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Developing a Model to Analyze Decision Maker's Preference in Portfolio Selection

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Abstract

The goal of the present research was to provide a paradigm to derive a model of decision maker's preference for portfolio optimization to maximize returns and minimize risks. This ex-post facto research gathered data via document-libraries methods and fell under quantitative-qualitative categories. To gather data, TadbirPardaz and DenaSahm software was used. The statistical population of the study consisted of all investment companies listed on the Tehran Stock Exchange. This research was carried out on the Stock Exchange in 2020 Summer that divided the trading days into two morning and afternoon groups. This was because the selected morning portfolio differs from the afternoon portfolio under the market signals. Also, the time interval from 2011 to 2019 was examined to investigate the investors' decision-making accurately. Tools to analyze data were MATLAB and SPSS software. Data analysis results based on the multi-criteria decision-making technique indicated that out of the 30 stocks selected via the coefficient of closeness to the ideal solution (return maximization, e.g., profitability, growth, and liquidity indicators, and risk minimization, e.g., financial, commercial and systematic as well as market price indicators), the optimal stocks for peoples' preference for investment included S16› S17› S19› S30. Also, the multi-criteria decision-making technique indicated that each of the main criteria of profitability, growth, risk, liquidity, and market were assigned the first, second, third, fourth, and fifth priorities, respectively, in selecting the optimal portfolio at the Tehran Stock Exchange. Genetic algorithm results suggested that the S16, S17, S19, and S30 stocks had an average maximization return of 0.956, and the optimal stocks of S25›S18›S2›S12›S26›S28›S27›S9›S16›S10›S7›S20›S30›S17›S23 had a moderate minimum calculation risk of 0.386 at 99% confidence level, which was lower than the average financial risk of 0.386. Thus, a 15-stock portfolio can be selected based on the minimum risk to choose an optimal portfolio.

Keywords:
Preference
Decision-maker
Optimal portfolio
Stocks

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INTRODUCTION

Over the past hundred years, many measures have been taken to direct investors on how to make investments, as countless models have been presented properly. Concepts of portfolio optimization and diversification serve as tools for the development and understanding of financial markets and financial decision-making. The introduction of Markowitz's Theory of Portfolio was the most important success in this direction. Considering the expansion of developments in various areas, especially in economics and commerce, one would say that, in the age of information, it is quite frustrating to enter the field of business without knowing investment methods and selecting stocks. Thus, investment in different projects could incur risks and returns (Tahsin & Hamdi, 2015).

The Modern Theory of Portfolio, introduced by Markowitz and later developed by his students Sharpe and Lintner, and the Efficient Investment Market Hypothesis, initially presented by Fama, were introduced in the early 50s onwards as the foundation of later research. However, the complexity of financial markets led scientists to conduct more research; thus, much research was born on the formation of a portfolio, as in most models introduced in the study, the criteria of return and risk were taken from financial debates, while optimization criteria from planning discussions. In capital markets, the presence of hundreds of stocks and such limitations as a large number of stocks, limited weight values, etc., have broadened the space of search, which have rendered mathematical models impossible; hence, metaheuristic algorithms such as genetic, ant, etc. assume significance status (Abbasi et al. 2011).

On the other hand, since investors seek ways to achieve good incomes from their investments, they consider two criteria before acquisition. First, investment should create the highest possible return and be fixed and durable. Second, the measurement of this constancy constitutes investment risk. The diversification and formation of a portfolio and its optimization are one of the conditions for success in effective capital markets. Thus, it is highly critical to implement scientific and systematic manners in such expanding markets (Kiani et al. 2014). A modern portfolio is a holistic attitude to the stock market. Unlike other theories (technical and fundamental methods), this theory pays attention to the total stocks in a portfolio or a market. In other words, the macro-level perspective stands against the micro-level perspective. In the creation of a portfolio, the association between risk and stock returns assumes importance. This perspective relies on statistical and mathematical calculations. Using optimization models and the modern theory of portfolios, portfolios can be developed with the lowest risk to the expected returns or the highest return to the predicted risk (Pakmaram et al. 2017). Thus, portfolio optimization is a two-objective optimization problem aimed at maximizing the expected return and minimizing the risks.

Recently, Fernandez et al. provided an extension of the extrovert approach that uses its incomplete knowledge to deal with model parameters and criterion scores. Although decision-makers feel comfortable with the direct creation of model parameter values as quantitative numbers, this approach does not prevent the convenience of indirect regulation (Fernandez et al., 2019). Thus, it would be easier to provide an indirect and flexible method of selection, instead of accurate data, to measure the size of parameters as the ranges of numbers, where incomplete knowledge about parameter values exists.

