Genetic Fuzzy System in Hybridization

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Abstract—Genetic Algorithms (GAs) are general-purpose search algorithms which use moralities stimulated by usual population genetics to afford solutions to problems. Among the system variables, this fuzzy system in itself is a broad domain to model for interactions and relationships. The population enthused towards better solutions by smearing genetic operators such as crossover and alteration. In each generation, auspicious solutions generate offspring that replaces the inferior characters. Crossover hybridizes the genetic factor of two parent chromosomes in order to exploit the search universe and constitutes the foremost genetic operator in GAs. Mutation is used to preserve the assortment of the gene pool. An evaluation or capability function plays the role of the environment to differentiate between good and bad clarifications. This paper explains the different techniques of hybridization in GFS for understanding machine learning. In complex spaces, genetic algorithms are empirically confirmed to provide vigorous search aptitudes.

Keywords—*Genetic Fuzzy System, Iterative Rule Learning Approach, Layers of GFS, Michigan Approach, Pittsburgh Approach.*

I. INTRODUCTION

Computational Intellect techniques such as artificial neural networks, fuzzy logic and genetic algorithms (GAs) are current exploration focuses, since they can deal with intricate engineering problems which are grim to solve by conventional methods.

Hybrid approaches have concerned substantial attention in the computational intelligence community. One of the furthermost prevalent approaches is the hybridization amid fuzzy logic and GAs prominent to genetic fuzzy systems (GFSs). A GFS is basically a fuzzy system enlarged by a learning progression based on evolutionary computation, which contains genetic algorithms, genetic programming, and evolutionary strategies, among additional evolutionary algorithms (EAs).

A Genetic Fuzzy System is built by using genetic algorithms, increased by a learning development founded on evolutionary computation. [13] It includes genetic algorithms, genetic programming, and evolutionary strategies, which caricaturist the process of natural evolution, to identify its structure and parameter.

Fig. 1 shows the framework of Hybridization of intelligence techniques where dissimilar techniques like Fuzzy Logic, Neural Networks, Evolutionary Computation, Probabilistic Reasoning, etc. are closely coupled together.

In the area of intellectual verdict support system, major application extents are taking rewards of machine learning methods, especially Genetic-Fuzzy hybridization. An appraisal during research in the area of innumerable designed requests is familiar. This investigation covers several important applications domains where the appliance intelligence is mandatory to be built. The real life applications of wide-ranging fields such as cataloging, remedy, control systems, automation, travel industry, stock, and share, schmoozing, etc., employ hybrid structures of GFS in demand to achieve augmented rule learning.

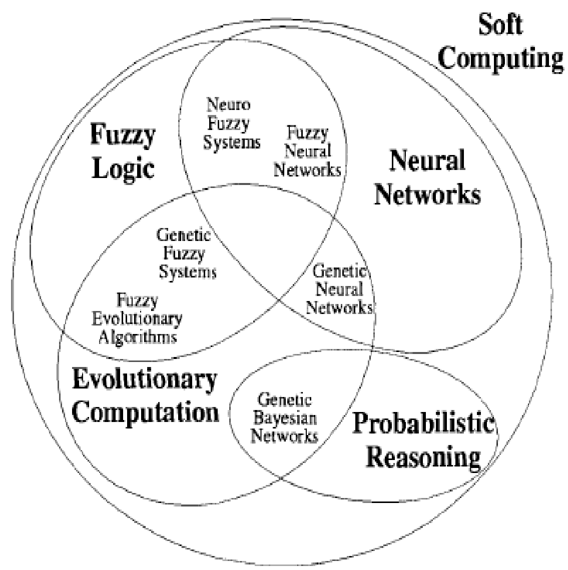

Fig.1. Framework of Hybridization of intelligence techniques.

In the pitch of artificial intelligence, Genetic Algorithms are exploration heuristics, based on usual genetics that distribute robust search competencies in complex universes. This heuristic is usually used to generate useful determinations to optimization and pursuit glitches. [6] Analysis of the literature shows that the most protuberant types of Genetic Fuzzy Systems are Genetic Fuzzy Rule Based Systems (GFRBSs). Fig. 2 shows the concept of a system where genetic design and fuzzy processing are the two ultimate constituents. It is possible to differentiate among parameter optimization or rule generation procedure, that is, adaptation and learning.

