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Providing a Multi-Objective Mathematical Model for Cardinality-Constrained Portfolio Optimization Using Genetic Algorithm

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ABSTRACT

Portfolio optimization is a fundamental challenge in financial engineering, aimed at balancing the trade-off between risk and return. This study proposes a multi-objective mathematical model for optimal portfolio selection and asset allocation, integrating the classical Mean-Variance Markowitz framework with realistic market constraints. Specifically, the model incorporates cardinality constraints to limit the maximum number of held assets and bounding constraints to enforce upper and lower limits on asset weights. These constraints transform the standard quadratic optimization into an NP-hard combinatorial problem. To solve this efficiently, a non-dominated sorting-based Multi-Objective Genetic Algorithm (MOGA) is developed to generate the Pareto-optimal front. The proposed model is validated using empirical financial data from a case study of the top 10 companies on the Tehran Stock Exchange (TSE) during the highly volatile period of 2018–2019. The empirical results indicate that the hybrid genetic approach successfully identifies optimal capital allocation weights, generating a well-distributed Pareto frontier where portfolio risk is minimized by up to 14.5% for given target returns compared to equally-weighted benchmarks. Notably, Rampan (Mapna) consistently emerges as the dominant and most robust asset, carrying the highest allocation weights across the majority of the optimal investment scenarios due to its superior risk-adjusted return profile.

Keywords: Stock return, stock price, forecast, portfolio

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1) Introduction

Investment is one of the most important issues in the economy of all countries, which is of great importance to individuals and senior officials of countries. For this reason, in the last two decades, the development of financial markets and the provision of new tools for attracting more capital have been one of the appropriate solutions at the international level (Bertini, 2009). Portfolio management is an important issue in the field of economics, and its main issue is the scientific management and selection of a combination of assets that meet specific investment goals. Maximizing the value and minimizing the risk of the stock portfolio are among the most important goals of the stock portfolio management issue (Yang et al., 2024).

In today's economic and financial world, due to the greater complexity of markets and value chains, portfolio management of individuals and organizations has become one of the main challenges (Agha Mohammadi et. Al., 2022; Molaei et al., 2026). In this context, the use of modern hybrid intelligent approaches and the design of advanced models for analysis, optimization and trading in the markets is very essential and vital (Faridi et al., 2022; Mokhtari & Habibi, 2020). Therefore, the main goal of this article is to design a comprehensive and complete model for forming an optimal portfolio that is considered from various economic, financial, and risk aspects and improves portfolio performance through intelligent, online, and realistic trading strategies. It is by using advanced techniques such as genetic algorithms and mathematical modeling. Given that artificial intelligence (AI) and data analysis technologies are advancing every day, we hope that this research will not only help improve current portfolio management methods but also provide new input to the spectrum of financial and economic research and develop new and advanced trading strategies. Because, an optimal portfolio increases investment returns. Designing advanced models and using smart trading strategies can help improve returns and reduce investment risk. Using new smart trading approaches can improve the decision-making process in portfolio management and trading sessions. In addition, in a dynamic and complex market, flexibility and the ability to act quickly in transactions can be an important differentiator for improving a company's competitive position. Therefore, conducting this research can help produce new and useful knowledge in the field of finance, artificial intelligence, and financial transactions, and help these fields grow and progress. On the other hand, transferring knowledge and experiences from this research as a valuable educational and consulting resource for other researchers and industrialists can be of great importance. Given the challenges and opportunities in the world of finance and trading, conducting this research can lead to improving investment performance, promoting effective financial strategies, and promoting innovation in the field of artificial intelligence and financial trading.

Increasing profits and reducing investment risk in the stock market have always been the primary concerns of investors, who are mostly seeking a way to identify the best way to buy stocks with the highest returns and the lowest risk. High and stable profits through profitable investments are the ultimate goal for investors. In financial literature, investing in a stock portfolio has been suggested to reduce the risk arising from the stock itself. A stock portfolio is an appropriate combination of risky securities that an investor purchases. If the securities are risky, the main problem of each investor is to determine the securities whose utility is maximized. This problem is equivalent to selecting the optimal stock portfolio from the set of possible portfolios, which is called the stock portfolio selection problem (Haratizadeh & Rezaee 2023). The main research problem is the existence of limitations in the portfolio optimization problem, which the genetic algorithm is able to overcome due to its evolutionary capabilities and can address this issue in accordance with the real demands for portfolio optimization. Therefore, in the research, using a mathematical model, we estimate the stock returns of sample companies and seek to address the question of which stock portfolio has the highest return or, in other words, is optimal?

