Journal of Positive School Psychology http://journalppw.com
2022, Vol. 6, No. 6, 107 – 114

Evolutionary Algorithms Application in Portfolio Problem Selection

[1]Kaies NCIBI, [2]Faical Gasmi

[1]Phd. Doctor in quantitative methods, A member of Modeling and Optimization for Decisional, Industrial and Logestic Systems Laboratory Faculty of Management and Economic Sciences, 3018 Sfax, Tunisia, quayesn@yahoo.fr
[2]Phd. Doctor in Economics Sciences College of Administrative Sciences, Najran University, B.P. 1988, Najran, 66462, Saudi Arabia, fagasmi@nu.edu.sa

Abstract

This paper focuses on portfolio selection problem solving through the application of some evolutionary algorithms such as genetic algorithms (GA), particle swarm (PS) and differential evolution (DE).Therefore we focus mainly on the performance of genetic algorithms compared to the other two techniques on data collected from the Tunis Stock Exchange over a period of 5 years. We find in this context that genetic algorithms are similarly more efficient in choice of the optimal of portfolio compared to PS and DE.

Keywords: Portfolio Selection, Evolutionary Algorithms, Quadratic Function, GA, PSO, DE.

1. INTRODUCTION

The theory of portfolio management was one of the most interesting research problems in the scientific life of some authors. This area of research was developed by H.Markowitz in 1952 in his seminal work entitled "Portfolio selection". It is also developed by many models such as the CAPM "the financial asset equilibrium model" and the APT "arbitrage price theory". Thus various methods and approaches have been proposed for portfolio optimization such as goal programming, simulated annealing, tabu search and evolutionary algorithms etc. In this sense, we are basing ourselves in our study on the application of three evolutionary algorithms which are the GA, PSO and DE for the selection of best optimal portfolio and to test the performance of GA compared to PSO and DE. We carry out an empirical study on data collected from the Tunisian stock exchange composed of 21 companies listed over a period of 5 years which ranges from 02/01/2012 to 31/12/2016. This paper is supposed to use three evolutionary algorithms, and to check the reliability of these techniques, a quadratic function of Markowitz has been programmed under MALTAB to solve the problem.

2. Portfolio Selection Concepts:

The work of H.Markowitz in 1952 was the starting point for studies in modern portfolio theory whose goal is to achieve the best optimal choice. Indeed, since Markowitz (1952) several analyzes have been considerably developed namely the mathematical analysis of risk which proposes that the variance is the mathematical measure of the most popular risk for a of portfolio selection problem, Thus Markowitz exposes the analysis the mean-variance approach, which is the main component of a portfolio on which its profitability will be traded, also formalizes the diversification effect in the total risk reduction incurred for a given expected rate of return. In this sense, several researchers have studied and incubated a variety of models using variance as a measure of risk in various situations, such as the studies by Houskova (2000), Chopra (1998), and Chow (1999) and others. Others have integrated semi-variance analysis as another alternative measure of risk, and several models have been structured on the basis of minimizing semi-variance in a portfolio selection problem namely Hamaifar (1999). , Huang (2008), Markowitz (1993), and Grootveld (1999) etc.

Thus the Markowitz model is defined by the following quadratic function:

$$Min \rho(x) = \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \sigma_{ij}$$

$$Max\ \mu(x) = \sum_{i=1}^{n} x_i \mu_i$$

under

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

$$\sum_{i=1}^{n} \delta_i \leq k$$

$$l_i \delta_i \leq x_i \leq u_i \delta_i \qquad i = 1,2,....,n$$

$$\delta_i \in \{0,1\} \qquad i = 1,2,....,n$$

n : *number of assets included in the portfolio*

x_i : *the proportion invested in each asset i*

$\mu(x_i)$: *expected yield*

σ_{ij} : *is the covariance between the yield of the asset i and j*

$\rho(x)$: *Portfolio risk*

δ_i = *It is a binary variable that can take a value of 0 or 1 if the asset is Choose or not*

k : *number of assets*

3. Evolutionary algorithms:

In the portfolio management field, various techniques (both single-objectives and multi-objectives) have been proposed to solve the portfolio optimization problems such as goal programming, simulated annealing, ant colony, genetic algorithms, particles swarm and differential evolution etc. indeed, these techniques have been developed by several researchers in different scientific, mathematical and computer fields such as airplane design, scheduling etc. They have also attracted more interest in financial circles, such as optimization problems in finance, regardless of whether they are multi-objective or single-objective. In our work we focus on three evolutionary algorithms that are genetic algorithms, particle swarms and differential evolution.

