OPTIMAL PORTFOLIO SELECTION WITH VALUE AT RISK CRITERION IN SELECTED TEHRAN STOCK EXCHANGE COMPANIES (PSO AND MPSO APPROACHES)

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Abstract

The optimal portfolio selection problem has always been the most important issue in the modern economy. In this Study, It has been 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 efficient portfolio and it is necessary to find solving the optimization problem. Hence, the Improved Particle Swarm Optimization algorithm is used. The value of Portfolio and its risk are applied as the parameters in optimizing aim and criterion value exposed to contingent risk. Three intended applications have been indicated to the portfolio. In the next stage ,to evaluate and validate the method and to estimate the value of the portfolio in the next days and hold the series of the stock prices ,within a specified period, to predict the price and The Autoregressive method algorithms is used for modeling of the time-series. Practical result achieved for solving the portfolio optimization problem in Tehran Stock Exchange for the next day, by choosing the basket which includes 20 companies among the 30 most active industry indicates the performance and high capability of the algorithms and used in solving constrained optimization and appropriate weighted portfolios.

Keywords: Portfolio Selection, Conditional Value at Risk, Particle Swarm Optimization algorithm, Price and Return Forecasting

JEL classification: C22, G12, G24

1. Introduction

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Today the connection between engineering and economics mathematics has become one of the famous fields in academic research. In this area, portfolio optimization problem has always been the most important problem in modern economy and because of its widely used and difficult calculation; it has still been the focus point of many researchers. Portfolio is the proper combination of stocks or other assets that are bought by an investor. In the other word, portfolio optimization is the selection of best financial assets combination, in a way that its return is maximized and its risk is minimized. So, the primary variables in risk management are risk, return and the pay off between them.

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 (Tehrani, Siri, 2009).

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.

However it is a stylized fact that the distribution of many financial return series is non-normal, with skewness and kurtosis pervasive. Furthermore there is ample evidence that agents often treat losses and gains asymmetrically. There is a wealth of experimental evidence for loss aversion <see, for example, Kahne-man et al., 1990). The choice therefore of mean variance ancient portfolios is likely to give rise to a nescient strategy for optimizing expected returns for financial assets whilst minimizing risk. It would therefore be more desirable to focus on a measure for risk that is able to incorporate any non-normality in the return distributions of financial assets. Indeed risk measures such as semi- variance were originally constructed in order to measure the negative tail of the distribution separately. Typically mainstream finance rests on the assumption of normality, so that move away from the assumption of normally distributed returns is not particularly favored; one drawback often stated is the loss in the possibility of moving between discrete and continuous time frameworks. However it is precisely this simplifying approach, whereby any deviations from the square root of time rule are ignored, which needs to be incorporated into current finance theory. The ability to focus on additional moments in the return distribution with the possibility of allowing for skewed or leptokurtic distributions enables additional risk factors along with the use of standard deviation) to be included into the optimal portfolio selection problem.

There are several reasons why we consider downside risk and shortfall constraints in optimal portfolio selection. First, there is an extensive literature on safety-first investors who minimize the chance of disaster, introduced by Roy (1952), Telser (1955), Baumol (1963), and Levy and Sarnat(1972). Safety-first investor uses a downside risk measure which is a function of Value-at-Risk (VaR).Roy (1952) indicates that most investors are principally concerned with avoiding a possible disaster and that the principle of safety plays a crucial role in the decision-making process. In other words, the idea of a disaster exists and a risk adverse safety-first investor will seek to reduce the chance of such a catastrophe occurring as far as possible. Second, we believe optimal portfolio selection under limited downside risk to be a practical problem. Even if agents are endowed with standard concave utility functions such that to a first- order approximation they would be mean-variance optimizers, practical circumstances such as short-sale and liquidity constraints as well as some loss constraints such as maximum drawdown commonly used by portfolio managers often impose restrictions that elicit asymmetric treatment of upside potential and downside risk. Third, the mean-variance portfolio theory developed by Markowitz (1952a, 1959) critically relies on two assumptions. Either the investors have a quadratic utility or the asset returns are jointly normally distributed (see Levy and Markowitz (1979), Chamberlain (1983) and Berk (1997)). Both assumptions are not required, just one or the other: (i) If an investor has quadratic preferences, she cares only about the mean and variance of returns; and the skewness and kurtosis of returns have no effect on expected utility, i.e., she will not care, for example, about extreme losses. (ii) Mean-variance optimization can be justified if the asset returns are jointly normally distributed since the mean and variance will completely describe the distribution. However, the empirical distribution of asset returns is typically skewed, peaked around the mode, and has fat-tails, implying that extreme events occur much more frequently than predicted by the normal distribution. Therefore, the traditional measures of market risk (e.g., variance or standard deviation) are not appropriate to approximate the maximum likely loss that a firm can expect to lose, especially under highly volatile periods

