PORTFOLIO OPTIMIZATION IN SELECTED TEHRAN STOCK EXCHANGE COMPANIES (SYMBIOTIC ORGANISMS SEARCH AND MEMETIC ALGORITHMS)

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Abstract

The optimal portfolio selection problem has always been the most important issue in the modern financial literature. So, in this paper, we had shown that how an investment with n risky share can achieve the certain profits with less risk that spread between stocks. Such a portfolio, it is called an optimal portfolio and it is necessary to find solving the optimization problem. Hence, meta-heuristic algorithms such as Symbiotic Organism Search (SOS) and the Memetic Algorithm which is combination of the Genetic and SOS algorithms have been utilized to solve portfolio optimization in 23 selected Tehran stock exchange market during the period of 2009-2017. The results of optimization indicated that at the same precision. Memetic algorithm despite its time consuming has better performance than other algorithms. Moreover, Genetic algorithm despite its performance has the lowest time consuming. Hence, the main policy implication policy of this study is that the investors and financial analyzers should adopt the Memetic method as a proper and optimal meta-heuristic algorithm for minimizing the risk and maximize the return investment in portfolio.

Keywords: Portfolio Optimization Problem, Sharpe ratio, Genetic Algorithm, Symbiotic Organism Search Algorithm, Memetic Algorithm

JEL classification: C22, G35, G43

1. Introduction

One of the important theories in determining the optimal portfolio in last decades is the "Modern Portfolio Theory" which is proposed by Harry Markowitz and William Sharpe. The modern portfolio theory is a holistic approach to the stock market. Unlike the technical ones, this method discuss about the whole stock in market. In other words, this theory has a macro perspective versus a micro view. So the portfolio and the optimal combination of stocks are emphasized. Although in making a portfolio, the relationship between risk and return of stocks is important. One of the most important criteria of decision making in stock market is the return of stocks. Return of stock itself includes information and investors can use them in their financial analysis. In portfolio selection theory, some of the risk`s measures, add some difficulty to the problem and make it non-convex or non-differentiable. Moreover, the constraints in model make the feasible area as a non-convex area. Because of the complicated problem, optimization tools are limited to the group of tools that can obtain proper simplicity. These constraints in the model are the reasons of evolutionary algorithms usage and their extensions (Chen, 2015).

Modern portfolio theory aims to allocate assets by maximizing the expected risk premium per unit of risk. In a mean variance framework risk is defined in terms of the possible variation of expected portfolio returns. The focus on standard deviation as the appropriate measure for risk implies that investors weigh the probability of negative returns equally against positive returns. Portfolio optimization should consider realistic constraints such as portfolio size, transaction costs, or additional demands from investors rapidly, which adds a complexity level that exceeds regular optimization methods which falls into class of considerably more difficult NP-hard problems (Shaw and et al., 2008). Therefore, several studies have focused on the heuristic algorithms for complex constrained portfolio optimization problems which will be discussed in section 2.

If the system is nonlinear, these techniques have better potential to allow a feasible solution through its expert approach to self-organization. It has been noticed that these techniques generate better results than the statistical approaches when the time series is chaotic.

Today, with real world constraints, mean-variance model loses it functionality. So the best solution to solve portfolio problem with real world constraints is heuristic and meta-heuristic algorithms. Meta-heuristic algorithms can be divided into two categories. The first category is population-based algorithms like GA[1], PSO[2] and the second ones is local search algorithm like Taboo search and simulated annealing. Recently mixed algorithms like memetic algorithm has been used for underlying problem. Hence, the main aim of this paper is to optimize the portfolio selection problem in selected Tehran Stock Market companies during the 2009-2017. The first purpose of this paper is to compare the performance of the new memetic algorithm with its comprising algorithms. In other word, our memetic algorithm is the combination of Genetic and SOS algorithm. We want to compare this mixed algorithm with SOS and Genetic algorithm. The second purpose of this paper is to compare these algorithms with benchmark algorithm. Our benchmark algorithm is quadratic programming. Since, quadratic programming is used as the benchmark algorithm, unconstraint portfolio problem used as the main model. Otherwise, quadratic programming will be inapplicable. So, the model of this study is unconstraint mean-variance portfolio problem, benchmark algorithm is quadratic programming and the meta-heuristic algorithms are used are memetic, genetic and symbiotic organism search algorithms and Sharpe ratio has been applied for evaluating the performance of these algorithms during the period of 2009-2017.

The rest of this paper has been arranged as follows: In next section the review of literature has been stated. In third section, the problem of portfolio optimization has been explained and in next section, we present the meta-heuristic algorithms such as genetic algorithm, symbiotic organisms search and memetic methods. In section 5, the empirical findings of portfolio optimization have been reported and finally, the concluding remarks of paper has been presented.

