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# Building Fuzzy Inference Systems with Similarity Reasoning: NSGA II-based Fuzzy Rule Selection and Evidential Functions

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***Abstract*—In our previous investigations, two Similarity Reasoning (SR)-based frameworks for tackling real-world problems have been proposed. In both frameworks, SR is used to deduce unknown fuzzy rules based on similarity of the given and unknown fuzzy rules for building a Fuzzy Inference System (FIS). In this paper, we further extend our previous findings by developing (1) a multi-objective evolutionary model for fuzzy rule selection; and (2) an evidential function to facilitate the use of both frameworks. The Non-Dominated Sorting Genetic Algorithms-II (NSGA-II) is adopted for fuzzy rule selection, in accordance with the Pareto optimal criterion. Besides that, two new evidential functions are developed, whereby given fuzzy rules are considered as evidence. Simulated and benchmark examples are included to demonstrate the applicability of these suggestions. Positive results were obtained.**

***Keywords-Fuzzy Inference System, Non-Dominated Sorting Genetic Algorithms-II, Similarity Reasoning, evidential functions, fuzzy rule selection***

## I. INTRODUCTION

Two interesting research areas in fuzzy modeling are considered, i.e., fuzzy rule selection and Similarity Reasoning (SR). On one hand, fuzzy rule section is a solution to the design of a fuzzy inference system (FIS) for pattern recognition, usually from numerical data, e.g. see [1-4]. Besides that, methods for fuzzy rule selection with the use of multi-objective evolutionary algorithms are available [1,4]. On the other hand, a variety of SR schemes, e.g., Approximate Analogical Reasoning Schema (AARS) [5], Fuzzy Rule Interpolation (FRI) [6], and qualitative reasoning [7], have been developed. These schemes are useful to deduce unknown fuzzy rules based on similarity of the given and unknown fuzzy rules. An example from Zadeh [7] is as follows:

*R1: If pressure is high, Then volume is small*
*R2: If pressure is low, Then volume is large*

Therefore, *If pressure is medium*, *Then volume is* $(w1 \cap small + w2 \cap large)$, where $w1 = sup\ (high \cap medium)$, and $w2 = sup\ (low \cap medium)$.

It is worth noting that traditional SR schemes usually focus on reasoning and/or interpolation of two neighboring fuzzy rules within a relatively small local region [8]. In our previous investigation [8], we have argued that SR may not be efficient for the whole domain, or even a relatively large region, in real-world applications. Furthermore, an optimization-based SR scheme for the monotonicity-preserving FIS was proposed, with a number of real world applications demonstrated [8-11]. The importance of the monotonicity property as an additional piece of qualitative information for modeling the FIS has been pointed out [12]. Our proposed optimization-based SR scheme [8-11] attempts to exploit the monotonicity property as additional qualitative information to increase reasoning accuracy for a relatively large range of operating region.

We have previously proposed two application frameworks that comprise SR-based schemes for tackling real-world problems, i.e., a two-stage framework [8] and an online updating framework [13]. The main aim of the two-stage framework [8] is to search for a set of *stage-1 fuzzy rules* in the whole domain such that reasoning and/or interpolation for a relatively large region can be avoided or minimized. *Stage-1 fuzzy rules* are solicited from experts. An SR scheme is then used to deduce the remaining fuzzy rules, which are denoted as *stage-2 fuzzy rules*. Applications of the two-stage framework [8] to two real-world problems, i.e., education assessment [10] and failure mode and effect analysis [8], have also been demonstrated.

In [8, 10], a genetic algorithm (GA) has been used to identify the *stage-1 fuzzy rules*. The GA objective is to minimize the number of *stage-1 fuzzy rules*, subject to a constraint. The constraint is a pre-defined minimal similarity measure between a set of *stage-1 fuzzy rules* and its *stage-2 fuzzy rules*. It is worth noting that various multi-objective evolutionary algorithms [14-17] have been widely used recently, owing to their ability to obtain pareto-optimal solutions. As a result, the main motivation of this paper is on the use of multi-objective evolutionary algorithm for selecting the *stage-1 fuzzy rules.* Specifically, the Non-Dominated Sorting in Genetic Algorithm II (NSGA-II) [14, 17] is used in this study to select the *stage-1 fuzzy rules*. Two objectives are considered: (1) minimize the number of *stage-1 fuzzy rules*; and (2) maximize the similarity measure between a set of *stage-1 fuzzy rules* and its *stage-2 fuzzy rules*. With the use of NSGA-II, a Pareto optimal selection of *stage-1 fuzzy rules* is obtained. The Pareto optimal selection