So, the purpose of present paper is to find portfolio x with favorable minimum risk. To find this portfolio, it is required to solve portfolio optimization problem. At first, an efficient criterion is introduced to measure risk and then, three applicable constraints are considered for portfolio. Next, optimization algorithms are used to solve portfolio problem. Also, in this paper, solving this problem for the next day is considered, and risk, return and capital value parameters are calculated for the next day.

2. Review of Literature

In general, portfolio theory can be divided into modern and post-modern groups. 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 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 (Artzener, Delbaen 1992).

To use natural selection process simulation for solving optimization problem is referred to 1930s and in 1960s the study of Fugle, Halen and Shefel has built the basis of evolutionary algorithms. Evolutionary algorithms are meta-heuristic stochastic optimization methods based on population that are referred to Darvin evolution theory in 1846. Evolutionary algorithms start with random initial population then the fitness of any member is evaluated by objective function. These algorithms in several divisions, are recognized as intelligent optimization methods and evolutionary calculation. The advantage of these algorithms is that they can search the optimal point without derivative of cost function. Genetic algorithm and Particle Swarm algorithm are the example of these algorithms.

Yin and Wang in 2006 used PSO algorithm in nonlinear source allocation problem and compare the efficiency of this algorithm with GA. Finally, they concluded that PSO algorithm is more efficient than GA. Kura in 2009 used PSO algorithm in constrained portfolio optimization. In that paper he used weekly stocks prices of a few companies and drew efficient frontier. Finally, he concluded that, PSO algorithm was really successful in portfolio optimization. In Iran, Abdolalizadeh and Eshghi (1382) study portfolio optimization by GA.

Khaluzadeh and Amiri (1385) despite the classical models that are based on variance and used for optimizing portfolio, he used value at risk as a portfolio risk criterion. Raie and Alibeigi (1389) in a study used PSO algorithm in portfolio optimization based on mean-variance model. In this study we use PSO algorithm in Markowitz model with the assumption of available data and add constraints in three different levels. In past years, PSO algorithm has been used for several research and application fields, and it is indicated that in several examples, PSO algorithm has better, faster and cheaper results than other methods (Kamali, 2014). This algorithm despite GA, does not have mutation and crossover operator. The other reasons that make PSO algorithm so exceptional and attractive is that, this algorithm need very few parameters for setting. A version of algorithm with few parameters can be used in several applications (Raie and Alibeigi, 1389). In Heidari thesis (1391) the superiority of PSO algorithm to GA and other algorithms in solving portfolio problem is indicated.