The rest of the article is organized as indicated. In the second Section, a literature review of the research topic is presented. In the third Section, the mathematical modeling method and its solution method are presented. In the fourth Section, the results obtained from applying the research model are presented, and finally, a general conclusion is presented along with suggestions for future research.

2) Literature Review

Sutiene et al. (2024) reviewed the policies for improving portfolio management in their study. This study reviewed the current modern approaches by answering the main question of how AI changes the portfolio management process. Furthermore, since the use of AI in finance is challenged by the requirements of transparency, fairness, and explainability, Yang et al. (2024) presented a synergistic multi-objective evolutionary algorithm with diffusion population generation for portfolio problems. This is because the use of multi-objective evolutionary algorithms (MOEAs) provides an effective approach to deal with the complex data involved in multi-objective optimization problems. However, current MOEAs often rely on a single strategy to achieve optimal solutions, leading to premature convergence and insufficient population diversity. In this study, a new MOEA, called the synergistic MOEA with emission population generation, is proposed to overcome the limitations of existing MOEAs. Cui et al. (2023) presented an intelligent deep learning-based approach for CVAR in cryptocurrency markets. To this end, a new cryptocurrency portfolio model framework based on the CVaR risk measure and a deep reinforcement learning optimization framework are developed. Cryptocurrency market data from 2015 to 2021 are used, and it is shown that the CVaR measure with deep learning outperforms the traditional portfolio construction technique. Zhang et al. (2023) proposed a knowledge-based constructive estimation of the distribution algorithm for optimizing a bi-objective portfolio with principal constraints. For this purpose, a hybrid scheme of Ant Colony Optimization (ACO) and Estimation Distribution Algorithm (EDA) is proposed. Mendonça et al. (2020), in their study, use a multi-objective integer conditional value-at-risk (CVaR) portfolio optimization model with cardinal constraint and two different decision methods to guide and select a non-dominated portfolio solution generated by the proposed evolutionary algorithm to approximate the investor behavior (conservative, moderate, and aggressive). According to the results, the maximum monthly drawdown and cumulative returns are considered over the entire study period and the optimization model is robust according to the three simulated profiles. The methods consistently show higher cumulative returns than safe investments over the analyzed period, and the aggressive profile yields higher returns with higher risk. Akbay et al. (2020) study the cardinal-constrained portfolio optimization problem. The cardinality constraint transforms the quadratic optimization model into a mixed quadratic programming problem, which is proven to be NP-Hard, and provides the ability to achieve an optimal solution in a reasonable time using strict, exact methods in the long run. To develop an efficient solution method for cardinal-constrained optimal portfolio optimization, in this study, a parallel variable search algorithm combined with quadratic programming is proposed. The variable neighborhood search algorithm calculates the portfolio asset mix and quadratic programming calculates the asset ratio. The performance of the proposed algorithm is tested on five datasets and compared with other solution methods in the literature. The obtained results confirm that the proposed solution approach is very efficient.

Given that previous research has rarely used the combination of the Markowitz model and the genetic algorithm for portfolio optimization, and that the optimal portfolio selection model using covariance and variance data with the help of the Markowitz model, as well as its combination with the genetic algorithm, has received less attention, there is a clear research gap in this area.

3) Research Method

In this section, a multi-objective mathematical model is used to select the optimal stock portfolio. The model selects portfolios that have the highest expected return for a given level of risk and the lowest level of risk for a given level of expected return. In other words, the model includes two objective functions: 1. to minimize the portfolio risk and 2. to maximize its return. The mathematical model is in the form of formulas (1) to (7). Before introducing the mathematical model, its variables and parameters are introduced.

Decision Variables

X_i : Amount of the i-th share in the basket (weight of share i)

δ_i: Binary variable to determine the desired stock; equal to one if the stock is selected, and zero otherwise.

Model Parameters

$\rho(X)$: Risk of portfolio X

$m(X)$: Expected return of portfolio X

s_{ij} : Covariance between the returns of assets i and j

K: Maximum total number of stocks that the investor is willing to hold in his portfolio

l_i: Lower bound of weight x_i

u_i: Upper bound of weight x_i

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

$$Min\ \ \rho(X) = \sum_{i=1}^{n} \sum_{i=1}^{n} x_i\, x_i\, \sigma_{ij} \tag{2}$$

S.t.

