Chapter 29
A Fuzzy Simulated Evolution Algorithm for Hard Problems

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ABSTRACT

As problem complexity continues to increase in industry, developing efficient solution methods for solving hard problems, such as heterogeneous vehicle routing and integrated cell formation problems, is imperative. The focus of this chapter is to develop from the classical simulated evolution algorithm, a Fuzzy Simulated Evolution Algorithm (FSEA) that incorporates the concepts of fuzzy set theory, evolution, and constructive perturbation. The aim is to improve the search efficiency of the algorithm by enhancing the major phases of the algorithm through initialization, evaluation, selection, and reconstruction. Illustrative examples are provided to demonstrate the candidate application areas and to show the strength of the algorithm. Computational experiments are conducted based on benchmark problems in the literature. Results from the computational experiments demonstrate the strength of the algorithm. It is anticipated that the application of the FSEA metaheuristic can be extended to other hard large scale problems.

INTRODUCTION

Intelligent soft computing algorithms, particularly biologically inspired evolutionary algorithms, have attracted the attention of many researchers and practitioners in a wide range of disciplines, including logistics engineering, business, economics, operations management, manufacturing systems design, production planning, and scheduling (Dostal, 2013; Senvar et al., 2013). Intelligent soft computing, unlike conventional (hard) computing, is known to be tolerant of imprecision, uncertainty, partial truth, and approximation. As such, this approach mimics the human mind and other natural phenomena when addressing real-world complex problems (Holland, 1992, 1997; Dostal, 2013). Some of the most popular algorithms are genetic algorithms, neural networks, simulated annealing, particle swarm intelligence, ant colony algorithms, and evolutionary algorithms. Oftentimes, these algorithms incorporate fuzzy set theory, fuzzy logic, and chaos theory, and other knowledge-

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based techniques. In order to enhance their operational efficiency and effectiveness. (Zadeh, 1978; Sugeno, 1985; Hererra & Lozano, 1996; Zimmerman, 1993; FLT, 2012; Vasant, 2013). In developing these algorithms, researchers seek to come up with enhanced heuristics for robust global optimization of real-world problems that cannot be solved by conventional approaches in polynomial time.

Most real-world problems have complex characteristics: 1.) they are combinatorial and computationally hard in nature, 2.) they are highly constrained or restricted, and 3.) they are fuzzy due to the presence of imprecise data, or 4.) they have numerous local optima. These inherent complex characteristics continue to pose serious challenges to decision makers in various disciplines across the globe. Although many heuristic and meta-heuristic algorithms have been developed, more and more complexities continue to arise in various research disciplines due to a combination of factors (Senvar et al., 2013). Consequently, the need for global soft computing and optimization algorithms continues to increase in industry. Therefore, the development of more enhanced and robust algorithms is imperative.

There are a number of advantages associated with the application of soft computing methodologies such as evolutionary algorithms. For instance, whereas most optimization approaches need rich domain knowledge in their application, evolutionary algorithms do not need much domain knowledge for effective application. Moreover, evolutionary computation techniques are general purpose solution methods that possess a remarkable balance between exploration and exploitation in searching the solution space, which enables the algorithms to intelligently escape from local optima. In the case of complex problems with multi modal objective functions (Michalewicz, 1996). Intelligent evolutionary computation methods can hardly be trapped in the local optima In the case of multi modal and non linear problems (Deb, 1999, 2001). In addition, evolutionary algorithms can handle many real world optimization problems characterised by uncertain or fuzzy variables, which are often intractable using conventional methods. Evolutionary techniques can effectively solve most practical problems under uncertain environment (Keedwell & Khu, 2005). Another important advantage in the application of soft computing evolutionary algorithms is that, for many real-world problems, the approaches can provide optimal or near optimal solutions within a reasonable computation time or after a reasonable number of iterations (Varela, Vela, Puente, & Gomez, 2003; Sakawa & Kato, 2003). Whereas conventional solution methods often face a number of drawbacks in the presence of highly constrained problems, soft computing evolutionary approaches can be applied efficiently and effectively by modifying the problem and using penalty parameters that are changed using heuristic rules (Sarkar et al., 2001, 2002). With hybridization and the use of adaptive operators, intelligent evolutionary algorithms can solve industrial large scale problems, even in the presence of multiple constraints. In retrospect, soft computing evolutionary algorithms are a potential decision support tools for the decision maker in a complex world.

In this chapter, fuzzy set theory is used to develop fuzzy evaluation criteria for typical combinatorial problems. The fuzzy evaluation concepts are merged with Simulated Evolution Algorithm (SEA) in order to develop an enhanced Fuzzy Simulated Evolution Algorithm (FSEA). Therefore, the main purpose of this chapter is to develop an effective fuzzy simulated evolution algorithm for solving hard combinatorial problems. In this vein, the specific objectives are as follows:

1. To develop enhanced fuzzy evaluation criteria for the FSEA, based on the concepts of fuzzy theory,
2. To develop an enhanced FSEA framework, comprising evaluation, selection and reconstruction, and,

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