2. Review of literature

In general, portfolio theory can be divided into modern and post-modern categories. Modern portfolio theory was introduce in an article by the name of (portfolio selection) by harry Markowitz in 1952. Thirty eight years later, Markowitz, Merton Miller and Sharpe won noble prize for (extended portfolio selection theory) in 1990. In 1952, he explained portfolio theory by Mean-Variance model. Some years later, this theory became the base of other theory. In a way that, risk became quantitative criterion for the first time. Before Markowitz, for evaluating portfolio performance investors focused just on one of the criteria. But Markowitz, explained the model in details and offered investors portfolio diversification in order to change stocks risk and return with portfolio risk and return criteria (Markowitz, 1952).

In post-modern portfolio theory, that introduced by Ram, Fergosen, Kaplan and Sigel in 1994, portfolio optimization and investors behavior was explained by return and downside risk. Down side risk is introduced as a risk measurement index, it means, the probability of minus return volatility in the future. In modern theory, risk in introduced as a volatility around the mean of return and is calculated by variance. Variance is considered as a balanced risk criterion, however in booming market, duo to investor`s short term goals, seek to gain positive fluctuation and just negative fluctuation is considered as a risk. So in this situation and according to investor`s risk aversion, investors are more risk averse than to find higher return. In other word, risk is not balanced and severely tends to downside risk. This theory, recognize the risk that is related to investor`s expected return. Other results that are better than expected return are not considered as a risk.

The advent of Value at Risk criterion as one of the accepted methods for quantifying market risk is the most important stage in risk management revolution. The word 'VaR' was

[1]. Genetic Algorithm
[2]. Particle Swarm Algorithm

introduced in a report by group of thirty in 1993. In that report 'VaR' was introduced as one of the branches of capital risk management. That report contributed a lot and emphasized on importance of risk measurement for tracing aim. Afterward, VaR became the most famous assessment economic risk method and as a risk measurer is widely used for tracing aim. Especially when G.P Morgan introduced the risk metrics in 1994. Today, value at risk is the most famous and applicable risk measurement method. This method is an intuitive method with capability of calculation and easy to understand to measure extended portfolio risk. This criterion can be introduced as a maximum loss in a specific time horizon with a confidence interval in a usual market situation. Although value at risk is a usual risk criterion, but it has undesirable mathematic features. So, Artzener and et al in 1992 introduced the idea similarity as a set of risk measurement feature in relation with the tail of distribution function. Conditional Value at Risk is one of the most important risk measurer that is introduced by Rakefeller and Uryaseff in 2000. CVaR has shown better feature than VaR and it can tell us that if the condition is unfavorable, how much loss do we expected (Farzi & Shavazi, 2015).

On the empirical point view, portfolio optimization has been used in most previous studies with multiple objectives, and many heuristic algorithms for solving this problem. Crama & Schyns (2003) used simulated annealing algorithm (SA) for optimizing portfolio selection problem. The objective function of their model was to reduce portfolio risk, and expected return of investor was assigned and set as a constraint. The method is an efficient solution in the scope; however, it is still a complicated solution to manage due to the space of feasible portfolios that is simplified in our algorithm. Lin & Liu (2008) proposed a decision making model for portfolio selection aimed at minimizing transaction lots. They solved the model with genetic algorithm (GA). Their method found the solution in a short reasonable time, but the current case that is the market is the only uncertainty in reality and some other risk cases must be added. In another study, Soleimani et al (2009) considered a new factor called market capitalization in addition to transaction cost and the number of stocks in the portfolio constraints. They utilized genetic algorithm for solving the proposed model. This method seems could be salient and an efficient method applied in portfolio problem but we would that it has had some limitations for the various markets with hard boundaries and still has a problem in scalable uncertain markets. Hami and Itmi (2010) proposed a new method for a modified particle swarm optimization algorithm (MPSO) combined with a simulated annealing algorithm (SA). This method has the relative advantage to provide best results comparing with all heuristics methods PSO and SA. In this matter, a benchmark of eighteen well-known functions is given. These functions present different situations of finding the global minimum with gradual difficulties. Findings of this study results showed the robustness of the MPSO-SA algorithm. Numerical comparisons with these three algorithms: Simulated Annealing, Modified Particle swarm optimization and MPSO-SA prove that the hybrid algorithm offers best results. Farzi et al (2010) proposed mean-variance model and employed two meta-heuristic algorithms based on improved PSO and GA algorithms to solve the underlying problem. The results of their studies showed that although GA algorithm presented higher return but PSO algorithm prepared lower risk and it can be the superiority of PSO algorithm. Zhu et al (2011) applied two heuristic algorithms for constrained and unconstrained mean-variance model. The results indicated that the PSO algorithm is better than GA algorithm in all cases. Tuba and Bacanin (2014a) employed mixed meta-heuristic algorithm in comparison to four algorithms for cardinality constrained mean-variance model. The underlying algorithm was mixed bee colony and firefly algorithm, other algorithms are GA, SA, TS and PSO. The results show that, the mixed algorithm has better performance than other methods. Tuba and Bacanin (2014b) utilized improved firefly algorithm for constrained and unconstrained portfolio optimization problem. Then compare this algorithm with other algorithms. Results indicate that improved firefly algorithm is better than other algorithms. In other studies, Salahi et al (2014) proposed constrained mean-variance portfolio problem and applied two meta-heuristic algorithms based upon improved PSO and HS algorithms. The results of this paper indicate that in finding the solution, improved HS algorithm is faster than PSO. Raie and Beigi (2010) proposed constrained and unconstrained mean-variance portfolio problem model and employed two meta-heuristic algorithms based on PSO and GA. The sample that was used for this study was 20 weekly security prices. The final results indicated that PSO algorithm performed much better than GA. Later, Eslami Bidgoli and Taiebi Sani

