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Original Research

Visualized Portfolio Optimization of Stock Market: Case of TSE

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ABSTRACT

An investment portfolio is a collection of financial assets consisting of investment tools such as stocks, bonds, and bank deposits, among others, which are held by a person or a group of persons. In this research, we use the Markowitz model to optimize the stock portfolio and identify the minimum spanning tree (MST) structure in the portfolio consisting of 50 stocks traded in the TSE (Tehran Stock Exchange). The observable which is used to detect the minimum spanning tree (MST) of the stocks of a given portfolio is the synchronous correlation coefficient of the daily difference of logarithm of the closure price of stocks. The correlation coefficient is calculated between all the possible pairs of stocks present in the portfolio in a given time course. The goal of the present study is to obtain the taxonomy of a portfolio of stocks traded in the TSE by using the information of time series of stock prices only. This research, reports results obtained by investigating the portfolio of the stocks used to compute 50 stocks of the Iran Stock Exchange in the period from January 2012 to October 2022.

1 Introduction

Portfolio optimization, which is an analytical process of selecting and allocating a group of investment assets, is an essential problem in risk management. Expected returns and risks are the most important parameters in portfolio optimization problems. Investors generally prefer to maximize returns and minimize risk [1]. The Markowitz mean-variance (MV) model, which was first developed in 1952, and is among the best models for solving the portfolio selection problem, can be described in terms of the mean return of the stock and the variance of return (risk) between these stock [2]. The Markowitz mean-variance (MV) the basic model obtains the ‘‘efficient frontier’’, which is the portfolio of stock that achieves a predetermined level of expected return at minimal risk. For every level of desirable mean return, this efficiency frontier indicates the best investment strategy.Hernandez (2014), and Palczewski et al. (2015) presented different approaches to dealing with portfolio management, but they mainly refer to the optimization of assets, especially in the stock exchange, which was the initial purpose of the Markowitz theory [3-4]. Logubayom and Victor (2019) used historical monthly data of the stock returns from 2011 to 2016 for portfolio optimization and showed how the Markowitz model can be applied to the Ghana Stock Exchange. They also unraveled the most efficient portfolio among selected stocks, to the relief of the investor [5]. Abdul and Yuliati

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(2020) studied the optimization of the investment portfolio with the Markowitz model. Optimization was done by using the Lagrange Multiplier method, and an equation was obtained to determine the ratio (weight) of fund allocation for each asset in the formation of the investment portfolio. The results showed that by using these equations, the determination of investment portfolio weights can be determined by capital [6]. Science et al. presented portfolio optimization with uncertain returns. First, an uncertain mean-variance-entropy model was formulated. Finally, they performed a numerical simulation to demonstrate the practicality and efficiency of their model. The results certified that asset liquidity and diversification degree of the portfolio affected the optimal investment strategies [7]. Financial Markets are complex systems whose structure and conduct are strongly dependent on their component's interrelations. In particular, network theory has contributed to characterizing and understanding the behavior of financial markets [8]. Many models based on physical phenomena have been suggested to analyze financial networks. These network models are very important in investigating complex phenomena theoretically [9]. The starting idea of building a network based on the log difference of equity prices comes from Mantegna, who proposes building a correlation matrix of log returns, an induced distance, and consequently a network of companies. The correlation matrix is dense and, the resulting network would have an overwhelming amount of linkages, Mantegna suggests building a minimum spanning tree (MST) [10] which can give an overview of the structure without cycles, which is therefore very comprehensible for professionals The proposal of MST provides a practical tool based on which many valuable types of research were conducted in studying different aspects of financial systems [11, 12]. In 1994, Peng [13] presented a method called defended fluctuation analysis (DFA) as an alternative to studying the long-range power-law correlations for DNA sequences [14]. Proposed a method for efficient stock selection using support vector regression (SVR) as well as genetic algorithms (GA). They first used the SVR method to create a surrogate for real stock returns, that in turn provided reliable stock ratings [15]. A fuzzy portfolio selection model with background risk based on the definitions of potential return and potential risk. The results showed that the background risk can better reflect the investment risk of the real economic environment, which make the investors choose a more suitable portfolio for themselves. Many studies have been published on a network analysis of a special stock market, in particular on the New York Stock [16, 17, 18].

