [29], which is a multi-objective version of weighted sum-based rule selection [28], was one of the earliest studies on multi-objective genetic fuzzy systems. In [29], a large number of candidate fuzzy rules were first extracted from numerical data using a heuristic rule extraction procedure. Subsequently, an Evolutionary Multi-objective Optimization (EMO) algorithm was used to search for a number of non-dominated subsets of the candidate fuzzy rules with respect to accuracy maximization and complexity minimization. Let  $N$  be the number of extracted candidate rules: A subset of  $N$  candidate rules is represented by a binary string of length  $N$  and handled as an individual in a two-objective genetic fuzzy rule selection. A subset of the  $N$  candidate rules is represented by a binary string of length  $N$  and handled as an individual in two-objective genetic fuzzy rule selection. Because binary strings are used as individuals, we can directly apply existing EMO algorithms, such as NSGA-II, SPEA, and SPEA2, with standard genetic operators to two-objective genetic fuzzy rule selection. The two-objective formulation in [29] was extended to the three-objective formulation in [119] by introducing the total number of antecedent conditions (i.e., the total rule length) as an additional complexity measure. A memetic EMO algorithm (i.e., a hybrid algorithm of EMO and local search) was used for three-objective genetic fuzzy rule selection in [101]. The same three-objective formulation as in [101, 119] was used for non-fuzzy rule selection in [120].

#### B. Multi-objective Fuzzy Genetics-Based Machine Learning (GBML)

Studies on genetics-based machine-learning algorithms are often divided into three classes: Pittsburgh, Michigan, and IRL approaches (see [3, 121] for GBML and [11, 14, 16, 122] for Fuzzy GBML). A rule set is handled as an individual in the Pittsburgh approach, whereas a single rule is handled as an individual in the Michigan approach. The final obtained rule set is usually the best individual in

the final population in the Pittsburgh approach, whereas it is the final population in the Michigan approach. Another category of GBML is the iterative rule-learning approach [18, 60, 123], where a single rule is obtained from its single execution.

Thus, multiple runs are required to generate a rule set in the iterative rule-learning approach. Multi-objective GBML algorithms are typically implemented in the framework of the Pittsburgh approach. In general, the antecedent part of each rule is coded as a substring in Pittsburgh-style GBML algorithms. The rule set is represented by a concatenated string.

A subtraction of integers and/or real numbers is often used to represent a single rule. A three-objective fuzzy GBML algorithm was compared with its rule selection version in [119]. A Pittsburgh–Michigan hybrid fuzzy GBML algorithm [124] was generalized as a multi-objective algorithm for interpretability-accuracy trade-off analysis in [125]. Other examples of multi-objective fuzzy GBML algorithms can be found in [114, 117, 126–128], where various aspects of fuzzy systems are adjusted by EMO algorithms (e.g., input selection, membership function tuning, and rule selection). Multi-objective GBML algorithms were also implemented for non-fuzzy classifier design (e.g., [129]).

#### C. Evolutionary Multi-Objective Data Mining

Evolutionary algorithms have been applied in the fields of knowledge discovery and data mining in various ways [130]. EMO algorithms have been used for two different tasks: searching for Pareto-optimal rules and searching for Pareto-optimal rule sets.

In data mining techniques, such as Apriori [131], support and confidence have frequently been used for rule evaluation. However, other rule-evaluation criteria have also been proposed. Among them are gain, variance, chi-squared value, entropy gain, gini, laplace, lift, and conviction [19]. For non-fuzzy rules, it was shown that the best rule according to any of these measures is a Pareto-optimal rule for the following two-objective rule discovery problem [132]:

$$\text{Maximize } \{\text{Support}(R), \text{Confidence}(R)\} \quad (1)$$

where  $R$  denotes a single rule.

The use of NSGA-II [133], which is a well-known and frequently-used EMO algorithm, was proposed in [134, 135] to search for Pareto-optimal classification rules of the two-objective problem in (1). A dissimilarity measure between classification rules was used in [136] instead of the crowding measure in NSGA-II to increase the diversity of obtained Pareto-optimal rules. The Pareto-dominance relation used in NSGA-II was modified in [137] in order to search for not only Pareto-optimal classification rules

but also near Pareto-optimal dominated ones. Similar multi-objective formulations to (1) were used to search for Pareto-optimal association rules [138] and Pareto-optimal fuzzy association rules [27]. In [139], the trade-off between the number of extracted fuzzy rules and the computation time for rule extraction was discussed in fuzzy data mining.

The above-mentioned studies on multi-objective genetic rule selection and GBML in the previous subsections can be viewed as data mining techniques for the search for Pareto-optimal rule sets. In [140], the use of Pareto-optimal fuzzy rules as candidate rules was examined in rule selection.

#### D. Evolutionary Multi-Objective Feature Selection

Feature selection [141] is an important issue in modeling, classification, knowledge discovery, and data mining. The basic idea of multi-objective feature selection is to minimize the size of a subset of features and maximize its performance.

A clear trade-off relationship exists between the size of the feature subsets and their performance on the training data. Evolutionary multi-objective feature selection has been discussed in several studies (e.g., [142–144]). Feature selection has also been discussed in the context of multi-objective genetic fuzzy systems [145].

#### E. Evolutionary Multi-Objective Clustering

Fuzzy clustering [146] has frequently been used for fuzzy rule generation. In evolutionary multi-objective clustering [147–150], multiple measures of cluster quality are optimized simultaneously. Evolutionary multi-objective clustering will play a very important role in multi-objective design of fuzzy systems whereas it has not been used in many studies so far.

#### F. Evolutionary Ensemble Design

A promising approach to the design of reliable classifiers is to combine multiple classifiers into a single one [151, 152]. Several methods have been proposed for generating multiple classifiers such as bagging [153] and boosting [154]. The point is to generate an ensemble of classifiers with high diversity. Ideally the classification errors by each individual classifier in an ensemble should be uncorrelated. EMO algorithms have been used to generate an ensemble of classifiers with high diversity. Non-dominated neural networks were combined into a single ensemble classifier in [155–158]. The choice of ensemble members seems to be an interesting issue when a large number of non-dominated neural networks are obtained. Design of fuzzy ensemble classifiers was discussed in [159]. Feature selection was used for neural network ensemble design in [160, 161].

#### G. Multi-objective Neural Network Design

In addition to ensemble design, EMO algorithms have also been used for multi-objective design of neural networks in various manners. An EMO algorithm was used to generate a number of non-dominated neural networks on a receiver

operating characteristic curve in [162]. Non-dominated radial basis function (RBF) networks of different sizes were generated in [163]. A multi-objective memetic algorithm was used to speed up the back-propagation algorithm in [164] where a number of neural networks of different sizes were evolved to find an appropriate network structure.

#### H. Multi-objective Genetic Programming

As in fuzzy systems and neural networks, there exists a clear trade-off relationship between training data accuracy and tree size in genetic programming. Multi-objective genetic programming has been discussed in several studies [165–169]. Multi-objective genetic programming is a promising tool for multi-objective design of tree-structured fuzzy systems.

Although the definition of accuracy in a certain application is straightforward, the definition of interpretability is rather problematic. Most researchers agree that interpretability involves the following aspects: the number of rules is sufficient to be comprehensible, rule premises should be easy in structure and contain only a few input variables, linguistic terms should be intuitively comprehensible, etc.

There is a need to propose new interpretability metrics that consider not only the number of rules, but also other aspects such as the number of labels of a rule, the shape of the membership functions, etc., with a better understanding and formalization of the notions of “interpretability”, “comprehensibility, or “simplicity”. More research on evaluation metrics is needed to provide an interpretability measure associated with the FRBSs, allowing us to compare different FRBSs for a problem from the interpretability point of view and including them as objectives in MOEAs.

### 6.1.2 GA-Based Techniques for Mining Fuzzy Association Rules and Novel Data Mining Approaches

Recent advancements in Genetic Fuzzy Systems (GFS) have leveraged Genetic Algorithms (GAs) to develop innovative techniques for mining fuzzy association rules and exploring novel data mining approaches. GAs, as a powerful optimization algorithm inspired by the process of natural selection, have shown significant potential in addressing the complexities of association analysis and pattern mining within fuzzy systems.

One noteworthy area of research in GA-based techniques for mining fuzzy association rules involves the integration of multi-objective optimization methods with genetic algorithms. By employing multi-objective optimization, researchers aim to simultaneously optimize conflicting objectives such as rule coverage, accuracy, and interpretability in the context of fuzzy association rule mining. These approaches not only enhance the quality of generated rules but also provide decision-makers with a diverse set of solutions that cater to different trade-off preferences.



Moreover, novel data mining approaches within the realm of GFS have been exploring the fusion of evolutionary algorithms with deep learning methodologies. Evolutionary Deep Learning frameworks combine the strengths of genetic algorithms in global exploration and deep learning in local exploitation to enhance the scalability and generalization capabilities of fuzzy systems. By integrating these technologies, researchers have been able to uncover intricate patterns and relationships within large and complex datasets, pushing the boundaries of traditional data mining techniques.

Additionally, recent studies have been focusing on incorporating uncertainty modeling techniques, such as probabilistic graphical models and Bayesian optimization, into the evolutionary process of mining fuzzy association rules [170]. These approaches aim to capture and reason with uncertain or imprecise information present in real-world data, enriching the interpretability and robustness of the generated fuzzy rules.

Overall, the evolution of GA-based techniques for mining fuzzy association rules and the exploration of novel data mining approaches within Genetic Fuzzy Systems present exciting avenues for advancing the field of knowledge discovery and decision support systems. By embracing the synergy of evolutionary algorithms and fuzzy logic, researchers are poised to unlock deeper insights from data, facilitate transparent reasoning processes, and drive innovation in the domain of intelligent data analysis.

Fayyad et al. defined knowledge discovery (KD) as the nontrivial process of identifying valid, novel, potentially useful, and understandable patterns in data [171]. KD may not be considered synonymous with DM; however, they are intimately related. KD is a wide-ranging process that covers the following distinct stages: comprehension of the problem, comprehension of the data, pre-processing (or preparation) of the data, DM, and post-processing (assessment and interpretation of the models). The DM stage is responsible for automatic KD at a high level, and from the information obtained from real data. Some of the important problems that DM and KD deal with are rule extraction, identification of associations, feature analysis, linguistic summarization, clustering, classifier design, and novelty/anomaly detection.

