Multiobjective Genetic Fuzzy Systems: Review and Future Research Directions

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Abstract— **Evolutionary algorithms have been successfully used in many studies to design accurate and interpretable fuzzy systems under the name of genetic fuzzy systems. Recently evolutionary multiobjective algorithms have been used for interpretability-accuracy tradeoff analysis of fuzzy systems. We first review a wide range of related studies to multiobjective genetic fuzzy systems. Then we illustrate multiobjective design of fuzzy systems through computational experiments on some benchmark data sets. Finally we point out promising future research directions.**

I. Introduction

Since fuzzy systems are universal approximators of nonlinear functions [1]-[3] as neural networks [4]-[6], theoretically we can improve their approximation accuracy on training data to an arbitrarily specified level by increasing their complexity. For such an accuracy improvement task, evolutionary algorithms have been successfully used under the name of genetic fuzzy systems [7]-[9] since the early 1990s [10]-[15]. Whereas learning techniques of neural networks such as the back-propagation algorithm were used mainly to fine-tune continuous parameters of fuzzy systems in neuro-fuzzy systems [16]-[19], evolutionary algorithms can be used to perform not only parameter tuning but also discrete optimization such as input selection, rule generation, rule selection and fuzzy partition. In those studies on genetic fuzzy systems and neuro-fuzzy systems, learning tasks can be viewed as the following optimization problem:

$$\text{Maximize } Accuracy(S), \tag{1}$$

where S is a fuzzy system, and $Accuracy(S)$ is an accuracy measure (e.g., classification rate).

The main advantage of fuzzy systems over other non-linear models such as neural networks is their linguistic interpretability. Accuracy improvement of fuzzy systems, however, often leads to deterioration in their interpretability. Since the late 1990s, the importance of interpretability in the design of fuzzy systems has been pointed out by some studies [20]-[31]. In other words, complexity minimization as well as accuracy maximization was taken into account to design accurate and interpretable fuzzy systems. Whereas accuracy maximization and complexity minimization were simultaneously considered, the single-objective optimization framework based on the following scalarizing objective function was used in those studies:

$$\text{Optimize } f(S) = f(Accuracy(S), Complexity(S)), \tag{2}$$

where $f(S)$ is a scalarizing objective function (i.e., a scalar fitness function), which combines an accuracy measure $Accuracy(S)$ and a complexity measure $Complexity(S)$. In some studies, the scalarizing objective function in (2) can be more appropriately written as

$$\text{Optimize } f(S) = f(Accuracy(S), Interpretability(S)), \tag{3}$$

where $Interpretability(S)$ is an interpretability measure.

An example of the scalarizing objective function $f(S)$ in (2) is the following weighted sum objective function [32]:

$$\text{Maximize } f(S) = w_1 \cdot Accuracy(S) - w_2 \cdot Complexity(S), \tag{4}$$

where $\mathbf{w} = (w_1, w_2)$ is a non-negative weight vector. The number of correctly classified training patterns and the number of fuzzy rules were used as an accuracy measure and a complexity measure in [32], respectively.

One difficulty in the weighted sum-based approach is that the specification of an appropriate weight vector is not easy and problem-dependent whereas the finally obtained fuzzy system strongly depends on its specification. Almost all the above-mentioned studies with scalarizing objective functions share similar difficulties (i.e., it is not easy to determine an appropriate scalarizing objective function).

Whereas a single fuzzy system is obtained from single-objective approaches, a large number of non-dominated fuzzy systems are obtained in multiobjective approaches by solving the following multi-objective problem:

$$\text{Maximize } Accuracy(S) \text{ and minimize } Complexity(S). \tag{5}$$

For example, a two-objective fuzzy rule selection method was proposed in [33] to search for non-dominated fuzzy classifiers with respect to the maximization of the number of correctly classified training patterns and the minimization of the number of fuzzy rules.

In [34], not only the number of fuzzy rules but also the total number of antecedent conditions (i.e., the total rule length) was minimized. In this case, the multi-objective problem in (5) can be rewritten as follows:

$$\text{Maximize } Accuracy(S) \text{ and}$$
$$\text{minimize } Complexity^1(S) \text{ and } Complexity^2(S), \tag{6}$$

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where $Complexity^1(S)$ and $Complexity^2(S)$ are complexity measures.

