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A new metaheuristic optimization methodology based on fuzzy logic

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ABSTRACT

Many processes are too complex to be manipulated quantitatively; however, humans succeed by using simple rules of thumb that are extracted from their experiences. Fuzzy logic emulates the human reasoning in the use of imprecise information to generate decisions. Unlike traditional approaches, which require a mathematical understanding of the system, fuzzy logic comprises an alternative way of processing, which permits modeling complex systems through the use of human knowledge. On the other hand, several new metaheuristic algorithms have recently been proposed with interesting results. Most of them use operators based on metaphors of natural or social elements to evolve candidate solutions. In this paper, a methodology to implement human-knowledge-based optimization strategies is presented. In the scheme, a Takagi-Sugeno Fuzzy inference system is used to reproduce a specific search strategy generated by a human expert. Therefore, the number of rules and its configuration only depend on the expert experience without considering any learning rule process. Under these conditions, each fuzzy rule represents an expert observation that models the conditions under which candidate solutions are modified in order to reach the optimal location. To exhibit the performance and robustness of the proposed method, a comparison to other well-known optimization methods is conducted. The comparison considers several standard benchmark functions which are typically found in scientific literature. The results suggest a high performance of the proposed methodology.

1. Introduction

There are processes that humans can do much better than deterministic systems or computers, such as obstacle avoidance while driving or planning a strategy. This may be due to our unique reasoning capabilities and complex cognitive processing. Although processes can be complex, humans undertake them by using simple rules of thumb extracted from their experiences.

Fuzzy logic [1] is a practical alternative for a variety of challenging applications since it provides a convenient method for constructing systems via the use of heuristic information. The heuristic information may come from a system-operator who has directly interacted with the process. In the fuzzy logic design methodology, this operator is asked to write down a set of rules on how to manipulate the process. We then incorporate these into a fuzzy system that emulates the decision-making process of the operator [2]. For this reason, the partitioning of the system behavior into regions is an important characteristic of a fuzzy system [3]. In each region, the characteristics of the system can be simply modeled using a rule that associates the region under which certain actions are performed [4]. Typically, a fuzzy model consists of a rule base, where the information available is transparent and easily readable. The fuzzy modeling methodology has been largely exploited in several fields such as pattern recognition [5,6], control [7,8] and image processing [9,10].

Recently, several optimization algorithms based on random principles have been proposed with interesting results. Such approaches are inspired by our scientific understanding of biological or social systems, which at some abstraction level can be represented as optimization processes [11]. These methods mimic the social behavior of bird flocking and fish schooling in the Particle Swarm Optimization (PSO) method [12], the cooperative behavior of bee colonies in the Artificial Bee Colony (ABC) technique [13], the improvisation process that occurs when a musician searches for a better state of harmony in the Harmony Search (HS) [14], the attributes of bat behavior in the Bat Algorithm (BAT) method [15], the mating behavior of firefly insects in the Firefly (FF) method [16], the social behaviors of spiders in the Social Spider Optimization (SSO) [17], the characteristics of animal behavior in a group in the Collective Animal Behavior (CAB) [18] and the emulation of the differential and conventional evolution in species in the Dif-

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ferential Evolution (DE) [19] and Genetic Algorithms (GA) [20], respectively.

On the other hand, the combination of fuzzy systems with metaheuristic algorithms has recently attracted the attention in the Computational Intelligence community. As a result of this integration, a new class of systems known as Evolutionary Fuzzy Systems (EFSs) [21,22] has emerged. These approaches basically consider the automatic generation and tuning of fuzzy systems through a learning process based on a metaheuristic method. The EFSs approaches reported in the literature can be divided into two classes [21,22]: tuning and learning.

In a tuning approach, a metaheuristic algorithm is applied to modify the parameters of an existent fuzzy system, without changing its rule base. Some examples of tuning in EFSs include the calibration of fuzzy controllers [23,24], the adaptation of type-2 fuzzy models [25] and the improvement of accuracy in fuzzy models [26,27]. In learning, the rule base of a fuzzy system is generated by a metaheuristic algorithm, so that the final fuzzy system has the capacity to accurately reproduce the modeled system. There are several examples of learning in EFSs, which consider different types of problems such as the selection of fuzzy rules with membership functions [28,29], rule generation [30,31] and determination of the entire fuzzy structure [32–34].

The proposed method cannot be considered a EFSs approach, since the fuzzy system, used as optimizer, is not automatically generated or tuned by a learning procedure. On the contrary, its design is based on expert observations extracted from the optimization process. Therefore, the number of rules and its configuration are fixed, remaining static during its operation. Moreover, in a typical EFSs scheme, a metheuristic algorithm is used to find an optimal base rule for a fuzzy system with regard to an evaluation function. Different to such approaches, in our method, a fuzzy system is employed to obtain the optimum value of an optimization problem. Hence, the produced Fuzzy system directly acts as any other metaheuristic algorithm conducting the optimization strategy implemented in its rules.

