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Using Genetic Algorithm in Solving Stochastic Programming for Multi-Objective Portfolio Selection in Tehran Stock Exchange

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ABSTRACT

Investor decision making has always been affected by two factors: risk and returns. Considering risk, the investor expects an acceptable return on the investment decision horizon. Accordingly, defining goals and constraints for each investor can have unique prioritization. This paper develops several approaches to multi criteria portfolio optimization. The maximization of stock returns, the power of liquidity of selected stocks and the acceptance of risk to market risk are set as objectives of the problem. In order to solve the problem of information in the Tehran Stock Exchange in 2017, 45 sample stocks have been identified and, with the assumption of normalization of goals, a genetic algorithm has been used. The results show that the selected model provides a good performance for selecting the optimal portfolio for investors with specific goals and constraints.

1 Introduction

In financial literature, a portfolio is considered as an appropriate collection of investments held by an individual or a financial institution. These investments or financial assets constitute shares of a company (often referred as equities), government bonds, fixed income securities, commodities (such as Gold, Silver, etc.), derivatives (incl. options, futures and forwards), mutual funds, and, various mathematically complex and business driven financial instruments. The individual responsible for making investment decisions using the money (or capital) that individual investors or financial institutions have placed under his/her control is referred as the Portfolio Manager. In principle, a portfolio manager holds responsibility for managing the asset and liability portfolios of a financial institution.

From a very simplistic viewpoint, consider we have a capital of One Lakh Rupees to invest in equities. Further, consider that there exists a market that has three equities: Infosys, Tata Steel

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and Reliance Industries. An investment perspective on the three equities raises the following fundamental questions:

- In which of these would we invest?
- How much would we invest in each of them?

Fundamentally, determining this optimal structure of weights is considered as the Portfolio Optimization problem in Mathematical and Financial literature. In principle, the portfolio may consist of any of the complex investment options available, and would have a variety of realistic constraints. For a thorough examination of the subject, it is important to pay attention to three points regarding the above problem:

1. What is the history of research on the issue of selecting stock portfolios with its precise and transparent expression?
2. What kind of programming is used to solve these issues?
3. Are the models used to program these issues NP hard or are they simple? And if the NP is hard, what methods have been used to solve these problems?

To answer the first question; In simple terms, a portfolio is said to be a combination of assets that is chosen by an investor for investment. Investors need to explore all portfolios for optimal asset selection. Stock selection strategies strongly affect portfolio performance. By allocating capital to a portfolio of stocks, investors strive to maximize their return while minimizing their risk. Hence, theories of financial behavior about investors can be used to indicate how risky and harmful a person is likely to affect the circumstances of the problem. Modern portfolio theory, which was developed by Markowitz [1], is an efficient portfolio theory that is based on the mean–variance relationship. In the mean–variance portfolio framework, diversified portfolio development secures the greatest possible expected return for a given degree of risk tolerance.

Following the introduction of the Markowitz Mean-Variability Model, the issue of choosing a multipurpose financial basket was considered by many decision-makers and financial planners. Several algorithms, including the Sharp model [2], in which part of the return on each share resulted from the multiplication of the market returns and a coefficient called beta and a segment independent of the market, was introduced. More recently, Ross's Arbitrage Pricing Theory (APT) [3] models the expected return of a financial asset as a linear function of various macro-economic factors (where, sensitivity to changes in each factor is represented by the factor-specific beta coefficients of the regression model) and Miller's Cost of Capital [4] or the Capital Structure Irrelevance Principle forms the foundation for looking at the capital structure. The model of Sharp [2] and Elton, Gruber and Potberger [5] were developed to linearize and improve the computational efficiency of the Markowitz covariance model. The Markowitz model was criticized for inefficiencies with conventional models of selection preferences under risk (Bell, Raiffa and Tversky, [6]). Levy [27] emphasized that models that are consistent with preferences are based on the relationship between randomized domination and utility theory. For this reason, Ballestero and Romero [7], for example, suggested maximizing the utility of the investor's expected returns on an efficient frontier.

