Evolutionary Multiobjective Fuzzy System Design

Hisao Ishibuchi
Osaka Prefecture University
1-1 Gakuen-cho, Naka-ku
Sakai, Osaka 599-8531, Japan
+81-72-254-9350
hisaoi@cs.osakafu-u.ac.jp

Yusuke Nojima
Osaka Prefecture University
1-1 Gakuen-cho, Naka-ku
Sakai, Osaka 599-8531, Japan
+81-72-254-9198
nojima@cs.osakafu-u.ac.jp

ABSTRACT
This paper briefly reviews genetic algorithm-based approaches to the design of fuzzy systems. In the 1990s, genetic algorithms were mainly used for the accuracy maximization of fuzzy systems. Various aspects of fuzzy systems were optimized by genetic algorithms such as the fuzzy partition of each input variable, the number of fuzzy rules, and the consequent part of each fuzzy rule. The accuracy maximization of fuzzy systems for training data, however, tends to increase their complexity. That is, the accuracy maximization often degrades the interpretability of fuzzy systems through the increase in their complexity. Some studies in the late 1990s tried to find a good tradeoff (i.e., compromise) between the accuracy and the complexity of fuzzy systems. The latest trend in the design of fuzzy systems is their evolutionary multiobjective design. A number of non-dominated fuzzy systems with different accuracy-complexity tradeoffs can be obtained by a single run of multiobjective approaches. In this paper, we briefly review the above-mentioned main stream of research on fuzzy system design.

Keywords
Fuzzy rules, fuzzy systems, genetic algorithms, evolutionary multiobjective optimization, multiobjective design.

1. INTRODUCTION
The main advantage of fuzzy systems over other nonlinear models such as neural networks is their interpretability. Fuzzy systems are understood through linguistic interpretation of each fuzzy rule. As a result, interpretability maximization has been an important goal in fuzzy system design. Accuracy maximization has also been an important goal as in other machine learning techniques. In this paper, we explain how these two conflicting goals have been handled in genetic algorithm-based approaches to the design of fuzzy systems.

2. ACCURACY MAXIMIZATION
Genetic algorithms have been successfully used to improve the accuracy of fuzzy systems under the name of genetic fuzzy systems [3], [7], [8] since the early 1990s [18], [21], [22]. Let S be a fuzzy system (i.e., a set of fuzzy rules). Then the learning task in those studies can be viewed as the following optimization problem:

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

where $Accuracy(S)$ is an accuracy measure (e.g., classification rate in the case of the design of fuzzy classification systems).

In the early 1990s, learning techniques of neural networks such as the back-propagation algorithm were also frequently used to improve the accuracy of fuzzy systems in neuro-fuzzy systems [9], [15]. Whereas continuous parameters were fine-tuned in neuro-fuzzy systems, genetic algorithms were used to perform not only parameter tuning but also discrete optimization such as input selection, rule generation, rule selection and fuzzy partition.

3. COMPLEXITY MINIMIZATION
It is well known that the accuracy maximization of learning systems for training data often leads to the decrease in their generalization ability for test data. Thus the determination of the optimal complexity with the maximum generalization ability has been an important research issue in machine learning (especially in statistical learning theory [1]). In the design of fuzzy systems, complexity minimization was discussed in the late 1990s not only for improving their generalization ability but also for increasing their interpretability [13], [17], [20]. Fuzzy system design in those studies can be viewed as the following optimization problem:

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

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 $Complexity(S)$.

An example of the scalarizing objective function $f(S)$ in (2) is the following weighted sum objective function [13]:

$$\text{Maximize } f(S) = w_1 \cdot Accuracy(S) - w_2 \cdot Complexity(S), \tag{3}$$

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 [13], respectively. Genetic algorithms were used to simultaneously perform the accuracy maximization and the complexity minimization.

One difficulty in the weighted sum-based approach in (3) 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).

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4. MULTIOBJECTIVE DESIGN

Whereas a single fuzzy system is obtained from (3) in single-objective approaches, a large number of non-dominated fuzzy systems are obtained in multiobjective approaches by solving the following multiobjective problem:

$$\text{Maximize } Accuracy(S) \text{ and minimize } Complexity(S). \tag{4}$$

For example, two-objective fuzzy rule selection was proposed in [10] 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 [11], [12], [14], not only the number of fuzzy rules but also the total number of antecedent conditions (i.e., the total rule length) was minimized. That is, the multiobjective problem in (4) was modified by using two complexity measures as follows:

$$\text{Maximize } Accuracy(S) \text{ and minimize } Complexity^1(S) \text{ and } Complexity^2(S). \tag{5}$$

The basic idea of multiobjective approaches is to search for a number of non-dominated fuzzy systems with different accuracy-complexity tradeoffs. Multiobjective genetic algorithms [4] have been used for this task.