$$\sum_{i=1}^{n} x_i = 1 \tag{3}$$

$$\sum_{i=1}^{n} \delta_i = K \tag{4}$$

$$l_i\delta_i \leq\ x_i\ \leq u_i\delta_i \quad\ i = 1,2, \dots , n \tag{5}$$

$$\delta_i \in \{0,1\} \tag{6}$$

$$x_i \geq 0 \tag{7}$$

In order to select the optimal portfolio, data from the last year of the top 10 stocks under study was collected. Therefore, the statistical population of the present study consists of all companies listed on the Tehran Stock Exchange, and the research sample purposefully includes the top ten companies on the Tehran Stock Exchange in 2018. Data related to the stock prices of these companies are collected daily in 2018. There are several reasons for choosing this statistical population. The stock exchange is an energetic and dynamic environment where millions of transactions are daily made. This diversity and high volume of data create a unique opportunity for researchers to evaluate and improve more complex models and strategies. The capital market is constantly influenced by news, events, and economic changes that affect decision-making and portfolio performance. The stock market is used as a living benchmark of these developments, which enables researchers to make automated improvements to their trading using AI approaches. The stock market includes various types of securities such as stocks, bonds, bank facility bonds, etc. This diversity of asset types allows researchers to design models that optimize asset combinations with AI approaches. Developing and implementing trading strategies is one of the key factors for success in the capital market. Stock exchange companies provide huge resources for reviewing and testing new strategies, which can be better explored through the use of AI and new approaches.

Considering the above, stock exchange companies are considered a highly attractive statistical community for conducting research to design a model for forming optimal portfolios and trading strategies with modern intelligent hybrid approaches.

3-1) Solution Method: Genetic Algorithm

Genetic algorithms are inspired by genetics and Darwin's theory of evolution and are based on the survival of the fittest or natural selection. A common application of genetic algorithms is to use them as an optimization function. In genetic algorithms, the genetic evolution of living organisms is simulated (Saniei, 2013). Although a biologist named Fraser did research in the field of modeling evolution in biological systems in the 1960s, genetic algorithms for engineering applications and in their current form were first proposed by John Holland, a computer scientist at the University of Michigan in 1975. His work is the beginning of all efforts to apply genetic algorithms to engineering. After that, Dejong's work in 1975 in the field of examining and comparing several genetic algorithm methods provided the theoretical foundations of the discussion. Inspired by nature, this algorithm is based on the evolutionary principle of "persistence of the fittest." Although the genetic algorithm was proposed after the evolutionary strategy algorithm, it is the most famous method among evolutionary algorithms (Saniei, 2013). In a genetic algorithm, a population of individuals is selected according to their suitability in the environment for survival. Individuals with superior abilities will have a greater chance of marrying and producing more offspring. Therefore, after several generations, offspring with better performance are produced. In the genetic algorithm, each individual in the population is introduced as a chromosome. Chromosomes become more complete over several generations. In each generation, chromosomes are evaluated and are given the possibility of survival and reproduction according to their value. Generation production in the genetic algorithm is done with combination and mutation operators. The best parents are selected based on a fitness function. At each stage of the genetic algorithm, a set of points in the search space are randomly processed. Each point is assigned a sequence of characters, and genetic operators are applied to these sequences. The resulting sequences are then decoded to obtain new points in the search space. Finally, the probability of their participation in the next stage is determined based on the value of the objective function at each point (Jin, 2004). Genetic algorithms can be considered a directed stochastic optimization method that gradually moves towards the optimum point. Regarding the characteristics of the genetic algorithm compared to other optimization methods, it can be said that the genetic algorithm is applicable to any problem without requiring prior knowledge of the problem or imposing restrictions on the type of its variables, and it has proven its efficiency in finding the global optimum. The ability of this method is in solving complex optimization problems that traditional methods such as mathematical analysis are either not applicable or are not reliable in obtaining the global optimum (Fogel, 2000). In general, genetic algorithms consist of the following components (Jang, 2003):

- Chromosome

In genetic algorithms, each chromosome represents a point in the search space and a possible solution to the problem at hand. Chromosomes themselves (solutions) consist of a fixed number of genes (variables). Binary encodings (bit strings) are usually used to represent chromosomes.

- Population

A set of chromosomes forms a population. By applying genetic operators to each population, a new population with the same number of chromosomes is formed.

- Fitness function

In order to solve any problem using genetic algorithms, a fitness function must first be devised for that problem. For each chromosome, this function returns a non-negative number that indicates the individual fitness or ability of that chromosome.