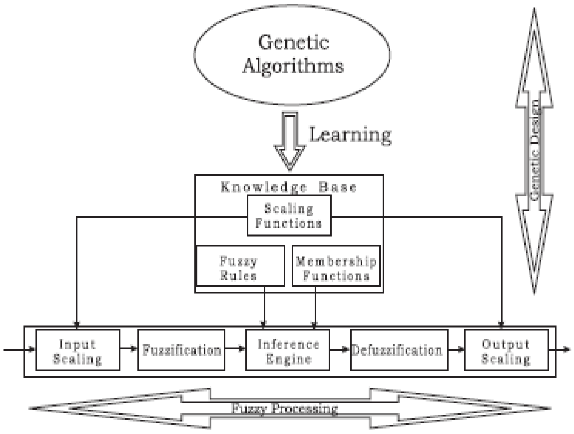

Fig.2. Genetic Design and Fuzzy Processing

II. GENETIC FUZZY SYSTEMS

A GFS is essentially a fuzzy system increased by a learning process based on evolutionary computation, which embraces any method of EC intimate such as genetic algorithms, genetic programming and evolutionary strategies. The most intensive GFS sort is that the Genetic Fuzzy Rule based mostly System (GFRBS), wherever GA is active to be told or tune (optimizing parameter) completely different elements of a Fuzzy Rule based mostly System (FRBS). within the style of GFS, a GA is employed to appear up the thought of the mathematical logic controller (FLC) however the presentation of FLC depends on its Knowledgebase (KB) entailing info (DB) and Rule base (RB).

In order to achieve the design of FRBS, tasks such as designing interpretation mechanism as well as a generation of the fuzzy rule set (KB or FRB) are obligatory to be gratified. FRBSs are not able to learn themselves, but require the KB to be derivative from practiced knowledge. In order to eradicate such limitation, the evolutionary learning process becomes important to employ to mechanize FRBS design.

By utilizing this type of learning process FRBS can be well-defined automatically. [11] The quantified type of design can be painstaking as an optimization or search problem. In order to solve optimization problems, GAs are selected due to major capabilities such as:

- Being global search method, GAs can discover large a search space;
- Able to find near ideal solutions in complex search spaces;
- Able to provide generic code assembly and independent performance.

Due to the above mentioned capabilities, it is possible to incorporate a priori information in GA which may be in form of linguistic variable, fuzzy membership function parameters, fuzzy rules, etc.

Fig.3 illustrates the general structure of Genetic Fuzzy Rule Based System. The design of GFRBS is constituted using three layers which are clarified as under.

A. Interface Layer

The bottom layer of the Genetic-Fuzzy Rule based mostly System is baptized as an associate degree interface layer. it's serene of 3 major components: surroundings, FRBS and Output Interface. This layer is essentially organized exploitation input interface, a distinction with a fuzzy system and treated output of FRBS. Here, the input interface describes the members of a submission domain and interrelate with FL layer which is responsible for designing and implementing the fuzzy system.

B. FL Layer

The middle layer of the Genetic Fuzzy Rule Based System is termed as FL layer. It interacts through the interface layer to have input variables. This layer consists of many components such as Fuzzification Interface, Inference Mechanism and Defuzzification Interface. This layer is liable to design the processes which are associated with fuzzy system implementation. The input interface resolves the affiliates or the variables of the solicitation domain in order to produce fuzzification. The inference mechanism is designed using the adherents which are nominated in the input interface and will be complicated in the progression of generating the FRBS. The output interface is accountable for defuzzification of input variables. It offers the results fashioned by Fuzzy System (FS).