3.1 Genetic algorithms (GA):

Genetic algorithms are evolutionary optimization techniques inspired by these foundations inspired by nature and biological evolution. Indeed, during the sixties, several researchers carried out studies in order to experiment with optimizing methods that were inspired by nature but without success.In this context John Holland who started these studies and research since the 60's was the first to observe and develop an optimization technique inspired by nature which is the genetic algorithms in his 1975 book named "Adaptation in Natural and Artificial System" inspired by Darwin's theory. This method consists of knowing more individuals to adopt in their environment from generation to generation to live better, so it is a technique allowing a population consisting of chromosomes in competition with each other to remain "alive". In this sense the potential solution of the problem that the consumer tries to solve is to give by each chromosome defined above by passing from generation to generation, these will be transformed according to different genetic operators inspired by biology who are in number of three: selection operator, crossover operator and mutation operator.

3.2 ParticlesSwarm(PS):

The PS technique is a natural heuristic optimization technique introduced by social psychologist James Kennedy and electrical engineer Russel Eberhart in 1995, which draws these foundations from cooperative behavior of flocks of birds or schools of fish.These so-called particles interact with each other. These particles are characterized by the kind of update of best past performance in the current flight. Thus, in the PS model applied in industrial optimization, each particle is associated with a set of parameters, the set of parameters is associated in the form of a vector with each particle and this vector is equal to the number of elements for each particle. All the particles and the size of this vector are equal to the size of the vector to optimize in the application. First, the vector elements of each particle are assigned arbitrary values in the allowed range. From these arbitrary values, the performance of each of the vectors is calculated. Thus for the application of PSO it is necessary to have a search space composed of an objective function to optimize and particles. This algorithm consists in moving these particles until the optimum arrival. Indeed, each of these particles is equipped with a position, a speed and a neighborhood and each of them knows at any moment its best visited position, that is to say the measured criterion value and that its coordinates, the position of the best neighbors of the swarm that is to say the optimum and finally the value it gives to the objective function because a comparison must be made between the criterion value provided by the current particle and the optimal value.

3.3 Differential evolution (DE):

Differential evolution presents one of the evolutionary algorithms noted DE is a technique designed for the constrained and unconstrained continuous optimization problems developed by Storn and Price in 1997. This algorithm aims to identify the future evolution of the search while serving information inferred from the current population. He draws on these foundations of AG (initialization, mutation and crossover operator, evaluation and selection) and geometric research strategies such as nelder Mead's simplex. As far as the functioning of DE is concerned, it is a technique which makes it possible to evolve the population in a progressive way while making the combination of the two following operators "mutation and crossing", it is a procedure applied to each individual until 'to obtain satisfactory solutions.

Thus each individual x of the population constitutes a conjuncture and characterized by a vector $\left(x_1, x_2, ..., x_n\right)$ illustrating the lateral resources of the n airplanes, for each vector $x(k)$ of the generation k , a vector $x(k+1)$ is constructed by the three randomly chosen vectors in the piece of the population remaining successively denoted by $\mathrm{a}(k), \mathrm{b}(k), \mathrm{c}(k)$ and different from $x(k)$

$$x_i\left(k+1\right)=\left(d_i\left(k+1\right), \alpha_i\left(k+1\right), 1_i\left(k+1\right)\right)$$

for all $i \in \{1, ..., n\}$, these components are measured as follows:

$$x_i^{(k+1)} = \begin{cases} a_i^{(k)} + F\left(b_i^{(k)} - c_i^{(k)}\right) & si\ \left(i = R\right) ou \left(r_i < CR\right) \\ x_i^{(k)} & si\ \ non \end{cases}$$

with

F : *differential weights* $\in [0,2]$: *this is a real constant that allows us to control the expansion of DE and avoid stagnation throughout the search.*

R : *removed randomly in* $\{1, ..., n\}$ *makes it possible to guarantee the existence of at least one component of* $x(k+1)$ *different from* $x(k)$.

r_i : *follows* μ $(0,1)$ *is randomly removed for each component and compared to* $P_{cr} \in [0,1]$.

$\mathrm{x}(k+1)$: *it is an individual who can replace* $x(k)$ *in the population if he improves the objective function.*

4. Empirical analysis:

In our empirical study we perform an algorithmic analysis to solve the problem of portfolio selection on data collected from the stock exchange of Tunis BVMT over a period of 5 years. This analysis consists in applying three evolutionary algorithms which are the genetic algorithms (GA), the particle swarm (PSO) and the differential evolution (DE) and knowing which one gives the best optimal choice of the portfolios in terms of yield, risk and fitness.