Interpretability is crucial in the field of DM/KD, where knowledge should be extracted from databases and represented in a comprehensible form, or for decision support systems, where the reasoning process should be transparent to the user. The use of linguistic variables and linguistic terms in the discovery process has been explored by different authors.

Over the past decade, frequent pattern mining has been the focus of DM research. Association analysis is a methodology that is useful for discovering interesting relationships hidden in large datasets. Uncovered relationships can be represented in the form of association rules or sets of

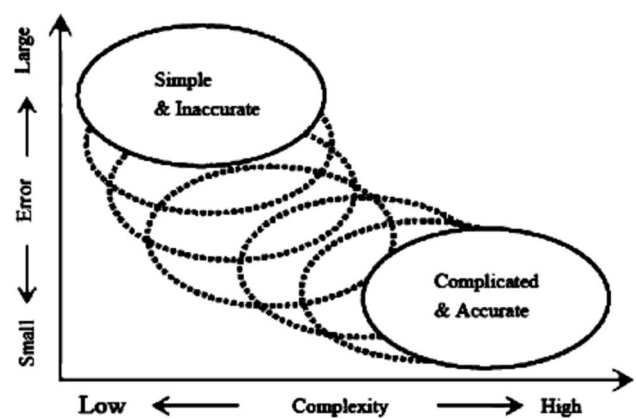


Fig. 16 Non-dominated fuzzy systems

frequent items. Abundant literature can be found that presents tremendous progress on the topic [172, 173].

As claimed in [174], the use of fuzzy sets to describe the association between data extends the types of relationships that may be represented, facilitates the interpretation of rules in linguistic terms, and avoids unnatural boundaries in the partitioning of attribute domains.

Linguistic variables with linguistic terms can contribute substantially to advancing the design of association rules and the analysis of data to establish relationships and identify patterns in general [104]. In contrast, GAs, particularly EAs, are widely used for evolving rule extraction and pattern association in DM/KD [71].

The conjunction in the GFS field provides novel useful tools for pattern analysis and for extracting new kinds of useful information with a main advantage over other techniques: its interpretability in terms of fuzzy if-then rules. At present, we have found interesting contributions focused on the genetic extraction of fuzzy association rules [27, 175–177].

We would like to focus on a subdivision of descriptive induction algorithms, which has recently received attention from researchers, called subgroup discovery.

It is a form of supervised inductive learning of Fig. 16 Non-dominated fuzzy system subgroup descriptions in which, given a set of data and having a property of interest to the user, attempts to locate subgroups that are statistically “most interesting” for the user. Subgroup discovery has the objective of discovering interesting properties of subgroups, obtaining simple rules (i.e., with an understandable structure and few variables), highly significant, and with high support (i.e., covering many of the instances of the target class). The concept was initially formulated by Klosgen in [178], his rule learning algorithm EXPLORA, and by Wrobel in [179], the MIDOS algorithm. Both use a rule-extraction model based on decision trees to obtain the best subgroups within the population. To evaluate the subgroups, evaluation measurements were defined to determine the interest

of an expression through a combination of unusualness and size. MIDOS tackles the problem of discovery in multirelational databases using the same approach. A recent study on this topic can be found in [180]. In [26] we found the first approach to the use of GFSs for subgroup discovery.

The use of GFSs for association analysis is a topic that would provide interesting future contributions focusing on the different research problems that can be found in the frequent pattern mining area [172].

### 6.1.3 Learning Genetic Models Based on Low Quality Data (Noise Data and Vague Data)

In the realm of Genetic Fuzzy Systems (GFS), the task of learning models from low-quality data poses a significant challenge yet offers valuable opportunities for research and innovation. Low-quality data, characterized by noise and vagueness, is commonly encountered in real-world applications across various domains, such as sensor data analysis, medical diagnostics, and financial forecasting.

The presence of noise data, stemming from measurement errors, missing values, or irrelevant features, can significantly impact the robustness and accuracy of learned models. Traditional machine learning algorithms may struggle to effectively handle noisy data, leading to suboptimal performance and reduced interpretability of the generated models. In this context, Genetic Fuzzy Systems provide a promising framework for robust modeling in the presence of noise, thanks to their inherent ability to capture uncertainty and imprecision through fuzzy logic representations.

Moreover, the challenge of learning from vague data, where information is inherently ambiguous or imprecise, underscores the importance of leveraging fuzzy logic principles within GFS. Vague data can arise from subjective judgments, qualitative assessments, or incomplete information, making it particularly suitable for treatment using fuzzy sets and fuzzy reasoning approaches. By incorporating vague data into the learning process of GFS, researchers can explore the capacity of fuzzy classifiers to handle uncertainties and complex decision-making scenarios that conventional models may struggle to address.

Efforts in the research community have begun to explore novel formalizations for defining fuzzy classifiers that are specifically tailored to handle low-quality data, including noise and vagueness. By linking concepts from fuzzy statistics with genetic modeling techniques, researchers have delved into the design of fitness functions and optimization strategies that are robust to the uncertainties present in noisy and vague datasets. These initiatives aim to enhance the adaptability and generalization capabilities of GFS when confronted with challenging data scenarios.

The exploration of learning genetic models based on low-quality data represents a burgeoning area of research

that holds great potential for advancing the capabilities of Genetic Fuzzy Systems in real-world applications. By addressing the nuances of noise and vagueness in data, researchers are paving the way for more resilient, interpretable, and effective modeling solutions that can thrive in complex and uncertain environments [181].

There are many practical problems requiring learning models from uncertain data. The experimental designs of GFSs learning from data observed in an imprecise way are not being actively studied by researchers. However, according to the point of view of fuzzy statistics, the primary use of fuzzy sets in classification and modelling problems is for the treatment of vague data. Using vague data to train and test GFSs we could analyse the performance of these classifiers on the type of problems for which fuzzy systems are expected to be superior. Preliminary results in this area involve the proposals of different formalizations for the definition of fuzzy classifiers, based on the relationships between random sets and fuzzy sets [182] and the study of fitness functions (with fuzzy values) defined in the context of GFSs [96]. This is a novel area that is worth being explored in the near future, and can provide interesting and promising results.

### 6.1.4 Genetic Learning of Fuzzy Partitions and Context Adaptation

The DB learning comprises the specification of the universes of discourse, the number of labels for each linguistic variable, as well as the definition of the fuzzy membership functions associated to each label. In [183] it was studied the influence of fuzzy partition granularity in the FRBS performance, showing that using an appropriate number of terms for each linguistic variable, the FRBS accuracy can be significantly improved without the need of a complex RB learning method.

On the other hand, the idea of introducing the notion of context into fuzzy systems comes from the observation that, in real life, the same basic concept can be perceived differently in different situations. In some cases, this information is related to the physical properties or dimensions of the system or process, including restrictions imposed due to the measurement acquisition or actuators. In the literature, context adaptation in fuzzy systems has been mainly approached as scaling of fuzzy sets from one universe of discourse to another by means of non-linear scaling functions whose parameters are identified from data.

Different approaches have been proposed to deal with the learning of membership functions, granularity, nonlinear contexts using GAs, ...[49, 184–188].

Although there are an important number of contributions in the area of DB Learning, but it is still an important research area where can be obtained important results, due

to the importance of using the adequate membership functions and the adequate context. The use of GFSs is very important due to the flexibility for encoding DB components together with other fuzzy system components.

### 6.1.5 Genetic Adaptation of Inference Engine Components

We know that it is possible to use parametric aggregation operators in the design of the inference system and the defuzzification method, trying to get the most appropriate parameter configuration in any application. The tuning of these components can be considered to get more accurate fuzzy models. We come across different GFS approaches for finding the most appropriate parameters [22, 23].

This is an interesting research area that can provide us with the opportunity to adapt the inference parameters to an FRBS and to design learning models that can coevolve the inference engine parameters together with the KB components.

(6) Revisiting the Michigan-style GFSs. The first description of a Michigan-style GFS was given in [59]. All the initial approaches in this area were based on the strength in the sense that a rule (classifier) gets strength during interactions with the environment (through rewards and/or penalties). This strength can then be used for two purposes: resolving conflicts between simultaneously matched rules during learning episodes; and as the basis of fitness for the GAs.

A completely different approach can be considered in which a rule's fitness, from the point of view of the GA, is based on its "accuracy", i.e., how well a rule predicts payoff whenever it fires. Notice that the concept of accuracy used here is different from the traditionally used.

in fuzzy modelling (i.e., capability of the fuzzy model to faithfully represent the modelled system). This accuracy-based approach offers a number of advantages such as avoiding over-general rules, obtaining optimally general rules, and learning of a complete covering map. The first accuracy-based evolutionary algorithm, called XCS, was proposed in [189] and it is currently of major interest to the research community in this field.

Casillas et al. proposed in [95] a new approach to achieve accuracy-based Michigan-style GFSs. The proposal, Fuzzy-XCS, is based on XCS but properly adapted to fuzzy systems, with promising results for function approximation problems and for robot simulation online learning. In [190] it is proposed an extension of UCS algorithm, a recent Michigan-style genetic learning algorithm for classification [191].

These approaches build a bridge between the Michigan style genetic learning studies and the fuzzy systems models. This is an interesting research line that can provide interesting results in the near future.

## 6.2 Some Critical Considerations

This subsection is discussed the critical issues in some publications by focus on two aspects, the EAs used in the GFSs and the experimental study.

### 6.2.1 The EAs Used in the GFSs

In the realm of Genetic Fuzzy Systems (GFSs), various Evolutionary Algorithms (EAs) have been employed to optimize fuzzy systems and enhance their performance. The use of a novel EA must be justified from whatever meaningful point of view: efficiency, efficacy/precision, interpretability, scalability, etc. Here is a comprehensive list of Evolutionary Algorithms commonly used in Genetic Fuzzy Systems research:

**6.2.1.1 Simple GAs** In an important number of contributions, a description of the simplest GAs, with a classical parameter coding (binary alphabet) and simple components can be found.

There exists a wide literature on GA's, in particular, and EAs in general, with important approaches that introduce important advances. Some examples are the real coding for continuous variables, different selection methods, different parent replacement strategies, adaptive components, dynamic mutation rate, etc. On the other hand, there are specific kinds of GA's for different tasks, such as niching GA's for multimodal functions, hybrid combinations of GAs and local search (memetic algorithms), Chaotic GA's, etc.

Authors must really know GA components and models before applying a simple GA, and choose an adequate algorithm, if necessary, for getting a good GFS.