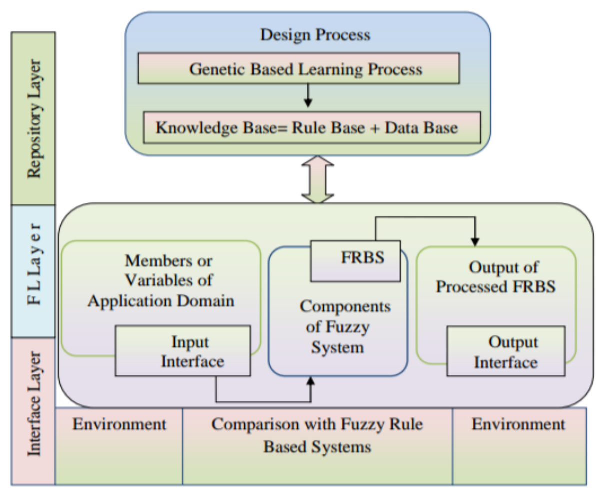

Fig.3. General Structure of Genetic Fuzzy Rule Based System

C. Repository Layer

The top most layer of the Genetic Fuzzy Rule Based System is entitled as repository layer. [8] This layer is responsible for scheming of FRBS. In order to design, GFRBS, evolutionary techniques are required to be united in order to realize automatic generation or alteration of entire part of the Knowledge Base (KB). KB is a mixture of Data Base (DB) and Rule Base (RB). The strictures of knowledgebase include fuzzy rules and membership functions. Both the constituents intermingle with inference mechanism of the middle layer. In order to achieve optimization, it is essential to find an applicable KB.

III. TECHNIQUES OF HYBRIDIZATION FOR GFS

Although GA was not precisely designed for erudition, they are used as global search algorithms. Apart from the searching task, they do offer a usual of recompenses for machine learning. Many methods for machine learning are based on the rifle of a virtuous model and they are very malleable because the same GA can be used with different depictions [10]. In a rule based system, to achieve chore of learning rules, there are two major styles obtainable to encode rules within popular of individuals of GA as shown in Fig.4 Style 1: The ‘‘Chromosome = Rule’’ Approach In the style 1, each discrete arranges a single rule, and the entire rule set is provided by merging some individuals in a population recognized as rule cooperation or via dissimilar evolutionary runs known as rule competition. For example, the Michigan approach and the Iterative Rule Learning (IRL) approach are descriptive approaches of Style 1.

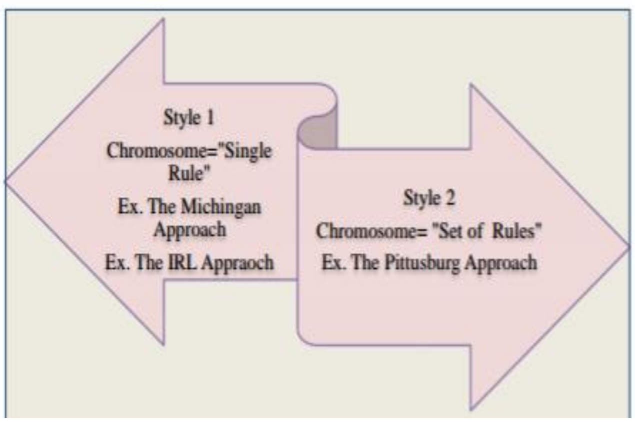

Fig.4. Popular Styles of Rule Encoding in Genetic-Fuzzy Hybrid Systems

Style 2: The Chromosome = Set of Rules Approach, in style 2, each discrete represents a rule set so it is widely known as the “Chromosome = Set of rules”. In this situation, [1] a chromosome evolves a whole RB and they strive among them along with the evolutionary process. E.g. the Pittsburgh approach is the descriptive approach of style 2. In order to afford rule based learning process with diverse levels of complications, the evolutionary algorithm provides three major approaches for developing such rule systems namely the Michigan Approach, the Pittsburg Approach, the Iterative Rule Learning (IRL) approach as shown in Fig.5.

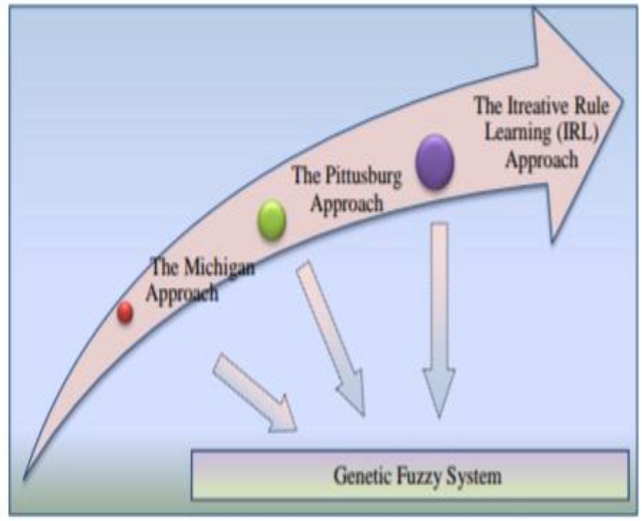

Fig.5. Major Approaches for Genetic Fuzzy System

A. Michigan Approach-Classifier System

Learning Classifier System (LCS) is a machine learning method which syndicates underpinning learning, evolutionary computing and other heuristics to return adaptive systems. This attitude signifies “Chromosome=rule” approach is directive to make populations of rules repeatedly, Classifier Systems (CSs) or production rule systems are intended. Learning Classifier Systems are a kind of rule-based system with common devices for dispensation the rules in parallel, for adaptive generation of innovative rules and for testing the usefulness of existing rules. These gadgets make a possible appearance and learning without the “fragile” features of the most proficient systems in AI. CSs typically activate in environments that demonstration one or more of the following characteristics:

