Metaheuristic Optimization of Constrained Large Portfolios using Hybrid Particle Swarm Optimization

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ABSTRACT

Classical Particle Swarm Optimization (PSO) that has been attempted for the solution of complex constrained portfolio optimization problem in finance, despite its noteworthy track record, suffers from the perils of getting trapped in local optima yielding inferior solutions and unrealistic time estimates for diversification even in medium level portfolio sets. In this work the authors present the solution of the problem using a hybrid PSO strategy. The global best particle position arrived at by the hybrid PSO now acts as the initial point to the Sequential Quadratic Programming (SQP) algorithm which efficiently obtains the optimal solution for even large portfolio sets. The experimental results of the hybrid PSO-SQP model have been demonstrated over Bombay Stock Exchange, India (BSE200 index, Period: July 2001-July 2006) and Tokyo Stock Exchange, Japan (Nikkei225 index, Period: March 2002-March 2007) data sets, and compared with those obtained by Evolutionary Strategy, which belongs to a different genre.

KEYWORDS
Cardinality Constraint, Class Constraint, Constrained Portfolio Optimization, K-Means Cluster Analysis, Particle Swarm Optimization, Sequential Quadratic Programming

1. INTRODUCTION

A portfolio is a combination of tradable assets such as bonds, stocks and securities held by an investor. Portfolio selection or optimization is concerned with finding optimal proportion of assets (weights) that best meets an investor’s needs, expressed by the twin objectives of maximizing the return on the portfolio and minimizing the associated risk. Solving the problem mathematically yields the efficient frontier which is a risk-return trade off curve. The efficient frontier serves to give the minimum level of risk to take for an expected level of portfolio return or alternatively the maximum return one can expect for a given level of risk.

Markowitz (1952) laid the framework for solving the portfolio selection problem and assumed a frictionless market – ignoring taxes, transaction costs and no restrictions on short selling etc. Hence the problem could be easily solved either analytically or using a traditional optimization technique such as Quadratic Programming. In reality, Portfolio optimization problems become difficult to solve especially when the objective function is augmented with constraints, modeling market frictions and/or investor preferences and/or regulatory limits. Fortunately, heuristic methods have served to provide alternative solutions with either optimal or mixed results in places where traditional optimization methods have failed.

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The basic Particle Swarm Optimization (PSO) and its variants, despite their noteworthy track records, have so far been used for portfolio optimization with mixed success, with most of the studies being in regard to diversification in small portfolios. Fischer and Roehrl (2005) combined particle swarm intelligence with a gradient search method to optimize German stocks. However, their problem formulation was somewhat different from the classical portfolio optimization framework, for the objective function had to be rendered differentiable for the use of the technique. Kendall and Su (2005) demonstrated that PSO was able to efficiently construct optimal portfolio sets when the number of assets was less than 15, but for larger portfolios the search time increased considerably. Thomaidis et al., (2009) employed PSO for the selection of portfolios with different cardinality that actively reproduces the FTSE/ATHEX20 Index of the Athens Stock Exchange. However, their demonstrations too were made for the selection of small portfolio sets that had less than 20 assets. Tunchan Cura (2009), Abbas and Haider (2009) also applied the classical PSO to the portfolio optimization problem model but governed either by cardinality or bounding constraints or on small portfolio sets. Interestingly, Zhu et al., (2010) showed that for the classical Markowitz model, though PSO outperformed Ant Colony Optimization (ACO) strategy for medium level portfolio sets, for large and small portfolios the performance of PSO could not match that of the ACO.

In such a background, the major objective of the work was to explore the application of PSO for the solution of a constrained portfolio optimization problem when the investor seeks diversification in large portfolio sets (with the number of assets typically of the order of 30 or more) and when the portfolio is governed by complex constraints. Thus the portfolio selection problem was formulated to include basic, cardinality, bounding and class constraints in a clear departure from the problem models this far worked upon using PSO and/or its variants.

The basic constraints (in the absence of short selling) emphasize on the individual weights to lie between 0 and 1 and their sum total to equal 1 (fully invested portfolio). In practice, it is quite often the case that an investor chooses to invest a definite proportion of weights bounded by a range, in specific stocks, and/or chooses to invest a proportion of weights in stocks related to specific sectors such as banking, energy, technology etc., with the sum total of weights in each specific sector bounded by limits. In the former case the constraint is referred to as bounding constraint and in the latter case as class constraint. Cardinality constraint is when the investor decides to invest in only \(K\) assets out of a universe of \(N\) assets, for a pre-specified value of \(K\). Choosing a ‘large’ value of \(K\) can serve to implement diversification in large portfolios.

For the complex constrained portfolio optimization problem, Pai and Michel (2009) attempted solving it using Evolution Strategy (ES). While ES was able to provide efficient solutions for small portfolio sets, it turned impracticable for large portfolio sets reporting excruciatingly long convergence and unrealistic time estimates. So, the objective of this work was to investigate the potential of an alternative heuristic method viz., PSO in solving the problem concerned especially for large portfolio sets. An independent application of PSO for the solution of the complex-constrained \(k\)-means clustered assets, targeting large portfolio sets is beset with the following problems:

PSOs are generally prone to premature convergence where the best particle found by the swarm gets trapped in the local maxima and to overcome which several improvisations have been investigated (van den Bergh & Engelbrecht, 2002; Trelea, 2003; Peer et al., 2003; Li et al., 2005; Wei gao et al., 2005). PSOs exhibit the characteristic of undertaking global search during the beginning of the run and scaling it down to local search towards the end of the run which can turn out to be a drawback for some applications (Min et al., 2007).

In the discipline of portfolio optimization, PSOs are proven to take unrealistic time estimates for the solution of even medium level portfolio sets (Kendall & Su, 2005; Zhu et al., 2010) and this for a problem model that was governed only by the basic constraints. A solution to the problem lies in making use of a PSO with high inertial weights (\(\omega\)) but varying with time, to enable a global search ensuring ‘exploration’ of the search space for the particle that represents the global best. The PSO is run for a moderate number of iterations and swarm size. The global best particle now acts as
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