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Prediction based mean-variance model for constrained portfolio assets selection using multiobjective evolutionary algorithms

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ABSTRACT

In this paper, a novel prediction based mean-variance (PBMV) model has been proposed, as an alternative to the conventional Markowitz mean-variance model, to solve the constrained portfolio optimization problem. In the Markowitz mean-variance model, the expected future return is taken as the mean of the past returns, which is incorrect. In the proposed model, first the expected future returns are predicted, using a low complexity heuristic functional link artificial neural network (HFLANN) model and the portfolio optimization task is carried out by using multi-objective evolutionary algorithms (MOEAs). In this paper, swarm intelligence based, multiobjective optimization algorithm, namely self-regulating multiobjective particle swarm optimization (SR-MOPSO) has also been proposed and employed efficiently to solve this important problem. The Pareto solutions obtained by applying two other competitive MOEAs and using the proposed PBMV models and Markowitz mean-variance model have been compared, considering six performance metrics and the Pareto fronts. Moreover, in the present study, the nonparametric statistical analysis using the Sign test and Wilcoxon rank test are also carried out, to compare the performance of the algorithms pair wise. It is observed that, the proposed PBMV model based approach provides better Pareto solutions, maintaining adequate diversity, and also quite comparable to the Markowitz model. From the simulation result, it is observed that the self regulating multiobjective particle swarm optimization (SR-MOPSO) algorithm based on PBMV model, provides the best Pareto solutions amongst those offered by other MOEAs.

1. Introduction

In the last few decades, portfolio optimization has emerged as a challenging and interesting multiobjective problem, in the field of computational finance. It is still receiving the increasing attention of researchers, fund management companies and individual investors. Selecting of a subset of assets and its corresponding optimal weights of each selected assets, are key issues in portfolio selection. The composition of each asset is to be selected in such a way, that the total profit (return) of the portfolio is maximized while simultaneously minimizing the risk.

The mean-variance model, proposed by Harry Markowitz [1], is an important contribution to the Modern Portfolio Theory (MPT). In the past few decades, this theory has been comprehensively studied in the field of portfolio optimization. Recently, several authors have tried to improve this model, by applying some model simplification techniques, or by proposing models having different risk measures. The semi-variance, mean absolute deviation and variance with skewness models are successfully applied as an alternative to Markowitz model [2]. The fundamental assumptions of all these models are (i) the time series of the returns of each stock follows a normal distribution, (ii) the mean of the past stock's return is taken as the expected future return, (iii) variance is taken as a measure of the risk associated with a stock, and (iv) the covariance of each pair of time series is considered as a measure of the joint risk of each pair of stocks [3]. But all these assumptions have been threatened by real world data because of reasons such as (i) the distributions of the series of returns often depart from normality, and exhibit kurtosis and skewness [4,5] that make the variance of the returns an inappropriate measure of risk [6]; (ii) the use of the mean returns as a prediction of the future returns of the stock imposes a low pass filtering effect on the dynamic behavior of the stock markets [7].

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Hence, the development of a model, free from those shortcomings is still a challenging field of research. There is a need to develop an efficient model which would calculate the expected future returns by some other means. In this paper, a novel prediction based mean-variance (PBMV) model has been proposed, as an alternative to these mean-variance models and successfully applied to the constrained portfolio asset selection problem.

In the proposed model, the expected future returns are directly predicted with a low complexity functional link artificial neural network (FLANN) using the past returns. The FLANN structure is a single layer network having no hidden layer. The weights of FLANN network can be updated either by gradient based methods, or by heuristic algorithm. In this paper, we have incorporated particle swarm optimization (PSO) based heuristic approach to train the FLANN model, that successfully reduces the computational time with efficient prediction. The portfolio risk is the variance of the joint Normal distribution of the linear combination of the participations and prediction errors of the stocks in a portfolio. Portfolio optimization refers to the selection of assets and their optimal weighting, in order to maximize the portfolio return while minimizing the total risk simultaneously. Hence, the portfolio asset selection problem is fundamentally a multiobjective problem. In recent years, many researchers have applied multiobjective evolutionary algorithms (MOEAs) such as Pareto ant colony optimization (PACO), Pareto simulated annealing and the non-dominated sorting genetic algorithm (NSGA), multiobjective particle swarm optimization (MOPSO) etc. to solve this problem [8–14].