The basic idea of multiobjective approaches is to search for a number of non-dominated fuzzy systems with different tradeoffs between accuracy and complexity. This idea is illustrated in Fig. 1 where each ellipsoid denotes a fuzzy system. Simple and inaccurate fuzzy systems are located in the upper left part of this figure while complicated and accurate ones are in the lower right part. There exist a large number of non-dominated fuzzy systems along the accuracy-complexity tradeoff curve. Multiobjective approaches try to search for non-dominated fuzzy systems as many as possible. Evolutionary multiobjective optimization algorithms [35]-[37] are used for this task.

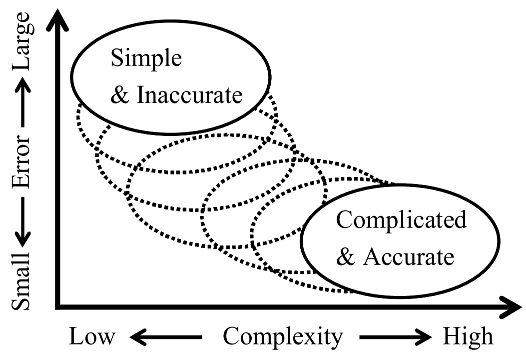


Fig. 1. Non-dominated fuzzy systems along the accuracy-complexity tradeoff curve.

Evolutionary multiobjective optimization (EMO) is one of the most active research areas in the field of evolutionary computation. A large number of EMO algorithms have been proposed in the literature [35]-[37]. Among them, NSGA-II [38], SPEA [39], and SPEA2 [40] are well-known and frequently-used EMO algorithms. Those EMO algorithms share some common ideas (with different implementation schemes) such as Pareto ranking-based fitness evaluation, diversity maintenance, and elitism.

The main advantage of EMO algorithms over non-evolutionary techniques in the field of multi-criteria decision making (MCDM [41]) is that a number of non-dominated solutions with a wide range of objective values can be simultaneously obtained by their single run. On the contrary, multiple runs are required when we try to find a number of non-dominated solutions using MCDM techniques.

II. Related Studies to Multiobjective Genetic Fuzzy Systems

In this section, we briefly review a wide range of related studies to multiobjective genetic fuzzy systems in various research areas. Of course, our review is far from exhaustive. See [7]-[9] for genetic fuzzy systems, [42], [43], [51] for interpretability-accuracy tradeoff of fuzzy systems, [44] for multiobjective approaches in machine learning, and [45] for multiobjective data mining.

A. *Multiobjective Genetic Fuzzy Rule Selection*

Two-objective genetic fuzzy rule selection for the design of fuzzy classifiers [33], which is a multiobjective version of weighted sum-based rule selection [32], is one of the earliest studies on multiobjective genetic fuzzy systems. In [33], first a large number of candidate fuzzy rules were extracted from numerical data by a heuristic rule extraction procedure. Then an 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 the extracted candidate rules. 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. Since 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 [33] was extended to a three-objective one in [34] 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 [46]. The same three-objective formulation as in [34], [46] was used for non-fuzzy rule selection in [47].

B. *Multiobjective Fuzzy Genetics-Based Machine Learning*

Studies on genetics-based machine learning algorithms are often divided into two classes: Pittsburgh and Michigan approaches (for example, see [48]-[50] for GBML and [7]-[9], [51] for fuzzy GBML). A rule set is handled as an individual in the Pittsburgh approach while a single rule is handled as an individual in the Michigan approach. The finally obtained rule set is usually the best individual in the final population in the Pittsburgh approach while it is the final population in the Michigan approach. Another category of GBML is an iterative rule learning approach [26], [52], [53] 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. Multiobjective GBML algorithms have usually been 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. A rule set is represented by a concatenated string. A substring 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 [34]. A Pittsburgh-Michigan hybrid fuzzy GBML algorithm [54] was generalized as a multiobjective one for interpretability-accuracy tradeoff analysis in [55]. Other examples of multiobjective fuzzy GBML algorithms are found in [42]-[44], [56], [57] where various aspects of fuzzy systems are adjusted by EMO algorithms (e.g., input selection, membership function tuning, and rule selection). Multiobjective GBML algorithms were also implemented for non-fuzzy classifier design (e.g., [58]).

