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RESEARCH ARTICLE

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A comparison on particle swarm optimization and genetic algorithm performances in deriving the efficient frontier of stocks portfolios based on a mean-lower partial moment model

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Abstract

In this paper, a portfolio optimization model on the basis of the risk measure of lower partial moment of the first order is discussed. Two meta-heuristic methods of particle swarm optimization and genetic algorithm performances are applied and compared from different aspects to derive the stocks portfolios efficient frontier. The data belongs to the monthly returns of 20 randomly selected and approved stocks in the New York Stock Exchange for the financial period of 2005–2011. The results prove that both algorithms are quite efficient in solving the mean-lower partial moment of the first order model with the particle swarm optimization being superior.

KEYWORDS

efficient frontier, genetic algorithm, lower partial moment, mean–variance, particle swarm optimization, portfolio selection

1 | INTRODUCTION

A financial system based on securities in capital markets is the starting point in harmonic development of an economic structure (Murugesan & Sakthi Priya, 2016). These markets are crucial for long term financing as according to Fisher (1906), capital markets are working as an injector of financial resources for economies. As the number of alternatives for choosing an optimum stock portfolio increases, predicting an efficient investment trend first becomes a necessity for the market and its investors success and second becomes more complex. Mathematical modelling since the major work of Markowitz (1952) has a long history addressing this issue. Markowitz (1952) applied the weighted average of each portfolio as its return and measured its risk by variance and covariance of stocks' returns.

Many theoretical and computational improvements regarding portfolio models by researchers gave birth to the models such as the semi-variance model, Mean absolute deviation model, Variance with Skewness model, Lower Partial Moment (LPM) model (Chang, Yang, & Chang, 2009) and others. Most of them include downside risk measures that have become dominant and more popular since their introduction. Portfolio models based on this kind of measure are known as post-modern ones (Grootveld & Hallerbach, 1999). According to Grootveld and Hallerbach (1999) the general idea of downside risk is the fact that the left-hand side of a return distribution involves risk while the right-hand side contains better investment opportunities.

Among the downside risk measures, LPM proposed by Bawa (1975, 1978) creates an important class with outstanding features, which represents a wide range of downside risk measures by changing its two main parameters. Like this study, LPM has been the centre of many studies. There is a considerable literature on its efficacy. Jasemi, Kimiagari, and Memariani (2010) develops a new set of axioms for assessing risk measures and proves LPM of the first order is significant according to the new measure and can be called Sensibly Coherent. Unser (2000) believes that LPM is of special importance for applications in financial decision-making and symmetrical risk measures but can clearly be dismissed in favour of shortfall measures. Harlow and Rao (1989) firmly recommend using LPM it for the development of asset pricing models rather than earlier equations. It is to be noted that in the category of shortfall measures, LPM is more consistent with how individuals actually perceive risk (Harlow & Rao, 1989). Jasemi, Monplaisir, and Amini Jam (2019) tackle one of the basic challenges with LPM that is computational difficulties. The study comes with an efficient methodology to approximate the LPM of the first order. Nesaz, Jasemi, and Monplaisir (2020) optimize a multi-period investment portfolio model with LPM as a measure of risk under transaction cost constraints.

As existing problems are mainly categorized as NP-Hard, meta-heuristic methods have recently been used for selecting the optimum portfolios and predicting capital and financial markets, comparing to the classic methods (Vetschera & Teixeira de Almeida, 2012). According to Bertsimas, Lauprete, and Samarov (2004) one of the basic challenges with applying LPM in financial models is its computational difficulties, so in this study the authors try to fill the gap and push the knowledge boundaries of the field by solving an advanced efficient frontier (EF) model. This study in fact has a minor development on Mehrjoo, Jasemi, and Mahmoudi (2014) while here more sophisticated model along with more advanced meta-heuristic algorithms, that are genetic algorithm (GA) and particle swarm optimization (PSO), are being used especially with support of the approximation techniques that are discussed by Jasemi et al. (2019).

