Portfolio Management using Particle Swarm Optimization in Knowledge Management

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Abstract: *In knowledge intensive organizations, many sources of competitiveness rely mostly on intangible parts of their organization. Portfolio management can be taken as a tool for knowledge management in organizations. Heuristic optimization techniques are more general purpose search methods that do not derive the solution analytically but by iteratively searching and testing improved or modified solutions until some convergence criterion is met. The techniques could be more suitable for solving problems in portfolio management than others. This paper focuses on investment management problems and shows how to manage financial portfolios using Particle Swarm Optimization (PSO). A PSO model is developed and tested on various restricted and unrestricted risky investment portfolios. Especially, a comparative study with genetic algorithms has been implemented. The PSO model demonstrates high computational efficiency in constructing optimal risky portfolios. Preliminary results show that the approach is very promising and achieves results comparable or superior with the state of the art solvers.*

Key words: *Portfolio management, Knowledge management, Particle Swarm Optimization, Sharp Ratio.*

INTRODUCTION

In knowledge intensive organizations, many sources of competitiveness rely mostly on intangible parts of their organization, such as the relationships of organization with its stakeholders, the knowledge and know-how of employees, its patents and trademarks. Management of these resources – also know as intellectual capital – should enable the organization to sustain viability, success, and basis for innovation [2], [9].

How exactly the knowledge resources and knowledge management processes tie to strategic, tactical, and operational business objectives and workflow is often left implicit or not addressed at all in business practice [6]. In order to specify these relationships, The "Knowledge governance framework" developed by Smits and de Moor [2004] has been developed. A modified version is shown in Figure 1, which shows that management can focus on the overall strategic objectives and directions set as part of governance of intellectual capital. In general new product development projects are usually proposed by technical staff, or by marketing and production staff and the focus of the projects can range from technical problems, product improvement demanded by customers, process improvement for production or development of new knowledge. However, usually only limited resources are available for innovative products and processes.

Portfolio management may refer to different areas, such as investment management; IT portfolio management and project management. All these fields are very central to enterprises or organizations knowledge management. In general, Portfolio Management is used to select a portfolio of new product development projects to achieve the following goals: (a) Obtain value maximization; (b) Support the strategy of the enterprise; and (c) Provide balance. Portfolio management can be taken as a tool for knowledge management in enterprises or organizations [1]. The optimal composition of portfolio is a set of new product development projects, where capacity constrains; strategic objectives and cash flow are carefully balanced. The theoretical foundation to portfolio management was laid by Harry Markowitz [5] by starting a parametric optimization model. With all its merits, the Markowitz model has major downsides: to get a grip of computational complexity, it has to rely on a number of rather strict technical assumptions which are more or less from reality [4]. The limitations of the original Markowitz framework have stimulated a number of extended or modified methods. One of these methods is using heuristic optimization techniques. The heuristic techniques are more general purpose search methods that do not derive the solution analytically but by iteratively searching and testing improved or modified solutions until some convergence criterion is met. Since they usually outperform traditional numerical procedures, they are well suited for empirical and computational studies.

