An Evolutionary Algorithm with A New Operator and An Adaptive Strategy for Large-Scale Portfolio Problems

Yi Chen
Shanghai Key Laboratory of Multidimensional Information Processing, Department of Computer Science and Technology, East China Normal University, 3663 North Zhongshan Road, Shanghai, China
52164500006@stu.ecnu.edu.cn

Aimin Zhou
Shanghai Key Laboratory of Multidimensional Information Processing, Department of Computer Science and Technology, East China Normal University, 3663 North Zhongshan Road, Shanghai, China
amzhou@cs.ecnu.edu.cn

Liang Dou*
Shanghai Key Laboratory of Multidimensional Information Processing, Department of Computer Science and Technology, East China Normal University, 3663 North Zhongshan Road, Shanghai, China
ldou@cs.ecnu.edu.cn

ABSTRACT

A portfolio optimization problem involves optimal allocation of finite capital to a series of assets to achieve an acceptable trade-off between profit and risk in a given investment period. In the paper, the extended Markowitz's mean-variance portfolio optimization model is studied with some practical constraints. We introduce a new operator and an adaptive strategy for improving the performance of the multi-dimensional mapping algorithm (MDM) proposed specially for the portfolio optimization. Experimental results show that the modification is efficient on tackling large-scale portfolio problems.

KEYWORDS

Multi-objective portfolio optimization; constraint handling; coding scheme; mixed variables

ACM Reference Format:
Yi Chen, Aimin Zhou, and Liang Dou*. 2018. An Evolutionary Algorithm with A New Operator and An Adaptive Strategy for Large-Scale Portfolio Problems. In *GECCO '18 Companion: Genetic and Evolutionary Computation Conference Companion, July 15–19, 2018, Kyoto, Japan.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3205651.3205712

1 INTRODUCTION

Portfolio selection problem is a well-known financial problem and appeals to allocate limited money among a finite number of available risky assets, such as bonds, stocks, and derivatives. According to the MV model [4], an investor attempts to maximize portfolio expected return for a given amount of portfolio risk or minimize portfolio risk for a given level of expected return. In this paper, the following four practical constraints [3] [5] are considered: (i)*cardinality constraint*, (ii)*floor and ceiling constraints*, (iii)*preassignment constraint* and (iv)*round lot constraint*. Recently, Chen et al. introduced a multi-dimensional mapping coding scheme (MDM) for multi-objective portfolio optimization, which uses a continuous string to present the continuous and discrete variables simultaneously in portfolio problem [2]. However, it may fail when the size of portfolio problem grows. In this work, we propose a diversity operator (DO) and an adaptive strategy for MDM, which is more likely to find diverse solutions. In this study, we consider the Decomposition Based Multi-objective Evolutionary Algorithm (MOEA/D) [7], and compare the performance of MOEA/D, MOEA/D with MDM and MOEA/D with MDM&DO. A large set of simulation experiments have been conducted over a number of instances. Results demonstrate that the proposed operator is highly efficient in terms of both finding solutions close to the true Pareto-front and good distribution along the Pareto-front.

In the portfolio problem, a high risk and high return solution is more likely to be an extreme capital allocation, which allocates major fund for a high return asset. Accordingly, the goal of DO is to find a high return asset and makes the allocation extreme as a exploitation operator. The mathematic process of DO is as follow:

$$Let \qquad p_i = {p_i}^2, \qquad i = 1, \dots, N$$

where N is the number of assets. The DO handles the equal distribution problem, because it has the ability of polarizing the allocation as

$$\frac{p_1}{p_1 + p_2 \dots + p_K} < \frac{p_1^2}{p_1^2 + p_2^2 \dots + p_K^2}$$

$$\frac{p_K}{p_1 + p_2 \dots + p_K} > \frac{p_K^2}{p_1^2 + p_2^2 \dots + p_K^2}$$

where the p_i is sorted in the descending order. Furthermore, the effectiveness of DO is studied in Section 2, and Figure 1(a) shows how the DO makes the solutions obtained by MDM, which trap in the low risk and low return area, to be diverse. In addition, the algorithms implemented in this study generate the new population by the Differential Evolutionary Algorithm (DE) [6]. Since DE aims to explore and DO aims to exploit in the new approach, it is necessary to make a balance on the using of DE and DO. So, we employ an adaptive strategy in this work.

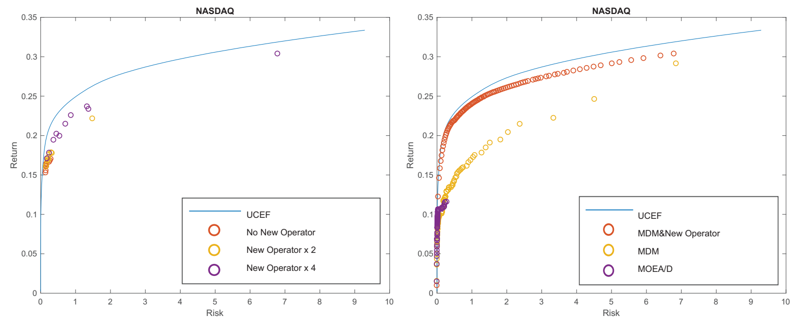
2 EXPERIMENTAL STUDY

In this section, five test problems are employed to study the performance of the three algorithms mentioned above, and Table 1 shows the details of these benchmark indices and their sizes. The first two

* Corresponding author: Liang Dou.