Answering the second question, Markowitz's core contributions to the world of finance can essentially be summarized as follows: (i) modeling returns as random variables and using their variance as a measure of risk; (ii) providing a formula to calculate the expected return and the variance of a portfolio from the expected returns and co-variances of its components and (iii) introducing an optimization framework to build efficient portfolios. Markowitz was the first one who formalized the measurement of portfolio risk and return in a mathematically consistent framework, in which, he subsequently expanded in Markowitz [1]. Acknowledging that measuring portfolio risk and portfolio return was only the first step, Markowitz introduced a methodology for assembling portfolios that considers the expected returns and risk characteristics of the underlying assets as well as the investor's appetite for risk. Therefore, it is necessary to examine these two aspects of the problem as well. Considering several criteria in models makes the problem complicated for decision making. In this regard, most researchers agree on goal programming and Chance Constrained Programming. The use of goal programming was first used by Lee and Chaser in [8] and the Chance Constrained Programming between Armani and Zeleny in [9] on the issue of portfolio selection. In the following, Ben Abdelaziz [10], Long and Nadu in [11] proposed multi objective stochastic linear programming models for such issues, [10,11].

Abdelaziz et al. [12] proposed a new deterministic formulation to multi criteria stochastic Programming by combining compromise programming and chance constrained programming models for Portfolio optimization. The criteria they considered are rate of return, liquidity measured as exchange flow ratio and the risk coefficient. They applied their method with 45 stocks from the Tunisian stock exchange. To answer the third question; The problem of optimizing Markowitz and determining the effective investment boundary is minimized by mathematical models when the number of investment assets and market constraints is low. But when the real world conditions and constraints are taken into consideration, it will be a complicated and difficult problem, which has been solving such complex problems for many years. Advanced math's and computers have come to the aid of human beings to help them eliminate environmental uncertainty and ambiguity. Among the ways in which the solution to many of the optimization problems has been the unifying point in recent years and has succeeded in responding to complex problems, the so-called innovative algorithms and algorithms are also called "super-enterprise". Innovative techniques designed to address the shortcomings of classical optimization techniques, with a thorough and random search, guarantee the possibility of achieving better results to a large extent.

2 Research Methodology

The purpose of this paper is to apply the Genetic Algorithm for selecting stock portfolios based on the three goals of maximizing stock returns, the power of liquidity of selected stocks, and accepting risk to market risk using real data. In the Tehran Stock Exchange, the first three-tier model of Ben Abdul Aziz and his colleagues [13] is described with restrictions. In the next section, how to select data from the Tehran Securities Market and in the end section, explain how to solve using the method of the Genetic algorithm. Finally, the findings of the problem are presented. So this paper examines the principles of Modern Portfolio theory which supports the diversification in an investment portfolio by utilizing beta coefficient to measure investment's performance, the power of liquidity of selected stocks, and accepting risk to market risk using real data.

The outline of this paper is as follows:

The components modelling is presented in Sections ‘‘Objectives and Research methodology’’. Problem formulation and design methodology are presented in Section ‘‘Problem formulation and design methodology’’. A case study is described in Section ‘‘Data’’. Results and discussion are described in Section ‘‘Results and discussion’’ and finally conclusions are presented in Section ‘‘Conclusions’’.

3 Proposed Model

In this research, a model for portfolio selection is proposed in which some of the parameters are random and have normal distribution. To this end, a Chance Constrained Compromise Programming model is used. In order to determine the amount of investment in industries, firstly, by reviewing the research, the existing criteria are collected and by ranking the views of the business experts, the criteria are identified. Then, by comparing the weights of industries, it is considered as a limitation in the mathematical model. The modeling process presented by Abdulaziz [13] includes three stages of defining the goal, defining constraints and calculating the ideal values for each goal.

Goals set for this issue are included as follows:

Objective 1: Return on the investment is the primary concern of Portfolio optimization. However, this return cannot be known with certainty until after the economic factors that define it are realized. Therefore, expected return comes out as the common basic criterion of most Portfolio optimization problems.

Expected return of a portfolio is given by the weighted expected returns of individual assets by their proportions in the portfolio. Maximize the return on each share at random, which has a normal distribution with a mean and standard deviation, and is calculated from the following equation.

$$(\tilde{R}_J) = \frac{\tilde{P}_{J.t} - \tilde{P}_{J.t-1} + \tilde{D}_{J.t}}{\tilde{P}_{J.t-1}}$$

$\tilde{P}_{J.t}$:The share price j at random time t, which has a normal distribution with mean and standard deviation.

$\tilde{D}_{J.t}$: The dividend of the contribution of j at random time t, which has a normal distribution with mean and standard deviation.

