Evolutionary Multiobjective Optimization and Multiobjective Fuzzy System Design

Hisao Ishibuchi
Department of Computer Science and Intelligent Systems, Osaka Prefecture University
1-1 Gakuen-cho, Naka-ku, Sakai, Osaka 599-8531, Japan
Phone: +81-72-254-9350
hisaoi@cs.osakafu-u.ac.jp

ABSTRACT
Evolutionary multiobjective optimization (EMO) is one of the most active research areas in evolutionary computation. EMO algorithms have been successfully used in various application areas. Among them are multiobjective design of neural networks and fuzzy systems. Especially, fuzzy system design has often been discussed as multiobjective problems. This is because we have two conflicting objectives in the design of fuzzy systems: accuracy maximization and complexity minimization. In this paper, we first explain some basic concepts in multiobjective optimization, a basic framework of EMO algorithms and some hot research issues in the EMO community. Next we explain EMO-based approaches to the design of fuzzy systems. We demonstrate through computational experiments that a large number of non-dominated fuzzy systems with different accuracy-complexity tradeoffs can be obtained by a single run of an EMO algorithm. Then we describe the use of EMO algorithms in other areas such as neural networks, genetic programming, clustering, feature selection, and data mining.

Categories and Subject Descriptors
I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *Heuristic Methods.*

General Terms
Algorithms.

Keywords
Evolutionary multiobjective optimization (EMO), many-objective optimization, fuzzy rule-based systems, multiobjective design, accuracy-complexity tradeoff.

1. INTRODUCTION
Evolutionary multiobjective optimization (EMO) algorithms have been successfully used in a wide range of real-world application tasks [1], [4]. One of their promising application areas is machine leaning [16] including knowledge discovery [6]. Especially, the design of fuzzy systems has frequently been discussed in the framework of multiobjective optimization since the mid-1990s. This is because we have two conflicting objectives: accuracy maximization and complexity minimization (i.e., interpretability maximization). One of the first EMO approaches in this area is multiobjective fuzzy rule selection [9]. In this paper, we explain EMO algorithms and multiobjective design of fuzzy systems.

2. MULTIOBJECTIVE OPTIMIZATION
A k-objective maximization problem can be written as follows:

$$\text{Maximize } \mathbf{f}(\mathbf{x}) = (f_1(\mathbf{x}),\ \ldots,\ f_k(\mathbf{x})) \ \text{ subject to } \ \mathbf{x} \in \mathbf{X}\,, \qquad (1)$$

where $\mathbf{f}(\mathbf{x})$ is the k-dimensional objective vector, $\mathbf{x}$ is the decision vector, and $\mathbf{X}$ is the feasible region in the decision space. When the following relation holds between two solutions $\mathbf{x}$ and $\mathbf{y}$, $\mathbf{x}$ is said to be dominated by $\mathbf{y}$ (i.e., $\mathbf{y}$ is better than $\mathbf{x}$):

$$\forall i\,,\ f_i(\mathbf{x}) \le f_i(\mathbf{y}) \quad \text{and} \quad \exists j\,,\ f_j(\mathbf{x}) < f_j(\mathbf{y})\,. \qquad (2)$$

When there is no feasible solution in $\mathbf{X}$ that dominates $\mathbf{x}$, $\mathbf{x}$ is referred to as a Pareto-optimal solution. The set of objective vectors corresponding to all Pareto-optimal solutions is referred to as the Pareto front. EMO algorithms have been designed to find a large number of well-distributed Pareto-optimal solutions with a wide range of objective values over the Pareto front.

Popular EMO algorithms such as NSGA-II [5] and SPEA [19] can be characterized by the following three common features: Pareto dominance-based fitness evaluation, diversity maintenance, and Pareto dominance-based elitism. A number of EMO algorithms and test problems are available in some web sites [3], [18].

A hot issue in the EMO community is the handling of many-objective problems. Whereas Pareto dominance-based algorithms usually work very well on multiobjective problems with two or three objectives, their search ability is severely deteriorated by the increase in the number of objectives. See [13], [14] for various approaches to the scalability improvement of EMO algorithms.

3. FUZZY SYSTEM DESIGN
The main advantage of fuzzy systems over other nonlinear models such as neural networks is their interpretability. Thus the design of fuzzy systems involves two conflicting objectives: accuracy maximization and complexity minimization (i.e., interpretability

maximization). These two objectives have often been integrated into a scalar objective function. For example, the classification accuracy and the number of fuzzy rules were combined into a weighted sum fitness function in genetic algorithm-based fuzzy rule selection for the design of fuzzy rule-based classifiers [12].