**6.2.1.2 Genetic Programming (GP)** Genetic Programming is an evolutionary approach to generating computer programs that can evolve solutions to complex problems. In the context of GFSs, GP can be utilized to evolve fuzzy rule sets, optimize rule bases, and improve the modelling capabilities of fuzzy systems.

**6.2.1.3 Evolutionary Strategies (ES)** Evolutionary Strategies are optimization algorithms that use mutation and recombination operations to adapt candidate solutions over generations. In GFSs, ES can be applied to evolve fuzzy rule bases, optimize membership functions, and improve the performance of fuzzy systems.

**6.2.1.4 Particle Swarm Optimization (PSO)** Particle Swarm Optimization is a population-based optimization algorithm that models the social behavior of organisms. In GFSs, PSO can be used to optimize fuzzy system parameters, member-

ship functions, and rule weights to achieve better accuracy and generalization.

**6.2.1.5 Differential Evolution (DE)** Differential Evolution is a simple yet powerful optimization algorithm that iteratively improves candidate solutions by combining mutation and crossover operations. DE can be employed in GFSs to fine-tune fuzzy systems, adjust parameters, and optimize rule bases for improved modelling performance.

**6.2.1.6 Cultural Algorithms** Cultural Algorithms combine evolutionary computation with a cultural framework to efficiently explore the search space. In GFSs, Cultural Algorithms can be used to evolve fuzzy rule sets, incorporate knowledge sharing mechanisms, and promote diversity in the population to enhance the overall robustness of fuzzy systems.

**6.2.1.7 Estimation of Distribution Algorithms (EDAs)** Estimation of Distribution Algorithms focus on probabilistic models to represent and evolve the population of solutions. In GFSs, EDAs can be utilized to optimize fuzzy systems by capturing the dependencies among fuzzy rules, membership functions, and input data to improve the modelling accuracy and efficiency.

**6.2.1.8 Memetic Algorithms** Memetic Algorithms combine traditional evolutionary algorithms with local search techniques to enhance the global optimization process. In GFSs, Memetic Algorithms can be applied to evolve fuzzy rule bases, fine-tune system parameters, and improve classification accuracy.

**6.2.1.9 Multi-Objective Evolutionary Algorithms** These algorithms focus on optimizing multiple conflicting objectives simultaneously. In GFSs, Multi-Objective Evolutionary Algorithms can be used to find a set of trade-off solutions that balance model accuracy, interpretability, and complexity.

**6.2.1.10 Hybrid Evolutionary Algorithms** Hybrid Evolutionary Algorithms integrate multiple evolutionary and non-evolutionary techniques to exploit their complementary strengths. In the context of GFSs, Hybrid Evolutionary Algorithms can combine evolutionary optimization with other optimization techniques to enhance the performance and robustness of fuzzy systems.

## 6.2.2 Experimental Study

At this point, four aspects are focused on to analyse: benchmark problems, reproducibility, comparison with the state of the art and statistical analysis.

### (a) Benchmark problems.

When the experimental analyses are read a different set of benchmark problems in every paper can be found. In particular, the specific applications for learning from data without any possibility for getting the data set can be found such that it is impossible to reproduce the same experimental study. It is necessary to manage adequate and unified sets of benchmark problems for learning from data, providing all the necessary information for reproducing the experimental study.

### (b) Reproducibility.

In the same way, it is not possible to reproduce some algorithms due to the lack of the parameters values used by the authors in the experimental study. It is necessary to give a complete description of the algorithm components (coding approach, operators, parameters, ...) for allowing the reader to reproduce the algorithms.

### (c) Comparison with the state of the art.

When authors propose a new approach, they must first justify its usefulness, indicating which is the objective and we must find a measure for evaluating it (precision, complexity, ...). Then, it is necessary to make an experimental study comparing with the best approach according to the same objective and same fuzzy system components that are considered. Unfortunately, we do not have a study determining the state of the art in every area of the categorization as the level to reach for a new proposal. However, this is a real need for the near future. In any case, authors must compare with the most well-known approaches that exist in the abundant literature, discussing the advantages of the proposal. It is not enough to compare with a simple approach that is not the state of the art at the present.

### (d) Lack of experimental statistical analysis.

Another critical point is related to the comparative study. Currently there is not a systematic evaluation methodology for GFSs.

Experimental results reported in the machine learning literature often use statistical tests of significance to support the claim that a new learning algorithm generalizes better. In fact, the performance analysis of learning algorithms has always centred the attention of investigators in the machine learning area, and different comparison proposals have been developed (cross validation, uses of  $5 \times 2cv$ , leave one out, etc.) in terms of their type I and type II errors, both on synthetic datasets, and standard benchmarks of machine learning [192, 193]. The use of statistical analysis tools is a peremptory necessity in the analysis of GFS models as it is in classical machine learning.



## 7 Genetic Fuzzy Systems: Outlooks

The field of GFSs can be considered as an area that needs to advance towards more precision and accuracy together with more rapidity. In the following three research directions that are worth continuing the exploration are enumerated.

1. Interpretability quality.
2. New data mining tasks: frequent and interesting pattern mining, mining data streams, etc.
3. Dealing with high dimensional data sets.

### 7.1 Interpretability Quality

There exists another important feature for measuring the FRBS quality, the model interpretability. It is claimed on the interpretability but without metrics for measuring it. It is used as an objective during the use of MOEAs for extracting fuzzy models but only considering the size of the rule base or the number of variables that participate per rule.

Interpretability is considered to be the main advantage of fuzzy systems over alternatives like neural networks, statistical models, etc. As authors claim in [109], interpretability means that human beings are able to understand the fuzzy system's behaviour by inspecting the RB. Fuzzy systems constructed from expert knowledge -the traditional approach- are usually well understandable.

In the recent years, research has started to focus on the trade-off between interpretability and accuracy [126, 127]. Analysis of the model interpretability and comprehensibility is always convenient, and it is a necessity when accuracy is not a model feature.

The inclusion of novel interpretability measures in the fitness function of GFS models will provide novel and interesting approaches for getting a good balance between interpretability and precision.

### 7.2 New Data Mining Tasks: Frequent and Interesting Pattern Mining, Mining Data Streams, etc

Many new problems have emerged and have been solved by the data mining researchers, but there are still a lot of problems that receive attention and new proposals are under development. We can find a lot of novel problems far from the classic classification and regression problems, problems such as frequent pattern mining open questions, data streams, sequential and time series data, adversary data mining, anomaly detection, non-static, imbalanced data... [194].

As mentioned, linguistic variables with linguistic terms can contribute in a substantial way to advance in the design

of data analysis approaches to establish relationships and identify patterns in some of the enumerated problems. The development of GFSs may be useful for providing algorithms and solutions to the mentioned problems.

### 7.3 Dealing with High Dimensional Data Sets

It is usual to find big databases, i.e., with high number of features and/or instances. Regarding the interpretability of linguistic FRBSs, the difficulty comes from the exponential growth of the fuzzy rule search space with the increase in the number of features/instances considered. Usually, human users do not want to check hundreds of fuzzy rules, the number of fuzzy rules is closely related to the interpretability of FRBSs. On the other hand, the rule length is also closely related to the interpretability of FRBSs.

This problem can be tackled in different ways:

(a) Compacting and reducing the rule set.

As a post-processing approach, this is done under an initial rule extraction process that provides a big number of rules. It appears the problem of the number of rules and the size of the coding representation, with the necessity of efficient and effective EAs.

(b) Using data reduction techniques.

Carrying out a feature selection process, that determines the most relevant variables before or during the inductive learning process of the FRBS, and removing irrelevant training instances prior to FRBS learning. The first approach has been already tried in the GFS specialized literature [195–197], but the latter, up to our knowledge in the topic, has not been used for learning FRBS. For example, it has been used for extracting decision trees, see [198, 199].

Feature and instance selection provide smaller training sets, which may get more accurate and more compact models. And in both cases, GAs are used frequently, because the selection problem may be defined as the problem of searching the optimal subset of features/instances.

The inclusion of genetic data reduction processes inside of a GFS model is a research direction that allows us to advance in the extraction of FRBSs with an appropriate balance between interpretability and accuracy in high dimensional problems.

(c) Using genetic programming for learning compact FRBSs.

Genetic programming is an extension to the inspiration of GA, where the main problem of GAs concerning the fixed problem definition is avoided by using variable-length trees instead of fixed-sized individuals. The definition of context-free grammars for rule construction has been revealed of special utility for this purpose [58]. The use of genetic programming in a GFS model can lead us to obtaining a reduced fuzzy rule set, with few antecedents conditions per



rule and high-generalization capability, getting FRBSs with high interpretability for high-dimensional problems.

(d) Algorithm scalability.

Another problem when we deal with high dimensional problems is the analysis of the algorithm scalability on big databases, emphasizing the training time and the convergence towards compact and interpretable models. The balance between problem size and algorithm scalability is another important aspect for GFSs that are worth studying in depth. At this point, we must remark the existence of efficient parallel GAs [200] as a kind of GAs that would be evaluated for designing GFSs for large databases putting special emphasis on aspects of scalability and efficiency. Another interesting idea that has been advanced in [201] consisting of dividing training data sets and the population.

They are divided into the same number of subpopulations and training data subsets, which is also the same as the number of client CPUs. Then each client CPU performs genetic learning (genetic rule selection in this contribution) using a single training data subset and a single sub-population given by the server CPU. It seems that each sub-population is likely to over-fit the corresponding training data subset. To avoid that, the assignment of the training data subsets to the client CPUs changes after a pre-specified number of generations (i.e., every ten generation).

## 8 GFS Current and Future trends

In this part, the current and future trends of GFSs are probed. The topics that in the recent years have been in attention point or they have the capability of research in order to improve the accuracy, precision and rapidity of GFSs simultaneously or to cover and solve more real problems with GFS approach.

### 8.1 Genetic Type-2 Fuzzy System

The additional power to represent uncertainty in different levels and some robustness exhibition in comparison with type-1 fuzzy systems has motivated the interest of the study of type-2 fuzzy sets despite of their more difficulty to understand and use than type-1 fuzzy sets. In representing linguistic nature of knowledge, the fixed membership function design of type-1 based fuzzy logic controller (FLC) leads to the difficulty of rule-based control design. In type-2 FLC as the expanded type of type-1 FL, the control characteristic by using the footprint of uncertainty (FOU) of the membership functions can be effectively improved.

