



## **Chapter VII**

# **Integrating Evolutionary Computation Components in Ant Colony Optimization**

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## **ABSTRACT**

*This chapter introduces two different ways to integrate Evolutionary Computation Components in Ant Colony Optimization (ACO) Meta-heuristic. First of all, the ACO meta-heuristic is introduced and compared to Evolutionary Computation to notice their similarities and differences. Then two new models of ACO algorithms that include some Evolutionary Computation concepts (Best-Worst Ant System and exchange of memoristic information in parallel ACO algorithms) are presented with some empirical results that show improvements in the quality of the solutions when compared with more basic and classical approaches.*

## **INTRODUCTION**

Complex combinatorial optimization problems arise in many different fields such as economy, commerce, engineering or industry. These problems are so complex that there is no algorithm known that solves them in polynomial time (Garey & Johnson, 1979). These kinds of problems are called *NP-hard*.

Still, many of these problems have to be solved in a huge number of practical settings and therefore a large number of algorithmic approaches were proposed to tackle them. The existing techniques can roughly be classified into exact and approximate algorithms. *Exact algorithms* try to find an optimal solution and to prove that the solution obtained is actually an optimal one. These algorithms include techniques such as backtracking, branch and bound, dynamic programming, and so forth (Brassard & Bratley, 1996; Papadimitriou & Steiglitz, 1982). Because exact algorithms show poor performance for many problems, several types of approximate algorithms that provide high quality solutions to combinatorial problems in short computation time were developed.

*Approximate algorithms* can be classified into two main families: deterministic and probabilistic. Deterministic algorithms always produce the same solution when the starting conditions are the same, while the latter algorithms are characterized by a non-deterministic behavior; that is, for a specific problem and in the same execution conditions (same seeds from the random number generators, same values of the different parameters, same number of iterations, and so on), they return different solutions.

A different classification for approximate algorithms distinguishes between *construction algorithms* and *local search algorithms*. The former are based on generating solutions from scratch by adding solution components step by step. The best-known example is greedy construction heuristics (Brassard & Bratley, 1996). Their advantage is speed: they are typically very quick and, in addition, often return reasonably good solutions. However, these solutions are not guaranteed to be optimal with respect to small local changes. Local search algorithms repeatedly try to improve the current solution by movements to (hopefully better) neighboring solutions. The simplest case are iterative improvement algorithms: if in the neighborhood of the current solution  $s$ , a better solution  $s'$  is found, it replaces the current solution and the search is continued from  $s'$ ; if no better solution is found, the algorithm terminates in a local optimum. Nowadays, hybridizations of both techniques are usually used: any construction algorithm builds an initial solution, which is then improved by a local search algorithm.

Unfortunately, iterative improvement algorithms may become stuck in poor quality local optima. To allow for them a further improvement in solution quality, in the last two decades the research in this field has moved attention to the design of general-purpose techniques for guiding underlying, problem-specific construction or local search heuristics. These techniques are called meta-heuristics (Glover & Kochenberger, 2003). They involve concepts that can be used to define heuristic methods; that is, meta-heuristics can be seen as a general algorithmic framework that can be applied to different (combinatorial) optimization problems with relatively few modifications if given some underlying, problem specific heuristic method. In fact, meta-heuristics are now widely recognized as the most promising approaches for attacking hard combinatorial optimization problems (Aarts & Lenstra, 1997; Michalewicz & Fogel, 2000; Reeves, 1995).

*Heuristics Based on Nature or Bioinspired Algorithms* (Colorni, Dorigo, Maffioli, Maniezzo, Righini & Trubian, 1996) are approximate algorithms that have achieved good results. All of them share at least one quality: they operate simulating some natural processes, although some of them have evolved in order to increase their effectiveness. However, these improvements sometimes include some aspects that do not have a direct natural inspiration.

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