$\tilde{R}_J$: return share of J.

$$Max\ z_1 = \sum_{j=1}^{45} \tilde{R}_J X_J$$

Objective 2: Liquidity is the degree a security can be sold without affecting its market price and without loss of value. It can also be defined as the ease a security can be traded within fair price levels. It is particularly important for investors who want to be able to instantly liquidate their assets. Some investors may have frequent payment liabilities, some of which may be without advance notice. Liquidity is usually characterized by the following aspects: time to trade, bid–

ask price range (spread) and effect of transaction on price. Sarr and Lybek [14] reviewed several liquidity measures. Volume-related liquidity measures are generally measured by the volume or quantity of shares traded per time unit. Time-related measures look at the number of transactions or orders per time unit. Spread-related measures study the difference between ask and bid prices with several measurement approaches. There are also multidimensional measures that combine different measures. We use a liquidity measure that is like a turnover ratio. We use the proportion of shares of a stock that are traded in a fixed time unit among the publicly outstanding number of shares of that stock. We use the most recent month for the number of outstanding shares of a stock. For the number of shares traded in that month, we take the daily average number. We calculate the liquidity measure of each stock using these numbers; the higher the liquidity measure's value is; the more liquid the corresponding stock is. Our liquidity criterion can be expressed as: Maximize liquidity calculated by the following equation.

$$L_J = \frac{N_J}{N_m}$$

L_J: Liquidity power of J share.
N_J: The number of trading days is J's share.
N_m: The number of trading days in the market.

$$Max\ z_2 = \sum_{j=1}^{45} L_J X_J$$

Objective 3: Risk taking at market risk level that uses the beta coefficient as a risk measure that depends on the return on the market and is calculated using the formula below.

$$(\beta_J) = \frac{cov(\tilde{R}_J . \tilde{R}_m)}{var(\tilde{R}_m)}$$

β_J: risk coefficient.
$\tilde{R}_m$: the rate of market return.
$\tilde{R}_J$: rate of return of stock j.

$$opt\ z_3 = \sum_{j=1}^{45} \beta_J X_J$$

It is well known that the portfolio beta measures portfolio volatility relative to the benchmark index or the capital market. Indeed, if a portfolio is well chosen such that returns of portfolio and benchmark index are highly correlated, then portfolio beta becomes the volatility ratio between the the ideal values of the objective i, f_i or $f_i^*$is obtained by maximizing or (minimizing) the single objective function under the system constraints. The system constraints can be defined as follows:

Setting a lower and an upper bound for each stock in order to diversify the portfolio, $0 \leq x_J \leq 0.1$, for j = 1,2, . . . , 4,5 where the x_J is the proportion to be invested in the stock j.

The sum of the proportions invested in stocks is equal to 1: $\sum_{j=1}^{45} x_J = 1$. In order to diversify the basket; for each share, the maximum amount is 10% of the total investment. In order to diversify the selected portfolios, we propose to:

invest less than 10% in basic metals,

invest less than 25% in automobile manufacturing,

invest less than 25% in Petroleum products, coke and nuclear fuel,

The definitive general model of the main problem is described in below Model.

$$Min\, Y = w_1(\in +d_1^+) + w_2(d_2^- + d_2^+) + w_3 d_3^{\pm}$$

St:

$$E\left(R^* - \sum_{j=1}^{45} \tilde{R}_J X_J\right) + \varphi^{-1}(1-a)\delta\left(R^* - \sum_{j=1}^{45} \tilde{R}_J X_J\right) - \in + d_1^-$$