GA's have been applied in Type-2 Fuzzy Systems (T2FS) on different reasons such as learning and performance evaluation and optimized designing of type-2 fuzzy inference systems, etc.

#### 8.1.1 Genetic Type-2 Fuzzy System Papers:

- (1) **S. Park, H. L. Kwang, "A designing Method for Type-2 Fuzzy Logic Systems Using Genetic Algorithms," Proc. of Joint 9th IFSA World Congress and 20th NAFIPS Intl. Conference, Vancouver, Canada, Vol. 5, pp. 2567–2572, 2001 [202].**

This paper is proposed a design method for a type-2 FLS using GAs. The proposed method determines the positions and the shapes of the MFs and the rules of a type-2 FLS that encodes type-2 fuzzy sets as feature parameters.

- (2) **D. Wu, W.W. Tan, "Genetic learning and performance evaluation of interval type-2 fuzzy logic controllers", Engineering Applications of Artificial Intelligence, Vol. 19, Issue 8, pp. 829–841, December 2006 [203].**

This paper is focused on advancing the understanding of interval type-2 fuzzy logic controllers (FLCs). First, a type-2 FLC is evolved using Genetic Algorithms (GAs). The type-2 FLC is then compared with another three GA evolved type-1 FLCs that have different design parameters. The objective is to examine the amount by which the extra degrees of freedom provided by antecedent type-2 fuzzy sets are able to improve the control performance.

- (3) **W.W. Tan, D. Wu, "Design of Type-Reduction Strategies for Type-2 Fuzzy Logic Systems using Genetic Algorithms", Advances in Evolutionary Computing for System Design Studies in Computational Intelligence, Vol. 66, pp. 169–187, 2007 [204].**

This paper has aimed at designing computationally efficient type-reducers using a genetic algorithm (GA). While a type-2 FLS has the capability to model more complex relationships, the output of a type-2 fuzzy inference engine is a type-2 FS that needs to be type-reduced before defuzzification can be performed. Unfortunately, type-reduction is usually achieved using the computationally intensive Karnik–Mendel iterative algorithm. In order for type-2 FLSs to be useful for real-time applications, the computational burden of type-reduction needs to be relieved. he proposed type-reducer is based on the concept known as *equivalent type-1 FSs* (ET1FSs), a collection of type-1 FSs that replicates the input–output relationship of a type-2 FLS. By replacing a type-2 FS with a collection of ET1FSs, the type-reduction process then simplifies to deciding which ET1FS to employ in a particular situation. The strategy for selecting the ET1FS is evolved by a GA. Results are presented to demonstrate that the proposed type-reducing algorithm has lower computational cost and may provide

better performance than FLSs that employ existing type-reducers.

- (4) **C. Wagner, H. Hagnas, “A Genetic Algorithm Based Architecture for Evolving Type-2 Fuzzy Logic Controllers for Real World Autonomous Mobile Robots” In: Proceedings of IEEE FUZZ Conference, London, UK, pp. 193–198, July 2007 [205].**

This paper will present a Genetic Algorithm (GA) based architecture to evolve the type-2 MFs of interval type-2 FLCs for mobile robots that will navigate in real world environments. Since autonomous mobile robots need control mechanisms such as type-2 FLCs which can handle the large amounts of uncertainties present in real world environments manually designing and tuning the type-2 Membership Functions (MFs) for this purpose is a difficult task and GA can perform this task with high performance.

- (5) **A. Cai, C. Quek, D.L. Maskell, “Type-2 GA-TSK Fuzzy Neural Network”, 2007 IEEE Congress on Evolutionary Computation (CEC 2007), pp.1578–1585, 2007 [206].**

In this paper a novel fuzzy-neural network, the type-2 GA-TSKFNN (T2GA-TSKFNN), combining a type-2 fuzzy logic system (FLS) and a Genetic Algorithm (GA) based Takagi–Sugeno–Kang fuzzy neural network (GA-TSKFNN) is presented. The rationale for this combination is that type-2 fuzzy sets are better able to deal with rule uncertainties, while the optimal GA-based tuning of the T2GA-TSKFNN parameters achieves better classification results. However, a general T2GA-TSKFNN is computationally very intensive due to the complexity of the type-2 to type-1 reduction. Therefore, this paper is adopted an interval T2GA-TSKFNN against other fuzzy neural networks.

- (6) **A. Celikyilmaz, I. Burhan Turksen, “Genetic type-2 fuzzy classifier functions”, Annual Meeting of the North American Fuzzy Information Processing Society (NAFIPS) 2008, Paper # 50,026, New York City, May 2008 [207].**

In this paper a new type-2 fuzzy classifier function system is proposed for uncertainty modeling using genetic algorithms—GT2FCF. Proposed method implements a three-phase learning strategy to capture the uncertainties in fuzzy classifier function systems induced by learning parameters, as well as fuzzy classifier functions. Hidden structures are captured with the implementation of improved fuzzy clustering. The optimum uncertainty interval of the type-2 fuzzy membership values are captured with a genetic learning algorithm.

- (7) **N.R. Cazarez-Castro, L.T. Aguilar, O. Castillo, “Hybrid Genetic-Fuzzy Optimization of a Type-2 Fuzzy Logic Controller”, In: Proceedings of the 2008 8th International Conference on Hybrid Intelligent Systems (HIS '08), IEEE Computer Society Washington DC, USA, pp. 216–221, 2008 [208].**

In this paper a Genetic—Type-2 Fuzzy approach is proposed to optimize the parameters of the Membership Functions (MFs) of a Type-2 Fuzzy Logic System (FLS) applied to control. A chromosome to represent the parameters of the MFs of a pre-established Type-2 FLS, design a fitness function and select genetic operators is designed. A case of study is proposed to evaluate the optimization process; this is to achieve the output regulation problem of a servomechanism with backlash. The problem is the design of a type-2 fuzzy logic controller which will be optimized by a GA to obtain the closed-loop system in which the load of the driver is regulated to a desired position. Simulations results illustrate the effectiveness of the optimized closed-loop system.

- (8) **D. Hildalgo, O. Castillo, P. Melin, “Type-1 and type-2 fuzzy inference systems as integration methods in modular neural networks for multimodal biometry and its optimization with genetic algorithms”, Information Sciences, Vol. 179, No. 13, pp. 2123–2145, June 2009 [209].**

In this paper a comparative study between fuzzy inference systems as methods of integration in modular neural networks for multimodal biometry is described. These methods of integration are based on techniques of type-1 fuzzy logic and type-2 fuzzy logic. Also, the fuzzy systems are optimized with simple genetic algorithms with the goal of having optimized versions of both types of fuzzy systems. First, the use of type-1 fuzzy logic and later the approach with type-2 fuzzy logic was considered. The fuzzy systems were developed using genetic algorithms to handle fuzzy inference systems with different membership functions, like the triangular, trapezoidal and Gaussian; since these algorithms can generate fuzzy systems automatically. Then the response integration of the modular neural network was tested with the optimized fuzzy systems of integration. The comparative study of the type-1 and type-2 fuzzy inference systems was made to observe the behavior of the two different integration methods for modular neural networks for multimodal biometry.

- (9) **R. Martinez, O. Castillo, L. T. Aguilar, “Optimization of interval type-2 fuzzy logic controllers for a perturbed autonomous wheeled mobile robot**

using genetic algorithms”, *Information Sciences*, Vol. 179, No. 13, pp. 2158–2174, June 2009 [102].

In this paper a tracking controller for the dynamic model of a unicycle mobile robot by integrating a kinematic and a torque controller based on type-2 fuzzy logic theory and genetic algorithms were described. Computer simulations are presented confirming the performance of the tracking controller and its application to different navigation problems.

- (10) **M. Lopez, P. Melin, O. Castillo**, “Comparative Study of Fuzzy Methods for Response Integration in Ensemble Neural Networks for Pattern Recognition”, *Bio-inspired Hybrid Intelligent Systems for Image Analysis and Pattern Recognition Studies in Computational Intelligence*, Vol. 256, pp. 123–140, 2009 [210].

In this paper a new method for response integration in ensemble neural networks with Type-1 Fuzzy Logic and Type-2 Fuzzy Logic using Genetic Algorithms (GA's) for optimization is described. In this paper pattern recognition with ensemble neural networks for the case of fingerprints to the test proposed method of response integration is considered. An ensemble neural network of three modules is used. Each module is a local expert on person recognition based on their biometric measure (Pattern recognition for fingerprints). The Response Integration method of the ensemble neural networks has the goal of combining the responses of the modules to improve the recognition rate of the individual modules. First GA's are used to optimize the fuzzy rules of the Type-1 Fuzzy System and Type-2 Fuzzy System to test the proposed method of response integration and after using GA's to optimize the membership function of the Type-1 Fuzzy Logic and Type-2 Fuzzy logic to test the proposed method of response integration and finally showed the comparison of the results between these methods. In this paper a comparative study of fuzzy methods for response integration and the optimization of the results of a type-2 approach for response integration is showed that improves performance over the type-1 logic approaches.

- (11) **M. Lopez, P. Melin, O. Castillo**, “Comparative study of fuzzy methods for response integration in ensemble neural networks”, *International Journal of Advanced Intelligence Paradigms*, Vol. 1, No. 3, pp. 291–317, 2009 [211].

In this paper a new method for response integration in ensemble neural networks with Type-1 and Type-2 Fuzzy Logic is presented. Genetic Algorithms (GA's) are used for fuzzy system optimisation. In this paper pattern recognition with ensemble neural networks for the case of fingerprints to test the proposed method

of response integration is considered. An ensemble neural network of three modules is used. Each module is a local expert on person recognition based on its biometric measure (Pattern recognition for fingerprints). The Response Integration method of the ensemble neural networks has the goal of combining the responses of the modules to improve the recognition rate of the individual modules.

- (12) **R. Hosseini, J. Dehmeshki, S. Barman, M. Mazinani, S.D. Qanadli**, “A Genetic type-2 fuzzy logic system for pattern recognition in computer aided detection systems”, In: *Proceedings of 2010 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE'10)*, Barcelona, Spain, pp. 1–7, July 2010 [212].