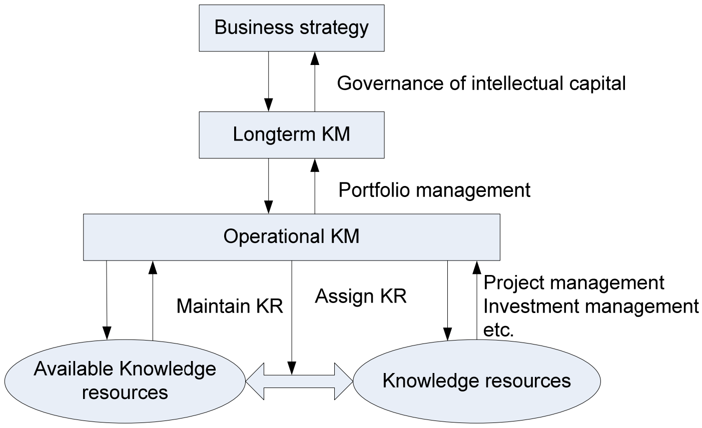

Fig.1. The modified knowledge governance framework

This paper focuses on investment management within portfolio management and shows how to manage financial portfolio using a heuristic approach PSO in knowledge management extent. The main motivation of this study is to employ a PSO algorithm for portfolio selection and optimization. First, we identify good quality assets in terms of asset ranking. Then asset allocation in the selected good quality assets is optimized using a PSO algorithm based on Markowitz's theory. Through the PSO process, an optimal portfolio can be determined.

MODELS FOR PORTFOLIO OPTIMIZATION (PO)

One of the fundamental principles of financial investment is diversification where investors diversify their investments into different types of assets. Portfolio diversification minimizes investors' exposure to risks, and maximizes returns on portfolios. The Markowitz Mean-Variance model [5] for security selection of risky portfolio construction is described as:

$$\mathrm{Min}\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}\,;\ sb.\sum_{i=1}^{N} w_i r_i = \mathrm{R}^*,\ \sum_{i=1}^{N} w_i = 1,\ 0 \le w_i \le 1\ \ i = 1,\cdots,N. \qquad (1)$$

where N is the number of different assets, σ_{ij} is the covariance between returns of assets i and j, w_i is the weight of each stock in the portfolio, r_i is the mean return of stock i and R^* is the desired mean return of the portfolio.

We can find the different objective function values by varying desired mean return R*, so a new named risk aversion parameter $\lambda\in[0,1]$ has been introduced, the sensitivity of the investor to the risk increase as λ increasing from zero to unity. With the λ, the model can be described as:

$$\mathrm{Min}\lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}\right] - (1-\lambda)\left[\sum_{i=1}^{N} w_i r_i\right];\quad sb.\quad \sum_{i=1}^{N} w_i = 1,\quad 0 \le w_i \le 1\ \ i = 1,\cdots,N \qquad (2)$$

In the model included parameter λ, we can draw a continuous curve that is called an efficient frontier according the Markowitz theory, the curve composed of mean return and variance according different λ, and every point on an efficient frontier curve indicates an optimum, which indicates that the portfolio optimization problem is a multi-objective optimization.

Instead of focusing on the mean variance efficient frontier, we seek to optimize the portfolio Sharpe Ratio (SR) [7]. The Sharpe ratio is quite simple and is a risk-adjusted measure of return, which is often used to evaluate the performance of a portfolio. It is described as the following formula:

$$SR = \frac{R_p - R_f}{StdDev(p)} \qquad (3)$$

where p is the portfolio, R_p is the mean return of the portfolio p, R_f is the test available rate of return of a risk-free security (i.e. T-bills), we select zero R_f in this study. StdDev(p) is the standard deviation of R_p. In other words, it is a measure of risk of the portfolio. Adjusting the portfolio weights w_i. We can maximize the portfolio Sharpe Ratio in effectively balancing the trade-off between the expected return and the corresponding risk. In this study, the PSO algorithm is used to find the most valuable portfolio with good stock combinations.

PARTICLE SWARM OPTIMIZATION (PSO)

Swarm Intelligence (SI) is an agent-based intelligent paradigm for solving optimization problems that originally took its inspiration from the biological examples by swarming, flocking and herding phenomena in social insects. The complex behavior of the swarm is based on that agents follow some simple rules. PSO is one optimization technique of Swarm intelligence The major feature of PSO algorithm is its simplicity in implementation and high computational efficiency in solving optimization problems., Researches in the filed of Swarm intelligence argue against the view that agents (individuals) are isolated information-processing entities and stresses the fact that intelligence arises among the interaction of intelligent agents.

The study of Swarm Intelligence has introduced a number of new optimization techniques into the field of Computational Intelligence. Kennedy and Eberhart [3] developed Particle Swarm Optimization based on the analogy of birds flocking and fish schooling. PSO has been shown to be powerful, easy to implement, and computationally efficient.