$$\sum_{j=1}^{45} \beta_J X_J + d_2^- - d_2^+ = 1$$

$$\sum_{j=1}^{50} L_J X_J + d_3^- = L^*$$

$$\sum_{j=1}^{45} x_J = 1$$

$$X_1 + X_2 \leq 0.02$$

$$X_3 + X_4 \leq 0.1$$

$$X_5 + X_6 \leq 0.08$$

$$X_7 \leq 0.005$$

$$X_8 + X_9 + X_{10} + X_{11} \leq 0.19$$

$$X_{12} + X_{13} \leq 0.01$$

$$X_{14} \leq 0.011$$

$$X_{15} + X_{16} \leq 0.03$$

$$X_{17} \leq 0.07$$

$$X_{18} + X_{19} + X_{20} \leq 0.05$$

$$X_{21} + X_{22} + X_{23} \leq 0.014$$

$$X_{24} + X_{25} \leq 0.03$$

$$X_{26} + X_{27} \leq 0.012$$

$$X_{28} + X_{29} + X_{30} \leq 0.04$$

$$X_{31} + X_{32} + X_{33} \leq 0.0179$$

$X_{34} + X_{35} + X_{36} + X_{37} + X_{38} + X_{39} + X_{40} \leq 0.197$

$X_{41} + X_{42} + X_{43} + X_{44} + X_{45} \leq 0.18$

4 Genetic Algorithm

Heuristics are used for difficult problems that are not practical to be solved to optimality. Instead of optimal solutions, heuristics aim for satisfactory solutions that can be obtained more easily with short computation times. PO problems get more difficult as we consider additional and/or nonlinear criteria, more investment options and constraints that lead to integer or binary variables. Heuristics have been used to handle such PO problems. Genetic algorithm is a stochastic optimization technique invented by Holland [15] and a search algorithm based on survival of the fittest among string structures (Goldberg, [16]). They applied the idea from biology research to guide the search to an (near-) optimal solution (Wong and Tan, [17]). The general idea was to maintain an artificial ecosystem, consisting of a population of chromosomes. In this study, each chromosome represents the weight of individual stock of portfolio and is optimized to reach a possible solution. Attached to each chromosome is a fitness value, which defines how good a solution the chromosome represents. By using mutation, crossover values, and natural selection, the population will converge to one containing only chromosomes with good fitness (Adeli & Hung, [18]). Recently, GA attracts much attention in portfolio formulations (Orito, Yamamoto, & Yamazaki, [19]; Xia, Liu, Wang, and Lai, [20]).

Cheong and et al. [21] Used genetic algorithm to support clustering-based portfolio optimization by investor information. Kalayci et al. [23] used an artificial bee colony algorithm with feasibility enforcement and infeasibility toleration procedures for cardinality constrained portfolio optimization [23]. Suraj S. Meghwani and Manoj Thakur for practical portfolio optimization and rebalancing with transaction cost use Multi-objective heuristic algorithms [25]. Genetic algorithms are a family of heuristic search techniques where a population of abstract representations evolves toward better solutions in successive generations. In genetic algorithms, we start with an initial population of feasible solutions. Each solution is represented by a set of chromosomes. From this population, parents that perform well with respect to the criterion/criteria of the problem are selected as parents to produce the offspring. To produce the offspring, we first apply crossover to the parents. Exchanging chromosomes between parents, we obtain children that contain properties from both parents. This is performed with the hope of obtaining better solutions than the parents [24]. After the crossover, we also apply mutation to some of the children created. The purpose here is to change some properties of the offspring so that we can obtain solutions that can bring differentiation to the population. After the mutation, we select best out of the starting population and the offspring, and treat the selected solutions as the new population for the next generation. This process is repeated for a number of generations, evolving toward better solutions.

To demonstrate the usefulness of the proposed GA portfolio scheme, a major benchmark index in Tehran Stock Exchange from march 2017 to June 2017 is used. For the comparison with conventional weight optimization algorithms, we used an algorithm labeled which optimizes the weights by minimizing over 1,000,000 random generations. In the process of GA, the crossover and mutation rates are changed to prevent the output from falling into local optima. The crossover rate runs from 0.5 to 0.8 and the mutation rate runs from 0.05 to 0.06, which uses 50 organisms in the population. The GA automatically stops when there is no improvement over 1% at the last 300 trials.

5 Data

The first objective in goals at random, so that $\tilde{R}_J$ normal random distribution with mean and standard deviation is known. The threshold of $\propto$ is 0.001, 0.025, and 0.05 according to the randomness of the model And Weights objective functions according to three weights based on three types of risk tolerance, risk taking and neutral risk in the following table.

Table 1: weight in three kind of risk

	risk-taking	risk neutral	risk aversion
Weight objective 1	0.54	0.33	0.13
Weight objective 2	0.13	0.33	0.54
Weight objective 3	0.34	0.34	0.34

The objectives considered, in this example, are the rate of return, the exchange flow ratio, and the risk b.

They are equally weighed. In Table 1 we present data concerning the different securities of the Tehran stock market for the year 2017. The five columns of the table are the securities, the expected and the maximum rate of return of each security, the exchange flow ratio, and the risk b.

