

## Chapter XXXIII

# Ant Colony Optimization and Multiple Knapsack Problem

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### ABSTRACT

*The ant colony optimization algorithms and their applications on the multiple knapsack problem (MKP) are introduced. The MKP is a hard combinatorial optimization problem with wide application. Problems from different industrial fields can be interpreted as a knapsack problem including financial and other management. The MKP is represented by a graph, and solutions are represented by paths through the graph. Two pheromone models are compared: pheromone on nodes and pheromone on arcs of the graph. The MKP is a constraint problem which provides possibilities to use varied heuristic information. The purpose of the chapter is to compare a variety of heuristic and pheromone models and different variants of ACO algorithms on MKP.*

### INTRODUCTION

Combinatorial optimization is a process of finding the best or optimal solution for problems with a discrete set of feasible solutions. Applications occur in numerous settings involving operations management and logistics. The economic impact of combinatorial optimization is profound, affecting diverse sections. While much progress has been made in finding exact solutions to some combinatorial optimization

problems (COPs), many hard combinatorial problems (NP-problems) are still not exactly solved in a reasonable time and require good meta-heuristic methods. The aim of meta-heuristic methods for COPs is to produce quickly good-quality solutions. In many practical problems they have proved to be effective and efficient approaches, being flexible to accommodate variations in problem structure and in the objectives considered for the evaluation of solutions (Lonnstedt, 1973). For all these rea-

sons, meta-heuristics has probably been one of the most stimulated research topics in optimization for the last two decades. Examples are decision making problems.

The ant colony optimization (ACO) is a new meta-heuristic method. ACO algorithms are applied in real life and industrial problems for which a good solution for a short time is required. ACO achieves good results for problems with restrictive constraints like multiple knapsack problem. It represents a multi-agent system where low-level interaction between single agents results in a complex behavior of the whole ant colony. It imitates the behavior shown by real ants when searching for food. Ants are social insects that live in colonies and whose behavior is aimed more to the survival of the colony as a whole than to that of a single individual component of the colony. An important and interesting aspect of ant colonies is how ants can find the shortest path between the food sources and their nest. Ants communicate information about food sources via a chemical substance called pheromone, which the ants secrete as they move along.

Analogously, ACO is based on the indirect communication of a colony of simple agents, called “artificial” ants, mediated by “artificial” pheromone trails. The pheromone trails in ACO algorithms serve as distributed numerical information, which ants use to probabilistically construct solutions to the problem to be solved and which ants adapt during the algorithm’s execution to reflect their search experience. Artificial ants not only imitate the behavior described, but also apply additional problem-specific heuristic information. The idea is developed by Moyson and Manderick (1988). The first example of ant algorithm is Ant System (Dorigo, Maniezzo, & Coloni, 1996), and it has been applied to and provided solutions for various hard combinatorial optimization problems. Recently, different versions of the ACO algo-

rithms such as the ant colony system (Dorigo, 1999a), the ant algorithm with elitist ants (Dorigo, 1999b), the max-min ant system (Stützle & Hoos, 2000), the ant algorithm with additional reinforcement (Fidanova, 2002), and the best-worst ant system (Cordón, Fernández de Viana, & Herrera, 2002) have been applied to many optimization problems. Examples are the traveling salesman problem (Dorigo, 1999a), the quadratic assignment (Gambardella, Taillard, & Agazzi, 1999), the vehicle routing (Gambardella, Taillard, & Agazzi, 1999), and the multiple knapsack problem (Fidanova, 2003).

The multiple knapsack problem (MKP) is a hard combinatorial optimization problem with wide applications which enlists many practical problems from different domains like financial and other management. It is an interesting problem of both practical and theoretical point of view: practical because of its wide application; theoretical because it is a constraint problem and gives various possibilities for heuristic constructions.

The aim of this chapter is to introduce ACO and its application on MKP.

## **ANT COLONY OPTIMIZATION ALGORITHM**

All ACO algorithms can be applied to any COP. They follow specific algorithmic scheme. After the initialization of the pheromone trails and control parameters, a main loop is repeated until the stopping criteria are met. The stopping criteria can be a certain number of iterations, a given CPU time limit, or a time limit without improving the result or if some lower (upper) bound of the result is known and the achieved result is close enough to this bound. In the main loop, the ants construct feasible solutions, and then the pheromone trails are updated. More precisely, partial problem solutions are seen as

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