4.1 Methodology:

The data is composed of 21 companies listed in the BVMT distributed by sector of activity over a period that extends from 02/01/2012 to 31/12 / 2016.Among all these listed companies we have tried in our empirical analysis to have those who constitute the optimal portfolio and who gives his investor a maximum of profitability at a minimum risk level by applying GA, PS, DE and three hybrid approaches combining the three techniques between them.

The general concept is to invest in different types of assets in order to build an optimal portfolio. For this purpose, we consider the expected return and the weight of a portfolio of risky assets by the following vectors $R\left(r_1,r_2,\ldots,r_n\right)'$ and $X\left(x_1,x_2,\ldots,x_n\right)'$. The variance-covariance matrix of the risky asset yield matrix is $V=\left(\sigma_{ij}\right)_{n*n}$. Thus the decision of an efficient portfolio under a number of constraints is given by the following quadratic model:

$$Min\sum_{i=1}^{n}\sum_{j=1}^{n}x_i x_j\sigma_{ij}$$

$$sc$$

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

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

4.2 Results and interpretations:

By applying the GA, PS and DE based on tunindexe we observe the following results in the tables presented below:

Table 1: *Analysis of the three evolutionary optimization techniques*

	GA	DE	PS
Z	0.0162	0.0185	0.0182
Return	0.0075	-0.0213	-0.0163
Risk	0.0339	0.088	0.0792
Epoches	48	80	22
Time	15.4074	46.2279	4.2134
number of improvements	2578	CAR	617

Table2: *Invested Proportions in an optimal portfolio*

	Company Name	Rates for GA	Rates for DE	Rates for PS
	MONOPRIX	1%	6%	9%
	SFBT	3%	6%	10%
	SOTRAPIL	0%	4%	6%
	TUNISAIR	3%	10%	3%

Optimal Portfolio	ENNAKEL AUTOMOBILES	81%	8%	7%
	MODERN LEASING	0%	4%	2%
	TUNISIE LEASING	0%	4%	2%
	BIAT	0%	2%	6%
	BNA	0%	3%	4%
	AMEN BANK	0%	3%	6%
	ATB	0%	6%	4%
	UIB	0%	6%	4%
	SIMPAR	0%	3%	2%
	SOTETEL	0%	5%	5%
	SERVICOM	0%	3%	7%
	SOTUVER	0%	1%	8%
	ELECTROSTAR	0%	5%	4%
	ADWYA	0%	4%	4%
	CIMENTS DE BIZERTE	0%	5%	3%
	CARTHAGE CEMENT	12%	9%	3%
	STAR	0%	3%	0%

Table3: *Number of improvement for the three techniques*

Techniques	Methodology	Number of improvement
GA	Crossing by sequence change	1541
	Mutation based on reversal	72
	Change based on change of place	128
	Mutation by one cancellation	337
	Mutation by two cancellation	500
DE	Schem DE/rand/1	133
	Schem DE/rand/2	132
	Schem DE/best/1	1661
	Schem DE/best/2	1377
	Schem DE/rand to best/1	302
	schem trigonometric/rand	185
	schem trigonometric/best	3414
PS	PS based on DE	0

	PS based on GA	0
	PS based on Euclidean distance	617

What matters from these results is to know the most suitable technique and the most effective in selecting the best optimal choice. The interpretation of the results is based on performance, risk and objective function in a first class, thereafter according to the number of improvement, bursts and optimal portfolio composition given by each evolutionary method. The rule is to choose the technique that has a positive return with a higher value, a lower risk, and a lower objective function. In this context we conclude that the GA method is the best and most efficient compared to the PSO and DE with a positive yield of 0.0075, a lower risk of 0.0339 and a lower objective function of 0.0163. Also it gives an optimal portfolio composition better and more or less diversify and profitable compared to the PSO and DE which is technically justifiable by the two types of mutation of GA which are the mutation by a single cancellation and the mutation by two cancellations. Also the algorithms could improve the solution 2578 times.Subsequently by introducing some hybrid approaches between the three techniques for optimal portfolio selection, we obtain the following results:

Table 4: *Results of three hybrid approaches combining the three main techniques*

	GA+ PS	**DE + PS**	**PS + DE + PS**
Z	0.0162	0.0176	0.0162
Return	0.0073	-0.0084	0.0073
Risk	0.0341	0.064	0.0342
Epoches	1125	27	159
Time	76.7043	2.8536	18.756
Number of improvement	10583	171	2663

Table5: *The proportions invested in the optimal portfolio by the three hybrid approaches*