- A Large amount of irrelevant or noisy data can be incorporated;
- Uninterrupted real time mandatory for action;
- Implicit or ambiguous goals.

Fig.6. shows the comparison of a traditional expert system and classifier system along with features of each of them. CSs are altered than traditional expert systems by providing numerous benefits such as rules are desirable to design by knowledge engineer in expert system whereas in Classifier System (CS), classifier rules are caused by a GA. In the expert system, rules are kept and processed in a modest way as well as no other parameter for rule system are presented to calculate rule forte, as well as an evolution of it, cannot be achieved. Each classifier has to permit through recital evaluation system and have a strength parameter; a number is allotted to each classifier, after that.

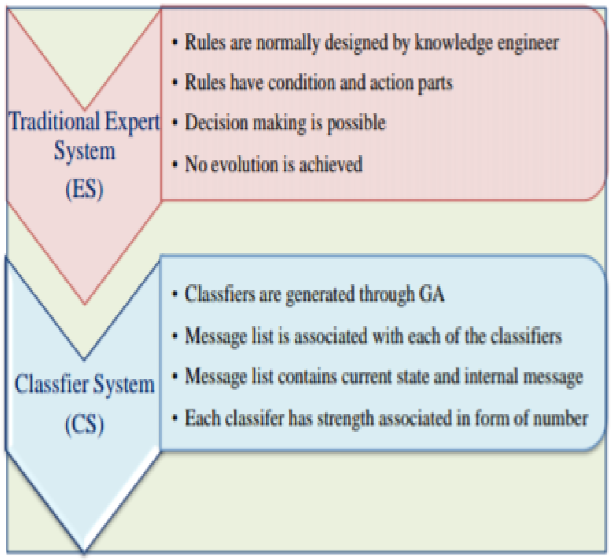

Fig.6. Comparison of Traditional Expert System and Classifier System

The prototype association of Classifier Systems (CSs) is tranquil of three sub systems which are described as shown below:

- A production system with a rule base which routes received messages from the environment and directs output messages to the environment.
- A design of credit system which accepts pay-off from the environment and regulates which rules had been responsible for the feedback.
- A Genetic Algorithm which recombines prevailing rules and familiarizes new rules. Fig.7. illustrated above mentioned subsystems along with the major task of respectively one.

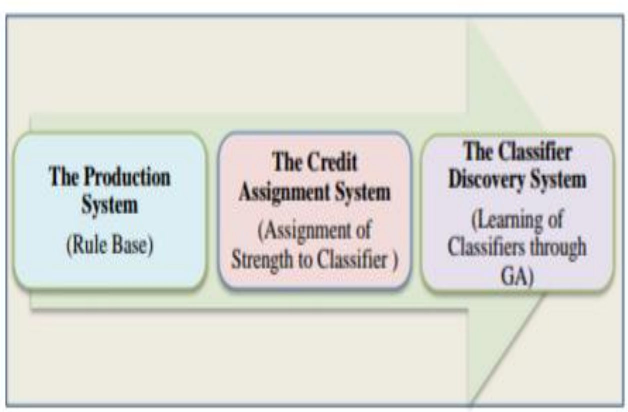

Fig.7. Subsystems of Classifier Systems (CS)

After instigating the above sub-systems, the working of classifier system is concise as below: The working of classifiers is reinforced through the Credit Assignment (CA) system. Basically, a GA chooses high suitability classifiers as parents forming offspring by recombining gears from the parent classifiers.[9] Here, traditional fitness function of GA is not recycled; instead, the fitness of a classifier is firm by strength premeditated with the CA system. In distinctive CS implementations, from the set of classifiers, high strength classifiers create the GA population. The scheme of GA is to replace the vilest set of classifiers by newly fashioned strong classifiers. Due to this approach, the high concert of the classifier can be achieved.

