Chapter IV
Towards a More Efficient Multi-Objective Particle Swarm Optimizer

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ABSTRACT

This chapter presents a hybrid between a particle swarm optimization (PSO) approach and scatter search. The main motivation for developing this approach is to combine the high convergence rate of the PSO algorithm with a local search approach based on scatter search, in order to have the main advantages of these two types of techniques. We propose a new leader selection scheme for PSO, which aims to accelerate convergence by increasing the selection pressure. However, this higher selection pressure reduces diversity. To alleviate that, scatter search is adopted after applying PSO, in order to spread the solutions previously obtained, so that a better distribution along the Pareto front is achieved. The proposed approach can produce reasonably good approximations of multi-objective problems of high dimensionality, performing only 4,000 fitness function evaluations. Test problems taken from the specialized literature are adopted to validate the proposed hybrid approach. Results are compared with respect to the NSGA-II, which is an approach representative of the state-of-the-art in the area.

INTRODUCTION

Despite the considerable volume of research developed on evolutionary multi-objective optimization during the last 20 years, certain topics such as algorithmic design emphasizing efficiency have become popular only within the last few years (Coello Coello, Van Veldhuizen, & Lamont, 2002).

In this chapter, we propose a new hybrid multi-objective evolutionary algorithm (MOEA) based on particle swarm optimization (PSO) and scatter search (SS). The main motivation of this work was to design a MOEA that could produce a reasonably good approximation of the true Pareto front of a problem with a relatively low number of fitness function evaluations. The core idea of our proposal is to combine the high convergence rate of PSO with the use of SS as a local search mechanism that compensates for the diversity lost during the search (due to the high selection pressure generated by the leader selection scheme that we propose for our PSO). As we show later, our proposed hybrid scheme constitutes an efficient MOEA, which can produce reasonably good approximations of the Pareto fronts of both constrained and unconstrained multi-objective problems of high dimensionality, performing a relatively low number of fitness function evaluations. Our results are compared with respect to a MOEA that is representative of the state-of-the-art in the area: the NSGA-II (Deb, Pratap, Agarwal, & Meyarivan, 2002).

The remainder of this chapter is organized as follows. First, we provide some basic concepts from multi-objective optimization required to make the chapter self-contained. This includes an introduction to the PSO strategy and to SS. We also present a brief review of several multi-objective particle swarm optimizers previously proposed in the specialized literature. Then, we provide the details of our proposed approach and the mechanism adopted to maintain diversity. Our comparison of results is provided in a further section. Our conclusions are presented after that, and some promising paths for future research are then briefly described. Finally, for those interested in gaining more in-depth knowledge about the topics covered in this chapter, a list of additional readings is provided at the end of the chapter.

BASIC CONCEPTS

In this section, we introduce some basic definitions which aim to make the paper self-contained. We introduce some basic terminology from the multi-objective optimization literature (assuming minimization) and we provide an introduction to both particle swarm optimization and scatter search.

Multi-Objective Optimization

The multi-objective optimization problem can be formally defined as the problem of finding:

$$\vec{x}^* = [x_1^*, x_2^*, \ldots, x_n^*]^T$$

which satisfies the m inequality constraints:

$$g_i(\vec{x}) \leq 0; i = 1, \ldots, m$$

the p equality constraints:

$$h_i(\vec{x}) = 0; i = 1, \ldots, p$$

and optimizes the vector function:

$$\vec{f}(\vec{x}) = f_1(\vec{x}), f_2(\vec{x}), \ldots, f_k(\vec{x})$$

In other words, we aim to determine from among the set $\boldsymbol{F}$ of all vectors (points) which satisfy the constraints those that yield the optimum values for all the k-objective functions simultaneously. The constraints define the feasible region $\boldsymbol{F}$ and any point $\vec{x}$ in the feasible region is called a feasible point.

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