A metaheuristic algorithm is conceived as a high-level problem-independent methodology that consists of a set of guidelines and operations to develop an optimization strategy. In this paper, we describe how the fuzzy logic design methodology can be used to construct algorithms for optimization tasks. As opposed to "conventional" metaheuristic approaches where the focus is on the design of optimization operators that emulate a natural or social process, in our approach we focus on gaining an intuitive understanding of how to conduct an efficient search strategy to model it directly into a fuzzy system.

Although sometimes unnoticed, it is well understood that human heuristics play an important role in optimization methods. It must be acknowledged that metaheuristic approaches use human heuristics to tune their corresponding parameters or to select the appropriate algorithm for a certain problem [35]. Under such circumstances, it is important to ask the following questions: How much of the success may be assigned to the use of a certain metaheuristic approach? How much should be attributed to its clever heuristic tuning or selection? Also, if we exploit the use of human heuristic information throughout the entire design process, can we obtain higher performance optimization algorithms?

The use of fuzzy logic for the construction of optimization methods presents several advantages. (A) Generation. "Conventional" metaheuristic approaches reproduce complex natural or social phenomena. Such a reproduction involves the numerical modeling of partially-known behaviors and non-characterized operations, which are sometimes even unknown [36]. Therefore, it is notably complicated to correctly model even very simple metaphors. On the other hand, fuzzy logic provides a simple and well-known method for constructing systems via the use of human knowledge [37]. (B) Transparency. The metaphors used by metaheuristic approaches lead to algorithms that are difficult to understand from an optimization perspective. Therefore, the metaphor cannot be directly interpreted as a consistent search strategy [36]. On the other hand, fuzzy logic generates fully interpretable models whose content expresses the search strategy as humans can conduct it [38]. (C) Improvement. Once designed, metaheuristic methods maintain the same procedure to produce candidate solutions. Incorporating changes to improve the quality of candidate solutions is very complicated and severely damages the conception of the original metaphor [36]. As human experts interact with an optimization process, they obtain a better understanding of the correct search strategies that allow finding the optimal solution. As a result, new rules are obtained so that their inclusion in the existing rule base improves the quality of the original search strategy. Under the fuzzy logic methodology, new rules can be easily incorporated to an already existent system. The addition of such rules allows the capacities of the original system to be extended [39].

In this paper, a methodology to implement human-knowledge-based optimization strategies is presented. In the scheme, a Takagi-Sugeno Fuzzy inference system [40] is used to reproduce a specific search strategy generated by a human expert. Therefore, the number of rules and its configuration only depend on the expert experience without considering any learning rule process. Under these conditions, each fuzzy rule represents an expert observation that models the conditions under which candidate solutions are modified in order to reach the optimal location. To exhibit the performance and robustness of the proposed method, a comparison to other well-known optimization methods is conducted. The comparison considers several standard benchmark functions which are typically found in the literature of metaheuristic optimization. The results suggest a high performance of the proposed methodology in comparison to existing optimization strategies.

This paper is organized as follows: In Section 2, the basic aspects of fuzzy logic and the different reasoning models are introduced. In Section 3, the proposed methodology is exposed. Section 4 discusses the characteristics of the proposed methodology. In Section 5 the experimental results and the comparative study is presented. Finally, in Section 6, conclusions are drawn.

2. Fuzzy logic and reasoning models

This section presents an introduction to the main fuzzy logic concepts. The discussion particularly considers the Takagi-Sugeno Fuzzy inference model [40].

2.1. Fuzzy logic concepts

A fuzzy set (A) [1] is a generalization of a Crisp or Boolean set, which is defined in a universe of discourse X. A is a linguistic label which defines the fuzzy set through the word A. Such a word defines how a human expert perceives the variable X in relationship to A. The fuzzy set (A) is characterized by a membership function $\mu_A(x)$ which provides a measure of degree of similarity of an element x from X to the fuzzy set A. It takes values in the interval [0,1], that is:

$$\mu_A(x) : X \rightarrow [0, 1] \tag{1}$$

Therefore, a generic variable $x_c$can be represented using multiple fuzzy sets $\left\{A_1^c, A_2^c, \ldots, A_m^c\right\}$, each one modeled by a membership function $\left\{\mu_{A_1^c}(x_c), \mu_{A_2^c}(x_c), \ldots, \mu_{A_m^c}(x_c)\right\}$.

A fuzzy system is a computing model based on the concepts of fuzzy logic. It includes three conceptual elements: a rule base, which contains a selection of fuzzy rules; a database, which defines