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Construction of Fundamental and Technical Portfolio using a Multivariate Approach

Somaei Danesh Asgari[1] | **Emran Mohammadi**[2*]

1. Department of Industrial Engineering, Iran University of Science & Technology,Tehran, Iran. Email: s123.asgari@gmail.com
2. Corresponding Author, Department of Industrial Engineering, Iran University of Science & Technology,Tehran, Iran. Email: e_mohammadi@iust.ac.ir

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ABSTRACT

This paper applied the Measure of Attractiveness of Investment (MAI) as a representative indicator to enable investors to choose stocks according to attractiveness measured by some financial ratios of companies. It is integrated with β as the inherent risk of the market to construct a portfolio accounting for the companies' fundamental strength and the investment's long-term character. One may not know what the future investment environment will look like, but one can be better prepared for whatever comes through taking into account the uncertainty. The underlying key contribution of this study is related to the integration of MAI and β to construct a portfolio based on the companies' fundamental ratios and attractiveness of investments' long-term measures under uncertain conditions. To overcome the uncertainty, the Bertism and Sim algorithm is utilized which has some advantages such as linearity and the possibility of the adjusting protection level regarding the uncertainty degree. The empirical example shows that the proposed approach can be well implemented to deal with portfolio selection in uncertain conditions.

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1. Introduction

To create a portfolio, investors contemplate many objects such as minimization of the risk and return maximization. The classic model of portfolio optimization, called Markowitz mean-variance model, considers these objectives (Markowitz, 1952). In this model, it is supposed that the return has a normal distribution while it often is not true in practice. Also, in a real model of investment, different criteria other than risk and return are considered by decision-makers. Pysarenko, Alexeev & Tapon (2019) integrated Markowitz model and a fundamental approach to construct a novel portfolio. They found that a constructed portfolio has better diversification than that of fundamental analysis while it has a better risk-adjusted return than the classic Markowitz model. Safa and Panahian (2018) introduced the price-to earnings per share ratio as a measure and criteria for investors and contributors to the stock exchange to make more appropriate decisions. To employ this tool, decision-makers needed to estimate and predict the price and obtain the maximum return on investment. This issue motivated them to utilize the Harmony Search algorithm and neural network to forecast the stocks' prices and get the best return. They studied the stocks of 87 companies at Tehran Stock Exchange over 10 years between 2006 and 2015. They concluded that combining neural network with new approaches and algorithms has more accuracy than other forecasting techniques. To estimate the stock market, Azizi et al. (2021) investigated the effect of fundamental data such as stock prices. They gathered both stock indexes from Stock Exchange and published news in the under-studied period. The main purpose was the examination of the impact of news headlines obtained from an economic news website on the stock index. In their study, the news ranged from "very negative" to "very positive". The authors utilized logistic regression to assess the connection between the stock index and news. The findings show that the published news affects the stock index and can have a positive or negative semantic burden. Wang (2011) applied data mining techniques to make a portfolio based on the stock trading data and financial data consisting of earnings per share, net asset value per share, total assets turnover ratio, principal businesses growth rate, and liquidity ratio. Dinandra, Hertono, and Handari (2019) examined various portfolio strategies using clustering methods in which seven financial ratios were investigated including earnings per share, price earning ratio, price/earning growth, return of equity, debt equity ratio, current ratio, and profit margin. Goudarzi, Jafari, and Afsar (2017) developed a portfolio in which, in addition to the investors' behavior, liquidity, and current ratios are also taken into account.

In the context of stock, there are two principal aspects to seeking various criteria. One technical analysis and the other fundamental one. In technical analysis, investment opportunities are assessed using statistical trends like price movement and volume. Unlike this method, the fundamental analysis measures the security's inherent value through the financial and economic statements of related companies and industries. In other words, this approach enables investors to decide based on historical and present market data. One can consider an alternative approach to portfolio selection. In this alternative setup, a decision-maker chooses stocks for the portfolio according to their attractiveness, measured by companies' financial ratios. This allows for the addition of a third dimension for the analysis of portfolio construction. For this purpose, MAI can be used to make it possible to create a portfolio regarding the companies' fundamental strengths and the investment's long-term character. In this paper, it is integrated with β as the systematic risk indicator to include market conditions in the portfolio construction.