In another study by Fernandez et al. (2019), this method was recently used to solve the portfolio optimization problem. This article offers an interesting pressure for selecting portfolios, considering the incomplete knowledge that characterizes the decision-maker's preference model, thus, directing the pressure towards portfolios interested by decision-makers. For this, applying evolutionary computations for the indirect extraction of parameters helps provide a portfolio that creates the highest possible returns. Therefore, the goal of the present research was to answer the question: “Which paradigm is used for deriving a model of decision-maker's preference in optimizing the portfolio?”

FACTORS AFFECTING THE ATTRACTION OF REAL CAPITAL ON THE STOCK EXCHANGE

Considering the highly critical role of Stock Exchanges in social and economic development, the National Stock Exchange has a great responsibility to meet the system's objectives; it should strive to use its abilities to materialize national ideals increasingly. Saving as a main source of investment on the stock exchange plays a pivotal role in the fulfillment of the objectives of this organization. However, one of the sources that supply saving to the Stock Exchange is the households, i.e., real persons, who make investments in the Stock Exchange; thus, this can play a constructive step in the materialization of the main philosophy of setting up the Stock Exchange in Iran (Farid & Dehghan-Menshadi, 2014).

Previous study results suggested thatLiesiöIn ,et al(2023), an article titled Incomplete risk-preference information in portfolio decision analysisthey paid.The results showed, the identification of the efficient frontier makes it possible to utilize additional information on the decision maker's risk-preferences to further reduce the set of admissible portfolio alternatives, and to analyze the implications this information has on the amount of capital that should be allocated to each individual asset. We illustrate the usefulness of these models with applications in project portfolio selection and financial portfolio diversification.

LiesiöIn ,et al(2021), an article titled Portfolio decision analysis: Recent developments and future prospects paid.The results showed, that PDA is a vibrant research field with close ties to practice, as a substantial share of articles present real applications or contain illustrative examples which are motivated by such applications. For continued knowledge accumulation, there is substantial promise in exploiting PDA concepts in deriving recommendations from decision models for problems which may not have been viewed as PDA problems; fostering the cross-fertilization of conceptual and methodological advances across application areas; and ensuring that new methodological advances are systematically evaluated through engagements with real decision makers.

also Previous study results suggested that in companies with valuable investment opportunities, the optimal investment level is higher than that of companies that enjoy investment opportunities of low quality because companies expect higher returns from valuable investment opportunities (Arab-Salehi et al. 2014). Investments are divided into two major forms: real and financial. Real investments usually include obvious assets such as lands, machinery, and equipment, while financial investments include written contracts on a piece of paper, such as equities or securities (Apartsin & Mymon, 2013). In the meantime, the history of profitability of investment on the Stock Exchange can be considered as one factor that affects the attraction of real persons' capital on the Stock Exchange. Also, advertisements through mass media by Stock Exchanges can encourage real people to invest there.

PORTFOLIO

As regards financials, various factors are involved in risk and investment returns. Factors affecting risk and investment returns in financial products fall under three general categories of macroeconomic factors, microeconomic factors, and non-economic factors, with each briefly investigated below:

Macro factors: These factors affect the market risk, as the CAPM model investigates the dependency of variations of each product price on marketplace price variations to measure the outcome and the effect of these factors on the market risk under the heading of the systematic risk. These factors include the following subsets:

Government policies: As a macro-level policy maker and regulator, the government has a key role in the capital market, as one of the government duties is to provide a plan that is capable of developing the capital market; however, the plurality of centers of power and policy-making, the ambiguity of their roles and relations, intervention by the three major powers of the nation, the lack of transparency of laws and different and conflicting interpretations of those laws, the presence of inappropriate and restrictive laws, the violation of economic freedom and political instabilities have all increased the systematic risk, and sharply reduced investment (Sharp et al. 1995). Also, measures taken by the government and its interventions in the economy, industries, and commerce can affect investment in financial products. This denotes that the greater the government's intervention in the economy (reduced participation of the private sector), the more systematic risk increases; thus, the level of investment in financial products decreases. For example, if the government begins to issue bonds to make up for the budget deficit, the volume of the bonds issued will increase in the price and interest rates of these bonds, which, on its own, would reduce the bond price and increase the interest rates (Abzari et al. 2015).

Cultural-Social Factors: In developed nations, the capital market is a market that paves the way for the participation of all people in society; however, in underdeveloped or developing countries, a small percentage of people contribute to this market due to a lack of an appropriate culture. In the meantime, the right platform and the creation of real attractions can help direct peoples' savings there. This increases national income, reduces inflation, allocates existing liquidity in the market, and increases investment and relative welfare in society (Abzari et al. 2015).