The original PSO algorithm is thought of a picture in which K particles of a population flys in the D-dimensional problem space (solution space). Each particle represents a solution of the problem, and has a value called "position" of the particle, and another value called called "velocity" used for evolving a new position in the search space. The velocity of each particle is dynamically adjusted by the flying experiences of its neighbors and its own. At each iteration, a particle moves to a new position based on the old position and an updated velocity.

How the algorithm works is briefly described as follows: 1. To initialize the size of the particle swarm and parameter; 2. To initialize the position and velocity for all the particles randomly; 3. To find the global best particle in the neighbor hood based on the fitness function; 4. All the particles are then accelerated in the direction of the global best particle and in direction of their own best solutions that they have discovered previously.

Occasionally the articles will overshoot their target, exploring the search space beyond the current best particles. All particles have the opportunity to discover better particles in route, in which case the other particles will change direction and head towards the new best particle. Since most functions have some continuity, a good solution will be near by these good, or better, solutions. By approaching the current best solution from different direction in search space, the chances are good that these neighboring solutions will be discovered by some of the particles.

The basic concept of PSO lies in accelerating each particle toward its pbest and the gbest locations, with a random weighted acceleration at each time step. Each particle tries to modify its position using the following information: (1) The current positions; (2) The current velocities; (3) The distance between the current position and pbest; and (4) The distance between the current position and the gbest.

In this paper, we apply PSO to a high-dimensional constrained optimization problem. That is to construct optimal risky portfolios for financial investments. A PSO solver is developed and test on various restricted and unrestricted portfolios. The results of experiments demonstrates that the PSO solve has high computational efficiency in constructing optimal risky portfolios.

FITNESS FUNCTION

Fitness function is a critical factor in the PSO method. The fitness function f_p is defined as :

$$f_p = \frac{\sum_{i=1}^{N} w_i r_i}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{ij}} \tag{4}$$

At each step, a particle's position and its velocity in the swarm are updated if an improvement of the fitness values is observed.

PARTICLES MOVING

Every particle moves towards its *pbest* position plus the *gbest* position particles of the swarm at each one of the iterations. Indeed, this movement depends on its current velocity and current position. a new velocity in the problem space is shown in Eq. (5).

$$\vec{v}_{ij}(t+1) = w\vec{v}_{ij}(t) + c_1 r_1[\vec{p}_{ij}(t) - \vec{x}_{ij}(t)] + c_2 r_2[\vec{p}_{gj}(t) - \vec{x}_{ij}(t)] \tag{5}$$

where index j is the dimension number of particle i, t is the iteration sequence, c_1 and c_2 are positive constant parameters called acceleration coefficients which are responsible for controlling the maximum step size, r_1 and r_2 are random numbers between (0, 1), w is a constant, and $\vec{v}_{ij}(t+1)$ is particle it's velocity on the jth dimension at iteration t+1. $\vec{v}_{ij}(t)$ is particle it's velocity on the jth dimension at iteration k. $\vec{x}_{ij}(t)$ is particle it's position on the jth dimension at iteration k.. $\vec{p}_{ij}(t)$ is the historical individual best position of the particle. $\vec{p}_{gj}(t)$ is the global best position of the swarm. Finally, the new position of particle *i*, $\vec{x}_{ij}$, is calculated by Eq. (6):

$$\vec{x}_{ij}(t+1) = \vec{x}_{ij}(t) + \vec{v}_{ij}(t+1) \tag{6}$$

There are two types of risky portfolios [4]. One is unrestricted risky portfolios, which do not have constraints on the short selling of stocks. Investors can choose to sell a stock that the investor does not own based on the condition that the investor must buy it back after a time of period, hopefully at a lower price. In other words, for unrestricted risky portfolios, assets could have negative weights. Another one is restricted risky portfolios, which place constraints on the short selling of portfolios' underlying equities, and require that all underlying assets must have positive weights. Both unrestricted optimal risky portfolios and restricted optimal risky portfolios must also satisfy another constraint, i.e., the total weights of all assets must sum to 1. To construct an optimal risky portfolio is to find the optimal combination of all assets in order to achieve the maximum Sharp Ratio. As the number of assets in the risky portfolio increases, construction of an optimal risky portfolio becomes an increasingly high-dimensional optimization problem with a variety of constrains.