Based on the above information, the average and standard deviation as well as the number of trading days of shares were calculated for the whole day in the market in four months and the benchmark Beta has been calculated and presented in the table below as input for the genetic algorithm.

Table 2: R mean, R STD, Beta and L for stocks

	R Mean	R STD	Beta	L
Vamaaden	1.818803965	0.186620412	-4.151615102	0.7375
Karoi	1.899420236	0.119860618	-8.306807994	0.9625
Shepaksa	1.850830838	0.023239778	-2.695771203	0.9625

Table 2: Continue

	R Mean	R STD	Beta	L
Shapoli	2.388574837	0.058976301	-0.104670226	0.9625
Takomba	1.932525812	0.117155271	8.531238888	0.9375
Fazar	1.839839627	0.136736978	-11.7356898	0.725
Vatoshe	1.777394256	0.118838322	4.156499425	0.925
Khezamia	1.976017516	0.125771366	0.873663848	0.8875
Khavar	2.910094641	0.145332184	6.59697356	0.75

Khepars	1.951578166	0.12150912	3.651827127	0.925
Khodro	1.930773002	0.16971895	0.337679211	0.8625
Damavand	1.790293103	0.117339168	2.136102029	0.925
Bemapna	1.855687869	0.122854529	-0.361450127	0.9
Vabmelat	1.853288302	0.116048372	9.923777059	0.9375
Chekaveh	1.962040886	0.17953013	-8.432968292	0.825
Chekaveh	1.902268915	0.025773788	-0.131706071	0.9625
Samega	1.446538069	0.765641549	34.40489882	0.875
Vagostar	1.987551227	0.120758926	1.129783713	0.9375
Vakharazm	1.999387762	0.01349447	-1.563224449	0.9625
Valsapa	1.800875831	0.120388681	-1.530386527	0.925
Hekeshti	1.951634241	0.124112963	3.764760328	0.825
Hesina	1.86128836	0.174064229	23.69621873	0.8375
Hepetro	1.954901916	0.186549611	-6.375121358	0.7375
Hamrah	1.854051412	0.173448367	4.579999128	0.85
Akhaber	1.761071232	0.117984687	17.23296041	0.9
Sabagh	1.829567209	0.018221051	-1.344011438	0.9625
Senosa	2.186235661	0.115730037	12.10467543	0.95
System	1.875539219	0.165147733	-6.195139899	0.925
Mafakher	1.941839021	0.119557613	-2.768942897	0.925
Pardakht	1.899980952	0.005145044	-0.288314472	0.9625
Ghegol	1.908823669	0.21931016	-5.728756368	0.775
Ghemarg	1.913416948	0.132669699	-14.92533953	0.7375
Ghebshahr	2.388574837	0.058940663	-1.357281887	0.9625
Vanaft	1.870631471	0.121967761	1.28010266	0.8875
Shapna	1.785015261	0.133825441	-6.835587822	0.8375
Sharaz	1.900958525	0.135642655	-4.424142345	0.8375
Shavan	1.143285853	0.987749868	126.4929916	0.8
Shatran	1.815773699	0.137696465	-6.674360367	0.825
Shabriz	1.834601176	0.13401256	-4.86692216	0.8375
Shebandar	1.98538165	0.123039906	0.011141361	0.9625
Kimia	1.847690949	0.178791824	-2.556559934	0.9625
Fameli	1.919153786	0.170368998	-5.135487005	0.9625
Hormoz	1.927315123	0.171944973	1.104561417	0.9625
Zob	2.028043473	0.129441716	-0.228932891	0.9625
Foulad	1.752908864	0.166759012	-5.204970425	0.9625

6 Results and Discussion

Given the input data described above and the basic parameters presented in the genetic algorithm, depending on the risk appetite of the investors, the output is as follows.

npop=50; maxit=300; pc=0.7;

nc=2*round(pc*npop/2); mu=0.3;

nmu=round(mu*npop);