State of Industry: Various industries and relevant companies can, under the influence of political, economic, social, and even internal and external geographic conditions, enjoy development or suffer from stagnation. For example, once global oil prices improve, oil-dependent industries are affected and have their stocks rise; in the meantime, once drought spells occur, agriculture-dependent sectors are affected and have their stocks stagnate (Kathleen, 2005). On the other hand, the more emphasis is laid on the intermediary and consumption industries; the more these industries depend on foreigners. These more systematic risks increase and reduce investment in these industries.

ECONOMIC CONDITIONS AND TRADE-FINANCIAL PERIODS

Reduction in interest rates can be the only effective factor for increasing return on investments. As interest rates decline, investment costs decrease, also; this will increase the return on investments. The issue becomes ideal when interest rates are determined based on supply and demand mechanisms because the reduced interest rates, if not regulated by appropriate mechanisms for controlling the outcomes, can increase the rate of investments. However, they will be directed towards non-productive sectors and sometimes cause detrimental economic impacts. On the other hand, if this is made without necessary projections, it could cause non-obvious loss (risk) for the depositors, given the inflation rate in the country (Pahlavan et al. 2022). Also, increasing the interest rate will increase its fluctuating risk because as the interest rate increases, bond prices will decrease at a constant interest. If the holders of these bonds sell them before maturity, they will sustain losses. In the meantime, rising expected inflation rates can affect investment in financial products. Hence, as the expected inflation rate increases, the expected return on physical assets will increase compared to financial support (financial products), with the physical assets replacing the financial assets in the portfolios (Dos et al. 2019).

Micro-level factors: These factors cause changes to the risk that is not related to the general status of the market, as it is specific to the status of each company.

Modern Approaches to Determining Optimal Portfolio

The problem of selecting an investment portfolio has been one of the classic issues of the world of finance, which was, for the first time, developed by Markowitz in 1959. This problem includes two main and inseparable parts of return and risk. The main goal of this problem was to maximize the expected return at a certain level of risk and to minimize the expected risk at a certain level of return. Markowitz's model constituted the basis for selecting the single-period investment portfolio. In real-time, an investor can review their investment portfolio at every period; for this, the investment portfolio management strategy is implemented in a multi-period form (Najafi & Moushakhian, 2014).

Multi-period portfolio refers to a portfolio that, after being formed at regular intervals, has its content investigated by the investor and modified under new conditions. The main problem in the Theory of Multi-Period Portfolio is determining an optimal trading policy to change the portfolio at the beginning of the period (Davoudi & Sadri, 2017). Investors always seek ways to gain an appropriate return on their investments. Before investing, each individual should consider two criteria; investment should bring about the highest possible returns, which are constant and durable. The measurement of this constancy forms the investment risk.

The diversification and formation of portfolios and their optimization are one of the conditions for success in effective capital markets. Thus, adopting scientific and systematic methods in such expanding markets is critical. In this connection, many measures have been taken in these markets, which have led to the introduction of modern techniques that, together with past methods, aim to find a response to maximize returns on investments in capital markets. Genetic, fuzzy logic, and neural network algorithms, among others, are all examples of these modern methods. The logic behind all these modern methods includes the "selection of a collection of stocks usually with the interaction between risk and return." In other words, the more the portfolio risk, the higher rate of returns. In real times, the extent to which people take risks is different, as the stock market is unpredictable due to various factors affecting it. This is because investors cannot be sure about the future (Rezaei-Pandari, 2011).

Selecting a portfolio suggests how an investor allocates their liquidity according to the objectives of efficiency and risk-return to various assets to gain a satisfactory portfolio of assets. A combination of the intended portfolio can result from random or irrelevant investment decisions or intentional planning (Aouni, 2009). The selection of techniques and instruments that can optimize the portfolio is a matter of interest in the capital world (Raei, 2012). The most famous and common approach to the portfolio optimization model is the selection of the average variance using Harry Coetzee's model, which bases the investment risk not only on the stocks' standard deviation but also on the investment risk. The following compares the advantages and disadvantages of metaheuristic algorithms to determine the optimal portfolio.