One of the principal problems with portfolio selection is the uncertainty of some parameters such as future returns. If the problem parameters take values other than nominal ones, some constraints may not be followed and the optimal solution obtained using nominal data, be no longer optimal or even feasible. Robust optimization is one of the effective methods to deal with data uncertainty. It supposes that the uncertain data lie in an uncertainty set. Under parameter uncertainty, Malliet, Tokpavi & Vaucher (2015) suggested a robust approach variance of the portfolio be minimized. The results indicated that a robust portfolio leads to a higher Sharpe ratio and lower variance. To suitable portfolio selection, Xidonas et al. (2017) applied a robust concept under scenario uncertainty to minimize the variance of the portfolio. To form a more robust portfolio, worst-case optimization was implemented by Kim et al. (2014 b). The results proved that the proposed approach has more robustness than Markowitz's classic model. For a robust investment, Kim et al. (2015) focused on the worst-case robust optimization. Ghaoui, Oks, and Oustry (2003) decreased the extreme portfolio sensitivity to errors in data by considering the worst-case VaR and entropy in a robust portfolio optimization problem in which the moments of return distribution belong to a predefined set. Erdogan, Goldfarb, and Iyengar (2006) examined portfolio construction as a second-order cone programming to select an active portfolio. In their study, Ben-Tal, Margalit, and Nemirovski (2000) investigated a severe uncertainty in the multi-period asset allocation problem. Bertsimas and Pachamanova (2008) compared the performance of their multi-period portfolio problem with a single one in which the return of stocks was considered uncertain. To overcome the uncertainty, the robust optimization approach was employed. Hanafizadeh and Seyfi (2006) examined the norm bodies of various uncertainty sets and formulated their robust counterparts. They employed the utility function of decision maker and uncertain return stocks to adjust a robust portfolio selection.

Despite extensive studies in the aforementioned fields, so far no attention has been paid to the uncertainty of MAI. This is important because ignoring the possibility of changing a company's financial ratios over time diverts investors from the main goal of optimal portfolio construction. The underlying key-contribution of this study is related to the integration of MAI and β to construct a portfolio based on the companies' fundamental ratios and attractiveness of investments' long-term measures under uncertainty conditions. To overcome the uncertainty, a robust optimization approach is used to create a robust portfolio.

The rest of this study has been structured as follows: section 2 introduces the definitions of relevant concepts and models. The proposed approach is given in section 3. A numerical example is surveyed in section 4. Finally, concluding remarks are presented in section 5.

2. Preliminaries

This section briefly reviews the systematic and non-systematic risk, MAI, and RO models as preliminaries.

2.1 Systematic and Non-systematic Risk

The portfolio total risk can be divided into non-systematic and systematic risk:
Total risk = non-systematic risk + systematic risk

Non-systematic risk is related to a specific industry or firm which can be eliminated using portfolio diversification. As systematic risk represents the inherent risk of market, it is hard for an investor to eliminate or reduce that. To assess the return of a stock, the single-index model is used. This model applied broadly in finance science developed by William Sharpe (1963). It supposes that stock return is influenced by only one factor, the market index, and expressed as follows:

$$R_i = \alpha_i + \beta_i R_m + \varepsilon_i \tag{1}$$

R_i The stock return
R_m The market return
α_i The abnormal return or stock alpha
β_i Responsiveness to the market return or systematic risk measure
ε_i Residual return

According to (1), systematic risk, β_i, is computed for each equity as follows:

$$\beta_i = \frac{cov(R_i, R_m)}{var(R_m)} \tag{2}$$

If $\beta < 1$, the stock is defensive; $\beta > 1$ defines an offensive stock, and $\beta = 1$ represents a neutral one in which equity systematic risk is equal to the market risk. That is, the stock return varies with the reduction or increase of return rate of the market total index.