GA is a proper method for predicting financial stock markets since it is based on collective intelligence which enables it to have a fitting strategy for comprehensive searches (Liua & O'Neill, 2016). There are many studies advocating GAs for predicting stock price noting its ability for solving non-linear and integrated mixed optimization problems which mainly are related to complex engineering issues (Chang et al., 2009; Majhi, Rout, & Baghel, 2013; Panda & Padhy, 2008). There are researches that believe GA, due to it discrete nature is more fitting to our model rather than the other meta-heuristic methods (Huang, 2008). However, other studies believe it is less suitable for searching the answer space compared to other meta-heuristic methods such as PSO (Jones, 2005).The PSO algorithm was first introduced in 1995 by Kennedy and Eberhart (1995). Its name is based on the collective and food seeking behaviour of birds which has been used for solving optimization problems. In the PSO algorithm, all possible solutions for the best answer are related and depend on experiences and findings of adjacent solutions. This algorithm can converge fast because of the different behaviour of particles in the search space in sharing information. Only the best collective solutions are transferring information. This single path information sharing makes convergence faster even in local points (Yin, Ni, & Zhai, 2015). Bao, Hu, and Xiong (2013) develops a model for stock market predictions applying the exploratory search logic of PSO in order to identify more potential answer space for optimization as well as pattern search. Zhu et al. (2011) applies PSO for optimizing multi-objective portfolio selection. Shao et al. (2016) develops Linear Decreasing Inertia Weight (LDIW)-PSO which increases optimized search efficiency in order to optimize investing shares.

The main goal of this study is a comprehensive comparison of the performances between GA and PSO for solving a Mean-LPM of the first order model of portfolio selection. The data is taken from the monthly returns of 20 randomly selected and approved stocks in New York Stock Exchange (NYSE) for the financial period of 2005–2011.

The article is structured as follows. Section 2 describes the model of the study including subsections that cover LPM of the first order, EF, LPM-GA, and LPM-PSO. Section 3 delivers the computational results, while Section 4 presents the conclusions of the study.

2 | MODEL

Deriving EF on the basis of historical information is an essential initial step to remove inefficient portfolios otherwise the complexity of decision-making increases considerably (Ballestero, Gunther, Pla-Santamaria, & Stummer, 2007). The collection of portfolios that have maximum return at a specified level of risk or have minimum risk at a specified level of return is called EF (Markowitz, 1952) and Ballestero and Romero (1996) recommend maximizing investors expected utility on EF.

2.1 | LPM of the first order

Fishburn (1977) developed the (α, R_{nec}) model of LPM like Equation (1).

$$LPM_a(R_{nec}, r) = \int_{-100}^{R_{nec}} (R_{nec}-r)^a df(r) = E\{(max[0, R_{nec}-r])^a\} \tag{1}$$

$F(r)$ is the cumulative density function of r, and $R_{nec}$is the target parameter. By changing α and R_{nec}, different risk measures can be made. For example, semi-variance corresponds to $R_{nec} = E(r)$ and $\alpha = 2$; the Roy's safety and the expected loss are achieved if $\alpha = 0$ and $\alpha = 1$ respectively. For this study$LPM_1(R_{nec}, r)$, Equation (2), that according to Fishburn (1977) concerns a risk-neutral investor and that is also discussed by Spreitzer and Reznik (2007), has been selected.

$$\int_{-100}^{R_{nec}} (R_{nec} - r) f(r) dr. \tag{2}$$

Equation (3) presents the discrete equivalence of Equations (2) and (4) presents its estimation.

$$LPM_1(R_{nec}, r) = \sum_{-100}^{R_{nec}} (R_{nec} - r) p(r). \tag{3}$$

In Equation (3), $p(r)$ is the probability function and the steps, according to Figure 1, are denoted by r_1, r_2, ..., m, where f_i is the frequency of r_i. If $r_k < R_{nec} < r_{k+1}$, the estimation of Equation (3) is formulated by Equation (4) (Jasemi et al., 2019).