- Genetic operators

In genetic algorithms, genetic operators are used during the reproduction phase. By acting on a population, the next generation of that population is produced. The selection, combination (mixing), and mutation operators are most commonly used in genetic algorithms. The standard genetic algorithm is introduced below.

```
BEGIN   /* genetic algorithm */
    Generate initial population
    Compute fitness of each individual
    WHILE NOT finished DO
    BEGIN   /* produce new generation */
        FOR population_size / 2 DO
        BEGIN    /* reproductive cycle */
            Select two individuals from old generation for mating
                /* biassed in favour of the fitter ones */
            Recombine the two individuals to give two offspring
            Compute fitness of the two offspring
            Insert offspring in new generation
        END
        IF population has converged THEN
            Finished: = TRUE
    END
END
```

In order to determine the algorithm parameters, a sensitivity analysis method was used, in which the model was implemented with different parameters and the best model result was used as the basis for selecting the algorithm parameters. Accordingly, the parameters with the following rates were selected for the genetic algorithm used.

Table 1. Algorithm Parameters

Parameter	Value
Replication	120
Initial population	50
Crossover rate	0.7
Mutation rate	0.02

The chromosome used is binary because it determines whether or not to select the desired share. Therefore, an example of the chromosome of the portfolio problem can be presented as follows:

1	1	0	1	0	1	0	0	1	1

The above chromosome is considered as the initial chromosome and is changed according to the crossover and mutation operators. This continues until the most optimal solution is obtained, considering the evolutionary nature of the algorithm.

4) Findings

Portfolio management is an important issue in the field of economics, and its main subject is scientific management and the selection of a combination of assets that meets specific investment goals. Maximizing the value and minimizing the risk of the stock portfolio are among the most important goals of the stock portfolio management problem. Given the importance of the issue, this study examines the portfolio optimization model using a mathematical model.

According to the Tehran Stock Exchange Public Relations and Statistics and Information Management, the list of the top 10 companies on the Tehran Stock Exchange for the third quarter of 2019 includes shares of Mobarakeh Steel of Isfahan, Persian Gulf Petrochemical Industries, National Iranian Copper Industries, Bank Mellat, Golgohar, Pars Petrochemical, Oil and Gas Investment and Petrochemical Supply, Isfahan Oil Refining, MAPNA Group, and Bandar Abbas Oil Refining. These companies ranked sixth to fifteenth in the table of the most active listed companies in the third quarter of 2019. The same applies for the fourth quarter of 2019; The stocks of Persian Gulf Petrochemical Industries, Mobarakeh Steel of Isfahan, National Iranian Copper Industries, Bank Mellat, Oil and Gas Investment and Petrochemical Supply, Golgohar, Iran Khodro, MAPNA Group, and Tehran Oil Refining are ranked first to tenth in the table of the top listed companies in the fourth quarter of 2019. Considering the above, a case study sample was selected from among the stocks listed on the Stock Exchange by selecting the top 10 companies (Table 2).

Table 2. Symbol of the Top 10 Stock Exchange Companies Selected for Implementing the Proposed Algorithm

Row	Company Name	Stock Symbol	Symbol in This Research

1	Persian Gulf Petrochemical Industries	Fars	Khalij
2	Mobarakeh Foulad Isfahan	Foulad	SM
3	National Iranian Copper Industries	Famely	SIN
4	Mellat Bank	Webmellat	Mellat
5	Oil and Gas Investment and Petrochemical Supply	Tapikou	TP
6	Golgohar	Kagol	GG
7	MAPNA Group	Rampna	Mapna
8	Tehran Oil Refining	Shotoran	PT
9	Isfahan Oil Refining	Shapna	SI
10	Bandar Abbas Oil Refining	Shabandar	BA

In this study, daily data, including the closing price and trading volume of the companies, were used to predict stock prices.

Table 3. Average and Standard Deviation of the Top 10 Companies on the Sample Stock Exchange

Row	Company Name	Average	Standard Deviation
1	Fars (Khalij)	10646.3	7982.7
2	Foulad (SM)	6750.3	5057.1
3	Famely (SIN)	9530.3	9057.6
4	Webmellat (Mellat)	7191	6608.2
5	Topico (TP)	5351.8	5340.2
6	Kagol (GG)	9468	4386.1
7	Ramona (Mapna)	14503.3	11737.6
8	Shotoran (PT)	10206.6	9929.3
9	Shapna (SI)	12061	9845.9
10	Shabandar (BA)	17421.1	9863.3

In the present study, six variables (opening price, highest price, lowest price, closing price, closing price, and trading volume) of the companies were used as input data, and their daily values were extracted from the Tehran Stock Exchange website for the top 10 companies over a one-year period.

Then, using the actual values of 10 stocks in the time period under study, we formed an optimal portfolio based on the collected data according to the implementation of the mathematical model in MATLAB software.