The first study in the context of risk control in portfolio optimization was proposed by Zhu, Li, and Sun (2010). The issue was addressed within a mean-variance structure that led to a non-convex quadratically constrained program. To solve the formulated model, an efficient branch-and-bound technique was employed. To assign the systematic risk in the portfolio selection problem, Li et al., (2013) addressed a mean-variance problem. The proposed model, also, can be used as a model for controlling risk sensitivity in portfolio optimization. The gained model is a non-convex quadratically constrained quadratic program but can be written in a special structure because of its properties related to systematic risk. A convergent ranch-and-bound algorithm was implemented under a second-order cone relaxation. The components of the non-systematic risk in a natural gas export portfolio were discussed in the research of Nowrouzi et al., (2019). These components were identified as the risk of gas dependency of gas importing countries and geopolitical risk. A quantitative index aggregate technique based on entropy was introduced through suitable sub-indicators. The findings verified that the minimum risk value is obtained when there is a meaningful rate of LNG transmission method in the gas export portfolio.

The Capital Asset Pricing Model directs risk analysis in modern financial problem and beta measure can power that. Yuan and Lee (2015) implemented genetic algorithm-Least squares support vector regression to predict the systematic risk measure (beta). The aim of employing the Genetic algorithm was to select optimal parameters for Least squares support vector regression and the mean square forecast error was utilized to assess the fitness. An empirical study using financial data between 2001 and 2010 concluded that the genetic algorithm-Least squares support vector regression has better predicting accuracy than the genetic algorithm-artificial neural network method. Lee et al., (2010; 1986) proved that beta prediction is affected by both accounting and market information using composite concepts. The model based on market information in the simplest condition considers stationary beta over time. Their proposed model can be implemented in security analysis and financial management to define how accounting information can be employed in beta coefficient prediction. Blume (1975) claimed a linear relationship between the future beta coefficient related to stock and its historical one. A linear relationship between the beta coefficient based on historical data and future coefficient was supposed by Klemkosky and Martin (1975). They studied the source of predict errors of beta coefficients and three adaptive processes introduced in the literature.

AlMahdi (2015) introduced market risk as the main portfolio's risk factor. The author examined several portfolios by the smart beta strategies. In his study, the smart beta implies portfolio management involving cap weight, minimum variance, and economic scale in which these options are integrated and constructed beta dynamic portfolios. Inspired by game theory, Shalit (2020) introduced the shapely value to quantify the risk factor related to the portfolio. He believed that the beta index is a necessary indicator in pricing of risky securities. The main concept in his research was considering the portfolios as cooperative games, played through assets to minimize the risk. Utilizing the shapely value, investors can calculate the exact contribution of each risky asset to the joint payoff. An empirical study for a portfolio involving three stocks examined the sharp value when the risk is minimized regardless of portfolio return. His study calculated the stocks' shapley value and indices for optimal mean-variance portfolios utilizing daily returns in the time-period 2016–2019. This results in the risk attributes assigned to securities in optimal portfolios. Finally, the smart Shapley values were analyzed and compared to the standard beta estimates to determine the ranking of assets concerning the pertinent risk and return.

2.2 Measure of Attractiveness of Investment (MAI)

The fundamental analysis has a deep and broad perspective and plays a particular and key role in long-term investment opportunities. Its basic knowledge helps investors to identify stocks trading at a lower or higher price than real value and lay a secure foundation for their investment decisions. Some capabilities of the fundamental techniques include predicting future price movement, evaluating management, and analyzing the strengths and weaknesses of the company whose stock is considered. It deals with some substantial questions such as: is the company experiencing a rising revenue? Does the company make an actual profit? In fundamental analysis, the investor is interested in examining the economic conditions and environment in which the entity operates, and finally, by exploring its development prospects, weakness and strength aspects, and financial health, the investor decides whether it is worth investing in its stock or not. In the study of a company's state, financial ratios computed from the financial reports are considered such as liquidity ratios (e.g. current ratio, instantaneous ratio), leverage and investment ratios (debt ratio, debt to equity ratio), activity ratios (periodicals collection, inventory period of material and goods, current capital turnover, fixed asset turnover, total assets turnover), and profitability ratios (net profit margin, operating margin, return on assets, return on capital, return on working capital). To exhibit the economic and financial standing of a company, a synthetic indicator based on selected ratios can be applied first introduced by Tarczyński

(1995). To assess the financial standing of the company, he introduced an indicator entitled the taxonomic measure of attractiveness of investment.