In 2013, Men Gram presented a simplified perspective of Markowitz's contributions to Modern Portfolio Theory. Instead of involving complex and advanced models that are based on statistical calculations, they only discussed this model’s theoretical basis and stated that this model, one of the leading theories for the last 6 decades, should be considered only a simple financial tool. They concluded that his theory is subject to and based on probable growth and expansion, and so where this advance leads is known [19]. In 2017, Gasser et al. evaluated Markowitz Portfolio Selection Theory completely, and they offered an adjustment that includes asset return and risk relationship specifically but also social responsibility measure in decision-making during the investment period. The model they use allowed investors to build their customized asset allocations and include all their requests related to risk, and return. According to the results of the analysis, they found that investors who wanted to maximize the social effects of investments experienced a decrease in expected returns, and findings regarding these results are statistically meaningful [20].

2 Methodology

One of the most important issues in portfolio optimization is risk mensuration. The problem of portfolio optimization is the determination of the amount of each share in the portfolio, with the two objectives of maximizing returns and minimizing risk [21]. This section presents the Markowitz mean-variance model and shows an efficient frontier calculation for 50 stocks of the Iran Stock. Finally, we draw a minimum spanning tree for 50 stocks.

2.1. Portfolio Optimization

Optimization can be defined as the process of finding conditions that give the maximum or minimum value of a function. The two most important components in deciding on an investment are the amount of risk and return on capital assets. Optimal asset selection is often driven by the trade-off between risk and return, and the higher the asset risk, investors expect higher returns. Identifying the asset boundary of the portfolio enables investors to derive the most expected return on their investment based on their utility and degree of risk aversion and risk-taking. Each investor selects a point on the effective boundary based on their risk-taking and risk aversion and sets their portfolio composition to maximize returns and minimize risk [22].

Portfolio optimization is the method of determining the best combination of securities and stock with the object of having less risk and obtaining more profit in an investment [23]. The basic theory of portfolio optimization can be traced back to Markowitz (1952), who advised the choice and allocation of investments based on mean-variance analysis. According to Markowitz, the two main factors in portfolio optimization are risk and return factors.

The main purpose of the Markowitz model is to institute a numeric relationship between return and risk and to obtain the average expected return at the lowest risk level or to obtain the maximum return at the average risk level [24].

2.2. Markowitz Mean-Variance Model

Markowitz was the one who introduced and developed the concept of portfolio diversification. He showed in general how the diversification of the portfolio reduces the risk for the investor. Investors can obtain an efficient portfolio for a given return by minimizing portfolio risk. Further, the above process can lead to the formation of efficient baskets called the mean-variance efficient boundary. Logical investors always pursue the lowest risk under a specific expected return or the highest return under a particular risk, choosing an appropriate portfolio to maximize the expected utility [25].

Markowitz model is a method used to optimize the portfolio and involves some mathematics, which makes it possible to construct a stock portfolio with different combinations. This model is all about maximizing return and minimizing risk, but simultaneously. The MVO model made use of mean and variance, which are calculated from historic stock prices, to quantify the expected return and risk of the generated portfolio. The MVO model maximizes the expected return for a certain level of risk or minimizes risk for a given [26].

In the model, firstly, each of the stocks was given equal weight and the optimal distribution was calculated according to various equation constraints. The equation constraints are shown below.

1) A Sum of stocks' weights will be a maximum of 1.
2) Changing variables for the optimization are the weights of the stocks.
3) To obtain an average return for the minimum risk, the standard deviation is arranged as a minimum during the optimization process.

4) To calculate the maximum return for the given level of risk, the average return of the portfolio is arranged as the maximum value during the optimization process.

To obtain the optimal portfolio selection in the Markowitz method that has the least variance for a specific level of return, we have the following linear programming model [24].