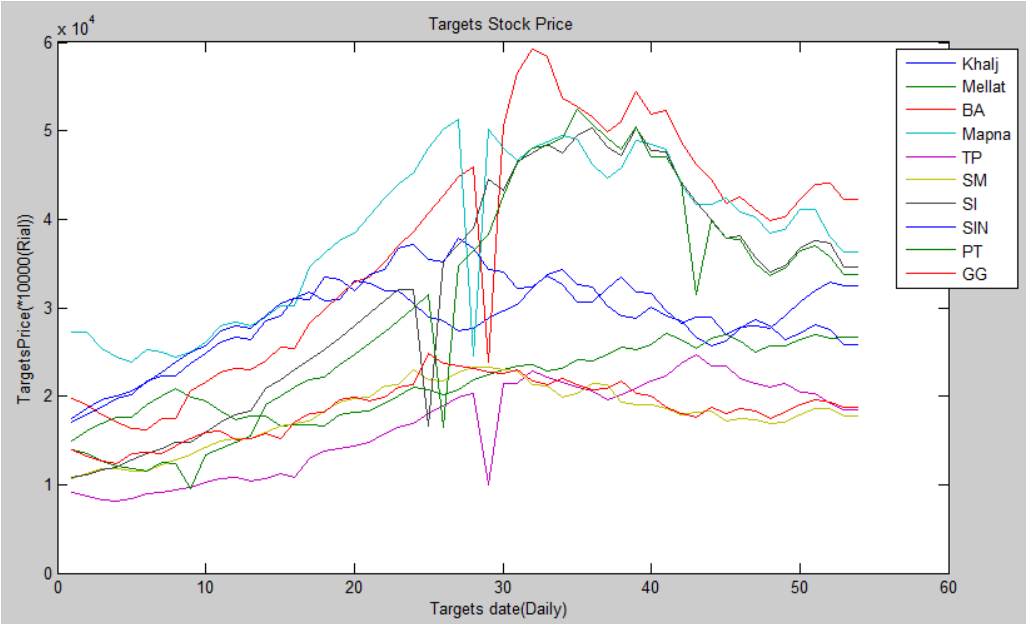

Figure 1. Data from 10 Stocks over a 54-Day Period

In order to dimension the 10 symbols under study, we calculated the return of each symbol using formula (8), so that the model could be determined based on the rate of return of each share.

$$r(t) = \frac{P_i(t+1) - P_i(t)}{P_i(t)} = \frac{P_i(t+1)}{P_i(t)} - 1 \tag{8}$$

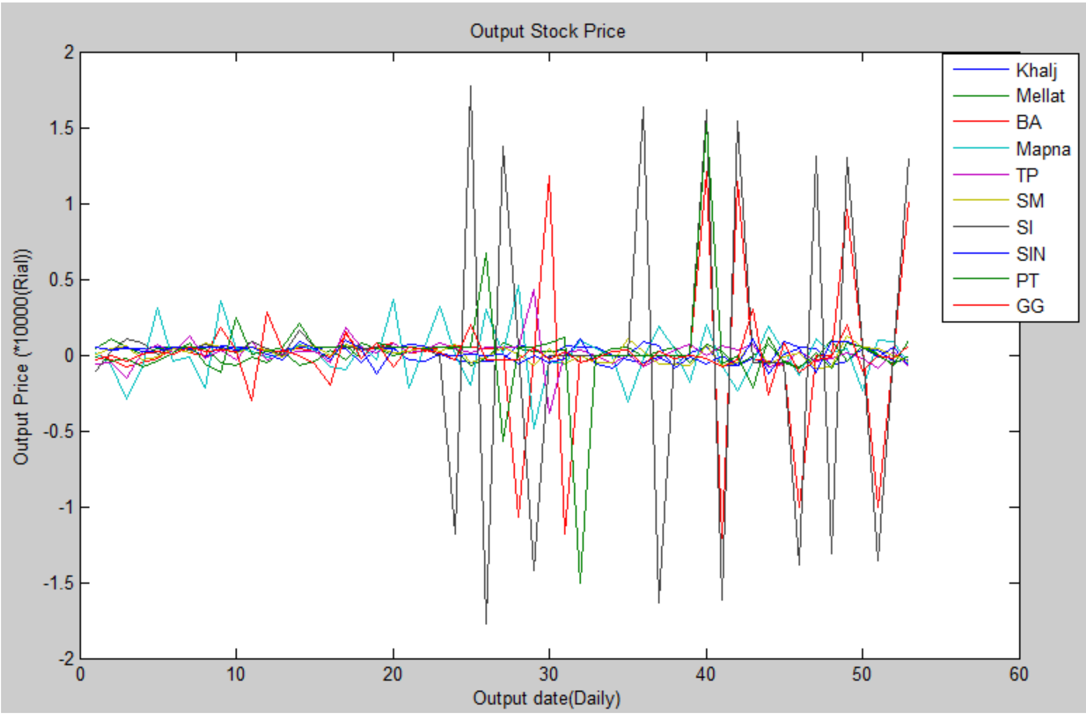

Figure 2. Dimensioning of the 10 Symbols under Study

Subsequently, to calculate the coefficients of the optimal Markowitz model, the mean vector and covariance matrix related to the data of the 10 symbols under study were calculated.