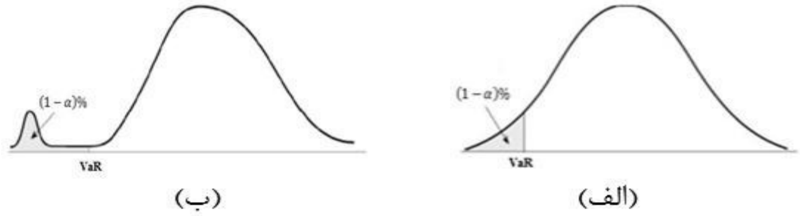
3. Constrained Portfolio Optimization Problem

To understand this problem consider a set of limited capital i = 1,2,…,n that can be any financial capital, stocks and bonds. At the moment, the most important institution performance evaluation is rate of stocks return. To put it simply, the profit that can be gained in an investing is return that is in specific time duration and according to its beginning and end of period prices. Assume that R_i is the return of stock S_i and $R` = (R_1, R_2, \dots, R_n)$ is the transposed profit vector of stocks $S_1, S_2, \dots, S_n$ and vertical vector $x_i$ is indicated the amount of invested money in stock $S_i$. $x \epsilon R^n$ also $R^*$ is a favorable investors` profit and σ_{ij} is a covariance between two stocks. Markowitz mean-variance model is:

$$\begin{aligned} &\textit{minimize} \quad \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \sigma_{ij} \\ &\textit{subject to} \quad \begin{cases} \sum_{i=1}^{n} R_i x_i = R^* \\ \sum_{i=1}^{n} x_i = 1 \quad , x_i \geq 0 \end{cases} \end{aligned} \qquad [1]$$

In Markowitz model, with increase in assets, calculation volume increased too much. Covariance criterion can be an acceptable criterion for financial assets that have normal distributions and traded in efficient market. Otherwise, it isn`t a proper risk criterion. Down side risk measures is divided into two parts, semi measure of risk and risk measures based on percentile. Value at risk and conditional value at risk are the most famous in the risk measures based on percentile division. VaR is a decreased risk measure and can indicate the worst loss in usual market condition in a specific time duration and confidence level. In (figure 1-A) although value at risk is a usual risk criterion but it has unfavorable mathematic features. CVaR, as a risk criterion has been shown better features than VaR. This method indicates that if the condition is not favorable, how much loss we expect to tolerate. In other word, it says the amount of loss in n-days' time period in a condition that we are in $1-\alpha$ percent in left bulge part of probability distribution curve figure 1-B)(Khaluzadeh & Amiri, 1385).

Figure1: probability distribution curve of asset return A-VaR criterion & B-CVaR criterion



Suppose that *f(x, y)* is the risk related to decision vector $x \epsilon X \subseteq R^n$ and random vector $y \epsilon R^m$. For simplicity, first we assume that *y* follows a continuous distribution and its density function is *p(0)*. Also we assume that for any *x*, $E(|f(x,y)|) < \infty$. For $x \in X$ probability of $f(x,y)$ is not more than α threshold:

$$\varphi(x,\alpha) = \int_{f(x,y)\le\alpha} p(y)dy \qquad [2]$$

For given confidence level of β and *x* value at risk is:

$$VaR_\beta(x) = min\{\alpha \in R: \varphi(x,\alpha) \ge \beta\}$$

$$CVaR_\beta(x) = \frac{1}{1-\beta}\int_{f(x,y)\ge VaR_\beta(x)} f(x,y)p(y)dy \qquad [3]$$

Rakefeller and uryasef (2000) has shown that CVaR calculation can be solved by determined function minimization with respect to α (Rockefeller, Uryasev 2003).

$$F_\beta(x,\alpha) = \alpha + \frac{1}{1-\beta}\int_{y\in R^m} (f(x,y)-\alpha)^+ p(y)dy \qquad [4]$$

Because in calculation, the most difficult part of CVaR optimization is to calculate the integral of multi variables and unsmooth function. To solve this problem we can use estimation. Mont Carlo simulation is one of the most efficient methods for calculating high dimensional integral. Rockefeller and urease (2000) through these methods can estimate $F_\beta(x,\alpha)$ in a way that $y_{[k]}$ shows k-the produced sample by random sampling with respect to *y* and *s* shows the number of samples (Ogryczak, Sliwinski 2010).