(2014) applied Memetic Ant Colony Algorithm for cardinality constrained mean-variance portfolio model and Value at Risk approach. (Value at Risk approach was risk criterion) the results indicated that in every respect, memetic algorithm has better performance than genetic algorithm.

Shadkam et al (2015) had studied the determination of the optimal portfolio with respect to stock returns of companies, which are active in Tehran's stock market during the 2008-2013. The empirical results of their paper showed more convergence rate and accuracy of the COA rather than the Genetic Algorithm in low iteration. Batabyal (2016) has investigated the increasing returns in a model with creative and physical capital. Results of this study showed that there is increasing return to scale in the growth model.

Eftekharian et al (2017) by applying a new efficient multi-objective portfolio optimization algorithm called 2-phase NSGA II algorithm is developed and the results of this algorithm are compared with the NSGA II algorithm. The results of this study indicated 2-phase NSGA II significantly outperformed NSGA II algorithm. Johanyák (2017) presents a modified version of the original method by combining PSO with a local search technique at the end of each iteration cycle. The new algorithm is applied for the task of parameter optimization of a fuzzy classification subsystem in a series hybrid electric vehicle (SHEV) aiming at the reduction of the harmful pollutant emission. The new method ensured a better fitness value than either the original PSO algorithm or the clonal selection based artificial immune system algorithm (CLONALG) by using similar parameters. Pantazis and Pelagidis (2017) analyzed the financial indicators affecting stock performance in the case of capital product partners. The results of this article indicated that there is a positive and negative relationship between financial indicators and stock performance in listed shipping companies.

Reviewing the empirical studies in Iran indices that, in previous studies in the context of portfolio selection, the SOS and MA has not considered for solving and optimizing the problems. So, the main contribution of this paper is to solve and optimize the portfolio selection in 23 selected of Tehran stock companies during the period of 2009-2016.

3. Portfolio optimization problem definition

There are many portfolio optimization problems. The one the basic ones is Markowitz mean-variance model. This model is quadratic objective function and linear constraints. It is formulated as follow:

$$Min\ \sigma_p^2 = \sum_{i=1}^{N}\sum_{j=1}^{N} w_i w_j \sigma_{i,j} \quad (1)$$

Subject to:

$$\sum_{i=1}^{N} w_i \mu_i = R^* \quad (2)$$

$$\sum_{i=1}^{N} w_i = 1 \quad (3)$$

$$0 \le w_i \le 1, \forall i \in (1,2,\dots,N) \quad (4)$$

In equation (1), N is the number of assets (*i and j*), σ^2 is the portfolio variance, w is the weight of each assets in portfolio or the proportion of total capital that is invested in security i and $\sigma_{i,j}$ is the covariance matrix of assets. In equation (2), R^* is the targeted return of portfolio and μ is the average return of each assets. Equation (3) indicates that, the sum of all assets weight must be equal to one. And in equation (4) it is indicated that the weight of each assets must be between zero and one.

Eq. 1 is objective function (risk) which is subjected to minimization. Eq. 2 is the predefined return. Budget constrained for feasibility is in Eq. 3 and in Eq. 4 indicates that all investment should be positive (no short selling).

This model can provide one portfolio. If we need efficient frontier, we must define a new parameter that is investor risk sensitivity. With this parameter, model can provide a portfolio for each investor`s sensitivity.

$$\min \lambda\left[\sum_{i=1}^{N}\sum_{j=1}^{N}[w_i w_j \sigma_{i,j}]+(1-\lambda)\left[-\sum_{i=1}^{N}[w_i \mu_i]\right]\right]$$

Subjected to:

$$\sum_{i=1}^{N} w_i = 1$$

$$0 \leq w_i \leq 1, \forall i \in (1,2,\ldots,N)$$

The parameter λ is investor sensitivity, when λ is equal to 1, model provides lowest risk portfolio and when λ is zero, model provide highest return portfolio in efficient frontier. There is a trade off in this model, it means that the more risk an investor can tolerate, the higher return portfolio he can earn. And the last thing that should be mentioned here is that, in efficient frontier for the given level of risk there is no portfolio that has higher return than efficient frontier portfolio return. It is the same for the given level of return.