The main advantages of the MOEAs over single objective evolutionary algorithms (SOEAs) in order to solve multiobjective problem is that, it gives a set of probable solutions in a single run, called as a Pareto optimal solution, in a reasonable amount of time. The Portfolio optimization problem with many practical constraints that are solved using MOEAs is reported in [10–14]. The literature survey reveals that the cardinality constraint has been addressed by using hybrid local search in the MOEA [10]. Recently, Mishra et al. have applied MOEAs to solve the portfolio optimization problem with only a budget constraint [11]. The cardinality, floor and ceiling constraints are handled by applying different MOEAs by the same authors [12]. Khin Lwin et al. have proposed a learning-guided multi-objective evolutionary algorithm for constrained portfolio optimization [13]. Sadra Babaei et al. have proposed Multi-objective portfolio optimization considering the dependence structure of asset returns [14]. G.A. Vijayalakshmi Pai et al. present a metaheuristic solution to obtain futures portfolio, which is a combination of several asset classes such as bonds, equity indices and currencies, considering different constraints like capital budgets imposed on each of the asset classes and other bounding constraints [15].

In the present study, the portfolio optimization problem with four practical constraints is taken into consideration, to make it more realistic. Three competitive multiobjective evolution algorithms (MOEAs) have been suitably modified and suggested to solve the portfolio optimization problem using the proposed PBMV model with all the constraints. The performance of these MOEAs using the proposed PBMV model, and Markowitz mean-variance model has been compared. This comparison includes four performance metrics such as generation distance, spacing, delta and convergence metrics. The nonparametric statistical analysis using the Sign test and Wilcoxon rank test are conducted for pair wise comparison of the MOEAs.

The remaining part of the paper is structured as follows. The multiobjective optimization is presented in a concise manner in Section 2. In Section 3, the portfolio optimization problem and multiobjective formulation of constraint portfolio optimization is outlined. The proposed multiobjective evolutionary algorithms's frameworks, which are suitably modified for portfolio optimization, are discussed in Section 4. The proposed functional link artificial neural network (FLANN) network has been depicted in Section 5. Section 6 highlighted the proposed prediction based mean-variance (PBMV) model. Section 7, provides the simulation results and the associated discussion. Finally, the conclusion and further possible extensions of the works are outlined in Section 8.

2. Multiobjective optimization: basic concepts and brief overview

Multiobjective optimization means simultaneous optimization of multiple objective functions having conflicting nature. It is defined as computation of a vector of decision variables that satisfy the constraints and optimize a vector function whose elements represent the objective functions. The generalized multiobjective minimization problem is formulated [16] as

$$\text{Minimize } f(\vec{x}) = \left(f_1(\vec{x}), f_2(\vec{x}), \ldots, f_M(\vec{x})\right) \tag{1}$$

$$\text{subjected to the constraints}: \; g_j(\vec{x}) \geq 0, \; j = 1, 2, 3\ldots\ldots, J \tag{2}$$

$$\text{and } h_k(\vec{x}) = 0, \; k = 1, 2, 3\ldots\ldots\ldots, K \tag{3}$$

where $\vec{x}$ represents a vector of decision variables $\vec{x} = \{x_1, x_{2,} \ldots\ldots, x_N\}^T$

The search space is limited by

$$x_i^L \leq x_i \leq x_i^U, i = 1, 2, 3\ldots\ldots, N \tag{4}$$

In (4) x_i^L and x_i^U represent the lower and upper acceptable values respectively, for the variable x_i. The symbols N and M represent the number of decision variables and the number of objective functions respectively. Any solution vector $\vec{u} = \{u_1, u_2, \ldots\ldots u_K\}^T$ is said to dominate over $\vec{v} = \{v_1, v_2, \ldots\ldots, v_k\}^T$, if and only if

$$\left.\begin{array}{l} f_i(\vec{u}) \leq f_i(\vec{v}) \quad \forall i \in \{1, 2, \ldots, M\} \\ f_i(\vec{u}) < f_i(\vec{v}) \quad \exists i \in \{1, 2, \ldots, M\} \end{array}\right\} \tag{5}$$

The solutions that are not dominated by other solutions for a given set are called as non-dominated solutions. The Pareto-optimal front (POF) is the front obtained by mapping these non-dominated solutions and is mathematically expressed as

$$POF = f(\vec{x}) = \left\{(f_1(\vec{x}), f_2(\vec{x}), \ldots\ldots\ldots, f_k(\vec{x})) | \; \vec{x} \in p\right\} \tag{6}$$

where p is the set of non-dominated solutions.

The generalized concept of the Pareto front was introduced by Pareto in 1986 [17]. The pioneering work in the practical application of the genetic algorithm to multiobjective optimization problem is the vector evaluated genetic algorithm (VEGA) [18]. In the recent past, the PESA-II [19], SPEA-2 [20], NSGA-II [21] and MOPSO [16] algorithms have been proposed by many authors to solve multiobjective problems.

3. The portfolio selection problem

The main objective of portfolio selection is to maximize of the returns and minimize the risk of portfolio. In addition to these two objectives, other restrictions known as constraints may be present. In the Markowitz model [22] for portfolio selection, variance is used as a measure of risk, which is mathematically expressed as

$$\sigma_p^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} w_i w_j \sigma_{ij} \tag{7}$$