Company Name	**RATESBY GA + PS**	**RATESBYDE + PS**	**RATES BY PS + DE + GA**
MONOPRIX	1%	1%	1%
SFBT	2%	10%	2%
SOTRAPIL	0%	0%	0%
TUNISAIR	4%	18%	4%
ENNAKEL AUTOMOBILES	86%	11%	83%
MODERN LEASING	0%	0%	0%
TUNISIE LEASING	0%	0%	0%
BIAT	0%	8%	0%
BNA	0%	3%	0%
AMEN BANK	0%	9%	0%
ATB	0%	4%	0%
UIB	1%	0%	1%

SIMPAR	0%	0%	0%
SOTETEL	0%	14%	0%
SERVICOM	0%	0%	0%
SOTUVER	1%	20%	0%
ELECTROSTAR	0%	3%	0%
ADWYA	0%	0%	0%
CIMENTS DE BIZERTE	0%	0%	0%
CARTHAGE CEMENT	6%	0%	9%
STAR	0%	0%	0%

Table 6: *Number of improvement for two hybrid techniques*

Techniques	**Methodology**	**Number of improuvement GA + PS**	**Number of improuvement GA + PS + DE**
GA	crossing by sequence change	381	606
	mutation based on reversal	2	7
	change based on change of place	16	42
	mutation by a single cancellation	26	54
	mutation by two cancellation	24	45
DE	Schem DE/rand/1	7	128
	Schem DE/rand/2	20	202
	Schem DE/best/1	40	73
	Schem DE/best/2	22	87
	Schem DE/rand to best/1	5	50
	schem trigonometric/rand	41	273
	schem trigonometric/best	20	122
	PS based on DE	16	472

PS	PS based on GA	5331	56
	PS based on Euclidean distance	0	381

The results of these approaches prove the effectiveness of the first approach combining the GA with the PSO and the last approach combining the GA, the PS and the DE since it presents the same values in terms of yield, risk and objective function respectively of 0.0073, 0.0341 and 0.0162 compared to the PSO which represents a negative return with a higher risk. The GA + PSO approach is thus more efficient in terms of speed with 18.7560 execution times compared to 76.7043 times elapsed by the GA + PSO + DE approach. The latter is also more efficient in terms of the number of improvements with 10583 times compared to 2663 times for the first approach. Also these two also gives us better optimal portfolio compositions more or less diversified and more profitable which is technically justifiable for the two approaches by the presence of GA with these two types of mutation which are mutation by a single cancellation and mutation by two cancellations.

5. Conclusion:

In order to solve the portfolio optimization problem we try to apply three evolutionary techniques and three hybrid approaches. In this study we need to solve a quadratic model by programming under MALTAB. The analyzes show the relevance and reliability of the genetic algorithm as an evolutionary optimization technique essentially in selecting the best optimal choice of portfolio in this case, as well as its performance in the different approaches cited. So in dealing with this subject, we notice that it is feasible in different other perspectives, for example, we can integrate and compare other more recent evolutionary techniques in solving a portfolio optimization problem that may be more effective than the algorithms we took into consideration. Also we can test other types of Markowitz problems like maximization, minimization or both sets. Finally, we can deal with this problem under the addition of various other constraints such as the setting of a maximum threshold of investment, not to exceed that can be by companies that is to say not to exceed a threshold of 10% in a company, or by sector ie to propose a maximum threshold not to be exceeded in a sector for example 42%.

References

[1] C. Darwin (1859), « on the origin of species », John Murray, London.

[2] G. Chow (1999), « Optimal Portfolios in Good Times and Bad », financial analysts journal, vol.55, n°3, p.2469-2273.

[3] H. Grootvelda (1999), « Variance vs downside risk: Is there really that much difference? », European Journal of Operational Research, vol.114, n°2, p.304-319.

[4] H. Markowitz (1952), « portfolio sélection », the journal of finance, mars, vol.7, n°1, p.77-91.

[5] H. Markowitz (1993), « Computation of mean-semivariance efficient sets by the Critical Line Algorithm», Annals of Operations Research, vol.45, n°1, p.307-317.

[6] Holland, J. H. (1962). Outline for a logical theory of adaptive systems'. The Journal of finance.

[7] H.Huang et al. (2008), « The crystal structure and identification of NQM1/YGR043C, a transaldolase from Saccharomyces cerevisiae», journal article, vol.73, n°4, p.1076-1081.

[8] J.Kennedy, R.Eberhart (1995), « particle swarm optimization», Purdue School of Engineering and Technology, vol.95, n°3, p.1942-1948.

[9] K. Chopra (1998), « improving optimization », the journal of investing, vol.3, n°3, p.51-59.

[10] R. Storn and K. Price. Differential evolution - a simple and efficient heuristic for global optimization over continuous spaces. Journal of Global Optimization, pages 341–359, 1997.