The study of the Artificial Neural Networks began in 1943 by Warren S. McCulloch & Walter Pitts. Since the aim of the artificial intelligence is to develop the humanly used paradigms or algorithms for machines, the artificial intelligence emulates the human brain performance. One neuron (nervous cell) is a certain biological cell, which processes the data. This cell is made up of a body of cells, Axon and Dendrites. The neuron receives signals (simulators) through dendrites (recipients) from the environment or from other neurons, and transmits the created signals by a body of cells, through Axon (sender). At the end of them, there are synopses. A synopsis is a basic structure and a functional unit between two neurons (one neuron at Axon, the other at Dendrite).

Synoptic connections can be corrected by passing signals through them whereby synopses may be engaged in learning process from their share of work. This historic dependence in synoptic connections acts as memory and may provide a response to the memory accordingly.

The first artificial neuron was presented by McCulloch & Pitts which is derived from the natural neuron. The inner connections and communications, i.e. the input and outputs, shape models out of Dendrite and Axon, communicative weights represent synopses and activity function, which estimate the body performance.

One of the major features of the artificial neural networks, whose function approximates more to that of human beings, is the power of learning. The neural networks use basic rules (like input-output links) out of a set of interpretive models for learning in place of pursuing a set of rules defined by an expert. In order to understand or design a learning process, first it is essential to have a model of the environment in which the network is involved. Such a model is named “learning algorithm”. Second the learning rules governing the updating process, or in other words, networks weight updating process should be known.

One of the most important learning algorithms in the neural network is the "back propagation algorithm" which per se is based on the rule of “error – correction”, and for the gradual decrease of error, where the actual output of (y) network is not equal to the desirable output (d), the neural weights can be corrected by using the error sign of (d-y).

Considering the way the neurons stand out , their interrelationship, the neural networks characterize a specific architecture out of which a well- known one is the multi–layer perception network where by the data direction is why they are called “Feed-forward neural network

4. Symbiotic organisms search algorithm

Symbiosis is derived from the Greek word for ‘‘living together’’. De Bary first used the term in 1878 to describe the cohabitation behavior of unlike organisms. Today, symbiosis is used to describe a relationship between any two distinct species. Symbiotic relationships may be either obligate, meaning the two organisms depend on each other for survival, or facultative, meaning the two organisms choose to cohabitate in a mutually beneficial but nonessential relationship. The most common symbiotic relationships found in nature are mutualism, commensalism, and parasitism. Mutualism denotes a symbiotic relationship between two different species in which both benefit. Commensalism is a symbiotic relationship between two different species in which one benefits and the other is unaffected or neutral. Parasitism is a symbiotic relationship between two different species in which one benefits and the other is actively harmed (Chen, & Prayogo,2014).

Algorithm pseudo code and equation

Initialization
Repeat

- **Mutualism**

$$X_{inew} = X_i + rand(0,1) * (X_{best} - Mutual_{vector} * BF_1)$$
$$X_{jnew} = X_j + rand(0,1) * (X_{best} - Mutual_{vector} * BF_2)$$
$$Mutual_{Vector} = \frac{X_i + X_j}{2}$$

In mutualism, organisms receive benefit from each other. Here means two categories of random numbers are generated and make mutual vector as an average numbers.

- **Commensalism**

$$X_{inew} = X_i + rand(-1,1) * (X_{best} - X_j)$$

Commensalism means benefiting from organisms is one sided. Here means, two kinds of random numbers are generated and subtract number from each other.

- **Parasitism**

Organism X_j is selected randomly from ecosystem and parasite vector generate and organism (generate random number). If the generated fitness of parasite vector is better than generated fitness of organism X_j, then parasite vector will be replaced by organism X_j.

Until (termination criterion is met)