C. Evolutionary Multiobjective Data Mining

Evolutionary algorithms have been applied in the field of knowledge discovery and data mining in various manners [50]. EMO algorithms have been used for two different tasks: One is to search for Pareto-optimal rules and the other is to search for Pareto-optimal rule sets.

In data mining techniques such as Apriori [59], *support* and *confidence* have frequently been used for rule evaluation. Other rule evaluation criteria, however, were also proposed. Among them are *gain*, *variance*, *chi-squared value*, *entropy gain*, *gini*, *laplace*, *lift*, and *conviction* [60]. It was shown for non-fuzzy rules that the best rule according to any of these measures is a Pareto-optimal rule of the following two-objective rule discovery problem [60]:

$$\text{Maximize } \{ Support(R)\,,\ Confidence(R) \}, \tag{7}$$

where R denotes a single rule.

The use of NSGA-II [38], which is a well-known and frequently-used EMO algorithm, was proposed in [61], [62] to search for Pareto-optimal classification rules of the two-objective problem in (7). A dissimilarity measure between classification rules was used in [63] 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 [64] in order to search for not only Pareto-optimal classification rules but also near Pareto-optimal dominated ones. Similar multiobjective formulations to (7) were used to search for Pareto-optimal association rules [65] and Pareto-optimal fuzzy association rules [66]. In [67], the tradeoff 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 multiobjective 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 [68], the use of Pareto-optimal fuzzy rules as candidate rules was examined in rule selection.

D. Evolutionary Multiobjective Feature Selection

Feature selection [69] is an important issue in modeling, classification, knowledge discovery and data mining. The basic idea of multiobjective feature selection is to minimize the size of a subset of features and maximize its performance. There exists a clear tradeoff relation between the size of feature subsets and their performance on training data. Evolutionary multiobjective feature selection was discussed in some studies (e.g., [70]-[72]). Feature selection was also discussed in the context of multiobjective genetic fuzzy systems [73].

E. Evolutionary Multiobjective Clustering

Fuzzy clustering [74] has frequently been used for fuzzy rule generation. In evolutionary multiobjective clustering [75]-[78], multiple measures of cluster quality are optimized simultaneously. Evolutionary multiobjective clustering will play a very important role in multiobjective 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 [79], [80]. Several methods have been proposed for generating multiple classifiers such as bagging [81] and boosting [82]. 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 [83]-[86]. 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 [87]. Feature selection was used for neural network ensemble design in [88], [89].

G. Multiobjective Neural Network Design

In addition to ensemble design, EMO algorithms have also been used for multiobjective 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 [90]. Non-dominated radial basis function (RBF) networks of different sizes were generated in [91]. A multiobjective memetic algorithm was used to speed up the back-propagation algorithm in [92] where a number of neural networks of different sizes were evolved to find an appropriate network structure.

H. Multiobjective Genetic Programming

As in fuzzy systems and neural networks, there exists a clear tradeoff relation between training data accuracy and the size of trees in genetic programming. Multiobjective genetic programming has been discussed in some studies [93]-[97]. Multiobjective genetic programming is a promising tool for the multiobjective design of tree-structured fuzzy systems.

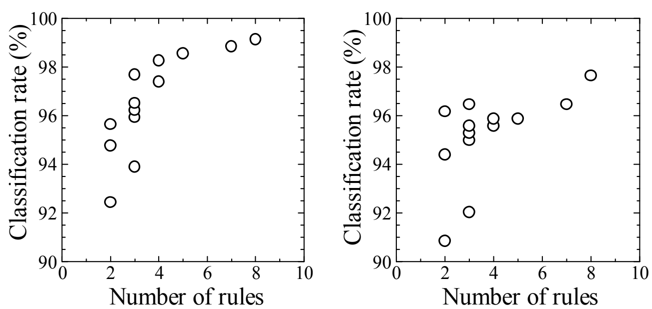
III. Illustration of Evolutionary Multiobjective Design of Fuzzy Systems

Through computational experiments on some data sets in the UCI machine learning repository, we show advantages of multiobjective approaches over single-objective ones. In our computational experiments, first we divided each data set into two subsets of the same size: training data and test data. Next we generated candidate fuzzy rules from training data. Then we performed three-objective genetic fuzzy rule selection to search for non-dominated rule sets (i.e., fuzzy classifiers) using training data. Finally the accuracy of each of the obtained non-dominated rule sets was evaluated for training data and test data.