Table 1: Comparing the advantages and disadvantages of metaheuristic algorithms to determine the optimal portfolio

Type of algorithm	**Developer**	**Yar**	**Advantages**	**Disadvantages**
Genetic	Holland	1975	Parallel system, flexibility, limitation, selection of the bets out of the population, great chance of achieving a global optimization, easy implementation	Higher costs need greater memory and computations
Ant colony	Dorigo	1992	Parallel system, positive feedback, easy finding, avoidance of initial convergence of dynamic problems	Difficult theory, lack of dependency, repetition of changes based on probability, indefinite time of convergence
Particle swarm	Kennedy-Eberhart	2001	Zero order, without need for complex math operations, higher flexibility, easy implementation,	Entrapment at the place

			memory, sharing of information, no deletion	reduced optimization Population diversity
Harmony search	Kim	2001	Relatively optimized, easy implementation, coordination, and participation, simple computation of simple concepts, fewer math obligations, a higher flexibility for searching for a better space	Entrapment in the local optimization in discrete problems
Bee colony	Karaboga	2005	Higher efficacy of many of the optimal solutions, control parameters, high convergence speed, minimum local outputs, higher flexibility multi-dimensional problems, global optimization, easy detection, regional and international search, higher probability of finding the response	Diversity of variable coordination , quantitative parameter, dependent on regulating relations, parameters, use of the method of probabilities
Firefly	Yang	2006	Constrained and unconstrained minimization and maximization issues with constraints, easy regulation, few parameters, very fast convergence, independence of members, the transition from local optimization, parallel implementation, automatic segmentation of the entire population, multi-quality optimization, diverse solutions	Lack of an accurate method for the determination of parameters, entrapment in the local optimization, no change at the moment, non-recall of the best optimization

Source: Zanjirdar (2020)

RESEARCH METHODOLOGY

The present study is an ex-post facto study with a basic goal. It seeks to expand evolutionary computations to derive a model of the decision-maker's preference in the portfolio optimization problem. Hence, the function of the study is applied. Data was gathered from document and library research. The research also falls under quantitative and qualitative research. Here, in this study, library methods and public archives of financial statements at the Stock Exchange Organization, available in CDs, as well as weekly and monthly reports of the organization using TadbirPardaz and DenaSahm software, were used.

As many as 30 managers of the companies listed on the Tehran Stock Exchange comprised the statistical population to respond to a researcher-developed questionnaire to determine decision-making indicators in an optimal portfolio. The second part of the research includes all investment companies listed on the Tehran Stock Exchange. The statistical population thus consists of 30 companies whose stocks are represented by S1, S2, S3, etc. This research was carried out in the summer of 2020, when the trading days were divided into morning and afternoon days because signals sent by the stock market could differ in the mornings and afternoons. Also, the time interval from 2011 to 2019 was considered to investigate investors' decision-making accurately.

Multi-criteria decision-making computations are aimed at determining necessary indicators to optimize portfolios in the Tehran Stock Exchange. Collected data from interviewing experts led to identifying indicators required to investigate portfolio optimization in companies listed on the Tehran Stock Exchange. Then, the ELECTRE method was used to determine the order of priority of the indicators. Below, the method is demonstrated.

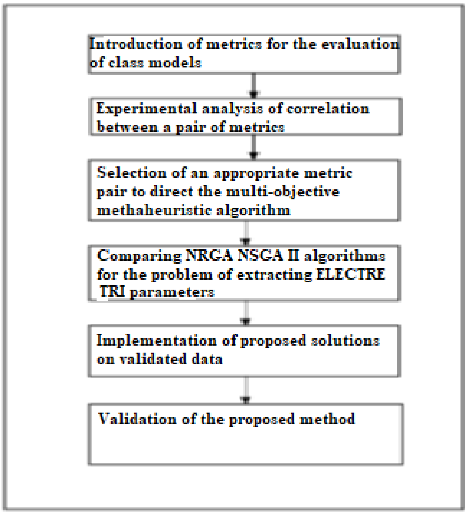

Fig 1: ELECTRE Diagram

The genetic algorithm was used to determine the optimal portfolio of companies on the Tehran Stock Exchange.

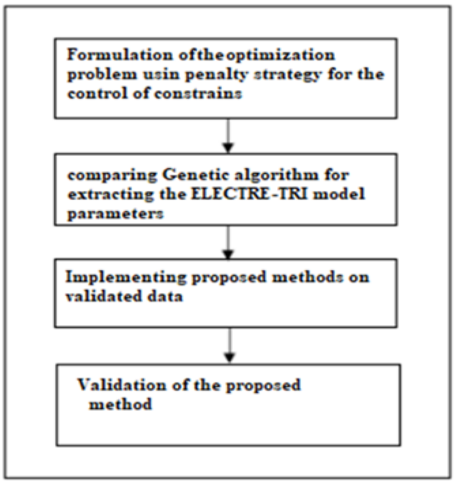

Fig 2: Stages of implementing the genetic algorithm in the present research

Tools to gather data in this research involved a researcher-developed questionnaire that aimed to determine decision-maker's (option) indicators on an optimal portfolio. The note-taking method was used to collect financial statements and data of companies listed on the Tehran Stock Exchange. The value-at-risk of each stock was used to determine the optimal portfolio via the Genetic Algorithm and to determine returns via the variance-covariance matrix. Also, to compare risk and returns, SPSS software was used. The statistical analysis method was the independent t-test, and the ranking was based on ELECTRE-TRI.