Following Markowitz (1952, 1959) we define the problem of portfolio selection as follows:

Suppose there are N stocks with a return $r_1, \dots, r_n$. Then the return expectancy value vector is given by [6]:

$$\mu^T = (\mu_1, \dots, \mu_N) \text{ , with } \mu_i = E[r_i], i = 1, \dots, N \quad (1)$$

And the covariance matrix is given by:

$$\Sigma = (\sigma_{ij})_{i,j=1,\dots,N}, \text{ with } \sigma_{ij} = cov(r_i, r_j) \text{ }, i, j = 1, \dots, N \quad (2)$$

The MVO model is described as follows:

$$Minimize \ \sigma_p^2 = \sum_{i=0}^{N} \sum_{j=0}^{N} w_i w_j \ cov(r_i \ , r_j) \quad (3)$$

$$Subject \ to \ \sum_{i=1}^{N} w_i \ E(r_i) = E(r_p)$$

$$\sum_{i=1}^{N} \mathrm{w_i}=1$$

$$w_i \geq 0 \qquad i = 1 , 2 , 3 , \cdots , N$$

In relation (3) we have:

σ_p^2 = Portfolio variance (risk)

w_i = Weight of each i stock in the portfolio

$E(r_i)$ = Average return on stock i

$E(r_p)$ = Expected return of the portfolio

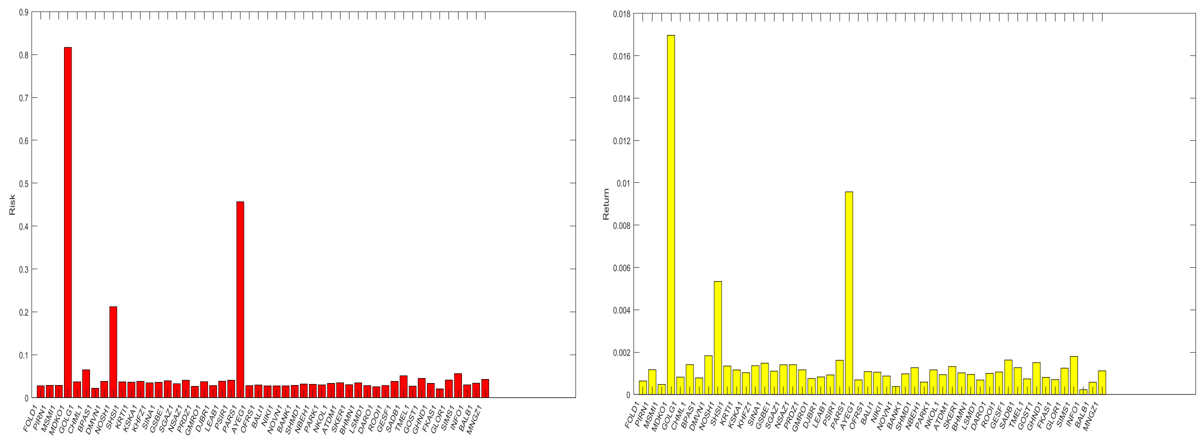

Fig. 1: Risk and Return Stocks

2.3 Structure Minimum Spanning Tree (MST)

The spanning tree with minimum weight is called the minimum spanning tree (MST) [27]. The MST provides an applied tool based on which many valuable types of research were conducted in studying different aspects of financial systems [28]. First, we quantify the degree of similarity between the simultaneous time evolution of a pair of stock prices by the correlation coefficient.

Let $p_i(t)$ be the closing price of stock i on day t. Then, the price return of stock i on day t, denoted by $r_i(t)$, is defined as:

$$r_i(t) = ln\left[\frac{p_i(t)}{p_i\ (t-1)}\right] \tag{4}$$

The correlation coefficient is defined as:

$$\rho_{i,j}(t) = \frac{\langle r_i\ r_j\rangle - \langle r_i\rangle\langle r_j\rangle}{\sqrt{(\langle {r_i}^2\rangle - \langle r_i\rangle^2)(\langle r_j^2\rangle - \langle r_j\rangle^2)}} \tag{5}$$

By definition, $\rho_{i,j}$(t) can vary from −1 (completely anti-correlated pair of stocks) to 1 (completely correlated to a pair of stocks). When $\rho_{i,j}(t) = 0$ the two stocks are uncorrelated. Where the brackets mean a temporal average over the period we studied. The correlation coefficient for logarithm price differences (which almost coincide with stock returns) is computed between all the possible pairs of stocks present in the considered portfolio. The matrix of the correlation coefficient is a symmetric matrix with $\rho_{i,j}(t) = 1$ in the main diagonal.