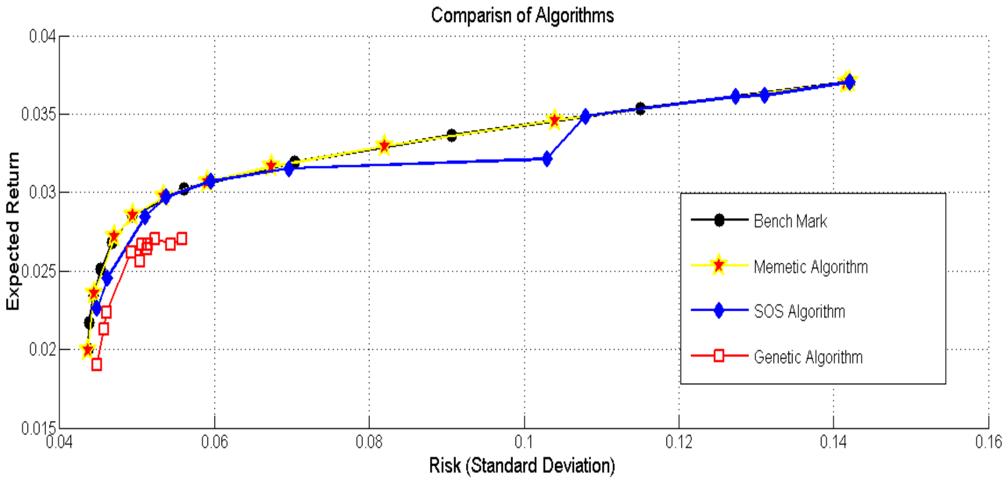
4.1. Memetic Algorithm

Since genetic algorithm has mutation and crossover as the only two operators, sometimes in some cases, the performance of genetic algorithm is not sufficient or satisfactory. So, we use other algorithm to contribute to genetic algorithm and undertake the local search operation. This mixed algorithm is called Memetic. Memetic algorithm can be constructed by combination of genetic and other algorithms. It means, the base algorithm is genetic and it can be combining by other algorithms to make Memetic algorithm. In this study, Memetic algorithm is comprise of GA and SOS algorithm. The data sets for stock price for 23 selected companies of Tehran stock exchange market during the period of 2009-2017 have been extracted from the financial reports of companies. Moreover, the calculation of return and risk of portfolio has been formulated in MATLAB software. We constrained the companies to the 23 companies of 50 companies of most active industry in stock market of Tehran. The main constraint of our sample selection is concerned to the availability of all data sets to these companies.

5. Empirical findings

In this paper, we propose unconstrained M-V model and apply three meta-heuristic algorithms and M-V model as a benchmark to obtain the efficient frontier line. At first, the algorithms are compared with their performances and then, Sharpe ratio is used to compare their best portfolios. The result of algorithm and benchmark for achieving efficient frontier has been shown in following figure:

Figure 1: Comparison the performances of algorithms

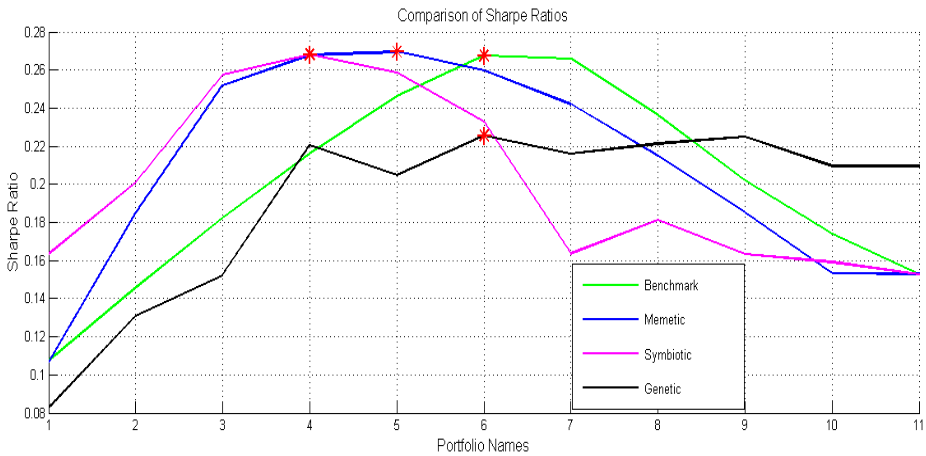


As it is depicted, the genetic algorithm that is shown by red color, can`t fully achieve the efficient frontier like Memetic algorithm. Hence it is shown the inefficiency of genetic algorithm. SOS algorithm is shown by blue color. Its performance is better than genetic algorithm but it stills have differences with benchmark. And finally, Memetic algorithm that is shown by yellow color can cover the benchmark with low error. The results of Sharpe ratio for each algorithm have been shown in Table 1:

Table 4: Algorithms Sharpe ratios

The Sharpe ratio of algorithms			
Markowitz	Memetic	SOS	Genetic
0.1072	0.1064	0.1634	0.0826
0.1457	0.1851	0.2008	0.1309
0.1823	0.2518	0.2576	0.1525
0.2162	0.2679	0.2680	0.2205
0.2461	0.2696	0.2587	0.2048
0.2696	0.2597	0.2331	0.2254
0.2658	0.2422	0.1636	0.2160
0.2361	0.2149	0.1811	0.2212
0.2020	0.1855	0.1634	0.2248
0.1742	0.1532	0.1592	0.2096
0.1528	0.1528	0.1528	0.2096
Maximum Sharpe ratio			
0.2696	0.2696	0.2680	0.2248