FINDINGS

A pairwise comparison questionnaire was developed by studying the literature review and the criteria selected. Then, the questionnaire was given to 30 financial experts who had a theoretical knowledge of financial and investment concepts and were practically involved in the capital market and entities related to the Stock Exchange. Later, using specified indicators, the portfolio was optimized in the stock exchange. Table 3 ranks companies based on the indicators. In other words, this table ranks stocks in the stock exchange organization based on the distance of each option from the positive solution (return maximization) and the negative solution (financial risk minimization) using the ELECTRE-TRI method. Table results indicate that because the ratio of return (profitability, growth, and liquidity) to risk (financial, commercial, systematic risks, and market price) is within the range of 0.26 to 0.68; all stock options are within an average pessimistic range of 0.65, excluding stocks 19 and 13 falling under the probable category based on the return-to-risk ratio.

Table 2 also gives the limits of the criterion of judgment in three pessimistic, probable and optimistic states. Accordingly, this table classified the stocks at the Tehran Stock Exchange using the ELECTRE-TRI method. This table indicates that stocks 19 and 13 falls under the probable category, and the remaining ones fall under the pessimistic category based on the return-to-risk ratio.

Table 2: Pairwise comparison matrix of the main criteria for selecting an optimal portfolio in the Tehran Stock Exchange

Main criteria	**Profitability**	**Growth**	**Market**	**Risk**	**Liquidity**
Profitability	(1,1,1)	(1,2,3)	(0.1, 2.9, 9.1)	(3.3, 4.3.,6.9)	(1,2,3)
Growth	(0.1, 0.33, 0.5)	(1,1,1)	(2.2, 3.76,3.86)	(1.3, 3,45.5)	(4,5,6)
Market	(0.0, 1.83, 0.5)	(0.26,0.36,0.4)	(1,1,1)	(0.0,0.2,14.17)	(2,3,4)
Risk	(0.0,0.26,3.26)	(0.0, 0.6, 29.34)	(5,6,7)	(1,1,1)	(3,4,5)
Liquidity	(0.0,0.26,3.26)	(5,6,7)	(0.0,0.5, 25.35)	(0.0, 0.3, 2.25)	(1,1,1)

Table 3: Threshold limits of the indicators based on the ELECTRE-TRI method.

	Return			Risk (financial+ commercial + systematic)		
Main criteria	Profitability	Growth	Liquidity	Risk	Market price	Return-to-risk ratio
Optimistic	0.504	1.94	3	1.15	1.84	1.21≥
Mean	1.81			1.49		
Pessimistic	0.266	1.51	2.2	1.8	2.24	0.65≤
Mean	1.32			2.02		
Probable	2.07	2.4	3.8	3.66	3.82	0.73
Mean	2.75			3.74		

Table 4: Ranking stocks at the Tehran Stock Exchange based on the coefficient of closeness to the positive solution (return maximization) and the negative solution (risk minimization) using the ELECTRE-TRI method

Rank	**Stocks**	**Closeness coefficient (return-to-stocks ratio)**	**Outcome**

30	19S	0.6852	Probable
29	13S	0.6618	Probable
28	7S	0.6238	Pessimistic
27	16S	0.6124	Pessimistic
26	30S	0.6085	Pessimistic
25	18S	0.5938	Pessimistic
24	22S	0.5737	Pessimistic
23	14S	0.5603	Pessimistic
22	9S	0.5524	Pessimistic
21	15S	0.5429	Pessimistic
20	26S	0.5403	Pessimistic
19	28S	0.5392	Pessimistic
18	1S	0.5386	Pessimistic
17	20S	0.5163	Pessimistic
16	4S	0.5137	Pessimistic
15	2S	0.5056	Pessimistic
14	11S	0.4988	Pessimistic
13	7S	0.4884	Pessimistic
12	21S	0.4840	Pessimistic
11	10S	0.4586	Pessimistic
10	8S	0.4321	Pessimistic
9	29S	0.4171	Pessimistic
8	12S	0.4170	Pessimistic
7	27S	0.4037	Pessimistic
6	25S	0.4011	Pessimistic
5	24S	0.363	Pessimistic
4	6S	0.3499	Pessimistic
3	3S	0.2668	Pessimistic
2	5S	0.2652	Pessimistic
1	23S	0.2627	Pessimistic