The approach proposed by Tarczyński (1995) was developed. For example, Rutkowska-Ziarko and Garsztka (2014) applied semi-variance as a risk indicator instead of variance. To consider the possible correlation among financial variables, Rutkowska-Ziarko (2013) employed the Mahalanobis distance. Staszak (2017) utilized this measure to construct an experimental portfolio from active companies on the Polish stock exchange. He studied the period 2004-2016 and concluded that the results of a fundamental portfolio utilized the taxonomic measure of attractiveness of investment outperforms the classical Markowitz model. Further studies can be found in (Kliber, 2019; Tarczyński and Łuniewska, 2005; Tarczyński and Łuniewska, 2018).

2.3 Robust Optimization

Uncertainty is an integral part of human life. In many cases, the exact prediction of the parameters and factors affecting the problem is not feasible, and at the best, only the estimated ones are available. Thus, the provision of methods for considering these uncertainties in solving problems has always been of interest to researchers because in many cases, the failure to pay attention to these uncertain factors can lead to system heavy costs and in some cases even reduce the value of the solutions provided.

Given the nature of the data uncertainty, there are various approaches to dealing with them. If randomness is the source of data uncertainty, the probability distribution function of the parameters is known, stochastic programming is used. The fuzzy optimization approach is used when there is no historical data on the desired parameter and therefore no probable function can be attributed to that parameter. Robust optimization, a new approach to dealing with uncertainty, seeks to provide a solution for the problem to be robust in uncertainty. In this approach, there is no information about date distribution, and only the interval of their perturbation is determined.

Seeyster (1973) presented a linear optimization model that gives the best answer to all input data so that any input data can take any amount of the interval. This approach tends to find answers that are too conservative. Ben-Tal and Niemerovsky (1998) provided an efficient algorithm based on elliptical sets.

To minimize the conditional value at risk under uncertainty Quaranta and Zaffaroni (2008) utilized a robust optimization approach. They found a linear robust copy of the bi- criteria minimization model introduced by Rockafellar and Uryasev. To produce input data, they utilized various methods for predicting the expected returns. The proposed model was verified in a portfolio selection example on the Italy Stock Exchange. To maximize the total return of created portfolio, Gregory, Darby-Dowman, and Mitra (2011) investigated the cost of robustness. They used the polyhedral uncertainty set to construct the convex set and formulate the robust counterpart. In the portfolio, the model was based on the min-regret approach and the relationship between uncertainty sets and various definitions of bounds. Kawas and Thiele (2011) introduced a new approach called Log- robust to manage a portfolio with uncertain parameters. This approach does not use any probabilistic assumption and integrates the randomness of the continuously compounded rates of return. A two-stage robust model introduced by Rahmani (2019) in which return and risk indicators of various industries settle the favorite value of an investment in each industry and the exact amount of investment is determined by considering systematic and non-systematic risk, the results of the first stage and stocks' return. To overcome the uncertainty in the proposed approach, they implemented a robust model and the goal programming was utilized to solve the multi-objective model. Verderame and Floudas (2011) investigated the robust models under continuous uncertainty sets (general, uniform, normal) and discontinuous uncertainty sets (general, binomial, Poisson).