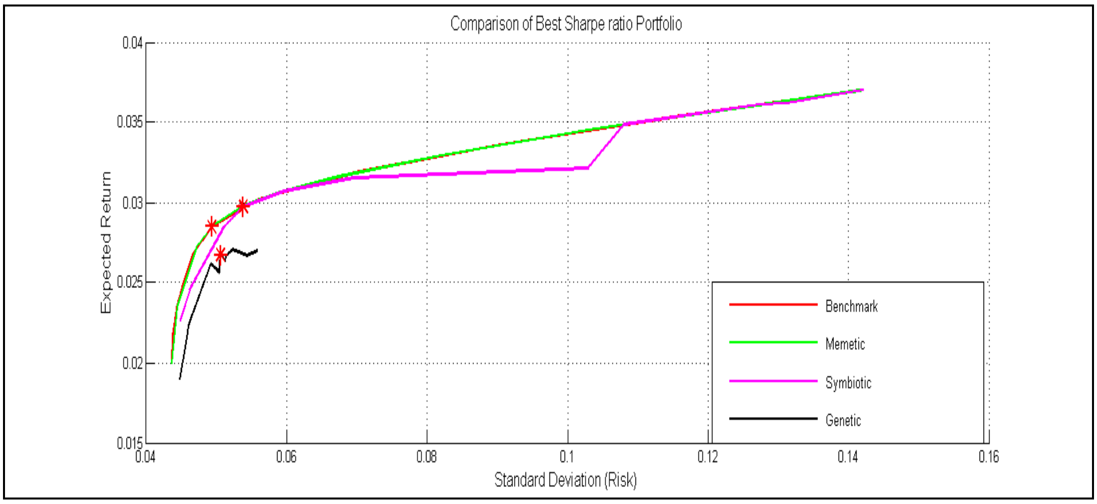
Figure 2: Best Sharpe ratio for each algorithm



The highest Sharpe ratio are indicated as the red star for each algorithm. As you can see above the blue line is memetic algorithm and its value is as the same as benchmark value. The purple line is symbiotic organism search algorithm. Its value is just slightly lower than memetic algorithm and the black ones is Genetic algorithm that has the lowest value. We choose the highest Sharpe ratio and its corresponding portfolio in each algorithm and plot them in figure bellow.

The result of Sharpe ratio for best portfolio in efficient frontier line:

Figure 3: best Sharpe ratio portfolio



Best portfolio in each algorithm efficient frontier line is shown by red star. As it is shown, there are three red stars for four efficient frontiers. It means that since Memetic algorithm has the same Sharpe ratio with benchmark, their best portfolios (red star) are exactly in the same place and we can see just three portfolios. The best Sharpe ratio portfolio is in the green line or (it is obtain by memetic algorithm) and worst Sharpe ratio is in the black line (obtained by GA).

In next section, the calculated portfolio value, risk and cost function for the two algorithms of SOS and Memetic have been tabulated as following table.

Table2. Comparison of final result for two algorithms

comparison	cost	portfolio value	risk
SOS	-5323.945	10324.177	5000.321
Memetic	-5588.964	12388.727	6799.762

Also, below table shows, the weights that are got by two algorithms in constrained portfolio problem.

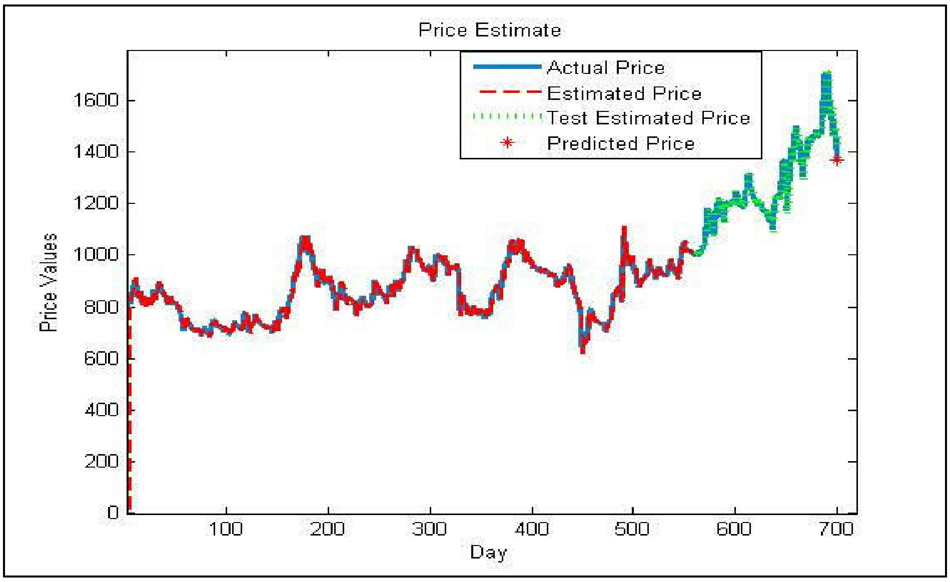
Table3: The weight allocated to any company in portfolio

	company	weights by SOS	weights by Memetic
1	Takin Co	0.0522	0.0123
2	Bu-Ali Investment	0	0
3	Transfo Iran	0.0176	0.01
4	Jaberebn Hayan Darou	0.0511	0.0141
5	Isfahan Folad	0.0274	0.0116
6	Fars Khozestan	0	0
7	Saipa	0	0
8	Service Anformatic	0.2997	0.2997
9	Behshar Toseeh	0	0.0104
10	Sina Bank	0.0106	0
11	Ghadir Investment	0.1599	0.1249
12	Building Iran	0.0246	0
13	Roy Iran	0.0202	0.01
14	Ama	0.00114	0.0112
15	Yasa Iran	0.1399	0.2934
16	Traktor	0.00241	0.0119
17	Iran Chini	0.00213	0.0105
18	Mokhaberat Iran	0	0.0105
19	Abadan Petroloshimi	0.1298	0.158
20	Hafari Shomal	0.01	0.0111
21	Zamyad	0.004	0.007
22	Saipa Azin	0.0021	0.008
23	Saipa Diesel	0.021	0.01309