An inherent difficulty in such an integrated approach is that the finally obtained fuzzy system strongly depends on the definition of a scalar objective function. Moreover, its appropriate definition is very difficult. On the other hand, EMO-based approaches can search for a large number of non-dominated fuzzy systems with different accuracy-complexity tradeoffs. Fuzzy rule selection [12] was reformulated as a two-objective problem in [9]. This problem was further extended to a three-objective problem by including the total number of antecedent conditions of fuzzy rules [10].

The same three-objective problem was handled by fuzzy genetics-based machine learning in [11]. A data mining technique was combined into three-objective fuzzy rule selection in order to handle large data sets [15]. A parallel distributed implementation of fuzzy rule selection was also discussed for large data sets in [17]. For more information on multiobjective design of fuzzy systems, see some survey papers [7], [8] and a web page [2].

4. RERATED STUDIES

The idea of multiobjective design has been applied to not only fuzzy systems but also other nonlinear systems such as neural networks. A number of obtained non-dominated neural networks can be used to find an appropriate network structure and to design ensemble classifiers. Multiobjective formulations have been also used in other fields such as genetic programming, feature selection, clustering, and data mining. See [6]-[8], [16] for details.

5. CONCLUDING REMARKS

The main advantage of EMO-based approaches to the design of fuzzy systems is that a large number of non-dominated fuzzy systems can be obtained by their single run. This means that we can easily perform accuracy-complexity tradeoff analysis in an empirical manner. The obtained non-dominated fuzzy systems can be used to determine the optimal complexity in terms of the generalization ability. When fuzzy systems are used as decision support systems in some human-centric application area such as business and healthcare, their interpretability is very important. This is because human users want to know why a particular final conclusion is obtained from their decision support system. In this case, they may prefer simpler fuzzy systems with slightly inferior accuracy rather than the optimal one with high complexity. EMO-based approaches can help human users to choose the most preferred fuzzy system by providing a number of non-dominated alternatives with different accuracy-complexity tradeoffs.

6. REFERENCES

[1] Abraham, A., Jain, L. C., and Goldberg, R. (eds.) Evolutionary Multiobjective Optimization: Theoretical Advances and Applications. Springer, Berlin (2005).

[2] Cococcioni, M. Evolutionary Multiobjective Optimization of Fuzzy Rule-Based Systems Bibliography Page. http://www2.ing.unipi.it:80/~o613499/emofrbss.html

[3] Coello, C. A. C. EMOO Web Page http://www.lania.mx/~ccoello/EMOO/

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

[5] Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. on Evolutionary Computation* 6, 2 (2002) 182-197.

[6] Ghosh, A., Dehuri, K. S., and Ghosh, S. (eds.) *Multi-objective Evolutionary Algorithms for Knowledge Discovery from Databases*. Springer, Berlin (2008).

[7] Ishibuchi, H. Evolutionary multiobjective design of fuzzy rule-based systems. *Proc. of 2007 IEEE Symposium on Foundation of Computational Intelligence* (2007) 9-16.

[8] Ishibuchi, H. Multiobjective genetic fuzzy systems: Review and future research directions. *Proc. of 2007 IEEE International Conference on Fuzzy Systems* (2007) 913-918.

[9] 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.

[10] 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.

[11] 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.

[12] 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.

[13] Ishibuchi, H., Tsukamoto, N., Hitotsuyanagi, Y., and Nojima, Y. Effectiveness of scalability improvement attempts on the performance of NSGA-II for many-objective problems. *Proc. of 2008 Genetic and Evolutionary Computation Conference* (2008) 649-656.

[14] Ishibuchi, H., Tsukamoto, N., and Nojima, Y. Evolutionary many-objective optimization: A short review. *Proc. of 2008 IEEE Congress on Evolutionary Computation* (2008) 2424-2431.

[15] 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.

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

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

[18] Zitzler E. Systems Optimization Group Web Page http://www.tik.ee.ethz.ch/sop/

[19] Zitzler, E., and Thiele, L. Multiobjective evolutionary algorithms: A comparative case study and the strength Pareto approach. *IEEE Trans. on Evolutionary Computation* 3, 4 (1999) 257-271.