Goli et al., (2019a) applied robust optimization and multi-objective invasive weed optimization to construct a product portfolio for Pegah Golpayegan Company. The profit margin was considered as the uncertain parameter and the results were compared with CPLEX and the genetic algorithm. Finally, the superiority of proposed approach was proved. In another study, they introduced a hybrid neural network and runner root meta-heuristic algorithm for dairy product industries and proposed two robust counterpart formulations to solve the proposed model (Goli et al., 2019b). Moon and Yao (2011) proposed a mean absolute deviation model for portfolio optimization under uncertain conditions and improving portfolio performance using the control of estimation errors. They examined the proposed approach on a real stock market and concluded that their model outperforms a nominal mean absolute deviation one. Gabrel et al., (2014) reviewed the robust optimization literature since 2007, gave a representative picture of subjects most interested, and highlighted their contributions in this field. New advances in robust portfolio selection in terms of operation research and financial aspects were sought by Fabozzi et al. (2010). They investigated all studies that used variance, mean-VaR, and mean-CVaR as risk measures as well as Bayesian robust approaches and optimal estimation methods. Goldfarb and Iyengar (2003) explored uncertainty sets can be reformulated in terms of an explicit second-order cone program. Also, the authors focused on applications of robust convex quadratic cone programs and proved that constructed uncertainty sets can be modeled by classic uncertainty sets. A multi-period portfolio problem in the presence of transaction costs with a linear and computationally efficient model was suggested by Bertsimas and Pachamanova (2008). The authors proved that the proposed multi-period model outperform the single-period mean-variance one. DeMiguel and Nogales (2009) introduced portfolios created by certain robust estimators. The suggested portfolios are solved using a single nonlinear program. These portfolios are less sensitive to variations in asset-return distribution and outperforms the classic portfolios.

Bertism and Sim (2004) introduced a different approach to control the level of conservatism. The advantage of this method is that it leads to a linear optimization model and is therefore applicable to discrete optimization models. In Bertsimas and Sim's approach, the uncertainty budget is defined as constraints' cardinality or the number of parameters that can fluctuate around their nominal values. Ghahtarani and Najafi (2013) solved the portfolio problem utilizing the integration of Bertism and Sim approach and goal programming. The results showed that as the price of robustness enhances, the conservatism of the solution increases. Also, they considered the decision makers' ideas in the proposed approach. In another work, they proposed a robust mean- absolute deviation approach with uncertain parameters based on Bertism and Sim's robust approach (Ghahtarani and Najafi, 2018). Li, Ding, and Floudas (2011) reviewed various uncertainty sets including interval, integration of interval and ellipsoidal, integration of interval and polyhedral, integration of interval, ellipsoidal, and polyhedral, adjustable box, pure box, and pure polyhedral, and investigated their geometric relationship. The authors examined different modes of existing uncertain parameters such as right-hand side, left hand side and, etc. a case study related to batch process scheduling and refinery production planning weas addressed.

The following optimization problem is assumed:

$$\begin{aligned} &\min c^T x \\ &\text{s.t.} \\ &Ax \le b \\ &l \le x \le u \end{aligned} \tag{3}$$

Suppose $A = a_{ij}$ is an uncertain matrix in which each a_{ij}vary between $a_{ij} - \hat{a}_{ij}$ and $a_{ij} + \hat{a}_{ij}$. In other words, $a_{ij}\epsilon[a_{ij} - \hat{a}_{ij} \quad a_{ij} + \hat{a}_{ij}]$. Consider the *i*th constraint of the nominal problem $a_i x \le b_i$. Let J_i be the set of coefficients a_{ij}, $j\epsilon J_i$ that are subject to parameter uncertainty; i.e., $\tilde{a}_{ij}$, $j\epsilon J_i$ takes values according to a symmetric distribution with a mean equal to the nminal value a_{ij} in the interval $[a_{ij} - \hat{a}_{ij} \quad a_{ij} + \hat{a}_{ij}]$. For every i, we introduce a parameter Γ_i , not necessarily integer, that takes values in the interval $[0 \quad |J_i|]$. As would become clear below, the role of parameter Γ_i is to adjust the robustness of the proposed method against the level of the conservatism of solution. Our goal is to be protected against all cases in which up to $\lfloor\Gamma_i\rfloor$ of these coefficients are allowed to change, and one coefficient a_{it} changes by $(\Gamma_i - \lfloor\Gamma_i\rfloor)\hat{a}_{it}$. Consider the following (still nonlinear) formulation:

$$\begin{aligned} &\min c^T x \\ &\text{s.t.} \\ &\sum_j a_{ij} x_j + max_{\{s_i \cup \{t\} | s_i \subseteq J_i, |s_i| \le \Gamma_i, t_i \epsilon J_i \setminus s_i\}} \left\{ \sum_{j \epsilon s_0} \tilde{a}_{ij} |x_j| + (\Gamma_i - \Gamma_i) \hat{a}_{it_i} |x_{t_i}| \right\} \le b_i \qquad \forall i \\ &-y_j \le x_j \le +y_j \qquad \forall j \\ &l_j \le x_j \le u_j \qquad \forall j \\ &y \ge 0 \quad \forall i, j \end{aligned} \tag{4}$$