Source: Empirical Findings

In the next level, in order to calculate and estimate the value of optimized portfolio and risk for the next day, we should predict the prices. In order to do this, AR(10) is used and the parameters of this model are estimated by RLS method. The prediction of this model is based on a step forward method. In this model, 80 percent of data are used as a training data and other 20 percent are used as a test data. For example, in this figure a time series is showed and the price of day 701 is predicted by price of 700 days.

Figure4. Estimation and prediction of a next step prices by RLS method



In order to be assuring of the estimation accuracy, we predict the price of days 650-700 and make a comparison between the real price and predicted price. To show the error of prediction, standard deviation is used. The error of estimation is the absolute difference of estimated prices and real prices as below:

Table 4. The absolute standard deviation of estimation error for 50 days price by RLS method

company	absolute standard deviation	company	absolute standard deviation
Takin Co	126	Ghadir Investment	95
Bu-Ali Investment	19	Building Iran	81
Transfo Iran	84	Roy Iran	73
Jaberebn Hayan Darou	138	Ama	239
Isfahan Folad	122	Yasa Iran	317
Fars Khozestan	96	Traktor	89
Saipa Dissel	46	Iran Chini	164
Service Anformatic	132	Mokhaberat Iran	67
Behshar Toseeh	109	Abadan Petroloshimi	202
Sina Bank	53	Hafari Shomal	98
Zamyad	59		
Saipa Azin	83		

To show the applicability of this method, this process has been done for all the stocks. In other word, we optimized portfolio with 50 predicted and real data by Memetic algorithm. In this table, is indicated that there is little difference between real and predicted cost function, portfolio value and risk. The optimized results are got from 100 iteration of algorithm.

Table 5. Comparison between real and predicted data by Memetic algorithm in optimization problem

Comparison of Data	Cost	Portfolio Value	Risk
average of exact data	-5610.215	12903.803	7293.587
average of exact data	-5620.821	12881.341	7260.518
error standard deviation	21.7	214.4	217.5

6. Concluding remarks

Since the stock market behavior is non-linear thus, the linear models are unable to describe the share return behavior. The systems can simply recognize a major portion of the system, which is non-linear. Each share is inspired by diverse factors and conditions which are sometimes systemic and at times non-systemic with unique models of import as well.

The parameters of Markowitz model, which are comprised of expected return of portfolios, variances and covariance, must be estimated.

This paper presents a new meta-heuristic algorithm that is called 'symbiotic organisms search' and then combines this algorithm with GA to make a new Memetic algorithm. Then, apply this three algorithm to solve unconstrained M-V model. Finally the results of this study reveal that in comparison to benchmark, Memetic algorithm has the best performance but it takes 40 seconds to solve the model. And the worst performance is dedicated to GA. GA has the worst performance but it is the fast algorithm among the others. The Sharpe ratios are provided by the algorithms are 0.2696, 0.2680 and 0.2248 that Memetic has the higher Sharpe ratio among the others. The most important and interesting result is that, Memetic algorithms has the same Sharpe ratio as the benchmark. This result indicates that, if there is not possibility for using quadrating programming (because of cardinality constraint e.g.), Memetic algorithm can be the best choice for solving this kind of problems. Because Memetic algorithm has shown its performance in comparison to benchmark!

The result of this paper is consistent with theoretical framework and empirical studies. Moreover, the main policy implication of this study is that the investors should adopt the Memetic algorithm to select the best approach in stock market.

7. References

Abad, P. and Benito, S. (2009), A Detailed Comparison of Value at Risk in International Stock Exchanges, Fundacion De Las Cajas De Ahorros, Documento De Trabajo (452/2009), pp. 1-45.

Algorithms for Cardinality Constrained Portfolio Optimization Problem. Advanced

Aranha, C., & Iba, H. (2009). The memetic tree-based genetic algorithm and its application to portfolio optimization. Memetic Computing, 1(2), 139-151.

Bacanin, Tuba, M., & Nebojsa. (2014). Upgraded Firefly Algorithm for Portfolio

Bamoul, W. J. (1963), An expected-gain confidence limit criterion for portfolio selection, Journal of Management Science, vol. 10, no. 1, pp. 174-182.

