learning.

The classification of any input pattern into the class depends on the measured maximum degree of association corresponding to the rule for that pattern. In the case of similarities, the random classification of pattern shall be done.

The objectives of fuzzy systems like Accuracy and interpretability depends on the maximum association degree of Pattern classified into a class corresponding to high dimensional rule base. During the design of fuzzy classifier, interpretability and accuracy are two main objectives which are opposite in nature i.e. one objective can be enhanced on the cost of another one. This condition is well known as I-A tradeoff.

In [52], problem of high dimensionality has been addressed with fuzzy clustering approach. A fuzzy classifier has been developed using MATLAB with evolutionary multi-objective optimization.

3. Interpretability-Accuracy Tradeoff

Interpretability is primarily focused in the Mamdani Fuzzy Systems (Linguistic Fuzzy modeling) and Accuracy is concentrated in Takagi-Sugeno-Kang Fuzzy Systems (Precise Fuzzy Modeling) [11]. A major research issue in area of developing evolutionary Fuzzy systems is to obtain many fuzzy systems on the arc of I-A tradeoff and out of that find out any one having a fine trade off.

The improvement of the objectives either Interpretability or Accuracy depends upon requirement of modeling, some modeling applications instead of focusing separately on accuracy or interpretability; require an optimum level of interpretability and accuracy. This will direct to I-A trade off. In [50], a survey on the I-A trade-off has been carried out in Evolutionary Multi-Objective Fuzzy Systems. This paper introduces the basic concepts of Evolutionary Multi-Objective Fuzzy Systems.

If complexity of any system is High then the Accuracy of system will be High and Interpretability will be Low and If the complexity of any system is Low then the Accuracy of system will be Low and Interpretability will be High. This condition is known as I-A tradeoff. [12] To deal with such tradeoff situation, multi objective optimization algorithms are used in the fuzzy systems design which is discussed in next section of this paper.

A classification of various issues related to multi objective optimization, taking in to account I-A trade off has been discussed in [13].

The two objective based approaches for I-A using EMO having major focus of feature selection and granularity learning is discussed in [14] and the accuracy of classification and number of rules is discussed in [15].

During Handling I-A tradeoff using EMO, tuning of membership functions and rule selection is a very important area discussed in [16-26]. Sum of antecedent conditions and root mean squared error [27], Fine fuzzy partition, and number of antecedent rule [28] are also major focus area for consideration during trade off.

In similar way there are so many classifications like three objectives based approach, Ensemble Classifiers, User preference, High dimensional problems, semantic coin tension and context adaptation having different focus areas of attributes for handling of I-A tradeoff in EMO algorithms.

4. Multi Objective Evolutionary Algorithm In Fuzzy Classifiers

To deal with the problems related to multi objective optimization evolutionary algorithms are highly capable, because evolutionary algorithms consists an approach based on population to get multiple solutions in single run. These algorithms are also capable to deal with huge uncertain and complex search space.

During design of fuzzy systems, handling of I-A tradeoff is identified as a multi objective optimization problem. Evolutionary multi objective optimization includes integration of any of the approach like genetic algorithm [29], evolution strategies [30], genetic programming [31] and evolutionary programming [32] to deal with multi objective problems.

There are two generations of MOEA, the first generation having features, fitness sharing and niching incorporated with the rank of Pareto. Non-dominated Sorting Genetic Algorithm (NSGA) [33], Niched Pareto Genetic Algorithm (NPGA) [34], and Multi-Objective Genetic Algorithm (MOGA) [35] are first generation MOEAs.

Second generation MOEA are incorporated with the idea of elitism. The method of generating a new population practically is to enable the best rule from existing generation to carry forward to the next without any alteration. This approach is called as elitist selection and guarantees that the quality of the output obtained by genetic algorithm will not be decremented in the next generation.

Few MOEAs of Second generation are Strength Pareto Evolutionary Algorithm (SPEA) [36], Strength Pareto Evolutionary Algorithm 2 (SPEA2) [37], Pareto Achieved Evolution Strategies (PAES) [38], Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [39], Niched Pareto Genetic Algorithm-II (NPGA-II) [40], Pareto Envelop based Selection Algorithm (PESA) [41], Micro Genetic Algorithm [42, 43].

5. Methodologies Related To Design Attributes Of A Fuzzy System

During design of fuzzy systems, generation and selection of rule are major factor to deal with I-A tradeoff. In a high dimensional fuzzy system, as and when inputs are joined, the rule numbers in rule base increase invariably, which result in increase of complexity and decrease of interpretability.

Fuzzy rule selection process using multi-objective genetic local search is defined in [44]. In this paper, two evaluation measures namely support and confidence have been discussed. These two measures are generally used in the area of data mining.

A method using numerical data for improving the fuzzy system design involving self generation and simplification process has been discussed in [45]. On the basis of fuzzy rules, difficulties with quantification of interpretability have been discussed in [46].

The many objectives (namely reliability, compactness, accuracy and transparency) optimization methodology is proposed in [47] for linguistic fuzzy modeling based on heuristic fully automated identification algorithms.

Many other methodologies for improving Interpretability-Accuracy simultaneously are discussed in [48, 49], which are mainly related to design attributes like rules and rule bases.

Type-2 fuzzy systems are much more capable to deal with fuzzy systems of type-1 because the fuzzy sets of type-2 have one extra dimension to deal with uncertainty. Interval fuzzy sets of type-2 are used to develop fuzzy knowledge base systems in [51], which are simpler than fuzzy systems of type-2. The implementation has been done using genetic algorithms. The interpretable fuzzy systems with improved accuracy are reviewed in [53].

6. Conclusion and Future Scope

In the design of fuzzy systems, output may be obtained by applying various rules into input variables, but there is huge number of permutations and combinations for the selection of the rule to find out the desired outcome. I-A tradeoff is identified as major issue in any fuzzy systems design.

A review and survey of I-A tradeoff, including multi-objective optimization, evolutionary algorithms, rule generation and selection, association degree, membership functions, fuzzy partitions etc is done in this paper.

In future, discovery and invention of new approaches for better I-A tradeoff, resulting improvement in the fuzzy systems design specifically for problems pertaining to classification i.e. fuzzy classifiers.

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