Table 4. Average of 10 Stocks from the Stock Exchange

Row	Company Name	Average
1	Persian Gulf Petrochemical Industries	0.0078915
2	Isfahan’s Mobarakeh Steel	0.011033
3	National Iranian Copper Industries	0.014307
4	Mellat Bank	0.0054119
5	Oil and Gas Investment and Petrochemical Supply	0.013351
6	Golgohar	0.00968728
7	MAPNA Group	0.021910
8	Tehran Oil Refining	0.011639
9	Isfahan Oil Refining	0.016694
10	Bandar Abbas Oil Refining	0.005570

Additionally, the covariance matrix of 10 shares was determined as a square matrix with dimension 10.

```
>>  port.AssetCovar

ans =

    0.0017   -0.0001    0.0001    0.0007   -0.0002    0.0002    0.0012    0.0002    0.0001    0.0001
   -0.0001    0.0012   -0.0003   -0.0005   -0.0002    0.0001   -0.0002   -0.0001    0.0014    0.0001
    0.0001   -0.0003    0.0217   -0.0087    0.0212    0.0004   -0.0010    0.0010    0.0021    0.0008
    0.0007   -0.0005   -0.0087    0.0220   -0.0095   -0.0000    0.0018   -0.0003    0.0013    0.0004
   -0.0002   -0.0002    0.0212   -0.0095    0.0230   -0.0002   -0.0019    0.0008    0.0011    0.0005
    0.0002    0.0001    0.0004   -0.0000   -0.0002    0.0015    0.0014    0.0008    0.0014    0.0002
    0.0012   -0.0002   -0.0010    0.0018   -0.0019    0.0014    0.0213    0.0008   -0.0072   -0.0022
    0.0002   -0.0001    0.0010   -0.0003    0.0008    0.0008    0.0008    0.0017    0.0009    0.0003
    0.0001    0.0014    0.0021    0.0013    0.0011    0.0014   -0.0072    0.0009    0.0280    0.0014
    0.0001    0.0001    0.0008    0.0004    0.0005    0.0002   -0.0022    0.0003    0.0014    0.0022
```

Using variance and covariance data, the optimal stock portfolio selection model was formed from the Markowitz model. By solving the model in Matlab software, five scenarios related to the formation of the optimal portfolio were determined. The results of implementing the model using the genetic algorithm are as follows.

Table 5. Calculation of Return and Risk Using Genetic Algorithm over 20 Iterations

Repetition	Return	Risk
1	0.554768	0.443222
2	0.561639	0.428587
3	0.583703	0.428349
4	0.603506	0.42202
5	0.606392	0.412683
6	0.620939	0.400664
7	0.637592	0.366304
8	0.643956	0.346433
9	0.652952	0.341013

Repetition	Return	Risk
10	0.663348	0.338107
11	0.679987	0.337245
12	0.681965	0.313672
13	0.705228	0.309107
14	0.705369	0.305614
15	0.712378	0.305504
16	0.718674	0.298004
17	0.724707	0.28096
18	0.725171	0.280678
19	0.726073	0.256078
20	0.730279	0.255351