This paper takes advantage of type-2 fuzzy sets as three-dimensional fuzzy sets with high potential for managing uncertainty issues in vague environments. Since a computer aided detection (CAD) system suffers from vagueness and imprecision in both medical science and image processing techniques. These uncertainty issues in the classification components of a CAD system directly influence the accuracy. In this paper, an automatic optimized approach for generating and tuning type-2 Gaussian membership function (MF) parameters and their footprint of uncertainty is proposed. In this approach, two interval type-2 fuzzy logic system (IT2FLS) methods based on the Mamdani rules model are presented for tackling the uncertainty issues in classification problems in pattern recognition. Furthermore, the Genetic algorithm is employed for tuning of the MFs parameters and footprint of uncertainty.

- (13) **A.H.M. Pimenta, H. de Arruda Camargo**, “Genetic Interval Type-2 Fuzzy Classifier Generation: A Comparative Approach”, *2010 Eleventh Brazilian Symposium on Neural Networks, Sao Paulo, Brazil, October 2010* [213].

This paper is concentrated on studying the use of interval type-2 fuzzy sets for the pattern classification problem and relied on the recent advances concerning the three-dimensional type-2 membership functions to focus on the genetic generation of type-2 fuzzy classifiers. In this work a three stage Genetic Algorithm Architecture is used to generate Fuzzy Classification Systems, composed of three Genetic Algorithms that generate the rule base, optimize the interval type-2 membership functions and optimize the number of rules. Fuzzy classifiers were generated using the Genetic Algorithm Architecture for both type-1 and type-2 fuzzy sets, and using another genetic generation method found in the literature.

- (14) **S. K. Oha, H. J. Janga, W. Pedrycz, “A comparative experimental study of type-1/type-2 fuzzy cascade controller based on genetic algorithms and particle swarm optimization”, *Expert Systems with Applications*, Vol. 38, No. 9, pp. 11,217–11,229, September 2011 [214].**

In this paper, the design methodology of an optimized fuzzy controller with the aid of particle swarm optimization (PSO) and Genetic Algorithm (GA) for ball and beam system is presented. To evaluate performance of each controller, controller characteristic parameters such as maximum overshoot, delay time, rise time, settling time, and a steady-state error were considered. In the sequel, the optimized fuzzy cascade controller is realized and also experimented with through running two detailed comparative studies including type-1/type-2 fuzzy controller and genetic algorithms/particle swarm optimization.

- (15) **P. Melin, D. Sanchez, L. Cervantes, “Hierarchical genetic algorithms for optimal type-2 fuzzy system design”, In: *Proceedings of 2011 Annual Meeting of the North American Fuzzy Information Processing Society (NAFIPS)*, El Paso, TX, Mexico, pp. 1–6, March 2011 [215].**

In this paper the application of genetic algorithms for optimal type-2 fuzzy system design is described and the approach with two cases is illustrated, one of designing optimal neural networks and the other of fuzzy control and the feasibility of using hierarchical genetic algorithms for designing type-2 fuzzy systems is shown by simulation.

- (16) **H. Gordan, A. Zare, S. Balochian, “A Simplified Architecture of Type-2 TSK Fuzzy Logic Controller for Fuzzy Model of Double Inverted Pendulums”, *Theory and Applications of Mathematics & Computer Science*, Vol. 2, No. 2, 2012 [216].**

This paper is proposed a novel inference mechanism for an interval type-2 Takagi–Sugeno–Kang fuzzy logic control system (IT2 TSK FLCS) by focusing on control applications for case both plant and controller use A2-C0 TSK models. The defuzzified output of the T2FLS is then obtained by averaging the defuzzified outputs of the resultant four embedded T1FLSs in order to reduce the computational burden of T2 TSK FS. A simplified T2 TSK FS based on a hybrid structure of four type-1 fuzzy systems (T1 TSK FS).

- (17) **D. Hildalgo, P. Melin, O. Castillo, “An optimization method for designing type-2 fuzzy inference systems based on the footprint of uncertainty using genetic algorithms”, *Expert Systems with Applications*, Vol. 39, No. 4, pp. 4590–4598, March 2012 [217].**

This paper proposed an optimization method for designing type-2 fuzzy inference systems based on the footprint of uncertainty (FOU) of the membership functions, considering three different cases to reduce the complexity problem of searching the parameter space of solutions. For the optimization method, the use of a genetic algorithm (GA) to optimize the type-2 fuzzy inference systems, considering different cases for changing the level of uncertainty of the membership functions to reach the optimal solution at the end is considered.

- (18) **K.J. Park, D.Y. Lee, “Genetic Design of Fuzzy Neural Networks Based on Respective Input Spaces Using Interval Type-2 Fuzzy Set”, *International Journal of Software Engineering and Its Applications*, Vol. 7, No. 5, pp. 15–24, 2013 [218].**

In this paper, the genetic design of fuzzy neural networks with multi-output based on interval type-2 fuzzy set (IT2FSFNNm) for pattern recognition is presented. IT2FSFNNm is the networks of combination between the fuzzy neural networks (FNNs) and interval type-2 fuzzy set with uncertainty. The premise part of the networks is composed of the fuzzy partition of respective input spaces and the consequence part of the networks is represented by polynomial functions with interval set. Also, a real-coded genetic algorithm to estimate the optimal values of the parameters of IT2FSFNNm is considered.

- (19) **D. D. Nguyen, L. T. Ngo, L. T. Pham, “Genetic Based Interval Type-2 Fuzzy C-Means Clustering”, *Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering*, Volume 109, pp. 239–248, 2013 [219].**

This paper deals with a genetic-based interval type 2 fuzzy c-means clustering (GIT2FCM), which automatically find the optimal number of clusters. A heuristic method based on a genetic algorithm (GA) is adopted to automatically determine the number of cluster based on the validity index. The proposed algorithm contains two main steps: initialize randomly the population of the GA and use the GA to adjust the cluster centroids based on the validity index which is computed by interval type 2 fuzzy c-means clustering (IT2FCM).

- (20) **O. Penangsang, M. Abdillah, R. S. Wibowo, A. Soeprijanto, “Optimal Design of Photovoltaic–Battery Systems Using Interval Type-2 Fuzzy Adaptive Genetic Algorithm”, *Scientific Research, Engineering*, Vol. 5, pp. 50–55, 2013 [220].**

This paper has proposed a new hybrid method to optimize Photovoltaic (PV)-Battery systems. The proposed method was named Interval type-2 fuzzy



adaptive genetic algorithm (IT2FAGA). Genetic algorithm (GA) has been successfully applied in various areas of power systems. To enhance the ability of GA to prevent trapping in local optima and increase convergence in a global optima, the crossover probability ( $p_{cross}$ ) and the mutation probability ( $p_{mut}$ ), parameters in GA, are tuned using interval type-2 fuzzy logic (IT2FL). The proposed method was also compared to fuzzy adaptive genetic algorithm (FGA) and standard genetic algorithm (SGA).

- (21) **D. Bernardo, H. Hagrass, E. Tsang, “A genetic type-2 fuzzy logic based system for the generation of summarised linguistic predictive models for financial applications”, *Soft Computing*, Volume 17, Issue 12, pp. 2185–2201, December 2013 [221].**

In this paper, a Genetic Type-2 Fuzzy Logic System (FLS) for the modeling and prediction of financial applications is proposed. In recent years computational intelligence techniques to develop predictive models for financial applications are applied. Some of the computational intelligence techniques like neural networks provide good predictive models, nevertheless they are considered as black box models which do not provide an easy-to-understand reasoning about a given decision or even a summary of the generated model. However, in the current economic situation, transparency became an important factor where there is a need to fully understand and analyze a given financial model. The proposed system in this paper is capable of generating summarized models from a specified number of linguistic rules, which enables the user to understand the generated financial model. The system is able to use this summarized model for prediction within financial applications. The proposed Genetic type-2 FLS has outperformed white box models like the Evolving Decision Rule procedure (which is a white based on Genetic Programming and decision trees) and gave a comparable performance to black box models like neural networks while the proposed genetic type-2 FLS provided a white box model which is easy to understand and analyze by the lay user.

- (22) **J.M. Mendel. *General type-2 fuzzy logic systems made simple: a tutorial. IEEE Transactions on Fuzzy Systems*. 2013 Nov 6;22(5):1162–82 [222].**

In this article, a comprehensive tutorial on general type-2 fuzzy logic systems is presented. The paper aims to provide an accessible and insightful guide for understanding the principles and applications of general type-2 fuzzy logic, a more expressive and flexible extension of traditional type-1 fuzzy logic. Mendel introduces the fundamental concepts, structure, and operations of general type-2 fuzzy logic systems,

highlighting their advantages in handling uncertainties and vagueness in real-world problems. Through detailed explanations and illustrative examples, the tutorial equips readers with the knowledge and tools necessary to implement and utilize general type-2 fuzzy logic systems effectively. The paper serves as a valuable resource for researchers, practitioners, and enthusiasts seeking a deeper understanding of advanced fuzzy logic methodologies.

- (23) **Z. Sun, N. Wang, Y. Bi. *Type-1/type-2 fuzzy logic systems optimization with RNA genetic algorithm for double inverted pendulum. Applied Mathematical Modelling*. 2015 Jan 1;39(1):70–85 [223].**

In this study, a novel approach for optimizing Type-1/type-2 fuzzy logic systems using an RNA genetic algorithm was proposed for the control of a double inverted pendulum system. The research, published in the *Applied Mathematical Modelling* journal, delves into the intricate process of enhancing the control system efficiency through the integration of fuzzy logic and evolutionary computation techniques. The utilization of RNA genetic algorithm facilitates the optimization of fuzzy logic systems, leading to improved performance in controlling complex and nonlinear systems like the double inverted pendulum. The findings from this research contribute to the advancement of control system design methodologies by demonstrating the effectiveness of integrating genetic algorithms with fuzzy logic systems in addressing challenging control problems.

- (24) **A. Starkey, H. Hagrass, S. Shakya, G. Owusu. *A multi-objective genetic type-2 fuzzy logic based system for mobile field workforce area optimization. Information Sciences*. 2016 Feb 1;329:390–411 [224].**

The paper presents a novel approach in the realm of mobile field workforce area optimization through the utilization of a multi-objective genetic type-2 fuzzy logic system. By harnessing the power of genetic algorithms and type-2 fuzzy logic, the study addresses the complexities of optimizing mobile workforce areas efficiently. The proposed system offers a unique perspective on tackling the challenges faced in field workforce management by considering multiple conflicting objectives simultaneously. The research results, published in the *Information Sciences* journal, showcase the effectiveness of the approach in enhancing the decision-making process for area optimization tasks. The findings shed light on the potential of integrating genetic algorithms and fuzzy logic in real-world applications, highlighting the importance of innovative computational techniques in addressing



complex optimization problems in mobile field workforce management.

