Symbiotic Multi-swarm PSO for Portfolio Optimization

Ben Niu[1], Bing Xue[1], Li Li[1], and Yujuan Chai[2]

[1] College of Management, Shenzhen University,
Shenzhen, Guangdong 518060, China
[2] Faculty of Science, McMaster University,
Hamilton, Ontario L8S4L8, Canada
drniuben@gmail.com

Abstract. This paper presents a novel symbiotic multi-swarm particle swarm optimization (SMPSO) based on our previous proposed multi-swarm cooperative particle swarm optimization. In SMPSO, the population is divided into several identical sub-swarms and a center communication strategy is used to transfer the information among all the sub-swarms. The information sharing among all the sub-swarms can help the proposed algorithm avoid be trapped into local minima as well as improve its convergence rate. SMPSO is then applied to portfolio optimization problem. To demonstrate the efficiency of the proposed SMPSO algorithm, an improved Markowitz portfolio optimization model including two of the most important limitations are adopted. Experimental results show that SMPSO is promising for this class of problems.

Keywords: Symbiotic PSO, particle swarm, portfolio optimization**.**

1 Introduction

Portfolio Optimization (PO), also known as mean-variance optimization (MVO), is risk management tool which allows you to construct optimal portfolios considering the trade-off between market risk and expected returns.

PO problem is NP-hard and non-linear with many local optima. Mathematical programming methods have been applied to this problem for a long time [1, 2, 3]. Nowadays, a number of different heuristic algorithms have been proposed for solving this problem, including genetic algorithms (GA) [4, 5], simulated annealing [6], neural networks [7] and others [8, 9, 10].

However most of the PO models used in those pioneer works may often be considered too basic, as it ignores many of the constrains, such as the transaction fee and whether short sale is permitted, and the upper and the lower bounds of proportion of each asset in the portfolio. In this work, we use a modified PO model considering the transaction costs and no short sales. The main motivation of this study is to employ an improved multi-swarm cooperative PSO (MCPSO) for the modified PO model.

MCPSO was firstly proposed by B. Niu in 2005[11], which is inspired by the phenomenon of symbiosis in natural ecosystems, where many species have developed cooperative interactions with other species to improve their survival. MCPSO has been successfully applied in many problems, including function optimization [11],

D.-S. Huang et al. (Eds.): ICIC 2009, LNAI 5755, pp. 776–784, 2009.

neural networks training[12], fuzzy modeling designing[13] etc. In this paper we will apply an improved MCPSO, i.e. symbiotic multi-swarm particle swarm optimization (SMPSO) to find efficient portfolio by solving the PO model.

The rest of the paper is organized as follows. Section 2 gives a review of PSO and a description of the proposed algorithm SMPSO. Section 3 describes portfolio optimization model. Section 4 gives the detailed experimental studies. Finally, conclusions are drawn in Section 5.

2 PSO and SMPSO

2.1 Particle Swarm Optimization (PSO)

The basic PSO is a population based optimization tool, where the system is initialized with a population of random solutions and the algorithm searches for optima by updating generations. In PSO, the potential solutions, called particles, fly in a *D*-dimension search space with a velocity which is dynamically adjusted according to its own experience and that of its neighbors.

The position of the *i*th particle is represented as $\vec{x}_i = (x_{i1}, x_{i2}, ..., x_{iD})$, where $x_{id} \in [l_d, u_d]$, $d \in [1, D]$, l_d, u_d are the lower and upper bounds for the *d*th dimension, respectively. The rate of velocity for particle i is represented as $\vec{v}_i = (v_{i1}, v_{i2}, ..., v_{iD})$, is clamped to a maximum velocity vector $\vec{v}_{\max}$, which is specified by the user. The best previous position of the *i*th particle is recorded and represented as $P_i = (P_{i1}, P_{i2}, ..., P_{iD})$, which is also called $pbest$. The index of the best particle among all the particles in the population is represented by the symbol g, and p_g is called $gbest$. At each iteration step, the particles are manipulated according to the following equations:

$$v_{id} = wv_{id} + R_1 c_1 (P_{id} - x_{id}) + R_2 c_2 (p_{gd} - x_{id}), \tag{1}$$

$$x_{id} = x_{id} + v_{id}. \tag{2}$$

Where w is inertia weight; c_1 and c_2 are acceleration constants; and R_1, R_2 are random vectors with components uniformly distributed in [0, 1]. For Eq. (1), the portion of the adjustment to the velocity influenced by the individual's own $pbest$ position is considered as the cognition component, and the portion influenced by $gbest$ is the social component. After the velocity is updated, the new position of the *i*th particle in its *d*th dimension is recomputed. This process is repeated for each dimension of the *i*th particle and for all the particles in the swarm.

2.2 Symbiotic Multi-swarm Particle Swarm Optimizer (SMPSO)

In our previous proposed MCPSO algorithm, the population is divided into several sub-swarms, in which some sub-swarms are master swarms and the other sub-swarms are slave swarms. Both the master and slave swarms have different properties. The master swarms update particles information according to the slave swarms and their own. While the slave swarms update the particles information only based on their own