Table 3. Output of genetic algorithm

alfa	0.05			0.025			0.001		
	risk-taking	risk neutral	risk aversion	risk-taking	risk neutral	risk aversion	risk-taking	risk neutral	risk aversion
vamaaden	0	0	0	0	0	0	0	0	0
karoi	0	0	0.0082	0	0.0901	0	0	0.0901	0
shepaksa	0	0.09667	0.0975	0.098	0	0.0929	0.09176	0.0798	0.09754
shapoli	0	0	0	0	0	0	0	0	0
takomba	0.0929	0	0	0	0	0	0	0.1	0
fazar	0	0	0	0	0	0	0	0	0
vatoshe	0.00619	0.09048	0	0.0825	0.0917	0.0917	0.09176	0.0917	0
Khezamia	0	0	0	0	0	0	0	0	0
Khavar	0	0	0	0	0	0	0	0	0
Khepars	0	0	0	0.0250	0	0.0784	0	0.0784	0
Khodro	0	0	0	0	0	0	0	0	0
Damavand	0.0929	0	0	0.093	0	0	0	0.01685	0.0929
Bemapna	0	0	0	0	0	0.0929	0.09048	0	0
Vabmelat	0.0071	0.07491	5E-05	0.0749	0.0749	0.0749	0	0.0749	0
Chekaveh	0	0	0	0	0	0	0	0	0
Chekaveh	0.0822	0.0929	0.1	0.036	0.1	0	0.09048	0.1	0
Samega	0.0348	0.0348	0.0348	0.034	0	0	0.0348	0.0348	0.0348
Vagostar	0.00038	0	0	0	0	0	0	0	0
Vakharazm	1.4E-17	0	0.09667	0	0	0	0	0	0
Valsapa	0.0901	0.09667	0	0	0.0966	0.0966	0.09667	0	0.0585
Hekeshti	0	0	0	0	0	0	0	0	0
Hesina	0	0	0	0.018	0.1	0	0	0	0.1
Hepetro	0	0	0	0	0	0	0	0.02404	0.02404
Hamrah	0	0	0	0	0	0	0	0	0
Akhaber	0.0905	0	0.0904	0	0	0.0904	0.09048	0	0
Sabagh	0.0975	0.1	0.1	0.1	0	0.1	0.09048	0	0.1
Senosa	0	0.00349	0	0	0	0	0	0	0
System	0.0839	0.00087	0	0.060	0	0	0.00624	0.0967	0
Mafakher	0	0	0	0	0	0	0	0	0
Pardakht	0.0095	0.0597	0.0967	0	0.0929	0	0.01744	0	0.0967

Table 3: Continue

alfa	0.05			0.025			0.001		
	risk-taking	risk neutral	risk aver-sion	risk-taking	risk neutral	risk aver-sion	risk-taking	risk neutral	risk aver-sion
Ghegol	0	0	0	0	0	0	0	0	0
Ghemarg	0.0175	0	0	0	0	0	0	0.0179	0.0179
Ghebshahr	0.0003	0	0	0	0	0	0	0	0

Vanaft	0	0.0972	0	0.097	0	0	0	0	0
Shapna	0.0901	0.1	0	0.065	0	0.004	0	0.0784	0.0967
Sharaz	0	0	0.1	0	0.1	0	0	0	0.1
Shavan	0	0	0	0	0	0	0.00115	0	0
Shatran	0.0972	0	0	0.0348	0.018	0.096	0.1	0.00799	0
Shabriz	0	0	0	0	0.0554	0.009	0.01798	0	0
Shebandar	0	0	0.09726	0	0	0	0	0	0.0005
Kimia	0	0.03704	0.1	0.1	0.0802	0.0802	0.00242	0.0082	0.0802
Fameli	0	0	0.078	0	0	0	0.08028	0	0
Hormoz	0.0066	0.07491	0	0	0	0	0	0.1	0
Zob	0	0	0	0	0	0	0.00031	0	0
Foulad	0.1	0.04031	0	0.080	0.1	0.1	0.09726	0	0.1

The output charts are based on the information provided by the three levels of investors' risk appetite with three values of alpha, as illustrated in Fig. 1. The best suggested genetic algorithm for the variable with alpha level is .001 and low risk-taking is as Table 4.