- (25) **A. Téllez-Velázquez, H. Molina-Lozano, L.A. Villa-Vargas, R. Cruz-Barbosa, E. Lugo-González, I.Z. Batyrshin, I.J. Rudas. A feasible genetic optimization strategy for parametric interval type-2 fuzzy logic systems. *International Journal of Fuzzy Systems*, 20, 318–338, 2018 [225].**

They present a novel genetic optimization strategy tailored for enhancing parametric interval type-2 fuzzy logic systems. The study addresses the challenges of optimizing the parameters of such fuzzy systems by developing a feasible genetic algorithm approach. Through their research, they aim to improve the performance and effectiveness of interval type-2 fuzzy logic systems in handling uncertainty and complexity in real-world applications. The proposed optimization strategy demonstrates promise in optimizing the parameters, including centers, widths, and modifiers, of fuzzy logic systems, paving the way for more robust and efficient decision-making processes in uncertain environments.

- (26) **Y. Chen, D. Wang, W. Ning. Forecasting by TSK general type-2 fuzzy logic systems optimized with genetic algorithms. *Optimal Control Applications and Methods*. 2018 Jan;39(1):393–409 [226].**

This study presents a novel approach to forecasting using TSK general type-2 fuzzy logic systems optimized with genetic algorithms. The researchers explore the application of genetic algorithms to optimize the parameters of the TSK general type-2 fuzzy logic systems for improved accuracy in forecasting tasks. The methodology demonstrates promising results in predicting future outcomes by effectively utilizing the flexibility and adaptability provided by fuzzy logic systems and the optimization capabilities of genetic algorithms. The findings highlight the potential of integrating genetic algorithms with fuzzy systems for enhancing predictive modeling in various domains. This research contributes to the advancement of genetic fuzzy systems in the field of optimal control applications and methods.

- (27) **J.C. Guzmán, I. Miramontes, P. Melin, G. Prado-Arechiga. Optimal genetic design of type-1 and interval type-2 fuzzy systems for blood pressure level classification. *Axioms*. 2019 Jan 15;8(1):8 [227].**

The utilization of AI methods like fuzzy logic, neural networks, and evolutionary computation holds significant importance in the medical field for delivering efficient and timely diagnoses. Fuzzy logic application enables the creation of fuzzy classifiers comprising fuzzy rules and membership functions,

which are crafted based on expert knowledge. In this specific scenario, a Mamdani-type fuzzy classifier was constructed, featuring 21 rules, two inputs, and one output, aimed at classifying blood pressure levels using expert-derived fuzzy rules. Subsequently, diverse architectures were developed for classification in both type-1 and type-2 fuzzy systems, involving adjustments to the membership function parameters (triangular, trapezoidal, Gaussian) and optimization of fuzzy rules based on expert-defined ranges. The primary contribution of the research lies in the development of an optimized interval type-2 fuzzy system utilizing triangular membership functions. The final type-2 system achieved a superior classification rate of 99.408% compared to the previously developed type-1 classifier in the study "Design of an optimized fuzzy classifier for the diagnosis of blood pressure with a new computational method for expert rule optimization," which achieved 98%. Furthermore, the classification rate outperformed other architectures proposed in the research.

- (28) **K. Mittal, A. Jain, K.S. Vaisla, O. Castillo, J. Kacprzyk. A comprehensive review on type 2 fuzzy logic applications: Past, present and future. *Engineering Applications of Artificial Intelligence*. 2020 Oct 1;95:103,916 [228].**

The paper provides an insightful examination of the evolution, current trends, and potential future directions of type 2 fuzzy logic applications. The review delves into the historical progression of utilizing type 2 fuzzy logic in diverse domains, highlights its present-day applications, and offers a forward-looking perspective on the advancements shaping its future trajectory. By synthesizing existing literature, the paper contributes a holistic overview that sheds light on the significance and versatility of type 2 fuzzy logic within the realm of artificial intelligence and engineering applications, paving the way for enhanced understanding and innovation in this evolving field.

- (29) **M.M. Madbouly, E.A. El Reheem, S.K. Guirguis. Interval type-2 fuzzy logic using genetic algorithm to reduce redundant association rules. *J. Theor. Appl. Inf. Technol.* 2021 Jan 31;99(2):316–28 [229].**

In the realm of data mining, the synergy of fuzzy logic and genetic algorithms has opened new frontiers for refining association rules in databases. Madbouly et al. present a groundbreaking study where Interval Type-2 Fuzzy Logic is harnessed in combination with a Genetic Algorithm framework to effectively trim redundant association rules. Through a meticulous analysis detailed in their work published in the *Journal of Theoretical and Applied Information Technology*, the authors demonstrate the novel approach's efficacy

in enhancing the rule sets' quality and reducing rule redundancy. This research contributes significantly to the optimization of data mining processes, offering a promising method to streamline association rule mining tasks through a fusion of advanced computational techniques.

- (30) **I. Khan, M.S. Rahman Khan, P. Chandra Shill, A Quantum Genetic Algorithm Based Approach for Designing Membership Functions and Rule Sets for Type 2 Fuzzy Logic Controller, International Journal of Engineering Research and Management (IJERM), Vol. 9 [230].**

The Authors present an avant-garde study on evolutionary computation and quantum computing fusion in the context of fuzzy logic systems. Their research introduces a Quantum Genetic Algorithm (QGA) framework tailored for optimizing the design of membership functions and rule sets for Type-2 Fuzzy Logic Controllers. By harnessing the power of quantum-inspired operations within a genetic algorithm paradigm, the authors propose a novel approach to enhance the performance and robustness of fuzzy logic controllers. Their work contributes significantly to the evolution of genetic fuzzy systems, showcasing the potential synergy between quantum computing principles and genetic algorithms in tackling complex design challenges in fuzzy logic control systems.

- (31) **G. Bhandari G, R. Raj, P.M. Pathak, J.M. Yang. Robust control of a planar snake robot based on interval type-2 Takagi–Sugeno fuzzy control using genetic algorithm. Engineering Applications of Artificial Intelligence. 2022 Nov 1;116:105,437 [231].**

In the realm of robotics and control systems, Bhandari et al. present a pioneering study on the robust control of a planar snake robot leveraging Interval Type-2 Takagi–Sugeno Fuzzy Control with the aid of Genetic Algorithms. Published in Engineering Applications of Artificial Intelligence, this research delves into advancing control strategies for complex robotic systems. By integrating Interval Type-2 Fuzzy Control with the optimization capabilities of Genetic Algorithms, the authors propose a method to enhance the robustness and adaptability of the snake robot's control system. Their findings showcase the effectiveness of the approach in navigating the challenges of controlling a planar snake robot, underscoring the potential of genetic fuzzy systems in the domain of robotics.

- (32) **X. Feng, Y. Yu, X. Wang, J. Cai, S. Zhong, H. Wang, X. Han, J. Wang, K. Shi. A hybrid search mode-based differential evolution algorithm for auto design of the interval type-2 fuzzy logic sys-**

**tem. Expert Systems with Applications. 2024 Feb 1;236:121,271 [232].**

In the ever-evolving landscape of computational intelligence, Feng et al. present an innovative study focusing on automating the design process of Interval Type-2 Fuzzy Logic Systems using a Hybrid Search Mode-Based Differential Evolution Algorithm. Published in the esteemed journal Expert Systems with Applications, this research introduces a cutting-edge approach to enhancing the efficiency and accuracy in developing fuzzy logic systems. By integrating differential evolution techniques with hybrid search modes, the authors propose a method that automates the intricate design of Interval Type-2 Fuzzy Logic Systems. Their findings underscore the algorithm's effectiveness in optimizing system design, thereby presenting a significant contribution to the advancement of genetic fuzzy systems.

### 8.1.2 Genetic Type-2 Fuzzy System Books:

Any book by this title or by this topic as a main topic has not been published. Only two books exist that each one assigns one chapter to this issue. And another book that assigns a section to Genetic Type-2 Fuzzy Systems.

1) **L. Grigorie, an edition book, “Fuzzy Controllers, Theory and Applications”, February 2011 under CC BY-NC-SA 3.0 license [233]**

Chapter 7 of this book titled “Building an Intelligent Controller using Simple Genetic Type-2 Fuzzy Logic System” written by I.A. Hameed, C.G. Sorensen and O. Gree discusses about Genetic Type-2 Fuzzy systems.

In this chapter in order to reduce the computational burden of T2FS, a simplified T2FS based on a hybrid structure of four type-1 fuzzy systems (T1FS) and a genetic algorithm (GA) is introduced. Despite the advantages offered by type-2 fuzzy systems (T2FS) in handling uncertainties in control applications, one major problem that hinders its wide-spread implementation in real-time applications is its high computational cost. In addition to its rule in providing the system with adaptability to cope with changing conditions, a GA provides the system with a tool to detect and illustrate the amount of uncertainty incorporated in the system. In order to show the robustness and reliability of the new implementation, the developed approach is applied to: (a) control a non-linear multi-input multi-output (MIMO) system equipped with various types of uncertainties as an example of using T2FS in industrial applications, and (b) evaluate students' learning achievement as an example of using T2FS in decision support systems.

2) **O. Castillo, P. Melin, “Recent Advances in Interval Type-2 Fuzzy Systems”, Springer Briefs in Applied**

**Sciences and Technology-Computational Intelligence, 2012 [234].**

In Chapter 4 of this book titled “Overview of Genetic Algorithms Applied in the Optimization of Type-2 Fuzzy Systems” a representative review of optimizing type-2 fuzzy system using different kinds of GAs is offered to illustrate the advantages of using a bio-inspired optimization technique for automating the design process of type-2 fuzzy systems. This overview has showed the diversity of applications that has been achieved using GAs for type-2 fuzzy system optimization.

**3) Castillo O, Melin P, Kacprzyk J, editors. Intuitionistic and type-2 fuzzy logic enhancements in neural and optimization algorithms: Theory and applications. Springer Nature; 2020 Feb 27 [235].**

Within the comprehensive volume "Intuitionistic and Type-2 Fuzzy Logic Enhancements in Neural and Optimization Algorithms" edited by Castillo, Melin, and Kacprzyk (2020), a significant section is dedicated to Genetic Fuzzy Systems. This section delves into the integration of genetic algorithms with fuzzy logic methodologies, offering insights into the advancement of computational intelligence and optimization techniques. The exploration of Genetic Fuzzy Systems within the broader context of neural networks and optimization algorithms showcases the interdisciplinary nature of modern research in fuzzy systems and computational intelligence. This section serves as a valuable resource for researchers and practitioners seeking to delve deeper into the fusion of genetic algorithms and fuzzy logic for tackling complex real-world problems.