Table 5: Results of the expected return on stocks using the genetic algorithm

Rank	Stocks	Return
20	1S	0.356
15	2S	0.453
13	3S	0.543
26	4S	0.275
22	5S	0.311
18	6S	0.390
6	7S	0.710
11	8S	0.567
9	9S	0.634
7	10S	0.652
28	11S	0.218
14	12S	0.527
2	13S	0.769
25	14S	0.277
21	15S	0.345
5	16S	0.712
3	17S	0.718
16	18S	0.431
1	19S	0.897
8	20S	0.644
23	21S	0.293
24	22S	0.287
19	23S	0.377
30	24S	0.210
17	25S	0.423
12	26S	0.545
10	27S	0.610
29	28S	0.217
27	29S	0.226
4	30S	0.715

Mean	0.956
Objective function value	0.05987

According to Table 5, the following relations should be focused on increasing stockholders' returns.
S19›S17›S30›S16›S7›S10›S20›S9›S27›S28›S26›S12›S2›S18›25›S6›S23›S1›S15›S5›S11›S22›S14›S4›S29› S11›S28›S24.

In other words, the highest return pertained to S19 (stock 19), and the lowest to S24 (Stock 24).

Table 6: Results of the expected risk of the stocks using the genetic algorithm

Rank	Stocks	Risk
20	1S	0.591
15	2S	0.02089
13	3S	0.0999
26	4S	0.903
22	5S	0.794
18	6S	0.476
6	7S	0.0089
11	8S	0.0901
9	9S	0.082
7	10S	0.081
28	11S	0.978
14	12S	0.0109
2	13S	0.00098
25	14S	0.888
21	15S	0.680
8	16S	0.086
3	17S	0.00099
16	18S	0.0305
19	19S	0.587
5	20S	0.0085
23	21S	0.821
24	22S	0.840

1	23S	0.0009
29	24S	1.02
17	25S	0.0476
12	26S	0.098
10	27S	0.091
30	28S	1.32
27	29S	0.930
4	30S	0.008
	Mean	0.386
	Objective function value	0.467

As noted in Table 6, the following relations govern the financial risk of the stocks; i.e., the lowest risk pertains to S23 and the highest risk to S28.
S23›S17›S30›S20›S7›S10›S16›S9›S27›S28›S26›S12›S2›S18›S25›S6›S19›S1›S15›S5›S11›S22›S14›S4›S29›S11›S24›S28.
Later, we investigate the constancy of the genetic algorithm in portfolio optimization using the parameters of profitability, growth, market price, and liquidity in the equations of stock returns and financial, systematic, and commercial risks as the portfolio risk derived from the ELECTRE method. To this aim, the test of genetic algorithm constancy was implemented five times. The test having been carried out, almost similar responses were extracted. Table 6 indicates that in the five rounds of implementation, the objective function values were not significantly different. Thus, the best objective function was noted in the third implementation with a value of 0.058790.

Table 7: Investigating constancy of the genetic algorithm in stocks optimization at the Tehran Stock Exchange

	Objective function	**Objective function**	**Objective function**	**Objective function**	**Objective function**	**F value**	**Sig.**
	Implementation 1	Implementation 2	Implementation 3	Implementation 4	Implementation 5		
	0.03987	0.04657	0.058790	0.0567	0.05309	0.8902	0.96
Mean			0.051166				
Variance			1.4567				

Experts were surveyed to determine appropriate metrics to direct multi-objective meta-heuristic methods, and a multi-criteria decision-making technique was used. Table 7 demonstrates that based on the weights obtained for each of the main criteria of selecting the optimal stocks portfolio, the criteria of profitability, growth, risk, liquidity, and market were assigned the first, second, third, fourth, and fifth priorities, respectively. In other words, the best stocks at the Tehran Stock Exchange are the ones that bring about the highest profitability, growth, and liquidity and reduce investment risk and market price. Accordingly, as regards the metaheuristic methods, the sub-criteria of profitability, development, and liquidity is maximized, and the sub-criteria of risk and market price is minimized.