In GFS, the fuzzy inference system is symbolized by the entire population having numerous rules contributing. In order to propose the best action, these rules are in endless competition and cooperate to form a competent fuzzy system. Identification of the specific rules liable for good system behavior is a very problematic task. This task requires the design of fitness function proficient of measuring the goodness of a solitary fuzzy rule as well as the eminence of its cooperation with other fuzzy rules in the population to give the greatest action as an output. Here, the GA is used to adapt the fuzzy relational medium of a one-input, one output fuzzy model using fuzzy relation matrix rather than the verdict table.

1. Limitations of the Michigan Approach

The major limitations of the Michigan approach area unit bestowed as follows:

a) Online rule learning process is realized in which every single rule is manipulated and hence requires an intense analysis of the concert of every rule. Such a system can familiarize to varying environmental circumstances automatically. In this case, the rule is altered every time.

b) The other limitation pragmatic is: the Michigan approach based association may fail if occupied with the complex environment; i.e. there is only a low prospect that important state orders are observed repeatedly.

c) Further, this approach represents the knowledge of a single individual that learns through contact with the environment and later being adapted to it rather than to fruition of possible solutions in form of rules.

B. Pittsburgh Approach

The dominant idea is to impart acumen through evolution. In this approach, an evolution can be created through competition amid the individuals and adaptation to the situation. This approach is mostly tailored for preparation in both inductive and non-inductive problems. In the Pittsburgh approach, each distinct represents a whole entity of knowledge and due to this type of construction; different entities do not require interacting with one alternative for the evaluation of the knowledge. Fig.8 represents the block diagram of subsystems of Pittsburg rule learning approach.

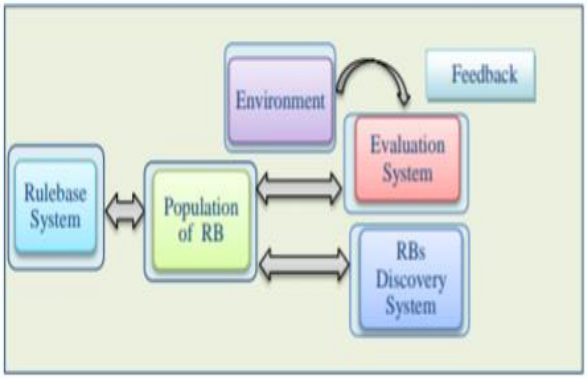

Fig.8.Subsystems of the Pittsburg Rule Learning Approach

1) The major components are described as follows:

a) Rule base and the Population of RBs

In order to produce the learning process, it is required to generate a population of probable solutions to the tricky. The population of potential solutions is deliberate from RBs through a common processing structure to resolve a specific problem. Each RB in the population is estimated by applying it to solve the problem. [2] Response is generated from the environment. Each RB is evaluated independently and no communication between entities of the population occurs during the estimation. To start the learning process, an original population of RB is prerequisite.

b) Evaluation System

This evaluation of RB is based on the result of the interaction of the rule based system, smearing the corresponding RB, with the environment. As a result of this interaction, the environment makes a feedback that is used by the evaluation system to create the estimate of the RB. The evaluation [4] is fairly different depending on the application and the environment. The evaluation system often becomes the most time consuming element of the process. Here, larger computational exertions for independent assessments are required; hence this approach is free from skirmishes, generated as an upshot of interaction.

c) Rule Base Discovery System

Once the process of evaluation of population of RB is completed, new RBs are to be searched, and, RB discovery system is to be introduced. This scheme generates a new population along with a set of the genetic operator to the earlier generation.

d) Level of Replacement

In the Michigan approach, the number of swapped individuals at each cohort has to be low adequate to reservation the system performance, as it is the result of the communication between the individuals whereas in Pittsburgh approach the performance of the best individual is attained and consequently due to that performance, there can endure steady as long as the best individual is preserved.

e) Timing of Evaluation and Discovery

In the Michigan approach, detection is applied with a lower incidence than credit assignment. [12] In this approach, continuous learning is made possible to reach a firm state situation before making a new generation while the Pittsburg approach gears predefined training cycle which has to be useful for each specific in the population. Consequently, the discovery phase takes place after a whole training cycle for each individual.