EXPERIMENTS AND DISCUSSION

The PSO experiments for the portfolio optimization has been performed on three unrestricted risky portfolio of 8 stocks,15 stocks and 49 stocks, and on three restricted risky portfolio of 8 stocks, 15 stocks and 49 stocks. Table 1 shows only the unrestricted and restricted risky portfolio of 8 stocks together with each stock's daily Expected Returns (ER) and Standard Deviations (SD). All stocks are selected from the Shanghai Stock Exchange 50 Index (the SSE 50 Index). Individual stock's historical daily returns are taken from 1st May 2009 to 3rd April 2009. Unrestricted portfolios do not have constraints on short selling. In other words, the proportion of an asset in the portfolio could be negative or greater than 1.

In order to evaluate the performance of PSO model, we compare PSO with another heuristic Algorithm, Genetic Algorithm. In the experiments, PSO Solver has been developed using Matlab as software development tool. Genetic Algorithm has been developed using GeneHunter. Meanwhile, we also compare the result of them with the result of the traditional method of VBA (Visual Basic Application).

For the computation of the optimal risky portfolios, three approaches: PSO algorithm, GA algorithm and VBA solver are implemented for the 8-stock, 15 stocks and 49-stock portfolios. In the experiment of both PSO and GA, the size of the population is 100 and the termination condition is 1000 iterations to find the optimal risky portfolio respectively.

The experiment shows that the SharpRatio value obtained by PSO is the best one shown in Table 1. In the experiment, we find the SharpRatio value from GA is unstable. The efficient frontier obtained from PSO is absolutely the best. We also note that when the number of stocks is 8 and 15, the VBA solver could be better than GA. However, the GA algorithm is significantly better than VBA solver as the number of stocks increases.

Table 1. 8 stocks unrestricted and restricted portfolio's results

		Unrestricted	Restricted
PSO Solver:	**ER**	1.14%	0.72%
	SD	4.22%	2.90%
	SharpRatio	19.84%	17.83%
GA Solver:	**ER**	0.60%	0.53%
	SD	4.17%	2.63%
	SharpRatio	7.24%	12.42%
VBA Solver:	**ER**	1.03%	0.76%
	SD	3.78%	3.17%
	SharpRatio	19.31%	17.55%
Risk Free		0.03%	0.02%

In conclusion, the performance of PSO algorithm is better than both GA and the traditional VBA solver. From the experiments on unrestricted and restricted portfolios, the PSO solver clearly demonstrates the efficiency and effectiveness in solving high-dimensional constrained optimization problems.

CONCLUSIONS AND FUTURE WORK

The modified "Knowledge Governance Framework" has been developed and we points out that portfolio management could be taken as a tool for enterprise/organization Knowledge Management. A fundamental principle of financial investments is diversification where investors diversify their investments into different types of assets. Portfolio diversification minimizes investors' exposure to risks, and maximizes returns on portfolios. The paper focuses on solving the portfolio optimization problem in finance investment management. A metaheuristic Particle Swarm Optimization method has been developed to optimize investment portfolios, which the objective functions and constraints are based on both the Markowitz model and the Sharp Ratio model. In order to make a valid comparison with other methods, different test problems were solved and the results obtained when compared with the results of Genetic Algorithms (GA), Visual Basic for Applications (VBA) demonstrated the superiority of the PSO algorithm. Future research may be conducted to further investigate the application of some derived models or hybrid models of PSO to other investment strategy problems, for example tracking the index and so on. Another further investigation may be put on methods for improving the efficiency of the PSO solver for large portfolios in investment management.

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