$$\sum_{-100}^{R_{nec}} (R_{nec} - r) p(r) = \sum_{i=1}^{k} (R_{nec} - r_i) \frac{f_i}{\sum_{j=1}^{n} f_i} = \frac{\sum_{i=1}^{k} (R_{nec} - r_i) f_i}{\sum_{j=1}^{n} f_i}. \tag{4}$$

2.2 | Efficient frontier

The general well-known model in literature to derive EF, as is also discussed in detail by Jasemi, Kimiagari, and Memariani (2011), is as follows:

$$min \frac{\sum_{i=1}^{k} (R_{nec} - r_{pi}(x_1, ..., x_n)) f_i}{\sum_{i=1}^{k} f_i}$$

$s.t$:

$$\sum_{i=1}^{n} x_i = 1$$

$$\sum_{i=1}^{n} x_i \bar{r}_i = R_d$$

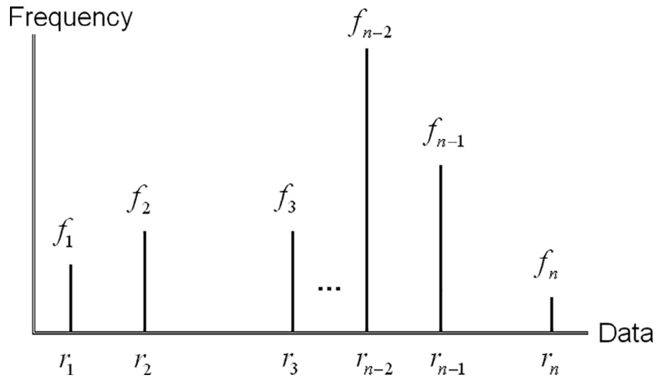

FIGURE 1 The frequency chart of past returns

$$\sum_{i=1}^{n} y_i = a$$

$$l_i y_i \le x_i \le u_i y_i \; i = 1, ..., n$$

$$x_i \ge 0 \; i = 1, ..., n$$

R_d The portfolio past return average

$\bar{r}_i$ Stock i past return average

a Desired number of stocks in the portfolio

l_i Lower limit for share of stock i in the portfolio

u_i Upper limit for share of stock i in the portfolio

r_{pi} The i^{th} smallest return of the portfolio whose shares of stocks are x_1, ..., x_n

f_i Frequency of the ith smallest return of the portfolio whose shares of stocks are x_1, ..., x_n

k Number of different portfolio returns.

x_i Share of stock i in the portfolio

y_i 1 if stock i gets invested, 0 otherwise

It should be noted that , r_{pi}, f_i are functions of (x_1, ..., x_n) and that makes solving of the model more complicated. The objective function is built exactly according to a methodology by Jasemi et al. (2019) that is called Approach 1; except for the fact that r_i (stock return) in the original study, has been replaced with $r_{pi}(x_1, ..., x_n)$ (portfolio return) in this study.

2.3 | LPM-GA

In the developed GA for this study, the chromosome has two parts. The first and second parts represent y_i and x_i, respectively. For the model second constraint a penalty function as Equation (5) is used and the penalty is added to the objective function as Equation (6). In fact, Equation (6) is the evaluation function of the algorithm where Obj_{Func} is the mathematical model objective function.

$$Vio = abs\left(\sum_{i=1}^{n} x_i \bar{r}_i - R_d\right) \tag{5}$$

$$Z = \mathrm{Obj}_{\mathrm{Func}} + \mathrm{Vio}. \tag{6}$$

The algorithm first does search to generate feasible solutions, and then goes after minimizing the objective function. In this study, single-point and uniform intersections beside Swap and Reversion mutation to generate mutated population are used. The population or chromosomes that contain the answers are continuously improved and revised.

It should be noted that the initial population is randomly produced on the basis of a specified size. Then, parents are selected. If the optimum fit regarding the objective function is met, it would be the proper composition for the portfolio and formation of the EF.