Experimental results are shown in Fig. 2 and Fig. 3. It should be noted that all the non-dominated rule sets denoted by open circles in each figure were obtained by a single run of three-objective genetic fuzzy rule selection. In each figure, the left and right plots show the classification rates on training data and test data, respectively. As shown in Fig. 2 (a) and Fig. 3 (a), similar tradeoff curves were obtained on training data for many data sets. On the other hand, totally different tradeoff curves were obtained on test data as shown in Fig. 2 (b) and Fig. 3 (b). This observation suggests that the choice of an appropriate complexity with the highest generalization ability is problem-dependent.

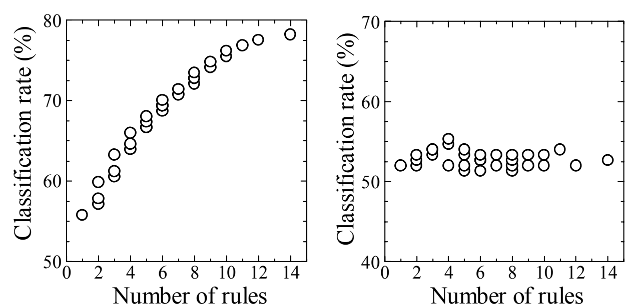
Since a large number of rule sets were obtained by a single run of a multiobjective approach, we can perform tradeoff analysis as in Fig. 2 and Fig. 3. When we use a single-objective approach, we can not efficiently perform such tradeoff analysis because only a single rule set is obtained from its single run.

The choice of a final rule set from a large number of obtained non-dominated ones depends on the preference of a user. For example, simple rules may be chosen when he/she thinks that the interpretability of fuzzy systems is much more important than their accuracy (e.g., Fig. 4).



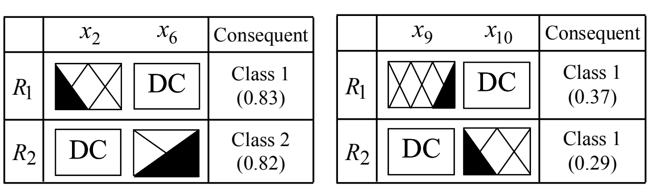
(a) Training data accuracy. (b) Test data accuracy.

Fig. 2. Obtained rule sets for the Wisconsin breast cancer data [68].



(a) Training data accuracy. (b) Test data accuracy.

Fig. 3. Obtained rule sets for the Cleveland heart disease data [68].



(a) Wisconsin breast cancer data. (b) Cleveland heart disease data.

Fig. 4. Examples of obtained non-dominated rule sets [98].

IV. FUTURE RESEARCH DIRECTIONS

One important issue is the formulation of interpretability of fuzzy systems as complexity measures. Various aspects are related to their interpretability (e.g., the number of inputs, the number of rules, rule length, fuzzy partition granularity, membership function separability, etc.). See [42], [43], [99], [100] for further discussions on interpretability. If we use those aspects as separate objectives, fuzzy system design is formulated as a many-objective problem. Pareto ranking-based EMO algorithms, however, do not work well on such a problem with many objectives [101], [102].

Another issue is theoretical analysis for maximizing the generalization ability of fuzzy systems. As shown in Fig. 2 and Fig. 3, multiobjective genetic fuzzy systems can be used for empirical analysis. Theoretical analysis such as statistical learning theory [103] seems to be required. Regularization methods can be discussed as multiobjective problems [104].

Incorporation of user's preference is a hot issue in the EMO community [105], [106]. User's preference will be incorporated in multiobjective design of fuzzy systems. The use of multiobjective clustering and multiobjective genetic programming will be also examined soon. Finally we need efficient tricks for the handling of large data sets by evolutionary algorithms (e.g., stratification [107]). Parallel algorithms seem to be a promising research direction.

V. CONCLUSIONS

First we briefly reviewed a wide range of related areas to multiobjective genetic fuzzy systems. Then we illustrated advantages of multiobjective approaches to the design of fuzzy systems over single-objective ones. Finally we pointed out promising future research directions.

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