5. FUTURE RESEARCH ISSUES

Recently multiobjective approaches have also been used in other areas such as neural networks, genetic programming, data mining, and input selection [5], [6], [16]. Since the accuracy maximization and the complexity minimization are main goals in the design of almost all learning systems, multiobjective approaches will become more popular in various areas related to machine learning. One future research issue is the formulation of interpretability of fuzzy systems. Another interesting research issue is the scalability improvement of genetic algorithm-based approaches to huge data sets. Parallel distributed implementation [19] seems to be a promising direction toward the scalability improvement.

6. CONCLUSIONS

This paper briefly reviewed the main stream of genetic algorithm-based approaches to fuzzy system design. For more complete reviews on genetic fuzzy systems, see [3], [7], [8]. A complete list of multiobjective genetic fuzzy systems is available in [2].

7. REFERENCES

[1] Cherkassky, V., and Mulier, F. *Learning from Data: Concepts, Theory, and Methods*. John Wiley & Sons, 1998.

[2] Cococcioni, M. The EMO of FRBSs Bibliography Page. http://www2.ing.unipi.it/~o613499/emofrbss.html

[3] Cordon, O., Gomide, F., Herrera, F., Hoffmann, F., and Magdalena, L. Ten years of genetic fuzzy systems: Current framework and new trends. *Fuzzy Sets and Systems* 141, 1 (2004) 5-31.

[4] Deb, K. *Multi-Objective Optimization Using Evolutionary Algorithms*, John Wiley & Sons, 2001.

[5] Ghosh, A., Dehuri, S., and Ghosh, S. (Eds.) *Multi-Objective Evolutionary Algorithms for Knowledge Discovery from Data Bases*, Springer, Berlin, 2008.

[6] Ghosh, A., and Nath, B. T. Multi-objective rule mining using genetic algorithms. *Information Sciences* 163 (2004) 123-133.

[7] Herrera, F. Genetic fuzzy systems: Status, critical considerations and future directions. *International Journal of Computational Intelligence Research* 1, 1 (2005) 59-67.

[8] Herrera, F. Genetic fuzzy systems: Taxonomy, current research trends and prospects. *Evolutionary Intelligence* 1, 1 (2008) 27-46.

[9] Horikawa, S., Furuhashi, T., and Uchikawa, Y. On fuzzy modeling using fuzzy neural networks with the back-propagation algorithm. *IEEE Trans. on Neural Networks* 3, 5 (1992) 801-806.

[10] Ishibuchi, H., Murata, T., and Turksen, I. B. Single-objective and two-objective genetic algorithms for selecting linguistic rules for pattern classification problems. *Fuzzy Sets and Systems* 89, 2 (1997) 135-150.

[11] Ishibuchi, H., Nakashima, T., and Murata, T. Three-objective genetics-based machine learning for linguistic rule extraction. *Information Sciences* 136, 1-4 (2001) 109-133.

[12] Ishibuchi, H., and Nojima, Y. Analysis of interpretability-accuracy tradeoff of fuzzy systems by multiobjective fuzzy genetics-based machine learning. *International Journal of Approximate Reasoning* 44, 1 (2007) 4-31.

[13] Ishibuchi, H., Nozaki, K., Yamamoto, N., and Tanaka, H. Selecting fuzzy if-then rules for classification problems using genetic algorithms. *IEEE Trans. on Fuzzy Systems* 3, 3 (1995) 260-270.

[14] Ishibuchi, H., and Yamamoto, T. Fuzzy rule selection by multi-objective genetic local search algorithms and rule evaluation measures in data mining. *Fuzzy Sets and Systems* 141, 1 (2004) 59-88.

[15] Jang, J. -S. R. ANFIS: Adaptive-network-based fuzzy inference system. *IEEE Trans. on Systems, Man, and Cybernetics* 23, 3 (1993) 665-685.

[16] Jin, Y. (ed.) *Multi-Objective Machine Learning*, Springer, 2006.

[17] Jin, Y., von Seelen, W., and Sendhoff, B. On generating FC^3 fuzzy rule systems from data using evolution strategies. *IEEE Trans. on Systems, Man, and Cybernetics - Part B* 29, 6 (1999) 829-845.

[18] Karr, C. L. Design of an adaptive fuzzy logic controller using a genetic algorithm. *Proc. of 4th ICGA* (1991) 450-457.

[19] Nojima, Y., Ishibuchi, H., and Kuwajima, I. Parallel distributed genetic fuzzy rule selection. *Soft Computing* (in press).

[20] Setnes, M., Babuska, R., and Verbruggen, B. Rule-based modeling: Precision and transparency. *IEEE Trans. on Systems, Man, and Cybernetics - Part C* 28, 1 (1998) 165-169.

[21] Thrift, P. Fuzzy logic synthesis with genetic algorithms. *Proc. of 4th ICGA* (1991) 509-513.

[22] Valenzuela-Rendon, M. The fuzzy classifier system: A classifier system for continuously varying variables. *Proc. of 4th ICGA* (1991) 346-353.