# Chapter 12
# Evolutionary Computing:
## Principles and Applications to Portfolio Optimization

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## ABSTRACT

*The field of evolutionary computation forms one of the tenets of the soft computing paradigm, which aims at deriving at some possible global optimal solutions to search problems. The field of industrial informatics, being an emergent field, faces tremendous data explosion and associated challenges of data redundancies and inconsistencies. Different evolutionary algorithms have been put to use to evolve intelligence out of redundancies immanent in industrial databases. Industrial portfolio management has been a much-talked affair nowadays, thanks to the evolving fields of data intelligent management and archival techniques. An overview of the different facets of evolutionary algorithms and their role in imbibing human intelligence in data management and retrieval is presented with regards to its application in the optimization of a collection of financial portfolio instruments.*

## INTRODUCTION

Human intelligence is often exhibited in the ability of dynamic decision-making supported by the optimization of avenues at hand. This facet of human intelligence aims at reaching at an optimal solution to the decision-making process. The evolutionary computing paradigm, as the name suggests, employs several search and optimization algorithms based on Darwinian laws of biological evolution and laws of natural genetics. The representative algorithms (also referred to as evolutionary algorithms) embed several search heuristics to finally converge at a near-optimal solution in their search

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space in a reasonable time. The search mechanism, which is inspired by several biological phenomena, takes recourse to characteristic operators to operate on the search space. Typical examples include genetic programming (GP), evolutionary programming (EP), evolutionary strategies (ES), and genetic algorithms (GAs). While GP algorithms are used for evolving programs, the EP algorithms focus on optimizing continuous functions without recombination. On the other hand, the ES algorithms focus on optimizing continuous functions with recombination and GAs are used to optimize general combinatorial problems. The most commonly used algorithms are the genetic algorithm (GA), the particle swarm optimization (PSO), the ant colony optimization (ACO), simulated annealing (SA), and the tabu search technique. Of late, advanced versions of these algorithms have been evolved to take into cognizance multiple fitness functions as well. These multiobjective evolutionary algorithms incorporate several objective functions specific to the problem domain having either symbiotic or conflicting interests among themselves. The ultimate end result is a set of paretooptimal solutions, which address the problem in one way or the other. Evolutionary algorithms find wide use in solving different combinatorial optimization problems either in a constrained or unconstrained mode. Notable among the application areas are the fields of image processing, pattern recognition, production engineering, industrial informatics, financial market operations, portfolio management, etc.

This chapter is devoted to an understanding of the concepts and practices of the evolutionary computing paradigm with reference to the underlying biological principles involved. A bird's eye view on the general algorithmic structure of the evolutionary algorithms is also a point of consideration. The intricacies of some representative algorithms would be dealt with due regards to the multiobjective scenario as well. The application perspectives of these algorithms would also be discussed with reference to a case study on portfolio optimization as it applies to the emerging field of industrial informatics.

Real time financial transactions involve the interrelation between the concepts of time, money and risk. A financial portfolio describes this interrelation in terms of the correlation between the assets present in a particular market condition. According to H. M. Markowitz (1952), an investor should not select its assets due to only characteristic features, but he/she needs to consider how each asset has co-moved with all other assets at hand. Markowitz was able to quantify risk, defined as the standard deviation of returns, and show how diversification into investments that have limited or no positive correlation in their movements can reduce overall risk. In Markowitz's view, this is measured by a correlation coefficient which varies between +1 and -1. Two investments with a correlation of +1 will move in lock-step with one another, while those with a correlation of -1 will move in exactly the opposite direction. Since the correlation coefficient is used to calculate the variance of a portfolio, any coefficient less than +1 will reduce the overall variance of that portfolio.

If these co-movements are taken into account (Elton, 1997), an investor can construct a portfolio that has a lesser risk than a portfolio constructed without paying any heed to the interaction between securities, given the same expected yield/return. Black et Al. (1972) modified this model to allow short-selling of assets or negative weights of assets, thereby forming a closed form solution to the problem.

Several approaches to solve the portfolio optimization problem are reported in the literature (Alexander2005, Crouhy2001). These techniques mainly incorporate a multitude of combinations of portfolio states thereby rendering the problem intractable and time-complex. Moreover, most of these techniques are unable to handle the nonlinearities in the objectives and constraints inherent in the problem.

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