## 8.2 Genetic Intuitionistic Fuzzy System (GIFS)

Genetic Intuitionistic Fuzzy Systems (GIFS) represent a fusion of genetic algorithms with intuitionistic fuzzy logic, offering a robust framework for tackling complex decision-making problems. This innovative approach leverages the optimization capabilities of genetic algorithms and the uncertainty modeling of intuitionistic fuzzy logic to enhance the performance and adaptability of fuzzy systems. By dynamically evolving membership functions and rule sets through genetic operators, GIFS exhibit promising capabilities in handling imprecise and uncertain information. This survey explores the principles, applications, and advancements in Genetic Intuitionistic Fuzzy Systems, shedding light on their potential in addressing real-world challenges through a synergistic blend of genetic algorithms and intuitionistic fuzzy logic.

### 8.2.1 Genetic Intuitionistic Fuzzy System (GIFS) Papers

**1) F.L.F. Barbosa, M. Tham, J. Zhang, A.D. Quelhas “Human Operator Based Fuzzy Intuitive Controllers**

**Tuned with Genetic Algorithms”, Advanced Control of Chemical Processes, Vol. 7, No. 1, pp. 715–720, 2008 [236].**

The present research has offered an alternative control scheme that intends to be a step towards introducing a new technology for practical implementation in industry. The controller is developed aiming to emulate human operators’ actions when manually controlling SISO systems, subject to disturbances. The developed control scheme is based on an intuitive hypothetical model that describes the way human operators (HO) act in a manual control loop, generating the Human Operator Based Intuitive Controller (HOBIC). Since human operators typically use vague terms when describing control actions, it is natural to use fuzzy logic to express manual control actions. The HOBIC is then extended using the Fuzzy Logic theory. Membership functions within Fuzzy-HOBIC are tuned using a genetic algorithm (GA). The tuning does not require a process model. It is based on historical process operation data containing manual operation actions from experienced operators. The traditional GA is modified to cope with real valued optimisation variables and their constraints.

**2) X. XU, Y. LEI, W. DAI, “Intuitionistic Fuzzy Multi-Objective Programming Based on Genetic Algorithm”, Electronics Optics & Control Journal, Vol. 1, 2009 [237].**

In this paper a model of intuitionistic fuzzy multi-objective programming based on genetic algorithm is presented. First, membership and non-membership functions of object and constrain functions were defined. Then, by using intuitionistic fuzzy "min–max" operator, an intuitionistic fuzzy multi-objective programming model was proposed. Then, the model was resolved by genetic algorithm, so it is suitable for both linear and nonlinear condition. It is claimed that the performance of the presented intuitionistic fuzzy multi-objective programming is better than fuzzy multi-objective programming.

**3) G. Chen, X. Liao, X. Yu, Z. Luo, J. Li, “An Interval Intuitionistic Fuzzy Number Portfolio Selection Model Based on Genetic Algorithms”, International Review on Computers & Software, Vol. 6, Issue 7, pp. 1339–1343. 4p, December 2011 [238].**

This paper has discussed a mean absolute deviation portfolio selection model with interval intuitionistic fuzzy number. A method for ranking interval valued intuitionistic fuzzy numbers is presented, then the non-inferior solutions to such problems are defined based on order relations between interval valued intuitionistic fuzzy numbers. Consequently, the model can be transformed to a parametric nonlinear programming problem. To avoid the model's complexity and difficulty in solving the problems by using conventional methods, a genetic algorithm is designed in the paper.

**4) S. Senthamilarasu, M. Hemalatha. A genetic algorithm based intuitionistic fuzzification technique for**

**attribute selection. Indian Journal of Science and Technology. 2013 Apr 1:4336–46 [239].**

Senthilarasu and Hemalatha (2013) delve into the realm of attribute selection within data mining through a novel approach utilizing Genetic Algorithms and Intuitionistic Fuzzification. Their study, published in the Indian Journal of Science and Technology, introduces a cutting-edge technique that harnesses genetic algorithms for optimizing attribute selection processes. By incorporating intuitionistic fuzzification methods, the authors enhance the robustness and flexibility of attribute selection in data mining tasks. The proposed genetic algorithm-based approach offers a promising avenue for refining attribute selection strategies, showcasing the synergy between evolutionary computation and fuzzification techniques in improving data analysis methodologies.

**5) M. Goyal, D. Yadav, A. Tripathi. Intuitionistic fuzzy genetic weighted averaging operator and its application for multiple attribute decision making in E-learning. Indian Journal of Science and Technology. 2016 Jan 10 [240].**

Goyal, Yadav, and Tripathi (2016) present a significant contribution to the field of e-learning through the introduction of an Intuitionistic Fuzzy Genetic Weighted Averaging Operator for multiple attribute decision-making processes. Their research, published in the Indian Journal of Science and Technology, focuses on enhancing decision-making capabilities within the e-learning domain by integrating intuitionistic fuzzy logic and genetic algorithms. By developing a specialized operator that combines genetic algorithms' optimization capabilities with intuitionistic fuzzy sets' flexibility, the authors offer a robust framework for handling complex decision scenarios in e-learning environments. This work underscores the potential of genetic fuzzy systems in addressing decision-making challenges in technology-enhanced learning settings, paving the way for more effective and adaptive educational platforms.

**6) W. Zang, W. Zhang, W. Zhang, X. Liu. A kernel-based intuitionistic fuzzy C-Means clustering using a DNA genetic algorithm for magnetic resonance image segmentation. Entropy. 2017 Oct 27;19(11):578 [241].**

In their captivating study published in Entropy, Zang et al. (2017) introduce a novel approach to magnetic resonance image segmentation through the fusion of kernel-based intuitionistic fuzzy C-Means clustering and a DNA genetic algorithm. The research presents a cutting-edge methodology that harnesses the power of genetic algorithms inspired by DNA for optimizing the clustering process in image segmentation tasks. By integrating intuitionistic fuzzy logic with advanced genetic algorithms, the authors propose a robust and efficient technique for delineating distinct regions in magnetic resonance images. Their work showcases the potential of combining bio-inspired optimization

techniques with fuzzy clustering algorithms to enhance the accuracy and efficiency of image segmentation processes.

**7) P. Melin. Genetic optimization of type-1, interval and intuitionistic fuzzy recognition systems. Notes on Intuitionistic Fuzzy Sets. 2018;24:106–28 [242].**

Melin (2018) presents a notable contribution to the field of computational intelligence with a focus on Genetic Optimization of Type-1, Interval, and Intuitionistic Fuzzy Recognition Systems. Published in "Notes on Intuitionistic Fuzzy Sets," the study dives into the application of genetic algorithms to optimize the performance of various fuzzy recognition systems. By leveraging genetic optimization techniques, the author explores the enhancement of Type-1, Interval, and Intuitionistic fuzzy systems, shedding light on the efficacy and potential of genetic algorithms in fine-tuning the parameters of fuzzy recognition models. This research underscores the significance of genetic fuzzy systems in advancing pattern recognition methodologies and showcases the versatility of genetic algorithms in optimizing diverse types of fuzzy systems.

**8) P. Hajek, V. Olej. Intuitionistic fuzzy inference system with genetic tuning for predicting financial performance. In 2018 3rd International Conference on Computational Intelligence and Applications (ICCI) 2018 Jul 28 (pp. 81–86). IEEE [243].**

Hajek and Olej (2018) showcase a cutting-edge application of computational intelligence in financial forecasting by introducing an Intuitionistic Fuzzy Inference System (IFIS) with genetic tuning capabilities. Presented at the 2018 International Conference on Computational Intelligence and Applications, this research delineates a novel approach for predicting financial performance utilizing the fusion of intuitionistic fuzzy logic and genetic algorithms. The integration of IFIS with genetic tuning mechanisms offers a robust methodology for enhancing the accuracy and reliability of financial predictions. By leveraging the adaptive capabilities of genetic algorithms, the proposed system demonstrates promise in addressing the challenges of forecasting in dynamic financial environments. This study underscores the potential of genetic fuzzy systems in improving forecasting accuracy in the realm of financial performance analysis.

**9) R.J. Kuo, W.C. Cheng, W.C. Lien, T.J. Yang. Application of genetic algorithm-based intuitionistic fuzzy neural network to medical cost forecasting for acute hepatitis patients in emergency room. Journal of Intelligent & Fuzzy Systems. 2019 Jan 1;37(4):5455–69 [244].**

Kuo et al. (2019) present a noteworthy study focusing on the application of a Genetic Algorithm-Based Intuitionistic Fuzzy Neural Network for medical cost forecasting in emergency room scenarios, specifically targeting acute hepatitis patients. Published in the Journal of Intelligent & Fuzzy Systems, this research delves into the fusion of genetic algorithms, intuitionistic fuzzy logic, and neural networks



to enhance the accuracy and efficiency of medical cost predictions. By leveraging a hybrid computational approach, the authors tackle the complexities of forecasting medical costs for acute hepatitis patients, providing valuable insights into optimizing healthcare resource allocation and management. The study showcases the practical utility of genetic fuzzy systems in healthcare settings, underlining their potential for improving decision-making processes and patient care outcomes.

**10) R.J. Kuo, T.P. Nguyen. Genetic intuitionistic weighted fuzzy k-modes algorithm for categorical data. *Neurocomputing*. 2019 Feb 22;330:116–26 [245].**

In the domain of data clustering and analysis, Kuo and Nguyen (2019) present a novel approach, the Genetic Intuitionistic Weighted Fuzzy k-Modes algorithm, tailored specifically for handling categorical data. Published in *Neurocomputing*, this research explores the fusion of genetic algorithms, intuitionistic fuzzy logic, and the k-Modes clustering algorithm to address the unique challenges posed by categorical data clustering. The proposed algorithm introduces a sophisticated method for optimizing cluster assignments and membership weights in complex categorical datasets. By leveraging the power of genetic intuitionistic fuzzy systems, the authors demonstrate substantial improvements in clustering performance and accuracy. This work contributes significantly to advancing data analysis techniques, offering a promising avenue for efficient handling of categorical data in real-world applications.