C. Iterative Rule Learning Approach (IRL)

The major drawback of the Michigan approach and the Pittsburg approach is the ingesting of an enormous amount of computer memory for penetrating abundant fuzzy rules. To overawe the above stated problem, an iterative rule learning approach (IRL) is intended. The IRL (Iterative Rule Learning) approach is built on the approach of “Chromosome is ruled”. [3] The major reason to change this approach is to assimilate the best features of Michigan and the Pittsburg approaches. In this approach, a new rule is added to the rule set, in an iterative fashion, for each run of GA.

This approach works by uniting the styles of Michigan and the Pittsburg approaches [15] Alike to the Michigan approach, each chromosome in the population characterizes a single rule, but similar to the Pittsburg approach, only the finest individual are measured to form part of the final solution. As a result of this kind of computation, the generated RB finally discards the residual chromosomes in the population. Therefore, in the iterative model, the GA provides an incomplete solution to the problem of learning and it is recurring multiple times to obtain the wide-ranging set of rules. Fig.9 represents sub components of IRL which are discussed as follows:

a) Criterion for selecting the best rule in each iteration

This component is used to regulate the good procedures. The selection criteria about the rule forte are also offered which includes a number of instances covered, gauges of consistency of the rule or criteria of effortlessness.

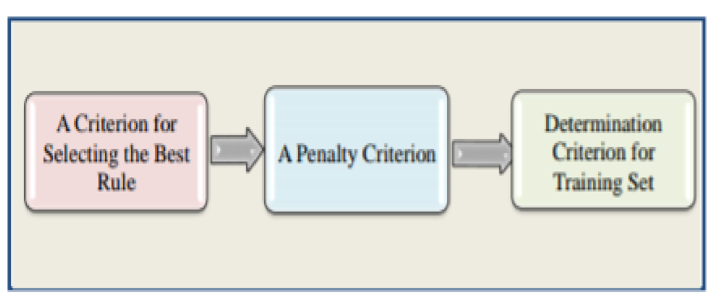

Fig.9. Sub Components of IRL

b) Penalty Criterion

This component of criterion is often allied, though it is not indispensable, with the purging of the examples covered by the earlier rules.

c) Determination Criterion

This component is used to govern the assurance about the inclusiveness of the set of rules. [5] It starts working when sufficient rules are available to signify the examples in the training set. The core functionality of this component is to check whether all the samples in the training set are appropriately covered or not.

Advantages offered by IRL Approach:

- The significant benefit of IRL is that it decreases the search space, because in each categorization of iterations, the learning method only explorations for a distinct best rule instead of the entire RB.
- This approach cartels the speediness of the Michigan approach with the effortlessness of the capability appraisal of the Pittsburgh approach.
- The Michigan approach offers online learning for non-inductive erudition problems whereas IRL approach simplifies off line inductive learning problems.

IV. CURRENT TRENDS IN GENETIC FUZZY SYSTEM

The current trends in genetic fuzzy system are given below:

a) Multiobjective genetic learning of FRBSs: interpretability-meticulousness trade-off.
b) GA-based methods for mining fuzzy association rules and unusual data mining approaches.
c) Learning genetic replicas based on low eminence data (noise data and vague data).
d) Genetic learning of fuzzy partitions and perspective adaptation.
e) Genetic adaptation of insinuation engine components [14].

V. CONCLUSION

The consequence of hybridization of soft computing approaches in order to design solution for real life solicitations with desired features. [7] The techniques of Genetic-Fuzzy pairing square measure structured victimization 2 prevailing kinds of encoding: “Chromosome is ruling approach and body is ready for rule approach”. The hybridization of Genetic-Fuzzy approaches is effectual in order to attain rule learning in an optimized approach and hence can be one of the furthermost appropriate methods for the machine learning. The significant opinion also says that there is not any generic framework yet established for problem lacking mathematical formulation using genetic fuzzy hybrid approach demand to achieve optimization for rule learning. The research exertion is a step towards the identical.

VI. FUTURE WORK

The hybridization between fuzzy systems and GAs in GFSs became a vital research area during the preceding decade. GAs allows us to signify dissimilar kinds of structures such as weights, features composed of rule parameters, etc., allowing us to code several models of knowledge illustration. This provides an extensive change of approaches where it is required to design exact genetic components for sprouting a specific depiction. Nowadays, it is an advanced research area, where researchers need to imitate in order to development towards strengths and distinctive structures of the GFSs, providing useful advances in the fuzzy systems model.

ACKNOWLEDEMENT

These papers explain the different kind of approaches for user learning. These layers are efficient for variants of application domain for users.

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