Chapter XIV
Portfolio Optimization Using Evolutionary Algorithms

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ABSTRACT

In this study, a double-stage evolutionary algorithm is proposed for portfolio optimization. In the first stage, a genetic algorithm is used to identify good-quality assets in terms of asset ranking. In the second stage, investment allocation in the selected good-quality assets is optimized using another genetic algorithm based on Markowitz’s theory. Through the two-stage genetic optimization process, an optimal portfolio can be determined. Experimental results obtained reveal that the proposed double-stage evolutionary algorithm for portfolio optimization provides a very useful tool to assist the investors in planning their investment strategy and constructing their portfolio.

INTRODUCTION

In modern portfolio theory, the mean-variance model originally introduced by Markowitz (1952) has been playing an important and critical role so far. Since Markowitz’s pioneering work was published, the mean-variance model has revolutionized the way people think about portfolios of assets, and it has gained widespread acceptance as a practical tool for portfolio optimization (Yu, Wang, & Lai, 2008). However, Markowitz’s portfolio theory only provides a solution to asset
allocation among predetermined assets. In the investment markets, several hundred different assets, such as stocks, bonds, foreign exchanges, options, commodities, real estates, and future contracts, are available for trading. The qualities of these assets vary from very good to extremely poor. Usually, investors find it difficult to seek out those good-quality assets because of information asymmetry and asset price fluctuations. Therefore, it is not wise to use portfolio theory blindly for optimizing asset allocation among some low-quality assets. The suitable way of constructing a portfolio is first to select some good-quality assets and then to optimize asset allocation using portfolio theory.

An obvious challenge is how to select and optimize good assets. With focus on business computing, applying artificial intelligence to portfolio selection and optimization is one good way to meet the challenge. Some studies have been presented to solve the asset selection problem. Levin (1995) applied artificial neural networks (ANNs) to select valuable stocks. Chu, Tsao, and Shieue (1996) used fuzzy multiple attribute decision making (MADM) to select stocks for portfolio optimization. Similarly, Zargham and Sayeh (1999) used a fuzzy rule-based system to evaluate the listed stocks and realize stock selection. Recently, Fan and Palaniswami (2001) utilized support vector machines (SVMs) to train universal feed-forward neural networks (FNN) to perform stock selection. For portfolio optimization, Maranas, Androulakis, Floudas, Berger, and Mulvey (1997) applied tabu search to find the optimal asset allocation, while some researchers, such as Casas (2001) and Chapados and Bengio (2001), trained neural networks to predict asset behavior and used the neural network to make the asset allocation decisions. In addition, Mulvey, Rosenbaum, and Shetty (1997) applied dynamic programming to construct a multistage stochastic model for solving the asset allocation problem.

However, these approaches have some drawbacks in solving the portfolio selection problem. For example, the fuzzy approach (Chu et al., 1996; Zargham & Sayeh, 1999) usually lacks learning ability, while the neural-network approach (Casas, 2001; Chapados & Bengio, 2001; Fan & Palaniswami, 2001; Levin, 1995) has an overfitting problem and it is often easy to get trapped into local minima. In order to overcome these shortcomings, we utilize evolutionary algorithms (EAs) to solve the portfolio selection and optimization problem. An EA is a generic population-based metaheuristic optimization algorithm. An EA uses some mechanisms inspired by biological evolution: reproduction, mutation, recombination, natural selection, and survival of the fittest.

Candidate solutions to the optimization problem play the role of individuals in a population, and the cost function determines the environment within which the solutions “live.” Typically, an EA includes four types: genetic algorithm (GA), genetic programming (GP), evolutionary programming (EP), and evolutionary strategy (ES). Of the four types, the GA is the popular one of EA. One seeks the solution of a problem in the form of strings of numbers (traditionally binary, although the best representations are usually those that reflect something about the problem being solved; these are not normally binary), virtually always applying recombination operators in addition to selection and mutation. This type of EA is often used in optimization problems. Compared to tabu search (Maranas et al., 1997), a GA is less problem dependent and provides a high chance of reaching the global optimum. In comparison with dynamic programming (Mulvey et al., 1997), GA allows the user to get the suboptimal solution while dynamic programming cannot, which is very important for some financial problems. Since time is limited in the financial world, investors often use a suboptimal but acceptable solution to allocate assets. Due to these advantages, we use a two-stage genetic algorithm to perform portfolio selection and solve the optimization problem.

The main motivation of this chapter is to employ a two-stage genetic algorithm for portfolio
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