2.4 | PSO-LPM

In PSO, the first most important step is the answer structure which in this problem is exactly the same as the GA's that was described in the previous section; i.e., there are two parts while the first and second parts represent y_i and x_i, respectively. For making the first part, n random numbers are generated between 0 and 1, then the stocks with the first largest a numbers get 1 and the other stocks get 0. For making the second part, that is, investment percentage in each stock, random numbers are generated between the lower and upper bounds for the stocks that got 1 in the first part while the summation of investment percentages is 1.

Neighbouring structure in this algorithm is based on updating the location and velocity of the PSO algorithm. Solving the model using the PSO algorithm makes dependency of each stock to another stock in each selected composition well illustrated since each particle (here portfolio) adheres to its adjacent particles. This causes positive homogeneity increase in each portfolio. Subsequently, it shows the relation between actual return and risk of investment which makes each portfolio improved based on the highest memorized fitness. Due to the model discrete nature, each particle should calculate the objective function based on Equation (7) that shows changes in each particle movement, for each position in the space and the EF model.

$$\begin{aligned} V_{id}(t+1) = \omega V_{id}(t) + C_1\varphi_1(P_{id}(t) - X_{id}(t)) \\ + C_2\varphi_2\left(P_{gd}(t) - X_{id}(t)\right), \end{aligned} \tag{7}$$

where p_{id} is the best individual memory, p_{gd} is the best group memory, C_1 is the individual recognition parameter, C_2 is the social recognition parameter, ω is the inertia coefficient, V is the velocity of each particle, $i = 1, 2, 3, \ldots,$ N denotes the particles, $d = 1, 2, 3, \ldots, D$ is the dimension of the feasible region in which each particle is or will be located, and φ_1 and φ_2 are random numbers between 0 and 1 with uniform distribution.

The coefficient of each part in Equation (7) would specify the particle tendency towards the defined positions. The term ω determines how much each particle in inclines to keep the current position. ω is usually less than 1 and mainly between 0.4 and 0.9. ω could be both constant and a linear or non-linear function of time. In this study ω is mainly determined by the market conditions. For instance, the more uncertain the market is, more tendency exists to keep the current state, so ω would be higher and vice versa. On the other hand, to avoid a pre-due convergence of PSO, the lower the ω is the faster the solution is achieved and the higher ω is more diverse answers are achieved.

Velocity coefficients are mostly determined by full recognition of the market. For example if it is decided to continue the successful trend of the previous investments, C_1 would get a higher value. In this case, personal learning would increase and gravity keeps each particle close to the previous successful position. The solutions can converge to the general optimum value in the final phases of PSO search. If it is decided to change the investment strategy for any reason, higher values should be assigned to C_2, so the group learning as well as the search space regarding LPM would increase. However according to a rule of thumb in this field, if C_1 and $C_2$are in [0, 2], both features would be embedded in the algorithm.

Moreover, each particle is updated in each algorithm iteration by adding the velocity variable to the position variable as Equation (8).

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1). \tag{8}$$

Finally, the evaluation function here is exactly the same as the one was described for the GA.

3 | EXPERIMENTS

Both GA and PSO based models are coded in MATLAB and conducted on a computer with the following features: Intel(R) Core(TM)2Duo CPU P8800 CPU 4 GB RAM.

3.1 | Input data

In this study, the input data belongs to 20 randomly selected and approved stocks from NYSE. The monthly returns are used for the seven financial year period of 2005 to 2011.

3.2 | Empirical results for LPM-GA model

In this study with this experiment, maximum iterations, *MaxIt*, is 500; population size, *NPop*, is 100; crossover rate, P_c, is 0.8; mutation rate, P_m, is 1; probability of mutation, *Mu*, is 0.3 and selection rate, T_S, is 3. Figure 2 summarizes the outcomes while a, number of stocks in the portfolio, takes different amounts of 8, 10, 12, 14, and 16 that are represented by different legends.