Batabyal, A. A. (2016), Increasing Returns in a Model with Creative and Physical Capital: Does Balanced Growth Path Exist? Regional Science Inquiry, Vol VIII, 31-65.

Bollerslev, T. (1986), Generalized autoregressive conditional heteroscedasticity, Journal of Econometrics, vol. 31, no. 3, pp. 307-327.

Campbell, R., Huisman, R. & Koedijk, K. (2001), Optimal portfolio selection in a Value-at-Risk framework, Journal of Banking & Finance, vol. 25(9), pp. 1789-1804.

Chang, J. F., Yang, T. W., & Tsai, P. W. (2014). Stock Portfolio Construction Using Evolved Bat Algorithm. In Modern Advances in Applied Intelligence (pp. 331-338). Springer International Publishing.

Chang, T. J., Yang, S. C., & Chang, K. J. (2009). Portfolio optimization problems in different risk measures using genetic algorithm. Expert Systems with Applications, 36(7), 10529-10537.

Chen, M.-Y., & Prayogo, D. (2014). Symbiotic Organisms Search: A new meta-heuristic optimization. Computers and Structures.

Costello, A., Asem, E. and Gradner, E. (2008), Comparison of historically simulated VaR: Evidence from oil prices, Energy Economics, vol. 30, issue 5, pp. 2154-2166.

Davidson, R. and Mackinnon, J. G. (2004), Econometric theory and methods, Oxford University Press.

De Jong, K. A. (1995). Analysis of the behavior of a class of genetic adaptive systems. Ph.d. Thesis, University of Michigan, USA, 1975.

Dockery, E. and Efentakis, M. (2008), An Empirical Comparison of Alternative Models in Estimating Value-at-Risk: Evidence and Application from the LSE, Int. J. Monetary Economics and Finance, 1(2), pp. 201-218.

Dowd, K., Blake, D. and Cairns, A. (2003), Long-term value at risk, Discussion paper: UBS Pensions Series 017, 468, Financial Markets Group, London School of Economics and Political Science, London, UK.

Engle, R.F. (1992), Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation, Econometrica, vol. 50, no. 4, pp. 987-1007.

Eslami Bidgolio, Gh. Vafi Sani, J. (2013). Memetic Ant Colony Algorithm for cardinality constrained mean-variance portfolio model and Value at Risk approach. Tehran Stock Exchange Journal, 5, 57-75.

Estrada, J. (2007), Mean- semi-variance behavior: Downside risk and capital asset pricing, International Review of Economics and Finance, vol. 16, pp. 169-185.

Estrada, J. (2008). Mean-semi-variance optimization: a heuristic approach. Journal of Applied Finance, 18(1), 57-72.

Etemadi, H., Anvary Rostamy, A. A., & Dehkordi, H. F. (2009). A genetic programming model for bankruptcy prediction: Empirical evidence from Iran. Expert Systems with Applications, 36(2), 3199-3207.

Fabozzi, F. J., Kolm, P. N., Pachamanova, D., & Focardi, S. M. (2007). Robust portfolio optimization and management. John Wiley & Sons.

Farzi, Pandari, & Shavazi. (2015). Using Quantum-Behaved Particle Swarm Optimization for Portfolio Selection Problem. The Information Arab Journal of Information Technology.

Bacanin, Tuba, M., & Nebojsa. (2014). Upgraded Firefly Algorithm for Portfolio Optimization Problem. UKSim-AMSS 16th International Conference on Computer Modelling and Simulation.

Chen, M.-Y., & Prayogo, D. (2014). Symbiotic Organisms Search: A new metaheuristic optimization. Computers and Structures.

Eslami Bidgolio, Gh. Vafi Sani, J. (2013). Memetic Ant Colony Algorithm for cardinality constrained mean-variance portfolio model and Value at Risk approach. Tehran Stock Exchange Journal, 5, 57-75.

Farzi, Pandari, & Shavazi. (2013). Using Quantum-Behaved Particle Swarm Optimization for Portfolio Selection Problem. The Information Arab Journal of Information Technology.

Pantazis, A. & Pelagidis, T. (2017), Financial Indicators Affecting Stock Performance The Case of Capital Product Partners, Regional Science Inquiry, Vol IX(2), 211-221.

Raie, R; Beigi, H. (2010). Constrained and unconstrained mean-variance portfolio problem model based on PSO. Financial research, 29, 21-40.

Salahi, M., Daemi, M., Lotfi, S., & Jamalian, A. (2014). PSO and Harmony Search Algorithms for Cardinality Constrained Portfolio Optimization Problem. Advanced Modeling and Optimization, 559-573.

Tuba, M., & Bacanin, N. (2014). Artificial bee colony algorithm hybridized with firefly metaheuristic for cardinality constrained mean-variance portfolio problem. Applied Mathematics & Information Sciences.

Zhu, H., Wang, Y., Wang, K., & Chen, Y. (2011). Particle Swarm Optimization (PSO) for the constrained portfolio. Elsevier, 161-169.