$$F_\beta(x,\alpha) = \alpha + \frac{1}{s(1-\beta)}\sum_{k=1}^{s}\left(f(x,y_{[k]})-\alpha\right)^+$$

$$CVaR_\beta(x) = min_{\alpha\in R}F_\beta(x,\alpha) \qquad [5]$$

Now, with respect to considered risk criterion, Markowitz model can be reformed by adding three applicable constrained. The first constrained is the sum of all stocks weight that must be equal to one. Next constraint is upper and lower bound. If we want to exert the number of chosen asset constraint for investing, the model should be like the bellow model and is called Cardinality Constrained Portfolio Selection.

$$minimize \quad \lambda[\mathcal{R}(x)] - (1-\lambda)\left[\sum_{i=1}^{n} z_i R_i x_i\right]$$

$$subject\ to \quad \begin{cases} \sum_{i=1}^{n} z_i = K \\ \sum_{i=1}^{n} x_i = 1 \\ \varepsilon_i z_i \le x_i \le \delta_i z_i \\ z_i = [0,1] \quad i = 1,\dots,n \\ x_i \ge 0 \quad i = 1,\dots,n \end{cases} \qquad [6]$$

Despite the first model (1) that is unconstrained portfolio based on variance as a risk criterion, in this study, we have *R(x)*, CVaR as a risk criterion. λ is a parameter that can be changed in [0,1] limitation and with respect to investor point of view the specific value can be chosen. For example, if $\lambda = 0$ all amount of weight coefficient is allocated to return. And if $\lambda = 1$, all amount of weight coefficient is allocated to the risk and without respect to return the least risk portfolio is chosen. If λ is determined between 0 and 1, both risk and return are considered to determined portfolios (Mozafari, Taffazoli 2013). Z_i parameter is the decision variable for investing in any stock. If z_i is equal to one, it means stock i can be in the portfolio. The total number of all stock is related to the third constraint that is k number and ε_i and δ_i are upper and lower bounds. There is no effective and efficient algorithm in mathematic programming to have exact solution. So, meat-heuristic algorithm is chosen to get the optimized weight of stocks (Xu, Zhang 2010).

4. Modified Particle Swarm Algorithm

The use of PSO algorithm in some problem has shown that, PSO algorithm gets to premature convergence and this result in inability in solving multiple peaks problems. To remove this problem, we can modify the algorithm with a little change. *w* is the inertia coefficient that has the most important role in algorithm`s performance. This coefficient makes a balance between local and global search. Little amount of *w* result in premature convergence whereas high amount avoid convergence. Usually, in implementation of PSO algorithm, *w* must be adjusted during training process. One of the way to adjust *w* is linear decrease of this amount (He, Wen 2003). A better way that has better result, is modeling *w* inertia coefficient. In this way, inertia coefficient is according to distance between particle of one generation and the best location that has been experienced by all particles. The amount of *w* is:

$$w = w_o(1 - \frac{dist_i}{max\ \_dist})$$

$$dist_i = \sqrt{\sum_{d=1}^{D} (gbest_d - x_{i,d})^2}$$

$$max\ \_dist = \underset{i}{argmax}(dist_i)$$

In formula above, w_0 is a random number in [0.5, 1] and $dist_i$ is a Euclidean distance between i-th particle and *gbest* the best location has been experienced by all. The problem has D dimension and *max_dist* is the furthest distance between a particle and *gbest* in each generation. The modeling of inertia coefficient cause to guide the furthest particle to the best location and finally, converge in optimize point. To reach to this optimized point and avoidance of premature convergence, we should assure of the particle motion in the next level. To reach to this aim, the location updating equation should be reformed as this:

$$x_{i,d}[t] = (1 - \rho).x_{i,d}[t-1] + v_{i,d}[t]$$

In formula above, ρ is a random number with uniform distribution in [-0.25, 0.25]. So, by adding this part to equation, particles get more mobility, even when they have low speed (Suresh, Ghosh, Kundu 2008) and (Wang, Wang 2010).