This model has an equivalent linear formulation as follows (Bertism & Sim, 2004):

$$
\begin{aligned}
&\max U \\
&s.t. \\
&u - \sum_{j \in N} c_{ij} x_j + z_i \Gamma_i + \sum_{j \in N} p_{ij} \le 0 \\
&\sum_{j \in N} a_{ij} x_j + z_i \Gamma_i + \sum_{j \in N} p_{ij} \le b_i \qquad \forall i \\
&z_i + p_{ij} \ge \hat{a}_{ij} y_j \qquad \forall i, j \\
&-y_j \le x_j \le +y_j \qquad \forall j \\
&l_j \le x_j \le u_j \qquad \forall j \\
&p_{ij}, y_j, z_i \ge 0 \qquad \forall i, j
\end{aligned} \tag{5}
$$

4. Proposed Approach

In this study, MAI (Measure of Attractiveness of Investment) and β (systematic risk measure) are respectively computed by fundamental and technical analysis. A portfolio consisting of *n* stocks is supposed. The current study's proposed approach is modeled as follows:

$$
\begin{aligned}
&max \sum_i MAI_i * x_i \\
&s.t. \\
&\sum_i R_i * x_i \ge R \\
&\sum_i \beta_i * x_i \le \beta \\
&\sum_i x_i = 1 \\
&x_i \ge 0
\end{aligned} \tag{6}
$$

x_i the share of *i*-th stock of portfolio
MAI_i the financial performance measure of *i*-th stock company
R_i the return of *i*-th stock
β_i systematic risk measure of *i*-th stock
R minimum preference return of investors
β maximum systematic risk determined by the decision-maker

The first constraint states that the portfolio return must be greater than the investor's expected return (R). In the second constraint, the risk of the Portfolio must be smaller than the intended risk of decision-maker. To compute β, the market total index and the return of stock are utilized in equation 2 (technical analysis). The third constraint is related to the budget limitation.

In objective function, MAI indicator measured using financial and economic status of the stock company is maximized. This makes it possible to construct a portfolio accounting for the companies' fundamental strengths and the investment's long-term character. MAI is the under-optimization measure. This is the main change compared to the classic model of Markowitz. A portfolio founded on the MAI criterion is optimal from the fundamental point of view, i.e. it chooses the best arrangement in terms of the company's economic and financial condition.

In this study, to compute MAI measure, four groups of financial ratios are implemented including liquidity ratios (current ratio, instantaneous ratio), leverage and investment ratios (debt ratio, debt to equity ratio), activity ratios (periodicals collection, inventory period of material and goods, current capital turnover, fixed asset turnover, total assets turnover), and profitability ratios (net profit margin, operating margin, return on assets, return on capital, return on working capital). These ratios are utilized as input and output factors of a Data Envelopment Analysis (DEA) model to evaluate companies' efficiency. In other words, MAI is the efficiency score of a company in which input and output parameters are financial ratios of that.

Since economic, political, social, and other factors are highly effective on the economic performance of companies, and if there is uncertainty, the company's future performance does not necessarily follow the past one, the values of MAI, R, and β can be uncertain.

$$\begin{aligned} & max \sum_i MAI_i * x_i \\ & \text{s.t.} \\ & \sum_i \tilde{R}_i * x_i \geq R \\ & \sum_i \tilde{\beta}_i * x_i \leq \beta \\ & \sum_i x_i = 1 \\ & x_i \geq 0 \quad \forall i \end{aligned} \tag{7}$$