3.3 | Empirical results of LPM-PSO algorithm

In this study with this experiment, maximum iterations, *MaxIt*, is 500; population size, *Npop*, is 100; inertia weight, ω, is 1; inertia weight decrease rate, ω damp, is 0.99; personal learning rate, C_1, is 2; and group learning rate, C_2, is 2. Figure 3 summarizes the outcomes while a, number of stocks in the portfolio, takes different amounts of 8, 10, 12, 14, and 16 that are represented by different legends.

3.4 | Models comparison results

Figure 4 illustrate the best disparity and convergence of the optimal portfolios with GA and PSO for a = 8 and a = 16 on the left and right respectively. For other a s quite similar patterns are discovered. Moreover, Table 1 shows the elapsed time of solving the problem by each model for all amounts of a.

There are three measures for algorithm comparison:

1. Estimated Time of solving the problem: it is obvious that PSO is faster in solving the problem.
2. Quality of the objective function fitness values: values in PSO have better qualities than those of GA.
3. Assessment count of objective functions: PSO has better performance in this index.

Although PSO and GA are similar in terms of the fact that they both are population-based search approaches and dependent on information sharing among their population members in order to enhance their search processes using combination of deterministic and probabilistic rules, in our case the former was the absolute winner. The reason behind the superiority of PSO over GA can be justified by the fact that PSO uses two searching logic of random and local search which improve the quality of existing answers and find better new feasible answers as well. Also, in PSO only the best particle gives out the information to others. It is a one-way information sharing mechanism, the evolution only looks for the best solution. Particles are semi-autonomous agents which see the status of each other and decide to change their status towards the best observed particle in their locality. But genes are not agent-like and do not have any abilities to sense their surrounding environment.

In this study, the two algorithms are also compared based on their financial performances. In this comparison, similar to the previous ones there are five sets of comparisons including 8 stocks out 20, 10 stocks out

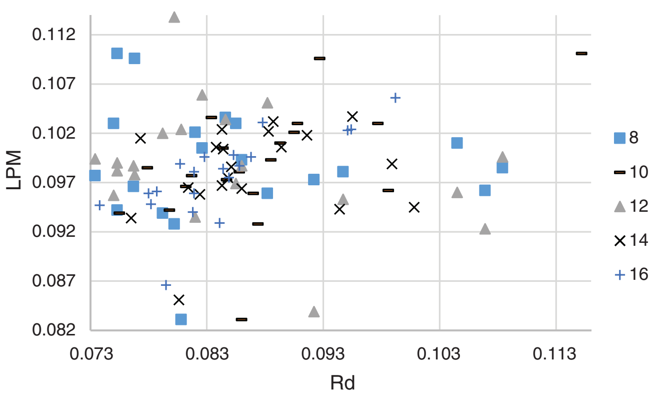

FIGURE 2 The genetic algorithm (GA) model results while a is taking different amounts of 8, 10, 12, 14, and 16 [Colour figure can be viewed at wileyonlinelibrary.com]

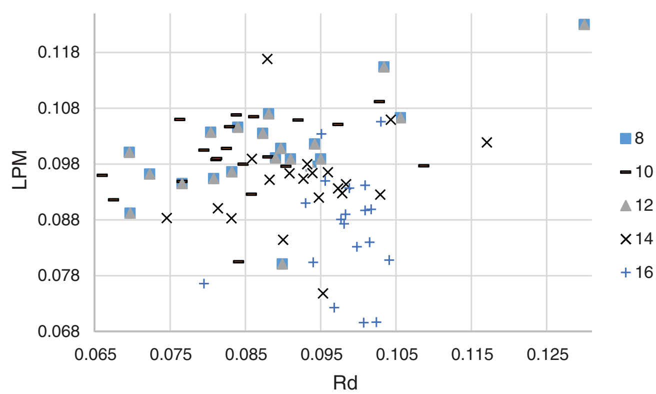

FIGURE 3 The particle swarm optimization (PSO) model results while a is taking different amounts of 8, 10, 12, 14, and 16 [Colour figure can be viewed at wileyonlinelibrary.com]