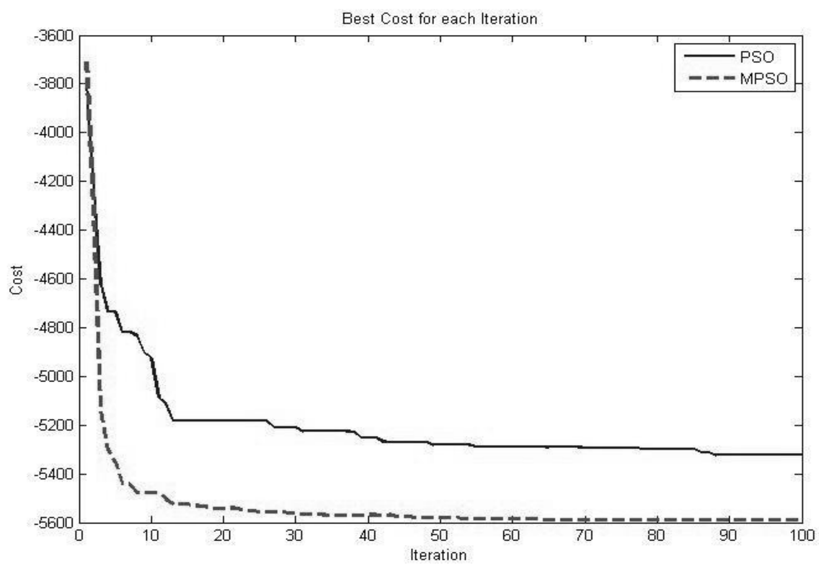
5. Modeling and Prediction of Stocks Price

Nowadays, one of the important favorable subjects of economist and financial analyst, is to determine price volatility trends. And now, there a lot of point of views about this subject. In this situation and with respect to unavailable precise information about effective factors on market volatility, predicting these changes is not easy at all. And based on this subject, efficient market theory has been mentioned. This theory mentions that, stock price volatility by this public and available information is unpredictable. In effect, this theory is based on random walk theory. To mention a theory against above theory means the predictability of stocks prices (khaluzadeh & Khakisedigh, 1377). Since the middle of 1970s and specific from 1980, new and extended attempt for predictability of stocks price by new mathematical method, long time series and professional tools started. A lot of test on prices and stock`s index in countries like England, United States, Canada, Germany and Japan has done in order to show fix structure of stocks price. Since 1997, in this field in Iran and in Tehran Stock Exchange some study has started. By using chaos theory that is powerful tool for analysis and process of stocks prices information, the related time series process will be distinguished from a random time series. And it is on the (R/S) basis or can be mention, the alteration of fluctuation source of time series of stock price, shows the consecutive nature of stock price (Khaluzadeh & Amiri, 1385). The purpose of this section, is to solve constrained portfolio problem by the mentioned algorithm for next day. So, in order to estimate risk and return parameters or estimate capital value for next day, price prediction methods are used. To do this, spatial and efficient algorithms can be used for predicting the next day of available stocks prices with specific time period. Then, we can repeat optimization problem for new time series and estimate the value of portfolio with its risk for the next day.

6. Empirical Results

In this study, portfolio problem is solved by historical data 700 days of 30 active industries. The time period is from Aug 18, 2008 to Sep 4, 2015. 20 companies are chosen for portfolio and through meta-heuristic algorithms the optimized stock`s weight are gained. The first constraint is, investing in 15 companies of 20. The upper bound is 0.3 and lower bound is 0.01 for any weight. In formula number [6] the risk and return coefficient is 0.5. As much as the risk decreases and the value of portfolio increases, the cost function will decrease. So, the purpose is to minimize cost function. First, with available price series in the time period, we get the weight of optimized portfolio by two PSO and MPSO algorithms. The software we use in this study is MATLAB. The figure below shows the way that cost function of two algorithms passed. It seems the cost function in MPSO algorithm is lower.