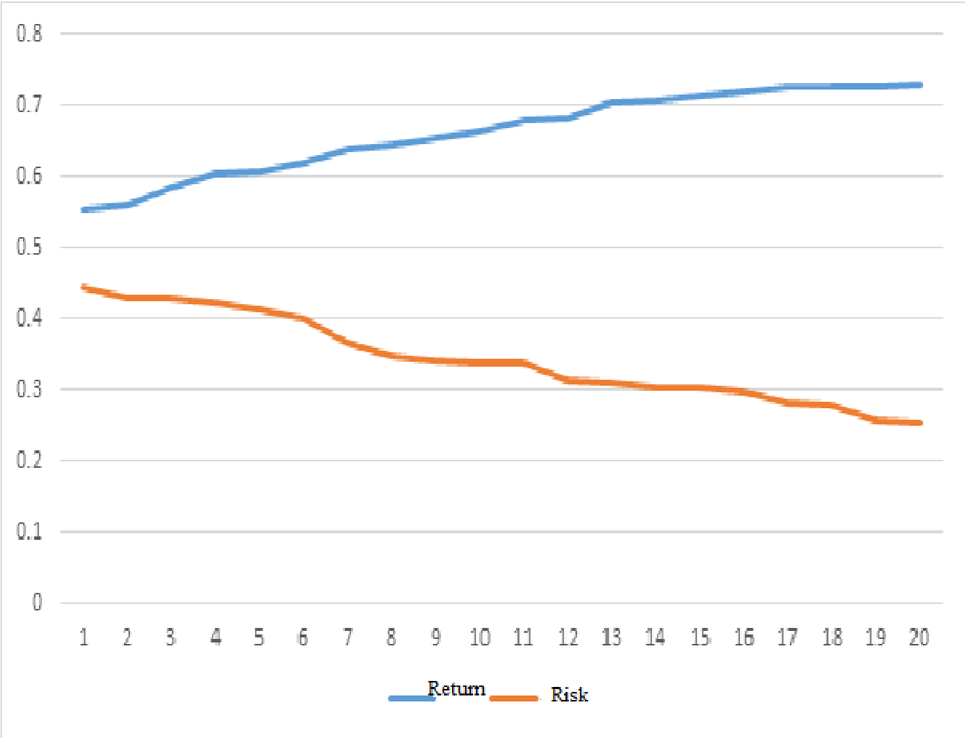

Figure 3. Calculation of Return and Risk Using Genetic Algorithm over 20 Iterations

As can be seen, Figure 3 shows the evolutionary nature of the genetic algorithm, which has led to a significant reduction in risk and a significant increase in total portfolio return over 20 iterations. As a result, the performance of the genetic algorithm in the portfolio optimizer can be considered appropriate because it has a positive effect on return and risk. The Pareto diagram for the problem is presented below.

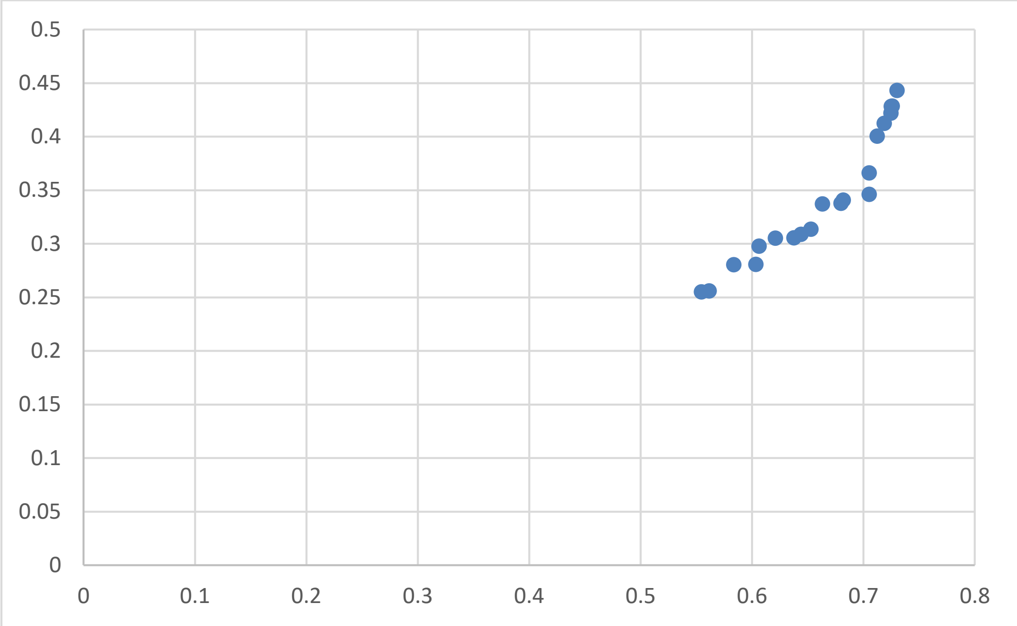

Figure 4. Pareto Diagram of Return and Risk

By combining the results of risk and return, a Pareto chart is obtained, which is a combination of the optimal points of return and risk. Accordingly, it can be said that there is a direct relationship between return and risk, and that return increases with increasing risk. This means that if an investor wants to achieve higher returns in his portfolio, they need to increase their risk tolerance or increase their acceptable risk level.