GECCO '18 Companion, July 15–19, 2018, Kyoto, Japan

ACM ISBN 978-1-4503-5764-7/18/07.
https://doi.org/10.1145/3205651.3205712



(a) (b)

Figure 1: Typical Pareto fronts obtained by DO (a) and the efficient frontier (b) obtained by three algorithms on largest instance

datasets (D1 and D2) are firstly introduced by Chang et al. [1], and The remaining three datasets (D3, D4, D5) are built from the data that employs the Yahoo Finance website. These instances have been used for portfolio optimization with the four constraints mentioned above. In addition, We have chosen to run all the algorithms with the same stopping criteria (i.e., the same number of evaluations) to generate the Pareto front. Each algorithm also uses the same repair mechanism when a newly constructed portfolio violates the considered constraints. Moreover, parameters are tuned for all algorithms using the smallest problem instance (D1).

In the paper, we study the effectiveness of the DO with respect to the quality of obtained efficient frontier. Figure 1(a) shows that the algorithm without new operator concentrate on the low risk and low return area of the solution space. In contrary, the algorithm with more times of running DO has a better diversity. Then, we compare the three algorithms in terms of the performance metrics. Figure 1(b) illustrates that MOEA/D with MDM&DO has the best efficient frontier, and Table 2 shows that it has the best IGD value on all the instances. Furthermore, the results obtained by MOEA/D with MDM&DO are much more better than MOEA/D with MDM on both IGD and PD, especially on large instances, such as D3, D4 and D5.

Table 1: The Benchmark instances.

instance	Origin	Name	Number of assets
$D1$	Hong Kong	Hang Seng	31
$D2$	Japan	Nikkei	225
$D3$	Korea	KOSPI Composite	562
$D4$	USA	AMEX Composite	1893
$D5$	USA	NASDAQ	2235

3 CONCLUSIONS

In this work, a new diversity operator and an adaptive strategy for MDM on large-scale portfolio problem are investigated. Firstly, the diversity operator acts as a exploitation operator, which changes the equal distribution of solutions obtained by MOEA/D with MDM. Then the adaptive strategy is a tradeoff of DE or DO in each generation, which is a tradeoff between exploration and exploitation in the evolutionary algorithm. In conclusion, we have demonstrated that implement of the diversity operator and the adaptive strategy (MOEA/D with MDM&DO) contributes to better performance than the two others via the analysis of simulation experiments.

Table 2: Statistical results of the IGD values of the final populations obtained by three algorithms on the test instances.

instance	MOEA/D		MDM		MDM&DO	
	mean	std.	mean	std.	mean	std.
$D1$	$1.400e-03$	$2.296e-04$	$2.460e-04$	$2.783e-05$	**1.620e-04**	$7.039e-06$
$D2$	$4.253e-04$	$1.259e-04$	$2.396e-04$	$4.498e-05$	**7.025e-05**	$2.404e-05$
$D3$	$2.539e+02$	$1.032e+01$	$1.117e+02$	$4.562e+01$	**1.710e+01**	$1.053e-01$
$D4$	$1.078e+02$	$2.600e+00$	$6.164e+01$	$4.492e+01$	**2.906e+01**	$4.433e+01$
$D5$	$1.112e+00$	$3.860e-02$	$6.780e-01$	$3.389e-01$	**9.630e-02**	$2.300e-03$

ACKNOWLEDGMENTS

This work is supported by the National Natural Science Foundation of China (No. 61731009, 61673180, and 61703382), and the Science and Technology Commission of Shanghai Municipality (No. 14DZ2260800).

REFERENCES

[1] T-J Chang, Nigel Meade, John E Beasley, and Yazid M Sharaiha. 2000. Heuristics for cardinality constrained portfolio optimisation. *Computers & Operations Research* 27, 13 (2000), 1271–1302.
[2] Yi Chen, Aimin Zhou, Rongfang Zhou, Peng He, Yong Zhao, and Lihua Dong. 2017. An Evolutionary Algorithm with a New Coding Scheme for Multi-objective Portfolio Optimization. In *Asia-Pacific Conference on Simulated Evolution and Learning*. Springer, 97–109.
[3] Khin Lwin, Rong Qu, and Graham Kendall. 2014. A learning-guided multi-objective evolutionary algorithm for constrained portfolio optimization. *Applied Soft Computing* 24 (2014), 757–772.
[4] H. Markowitz. 1952. Portfolio selection. *The Journal of Finance* 7, 1 (Mar 1952), 77–91.
[5] Antonin Ponsich, Antonio Lopez Jaimes, and Carlos A Coello Coello. 2013. A survey on multiobjective evolutionary algorithms for the solution of the portfolio optimization problem and other finance and economics applications. *IEEE Transactions on Evolutionary Computation* 17, 3 (2013), 321–344.
[6] Rainer Storn and Kenneth Price. 1997. Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization* 11, 4 (1997), 341–359.
[7] Qingfu Zhang and Hui Li. 2007. MOEA/D: A multiobjective evolutionary algorithm based on decomposition. *IEEE Transactions on evolutionary computation* 11, 6 (2007), 712–731.