Figure2: cost function in each iteration for PSO & MPSO algorithms



In below table shows, calculated portfolio value, risk and cost function for the two algorithms.

Table1: comparison of final result for two algorithms

comparison	cost	portfolio value	risk
PSO	-5323.945	10324.177	5000.321
MPSO	-5588.964	12388.727	6799.762

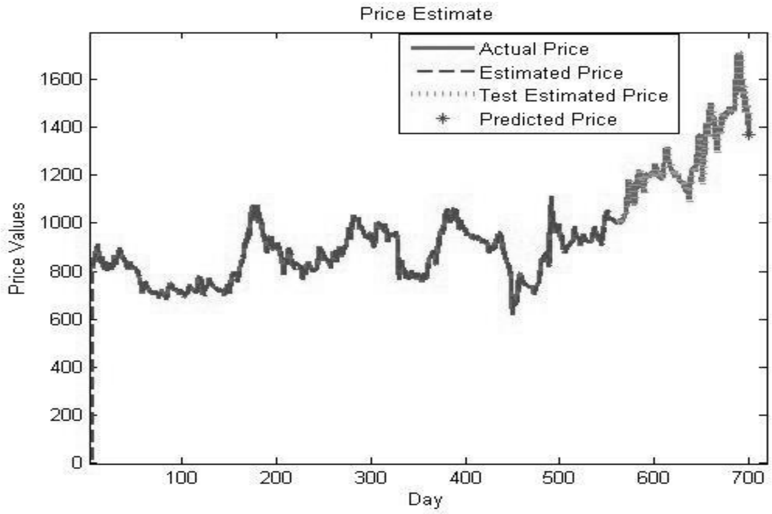
Also, below table shows, the weight that is got by two algorithms in constrained portfolio problem.

Table2: the weight allocated to any company in portfolio

	company name	weights by PSO	weights by MPSO
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	0.0114	0.0112
15	Yasa Iran	0.1399	0.2934
16	Traktor	0.0241	0.0119
17	Iran Chini	0.0213	0.0105
18	Mokhaberat Iran	0	0.0105
19	Abadan Petroloshimi	0.1298	0.158
20	Hafari Shomal	0.01	0.0111
21	sum	1	1

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 3: the absolute standard deviation of estimation error for 50 days price by RLS method

company name	absolute standard deviation	company name	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	46	Iran Chini	164
Service Anformatic	132	Mokhaberat Iran	67
Behshar Toseeh	109	Abadan Petroloshimi	202
Sina Bank	53	Hafari Shomal	98

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 MPSO 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 4: comparison between real and predicted data by MPSO algorithm in CCPS problem

comparison 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

7. Summery and Conclusion

The optimal portfolio selection problem has always been the most important issue in the modern economy. In this Study, It has been 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 efficient portfolio and it is necessary to find solving the optimization problem. Hence, the Improved Particle Swarm Optimization algorithm is used. The value of Portfolio and its risk are applied as the parameters in optimizing aim and criterion value exposed to contingent risk. Three intended applications have been indicated to the portfolio. In the next stage ,to evaluate and validate the method and to estimate the value of the portfolio in the next days and hold the series of the stock prices ,within a specified period, to predict the price and The Autoregressive method algorithms is used for modeling of the time-series. Practical result achieved for solving the portfolio optimization problem in Tehran Stock Exchange for the next day, by choosing the basket which includes 20 companies among the 30 most active industry indicates the performance and high capability of the algorithms and used in solving constrained optimization and appropriate weighted portfolios.

In present paper, the particle swarm algorithm and its modified version are used to optimize constrained portfolio. The results mention that MPSO is more efficient than PSO algorithm. Then, in order to make this study more applicable AR(10) model and RLS method are used to predict stocks price time series for the next day. Also, portfolio value and risk are predicted and compared with the result of real data. In order to make this result more reliable, we repeat this process and get the results for ten days. The results indicate that there is a little difference between the results of real and predicted data and this fact shows the high capability of this method in predicting optimized portfolio.

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