**11) C. Zhang. Classification rule mining algorithm combining intuitionistic fuzzy rough sets and genetic algorithm. *International Journal of Fuzzy Systems*. 2020 Jul;22(5):1694–715 [246].**

Zhang (2020) presents a significant advancement in the field of computational intelligence through the development of a novel Classification Rule Mining Algorithm that integrates Intuitionistic Fuzzy Rough Sets with Genetic Algorithms. Published in the *International Journal of Fuzzy Systems*, this research showcases a hybrid approach that leverages the strengths of both Intuitionistic Fuzzy Rough Sets and Genetic Algorithms to enhance the efficiency and accuracy of classification rule mining processes. By merging these two distinct computational paradigms, the proposed algorithm offers a synergistic solution for handling complex datasets and extracting meaningful classification rules. Zhang's work contributes to the evolution of genetic fuzzy systems by offering a promising avenue for addressing classification challenges in the realm of fuzzy systems and data mining.

**12) R. Gojković, G. Đurić, D. Tadić, S. Nestić, A. Aleksić. Evaluation and selection of the quality methods for manufacturing process reliability improvement—Intuitionistic fuzzy sets and genetic algorithm approach. *Mathematics*. 2021 Jun 29;9(13):1531 [247].**

Gojković et al. (2021) present a pioneering study in the realm of manufacturing process reliability improvement, focusing on the evaluation and selection of quality methods. Their research introduces a novel approach that integrates Intuitionistic Fuzzy Sets with Genetic Algorithms to address the complex task of enhancing process reliability. Published in *Mathematics*, this work details the application of advanced computational techniques in optimizing quality methods for manufacturing processes. By leveraging the synergy between Intuitionistic Fuzzy Sets and Genetic Algorithms, the authors demonstrate the efficacy of their approach in streamlining the selection process and improving reliability. This research offers valuable insights into the potential of genetic fuzzy systems in tackling real-world challenges in industrial settings.

**13) R.J. Kuo, C.K. Chang, T.P. Nguyen, T.W. Liao. Application of genetic algorithm-based intuitionistic fuzzy weighted c-ordered-means algorithm to cluster analysis. *Knowledge and Information Systems*. 2021 Jul;63(7):1935–59 [248].**

In the realm of cluster analysis, Kuo et al. (2021) introduce a pioneering study that combines Genetic Algorithms with Intuitionistic Fuzzy Weighted C-Ordered-Means Algorithm to enhance clustering processes. Published in *Knowledge and Information Systems*, this research presents an innovative approach to clustering analysis by incorporating genetic algorithm-based optimization techniques with fuzzy logic. The integration of intuitionistic fuzzy sets and weighted c-ordered-means algorithm demonstrates significant improvements in clustering accuracy and robustness. The authors' work sheds light on the potential of Genetic Fuzzy Systems in addressing complex data clustering tasks, highlighting the synergy between genetic algorithms and fuzzy logic for advanced knowledge discovery in data analytics.

**14) R. Paramanik, S.K. Mahato, N. Kumar, N. Bhattacharyee, R.K. Gupta. Optimization of system reliability for multi-level RAPs in intuitionistic fuzzy atmosphere using genetic algorithm. *Results in Control and Optimization*. 2022 Dec 1;9:100,175 [249].**

Paramanik et al. (2022) present a pioneering study on optimizing system reliability for multi-level Risk Assignment Problems (RAPs) in an intuitionistic fuzzy environment leveraging Genetic Algorithms. Published in *Results in Control and Optimization*, this research delves into enhancing system reliability under uncertain conditions using advanced computational techniques. By applying Genetic Algorithms within an intuitionistic fuzzy framework, the authors propose a method to improve the reliability of complex systems with multi-level RAPs. Their findings underscore the efficacy of the Genetic Algorithm-based approach in optimizing system reliability and mitigating risks in uncertain environments, offering valuable



insights for decision-makers and analysts navigating reliability challenges.

**15) N. Kumar, H. Kumar, D. Sharma. Hybrid fuzzy clustering technique to enhance the performance based on a fusion of intuitionistic modified fuzzy c-means and improved genetic algorithm. *International Journal of Data Science and Analytics*. 2023 Dec 14:1–24 [250].**

In the realm of data science and analytics, Kumar, Kumar, and Sharma (2023) present a cutting-edge study on enhancing clustering performance through a Hybrid Fuzzy Clustering Technique. Their research introduces a fusion approach that combines the Intuitionistic Modified Fuzzy C-Means algorithm with an Improved Genetic Algorithm, designed to optimize clustering results. Published in the *International Journal of Data Science and Analytics*, their work showcases the effectiveness of this novel hybrid methodology in improving clustering accuracy and efficiency. By merging the strengths of fuzzy clustering and genetic algorithm optimization, the authors provide a significant contribution to the field, offering a promising avenue for enhancing data analysis processes.

### 8.2.2 Genetic Intuitionistic Fuzzy System (GIFS) Books

**1) O. Castillo, P. Melin, J. Kacprzyk, editors. Intuitionistic and type-2 fuzzy logic enhancements in neural and optimization algorithms: Theory and applications. *Springer Nature*; 2020 Feb 27 [235].**

The book is a compendium of cutting-edge research encompassing the synergy between intuitionistic and Type-2 fuzzy logic with neural networks and optimization algorithms. This volume delves into the theoretical foundations and practical applications where fuzzy logic paradigms play a pivotal role in enhancing computational intelligence techniques. Covering a wide array of topics, from neural network design to optimization strategies, the book provides a comprehensive overview of the latest advancements in the field. Researchers and practitioners in the realms of fuzzy systems, neural networks, and optimization algorithms will find this book to be a valuable resource for exploring novel approaches and applications within the domain of genetic fuzzy systems.

### 8.3 Genetic Type-3 Fuzzy System

Genetic Type-3 Fuzzy Systems represent a cutting-edge advancement in the realm of computational intelligence, extending beyond traditional Type-1 and Type-2 fuzzy systems. These systems incorporate higher levels of uncertainty and abstraction, enabling them to model complex and dynamic systems more effectively. By integrating genetic algorithms with Type-3 fuzzy logic, researchers aim to

enhance the flexibility, adaptability, and robustness of fuzzy systems in dealing with intricate real-world problems. The evolution from Type-1 to Type-3 fuzzy systems signifies a paradigm shift towards accommodating and leveraging greater degrees of uncertainty and imprecision, thus offering promising avenues for addressing challenging decision-making tasks in diverse domains.

**1) Melin P, Sánchez D, Castillo O. Interval Type-3 Fuzzy Inference System Design for Medical Classification Using Genetic Algorithms. *Axioms*. 2023 Dec 20;13(1):5 [251].**

In their recent publication featured in "Interval Type-3 Fuzzy Systems: Theory and Design," Castillo, Castro, and Melin (2022) delve into the realm of Interval Type-3 Fuzzy Logic Systems (IT3FLS). This seminal work explores the intricacies and applications of IT3FLS, offering a comprehensive overview of this advanced fuzzy logic paradigm. By elucidating the theoretical foundations and design principles of IT3FLS, the authors shed light on the potential for leveraging higher-order uncertainty in practical decision-making scenarios. The insights presented in this work not only enrich the understanding of fuzzy systems but also pave the way for innovative applications in domains requiring robust handling of complex uncertainties. This contribution stands as a significant milestone in the evolution of fuzzy logic systems, emphasizing the importance of Interval Type-3 Fuzzy Logic in addressing contemporary challenges in decision support and control systems.

**2) Castillo O, Castro JR, Melin P. Interval type-3 fuzzy logic systems (IT3FLS). *Interval Type-3 Fuzzy Systems: Theory and Design 2022 Mar 14 (pp. 45–98). Cham: Springer International Publishing [252].***

Melin, Sánchez, and Castillo (2023) present a cutting-edge research study focusing on the design of an Interval Type-3 Fuzzy Inference System for medical classification tasks employing Genetic Algorithms. Published in *Axioms*, this research explores the application of advanced fuzzy logic techniques in the domain of medical data analysis. By integrating Genetic Algorithms into the design process, the authors propose an innovative approach to enhance the accuracy and interpretability of medical classification systems. Their work highlights the potential of Interval Type-3 Fuzzy Inference Systems in improving the decision-making process in medical diagnostics. This study contributes significantly to the field of genetic fuzzy systems, offering valuable insights into the synergies between fuzzy logic and evolutionary computation methodologies in medical applications.

## 9 Conclusion Remarks

The integration of Genetic Algorithms (GAs) with fuzzy systems in Genetic Fuzzy Systems (GFSs) has emerged as a significant research area over the past decades, offering a versatile framework for knowledge representation and modeling. GAs excel in encoding diverse structures, including weights, features, and rule parameters, enabling the evolution of multiple models of knowledge representation within a single system. This flexibility empowers researchers to design specific genetic components tailored to evolving specialized representations, thereby fostering innovation in fuzzy modeling and optimization.

Although the hybridization of fuzzy systems with GAs has been a fruitful avenue of exploration, particularly in evolving rule bases and optimizing fuzzy models, there remains untapped potential in extending this synergy to novel fuzzy concepts like Z-Numbers and Composite Weights-based fuzzy systems. The application of GAs to these emerging fuzzy paradigms presents a compelling opportunity for future research endeavors, offering new avenues for advancing the capabilities and applicability of Genetic Fuzzy Systems.

Exploring the integration of GAs with cutting-edge fuzzy concepts such as Z-Numbers and Composite Weights-based fuzzy systems holds promise for enhancing the robustness, interpretability, and decision-making capabilities of GFSs in complex and uncertain environments. By delving into these uncharted territories and developing tailored genetic components for evolving these novel fuzzy aspects, researchers can unlock new dimensions of knowledge representation and optimization within the realm of Genetic Fuzzy Systems.

In conclusion, the fusion of Genetic Algorithms with advanced fuzzy paradigms in GFSs presents a rich landscape for future research endeavors, calling for interdisciplinary collaborations and innovative methodologies to push the boundaries of intelligent systems modeling and optimization. The unexplored territory of applying GAs to new fuzzy aspects beckons researchers to embark on a journey of discovery, paving the way for transformative advancements in the field of Genetic Fuzzy Systems.

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## Declarations

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**Consent to Participate** It is not applicable.

**Consent for Publication** It is not applicable.

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