Table 8: Weights obtained for the criteria of selecting the optimal portfolio at the Tehran Stock Exchange

Main criteria	Sub criteria	Weight	Priority
Profitability	Earnings per share	0.1177	1
	Net profit margin	0.0597	
	Dividend ratio	0.1407	
	Return on equity holders	0.0692	
	Mean	0.096825	
Growth	Earnings per share growth rate	0.0353	2
	Operating profit growth rate	0.0887	
	Potential growth rate	0.1192	
	Mean	0.081066	
Market	Market value-to-book value ratio	0.0373	5
	Price-to-earnings per share ratio	0.0117	
	Price-to-sales ratio	0.0287	
	Mean	0.0259	
Risk	Systematic risk	0.0436	3
	Commercial risk	0.0658	
	Financial risk	0.0525	
	Mean	0.05396	
Liquidity	current ratio	0.0336	4
	Acid test ratio	0.0576	
	Cash ratio	0.0217	
	Mean	0.03763	

Later, using the univariate t-test, the best model was selected to determine the optimal portfolio. Results of the univariate t-test based on a survey of financial experts at the Tehran Stock Exchange indicated that among the metaheuristic algorithms, the genetic, ant colony, and bee colony algorithms appropriately determined the optimal portfolio at the levels of 1%. In comparison, the harmony search algorithm did this at a 5% error. In other words, the genetic, ant colony, and bee colony algorithms served appropriately non-stop at the optimal local points and sudden lack of convergence at the confidence level of 99%. In comparison, this rate was 5% for the harmony search algorithm.

Table 9: Appropriate metaheuristic model for the classification of the optimal portfolio using the ELECTRE model

Type of algorithm	Mean	SD	T value	Sig.
Genetic	4.17	0.33	49.34	**0.00001
Ant colony	3.81	0.71	16.16	**0.00001
Particle swarm	1.70	0.44	41.32	**0.00001
Harmony search	3.12	0.76	2.32	*0.02
Bee colony	3.90	0.76	16.57	**0.00001
Firefly	1.66	0.30	62.47	**0.00001

Source: Research findings, ** refers to significance at the level of 1%; * refers to significance at the level of 5%

Confirmatory factor analysis was used to meet the appropriate model sensitivity analysis goal to determine the optimal portfolio. The decision-making criterion in this section is the factorial load and the T statistic. As noted in Figure 3, confirmatory factor analysis results on an appropriate method for determining the optimal portfolio suggest that the T values of the genetic, ant colony, and bee colony algorithms were 3.59, 1.99, and 2.42, respectively. Since they were greater than 1.96, they were the most appropriate metaheuristic algorithms for determining the optimal portfolio. They prevent entrapment at the optimal local points and a lack of premature convergence. Also, Figure 4 illustrates that the factorial loads of the genetic, ant colony, and bee colony algorithms were 0.24, 0.7, and 0.8, respectively. Since they were higher than 0.2, they were the most effective metaheuristic methods in determining the optimal portfolio. Accordingly, the results indicated that the best metaheuristic algorithms in determining the optimal portfolio at the Tehran Stock Exchange were the genetic, ant colony, and bee colony algorithms. In other words, the sensitive analysis rejected the harmony algorithm to determine the optimal portfolio at the said exchange. Thus, because the T-value of the genetic algorithm was greater than the ant and bee algorithms, the present research used the multi-objective genetic algorithm based on the ELECTRE model to classify the optimal portfolio.

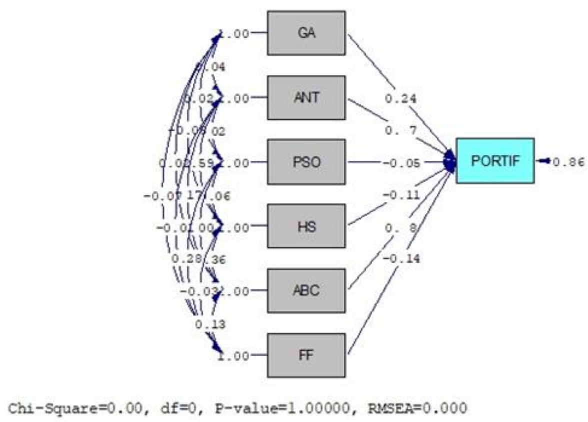

Fig 3: T statistic value in the prediction of the appropriate meta-heuristic algorithm for the classification of the optimal portfolio based on the ELECTRE method