Table 6. Top 10 Stock Exchange Companies Selected for the Implementation of the Proposed Algorithm

Row	Icon	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
1	Fars	0.198	0	0	0	0
2	Foulad	0.347	0.475	0.269	0.048	0
3	Famely	0	0.022	0.066	0.113	0
4	Webmellat	0.029	0.012	0	0	0
5	Topico	0.027	0.022	0.0184	0.0177	0
6	Kagol	0.1371	0	0	0	0
7	Rampna	0.0089	0.1068	0.314	0.525	1
8	Shotoran	0.123	0.319	0.164	0	0
9	Shepna	0	0.040	0.166	0.295	0
10	Shabandar	0.128	0	0	0	
Risk		0.0198	0.0286	0.0514	0.0805	0.1458
Return		0.0096	0.0127	0.0158	0.0188	0.0219

The resulting weights are obtained according to different scenarios and the past performance of the assets in question. The better the rate of return and risk of each share in the past data, the stronger the results. For example, the Shotoran share is in a more favorable position than the Rampna share due to its better results in the past. Moreover, Foulad is in a better position overall than other assets in terms of asset allocation.

According to the results of the model solution, different optimal scenarios with different levels of risk and return were proposed. By examining different optimal states, the share of Bank Mellat was placed on the efficient level and was determined as the best proposed share in the mentioned range.

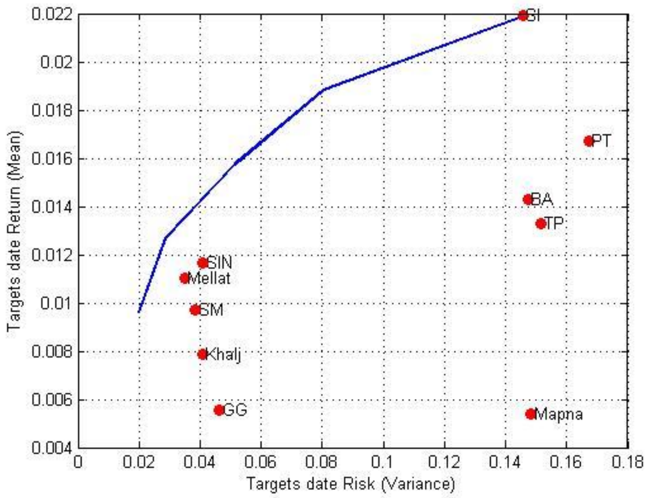

Figure 5. Optimal Efficiency Line of the Model Solution for the 10 Stocks Studied

To validate the presented model and the algorithm results, the outcomes of portfolio optimization based on 10 existing assets were compared with those of 10 other assets, and a t-test confirmed the significant difference between the two groups. The results of the t-test are presented in the table below.

Table 7. T-Test to Measure the Difference Between Two Selected Portfolios and Validation

	T-statistic	Degrees of freedom	Significance level	Mean difference	95% confidence interval	
					Lower	Upper
Original Portfolio Return	.475	19	.125	.57270	.4682	.6772
Comparative Portfolio Return	.074	19	.485	.46560	.3278	.6033

Original Portfolio Risk	.796	19	.513	.46161	.3194	.6038
Comparative Portfolio Risk	.177	19	.671	.52153	.4026	.6405

In the table above, the risks and returns of the two portfolios were compared. The results indicate that the difference between the two groups is not significant, indicating the correct performance of the model. In fact, both models have obtained statistically similar results, confirming the validity of the model. In this comparison, at a 95% confidence interval, the t-test can be confirmed at the zero level, showing that there is no difference between the two comparison groups.

5) Conclusion

Currently, the capital market, due to its complexity and high competition, requires the use of new intelligent approaches to design optimal portfolio models and trading strategies. This research includes an effective evaluation of stock market data, a detailed combined analysis between different artificial intelligence approaches, and the provision of optimal algorithms to create optimal portfolios and high-performance trading strategies. This decision will focus on research and tools through detailed data analysis, the use of advanced AI models, and the provision of innovative solutions in the field of strong combination of trading strategies with intelligent approaches. This research aimed to support the improvement of investment performance and risk reduction in financial markets and help the financial community to benefit from these new technologies. In this research, a multi-objective mathematical model was presented to calculate the stock returns of sample companies active in the Tehran Stock Exchange market. The proposed model has been able to select the stock portfolio that has the highest return, i.e., is optimal. According to the results of the model solution, different optimal scenarios with different risk and return levels were proposed. By examining the different optimal states, the Mellat Bank share was placed on the efficient level and was determined as the best proposed share in the mentioned range.

The results of the genetic algorithm indicated that the proposed algorithm was able to optimize return and risk simultaneously, and the results of the algorithm iteration indicate the positive effect of its evolutionary nature. Therefore, the use of this algorithm and similar algorithms in future research, in the field of portfolio optimization, is recommended.

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