Table 4: Optimal solution

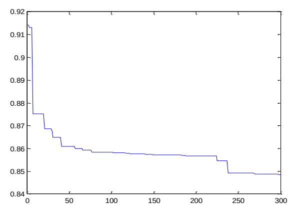
shepaksa	dama-vand	samega	valsapa	hesina	hepetro	sabagh	pardakht	ghemarg	shapna	sharaz
0.09754	0.093	0.0348	0.0585	0.1	0.024	0.1	0.09672	0.01798	0.0967	0.1

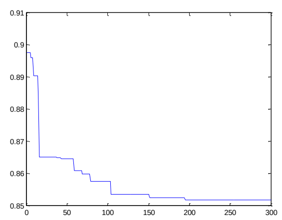
Best cost: 0.22957,   Elapsed time is 4.53004 seconds

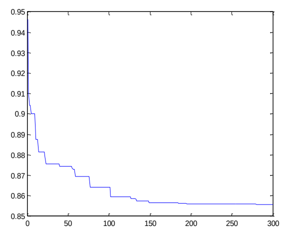
7 Conclusions

Portfolio selection problems are characterized by considering several conflicting objectives and where some parameters are random. Multi-objective stochastic programming allows the Decision maker to treat such problems. In this article, we have proposed a new deterministic formulation to multi-objective stochastic program. In our transformation, we first compute the best (ideal) values for each objective considered separately, and then we combine compromise programming and chance constrained programming models in order to convert the multi-objective stochastic program into a deterministic one.

In this research, based on the studies on optimal selection, Abdulaziz's model was selected as the base model and then, considering the Iranian market, the constraints of share selection for market share for each group were presented and the developed model with The use of data from Tehran's capital market has been evaluated over a four-month period using three levels of risk aversion. The results indicate that the genetic algorithm is efficient in selecting the portfolios for investment, and each investor can with a different risk, you can choose your own portfolio of expectations the investment.



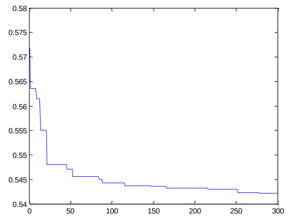


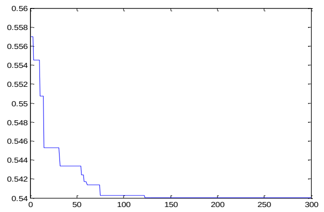


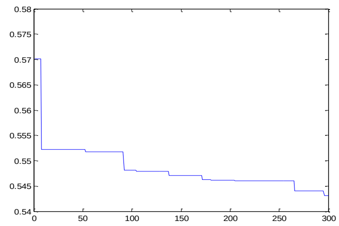
Alpha=.05;
W=[.54 .13 .34];
Best cost:0.85005 ,
Elapsed time is 4.568376 seconds.

Alpha=.025;
W=[.54 .13 .34];
Best cost:0.8518 ,
Elapsed time is 4.532738 seconds

Alpha=.001;
W=[.54 .13 .34];
Best cost:0.85557 ,
Elapsed time is 4.501752 seconds



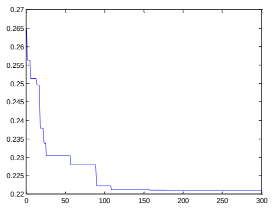


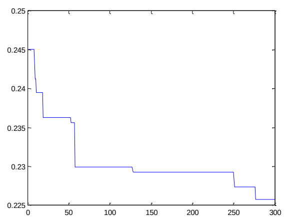


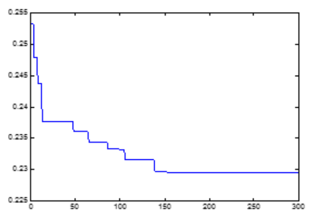
Alpha=.05;
W=[.33 .33 .34];
Best cost: 0.54219,
Elapsed time is 4.486112 seconds

Alpha=.025;
W=[.33 .33 .34];
Best cost:0.54005,
Elapsed time is 3.249 seconds

Alpha=.001;
W=[.33 .33 .34];
Best cost:0.54307 ,
Elapsed time is 4.575399 seconds







Alpha=.05;
W=[.13 .54 .34];
Best cost: 0.221,
Elapsed time is 4.033429 seconds

Alpha=.025;
W=[.13 .54 .34];
Best cost 0.22578 ,
Elapsed time is 4.481185 seconds

Alpha=.001;
W=[.13 .54 .34];
Best cost: 0.22957,
Elapsed time is 4.53004 seconds

Fig. 1: Illustration of the Results

For further work, this study recommends the following directions for future works:

- Different constraints for different stock portfolios will also be considered based on the investors' positive attitude to the problem.
- Other meta-innovative algorithms are evaluated for the proposed mathematical model and the results are compared with the model presented in the problem.

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