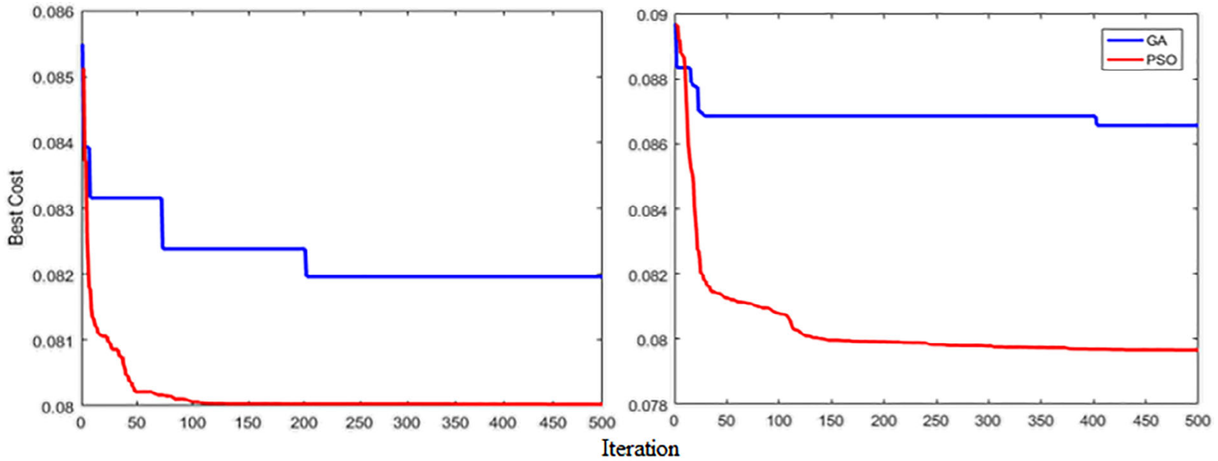

FIGURE 4 The disparity and convergence comparison between PSO and GA [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 1 The elapsed time of solving the model by each algorithm (in seconds)

a	GA	PSO
8	308.52	147.38
10	297.55	142.37
12	297.46	140.81
14	289.48	139.28
16	297.35	140.8

TABLE 2 The share of each algorithm in the EF (in percentage)

a	GA	PSO
8	50	50
10	0	100
12	60	40
14	40	60
16	0	100

20, 12 stocks out 20, 14 stocks out 20, and 16 stocks out 20. For each set, each algorithm generates 20 optimum portfolios according to 20 different R_ds. Therefore, for each set there are totally 40 optimum portfolios. The financial measure derives an EF out of these 40 points and checks share of each algorithm portfolios in the resulted EF. The results are shown in Table 2, and obviously again PSO shows superiority.

4 | CONCLUSION

In this study a thorough comparison between GA and PSO in solving a particular version of Mean-LPM has been done. Due to the computation difficulties of the Mean-LPM model, these are attractive approaches and make notable research contributions. The applied data was real monthly returns from 20 randomly chosen and approved stocks in NYSE during 2005–2011.

Four measures of 1, solving time; 2, fitness value; 3, assessment count; and 4, financial performance were considered to do the comparison. First, it revealed both algorithms are efficient and working to solve the model. However, with all of the four measures, PSO algorithm proved as the superior one. So it is highly recommended that all the EF models that are solved by the same methodology discussed in this paper, use the PSO algorithm.

The results are reliable since they are achieved across different sizes of portfolios from 8 to 16. However there is still a promising chance of continuing this research by working on the PSO model and improving its performance so it can accommodate more number of stocks and portfolios to get a smoother EF.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available at https://www.nyse.com/index. These data were derived from the following resources available in the public domain: https://www.nyse.com/market-data/historical.

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