According to model (5), the certain equivalent of the model (7) is as follows:

$$\begin{aligned} & \max U \\ & \text{s.t.} \\ & u - \sum_{j \in N} MAI * x_i + z_1 \Gamma_1 + \sum_i p_{1i} \leq 0 \\ & z_1 + p_{1i} \geq TMAI_i * x_i \qquad \forall i = 1, 2, \ldots, n \\ & \sum_i \beta_i x_i + z_2 \Gamma_2 + \sum_i p_{2i} \leq \beta \\ & z_2 + p_{2i} \geq \hat{\beta}_i * x_i \qquad \forall i \\ & -\sum_i R_i * x_i + z_3 \Gamma_3 + \sum_i p_{3i} \leq -R \\ & z_3 + p_{3i} \geq \hat{R}_i * x_i \qquad \forall i \\ & \sum_i x_i = 1 \\ & p_{1i}, p_{2i}, p_{3i}, z_1, z_2, z_3 \geq 0 \qquad \forall i \\ & x_i \geq 0 \qquad \forall i \end{aligned} \tag{8}$$

Since the decision variable (x) is positive, there is no need to variable change (y).

5. Numerical Example

To elucidate the details of implementation of our proposed approach, a numerical example is investigated. The empirical example presented here focuses on the active companies on the Tehran stock exchange between 2015 and 2019. At first, a DEA model with super efficiency is applied to compute the efficiency score of these companies. After, stocks related to ten top companies (excluding investment companies, banks, and insurers) are selected. Table 1 demonstrates 10 companies with the highest values of *MAI* measure.

Table 1. Ten top stocks based on fundamental analysis

NO.	Symbol	MAI
1	DSOBHAN	1.53
2	APP	1.16
3	ZAGROS	1.16
4	SHEPANTA	1.14
5	VKHARAZM	1.12
6	FPANTA	1.08
7	KFARAVAR	1.06
8	QCHAR	1.03
9	QGOLESTA	1.02
10	RTCO	1.00

Systematic risk (β) is obtained for each stock using equation (2). To calculate the return of each stock, the following equation is used:

$$R_t = \frac{p_t - p_{t-1} + D}{p_{t-1}} \tag{9}$$

R_t The stock current return
p_t The stock current price
p_{t-1} The stock price in the previous period
D The stock cash profit (zero in this study)

The integrated portfolio based on fundamental and technical analysis for stocks included in Table 1 and for various values of Γ has been constructed regarding model (8) and GAMS software. The results have been exhibited in Table 2.

Table 2. Constructed portfolio for different gamma values

	X_1	X_2	X3	X4	X5	X6	X7	X8	X9	X10	z
Γ = 0	1.000	0	0	0	0	0	0	0	0	0	1.530
Γ = 1	0.0026	0.177	0.210	0.352	0.040	0	0.183	0	0.012	0	1.091
Γ = 2	0.019	0.131	0.156	0.268	0.025	0.154	0.136	0.086	0.026	0	1.057
Γ = 3	0.013	0.089	0	0.190	0.286	0.020	0.188	0.092	0.022	0	1.036
Γ = 4	0.010	0.069	0.082	0.221	0.014	0.336	0.176	0.076	0.015	0	1.019
Γ = 5	0.005	0.034	0.088	0.265	0.008	0.361	0.195	0.037	0.008	0	1.009
Γ = 6	0	0	0	0.252	0	0.483	0.264	0	0	0	1.005
Γ = 7	0	0	0	0	0.252	0	0.483	0.264	0	0	1.005
Γ = 8	0	0	0	0	0.252	0	0.483	0.264	0	0	1.005
Γ = 9	0	0	0	0	0.252	0	0.483	0.264	0	0	1.005
Γ = 10	0	0	0	0	0.252	0	0.483	0.264	0	0	1.005

It is obvious that the objective function value does not being worse when the protection level (Γ) increases. Variations have been shown in Figure 1 for different Γ values. To validate the proposed model, uncertain parameters are realized for different values in their perturbation interval. It is expected that the robust solution has better performance on average after repeat simulations.

