Chapter 75
On the Convergence and Diversity of Pareto Fronts Using Swarm Intelligence Metaheuristics for Constrained Search Space

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ABSTRACT

This article reviews existing constraint-handling techniques then presents a new design for Swarm Intelligence Metaheuristics (SIM) to deal with constrained multi-objective optimization problems (CMOPs). This new design aims to investigate potential effects of leader concepts that characterize the dynamic of SIM in the hope to help the population to reach Pareto optimal solutions in a constrained search space. The new leader-based constraint handling mechanism is incorporated in Constrained Multi-Objective Cuckoo Search (C-MOCS) and Constrained Multi-Objective Particle Swarm Optimization (C-MOPSO) as specific instances of a more general class of SIMs. The experimental results are carried out using a set of six well-known test functions and two performance metrics. The convergence and diversity of C-MOCS and C-MOPSO are analysed and compared to the well-known Multi-Objective Evolutionary Algorithm (MOEA) NSGA-II and discussed based on the obtained results.

1. INTRODUCTION

Almost all optimization problems arising from real-world applications in different domains do have multiple objectives that should be optimized simultaneously. Most often, these objectives are conflicting with each other. This means that it is impossible to improve a given objective without deteriorating at least another one. Also, optimization problems are subject to some restrictions imposed by the particular environment's characteristics and available resources (Coello, Van Veldhuizen, & Lamont, 2002). These restrictions are generally expressed in terms of constraints, which must be satisfied in order to consider a giving solution as feasible.

Handling multiple objectives and constraints in the optimization algorithms is an important topic that deserves special attention, particularly when dealing with real-world problems. Therefore, a considerable amount of work was devoted to design and implement constraint-handling techniques. A great deal of effort was devoted to single-objective evolutionary algorithms. Besides, a variety of algorithms and techniques have been developed to tackle unconstrained multi-objective optimization problems. In particular, some work has combined constraint handling techniques with multi-objective evolutionary algorithm (MOEAs) (Fonseca & Fleming, 1998; Deb, Pratap, & Agarwal, 2002; Woldesenbet, Yen, & Tessema, 2009; Qu, & Suganthan, 2011; Long, 2014), However, there is still a need to investigate the ability of swarm intelligence metaheuristics to solve constrained multi-objective optimization problems (CMOPs).

Particle swarm optimization (PSO) and Cuckoo Search algorithm (CS) are two swarm intelligence metaheuristics. PSO has been chosen for this study as it is the pioneer in representing the basic concept of swarm-intelligence. PSO is inspired by the social behavior of bird flocking and fish schooling. It was developed in 1995 by Kennedy and Eberhart (1995). Since then, it has become the most popular and widely used algorithm in the literature. On the other hand, CS has been selected as it is considered as one of the latest proposed nature inspired metaheuristics. It was developed in 2009 by Yang and Deb (2009). CS is inspired by the obligate brood parasitism of some cuckoo species. Moreover, it is enhanced by the so-called Lévy flights rather than by simple isotropic random walks (Yang, 2010). In Yang (2010), the author assumes that CS is competitive compared to the existing metaheuristics including particle swarm optimization and genetic algorithms.

For Multi-Objective Optimization Problems (MOPs), due to the conflicting nature of objectives, the optimal solution is not a single solution as for single-objective optimization problems, but a set of trade-offs between the involved objectives. This solutions' set is usually identified by using the Pareto dominance relation. According to this relation, a given solution is said to dominate the second one if it is at least as good as this second solution in all objectives and strictly better in at least one objective. Therefore, the set of trade-off solutions is called Pareto optimal set and its representation in the objective space is called the Pareto front. Overall, the main goal of the multi-objective optimization is to obtain the Pareto optimal set and consequently the Pareto front. In fact, for a given problem all developed algorithms compete in achieving the best approximation to the global Pareto fronts, expressed in terms of convergence, and widely spread distribution of solutions, expressed in term of diversity (Deb, 2001).

The use of population within both Evolutionary algorithm and swarm intelligence metaheuristics makes them able to explore different regions of the solution space simultaneously and find a diverse set of optimal solutions in a single simulation run. Following this achievement, many evolutionary algorithms and swarm intelligence metaheuristics have been successfully extended to deal with multi-objective optimization problems and hence constrained problems (Deb, Pratap, & Agarwal, 2002; Zeltni & Meshoul, 2014; Sierra & Coello, 2005).

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