

# Chapter VI

## Evolutionary Multi-Objective Optimization in Finance

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### ABSTRACT

*This chapter provides a brief introduction of the use of evolutionary algorithms in the solution of multi-objective optimization problems (an area now called “evolutionary multi-objective optimization”). Besides providing some basic concepts and a brief description of the approaches that are more commonly used nowadays, the chapter also provides some of the current and future research trends in the area. In the final part of the chapter, we provide a short description of the sort of applications that multi-objective evolutionary algorithms have found in finance, identifying some possible paths for future research.*

### INTRODUCTION

Many real-world problems have two or more objective functions that we aim to minimize. Such problems are called multi-objective optimization problems and require an alternative definition of “optimality.” The most common notion of optimality normally adopted is the so-called *Pareto optimality*, which indicates that the best possible solutions are those representing the best trade-offs among the objective functions. In other words, the desirable solutions are those in which one objective cannot be improved without worsening another objective.

Evolutionary algorithms (EAs) are techniques based on the emulation of the mechanism of natural selection, which have been successfully used to solve problems during several years (Fogel, 1999; Goldberg, 1989). One of the problem domains in which EAs have been found to be particularly useful is in multi-objective optimization (Coello Coello, Van Veldhuizen, & Lamont, 2002). EAs are particularly suitable for solving multi-objective optimization problems because they deal simultaneously with a set of possible solutions (the so-called population) which allows us to find several members of the Pareto optimal set (i.e., the

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