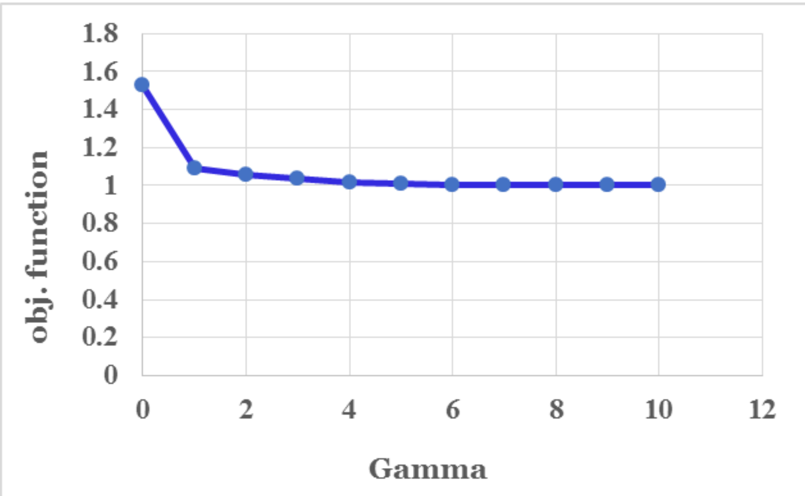

Figure 1. Changes in the objective function for different values of gamma

The relative deviation of *MAI* measure for different perturbations in nominal (Γ*=0*) and the most conservative case (Γ*=10*) has been shown in Figure 2. It is clear that the robust objective function is better. In other words, after realization, deviations of the robust case are less than that of in nominal one.

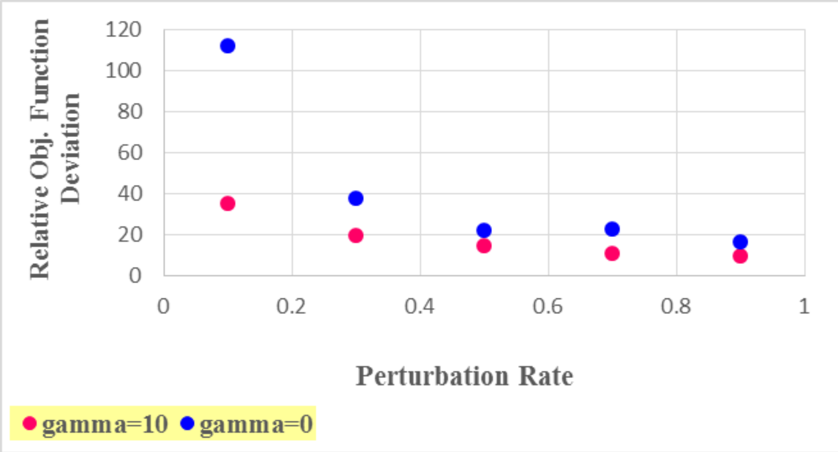

Figure 2. Comparison between the robustness of solution in nominal and the most conservative case

6. Conclusion

The present study proposes a novel approach to constructing a portfolio by considering several important aspects: *1) Uncertainty*- One of the existing problems in the real world, as well as portfolio optimization, is the uncertainty of input data. The effect of this uncertainty on the solution is such that only a small percentage of changes in the input data may greatly increase the probability of its infeasibility. In this paper, the applied strategy to face uncertainty is the Bertsimas and Sim's algorithm which has some advantages such as linearity and the possibility of adjusting protection level regarding the uncertainty degree. *2) Fundamental analysis*- in this analysis, the investor is interested in examining the economic conditions and environment in which the entity operates and, finally, by exploring its development prospects, weakness and strength aspects, and financial health, the investor decides whether it is worth investing in its stock or not. In this paper, MAI as a representative indicator was applied to enable the investor to choose stocks according to the attractiveness measured by some fundamental ratios of companies. *3) The risk of market*- in the present study, MAI measure was integrated with β as the inherent risk of market to construct a portfolio accounting for the companies' fundamental strength and the investment's long-term character. This helps decision-makers to achieve the best arrangement in terms of market and company's financial state and adds a dimension to the classical criteria of profitability and risk. The empirical example shows that the proposed approach can be well implemented to deal with portfolio selection in the condition of uncertainty.

For future studies, it would be interesting to perform some simulations to show the mitigation of parameter uncertainty. More broadly, research is also needed to determine the difference between in-sample and out-of-sample model performance to better understanding the performance of proposed approach. More historical data on MAI and β would help us to establish a greater degree of accuracy and less conservatism on robust solutions employing data-driven robust optimization techniques.

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