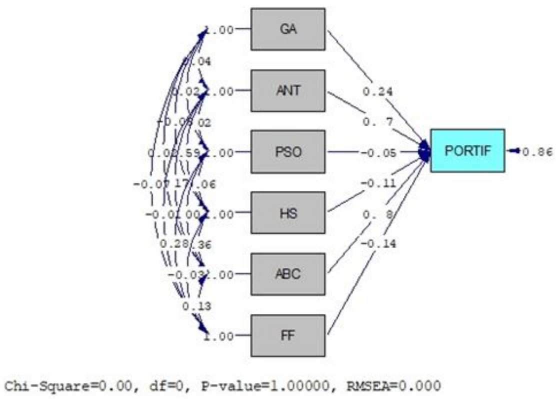

Fig 4: Factorial load value in the prediction of the appropriate meta-heuristic algorithm for the classification of the optimal portfolio based on the ELECTRE model

DISCUSSION

Results of the multi-criteria decision-making model indicated that out of the 30 stocks selected via the coefficient of closeness to the ideal solution (return maximization, e.g., profitability, growth, and liquidity indicators, and risk minimization, e.g., financial, commercial, and systematic as well as market price indicators), the optimal stocks for peoples' preference for investment included S19›S17›S30›S16›S7›S10›S20›S9›S27›S28›S26› S12›S2›S18›S25›S6›S23›S1›S15›S5›S11›S22›S 14›S4›S29›S11›S28›S24.

Also, the implementation of the genetic algorithm for the determination of the optimal portfolio to help decision-makers select the optimal portfolio based on the goal of the stock return maximization indicated the average return of 0.956 and the objective function value of 0.5987, with the position of each stock prioritized as follows:

S19›S17›S30›S16›S7›S10›S20›S9›S27›S28›S26› S12›S2›S18›S25›S6›S23›S1›S15›S5›S11›S22›S 14›S4›S29›S11›S28›S24.

In other words, the highest returns pertained to S19 and the lowest to S24. Also, the univariate T-test results to determine an appropriate and optimal portfolio suggested that S19, S17, S30, and S16 had an average return maximization of 0.956, with the distance of their returns not being significant.

Also, the implementation of the genetic algorithm for the determination of the optimal portfolio to help decision-makers select the optimal portfolio based on the goal of stock risk minimization indicated that the following relations govern the stock financial risks; in other words, the lowest risk pertained to S23, and the highest to S28.

S23›S17›S30›S20›S7›S10›S16›S9›S27›S28›S26› S12›S2›S18›S25›S26›S19›S1›S15S5›S11›S22›S 14›S4›S29S11›S24›S28.

On the other hand, univariate T-test results indicated that based on the average computation risk minimization (0.386), the order of priority of the optimal stocks was as follows:

S23›S17›S0›S20›S7›S10›S16›S9›S27›S28›S26› S12›S2›S18›S25.

Hence, at the confidence level of 99%, the average is lower than the average financial risk of 0.386. for this, a 15-stock portfolio can be selected based on the minimum risk to choose an optimal portfolio.

Also, the multi-criteria decision-making technique indicated that each of the main criteria of selecting the optimal portfolio, e.g., profitability, growth, risk, liquidity, and market, were assigned the first, second, third, fourth, and fifth priorities, respectively, in selecting the optimal portfolio at the Tehran Stock Exchange. In other words, the best stocks at the Tehran Stock Exchange are the ones that bring about the highest profitability, growth, and liquidity and reduce investment risk and market price. Accordingly, as regards the metaheuristic methods, the sub-criteria of profitability (e.g., earnings per share, net profit margin, dividend payout ratio, return on equity), growth (e.g., earnings per share growth rate, operating profit growth rate, and potential profit growth rate) and liquidity (e.g., acid test ratio, current and cash) should be maximized, and the sub-criteria of risk (e.g., financial, systematic and commercial risks), and market price (e.g., market value-to-book value ratio, price-to-earnings per share ration and price-to-sales proportion should be minimized.

Confirmatory factor analysis results indicated that the most effective metaheuristic methods to determine the optimal portfolio at the Tehran Stock Exchange were the genetic, ant colony, and bee colony algorithms. In other words, the sensitive analysis rejects the harmony algorithm to determine the optimal portfolio at the said exchange. Thus, because the T-value of the genetic algorithm is greater than the ant and bee algorithms, the present research uses the multi-objective genetic algorithm based on the ELECTRE model to classify the optimal portfolio.

In sum, the algorithm above was implemented five times to determine the constancy of the genetic algorithm. Objective function results using the analysis of variance indicated that the obtained objective functions were not significantly different. This analysis itself refers to the proportionality of the application of the genetic algorithm for the classification of the optimal portfolio.

Considering the sharp changes in stock prices in the stock exchange, it is proposed to perform this research on a yearly basis continuously.

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