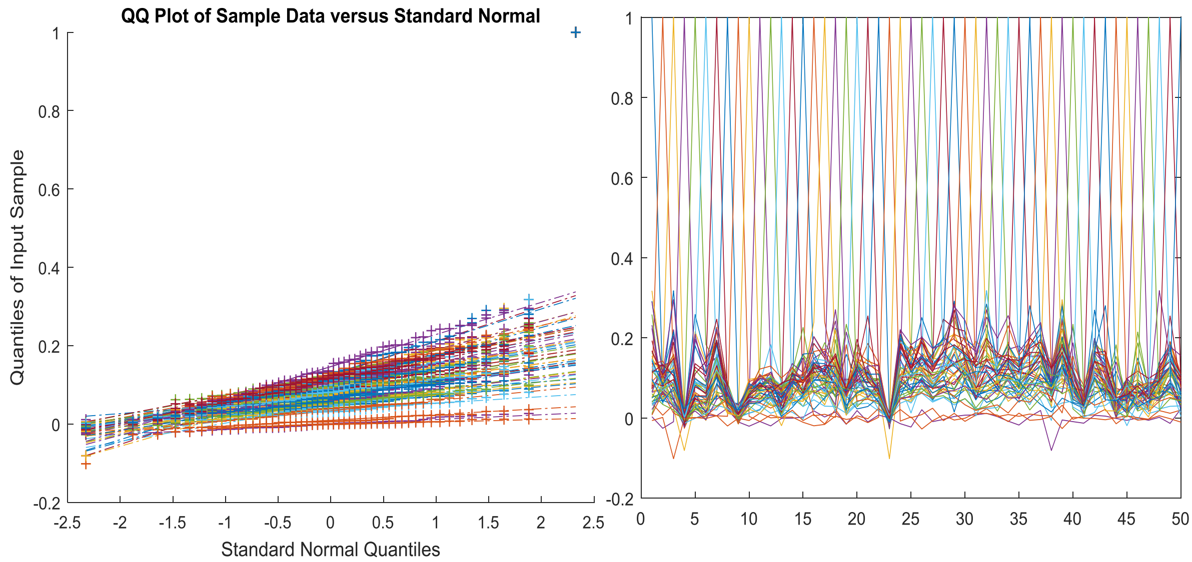

Fig. 2: Correlation between Stocks and QQ. Plot

A metric distance between a pair of stocks can be rigorously determined [29] by defining:

$$d_{i,j}\ (t) = \sqrt{2(1 - \rho_{i,j}(t))} \tag{6}$$

With this choice, $d_{i,j}$ (t) fulfills the three axioms of a metric:

1) $d_{i,j}$ (t) = 0 if and only if i = j
2) $d_{i,j}$ (t) = $d_{j,i}(t)$
3) $d_{i,j}(t) < d_{i,k}(t) + d_{k,j}(t)$

The distance matrix D(t) is then used to determine the MST connecting the 50 stocks. The MST is particularly appropriate for extracting the most important information when many linkages are under investigation [8].
According to the calculations made by coding in MATLAB, the correlation matrix between stocks is shown in Fig 3 as follows:

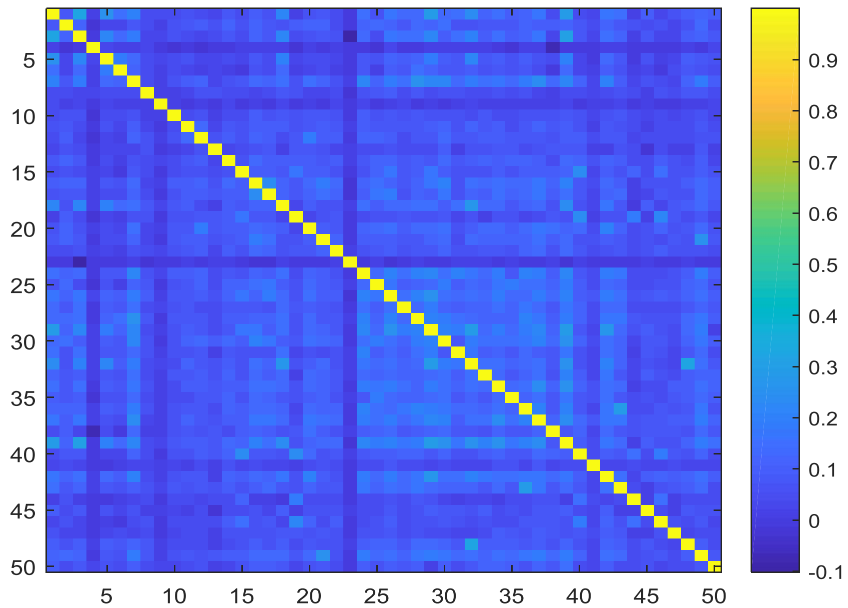

Fig. 3: Correlation Matrix between Stocks

Also, the distance matrix between stocks according to the calculations made in MATLAB is shown in Fig 4 as follows:

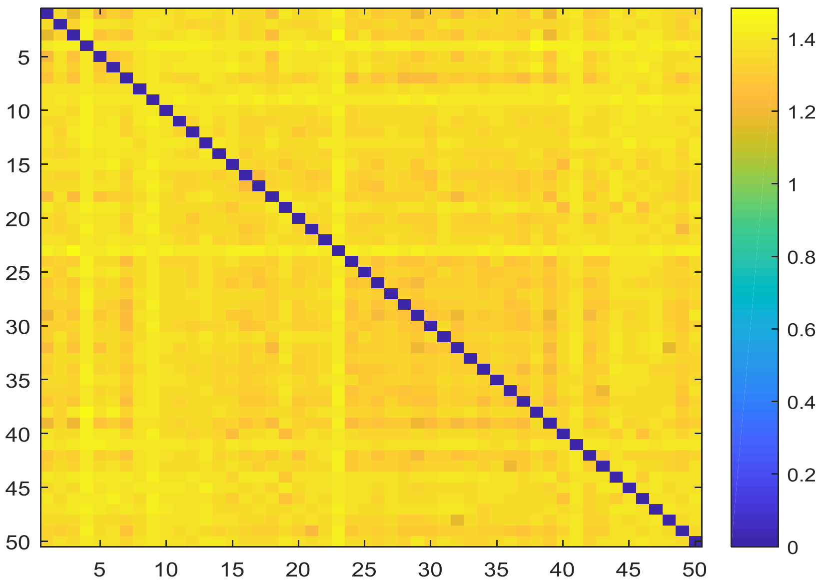

Fig. 4: Distance Matrix between Stocks

Based on all these results, the correlation network between stocks can be generated in Fig 5 as follows:

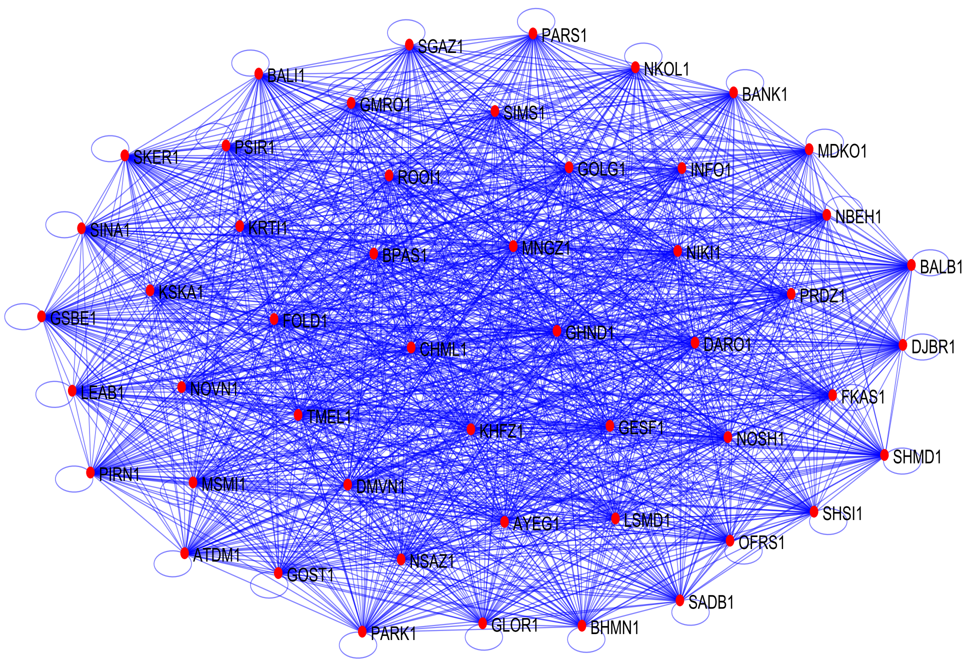

Fig. 5: Correlation Network between Stocks

Also, the graph of the stock distance matrix is calculated and shown in Fig 6 as follows:

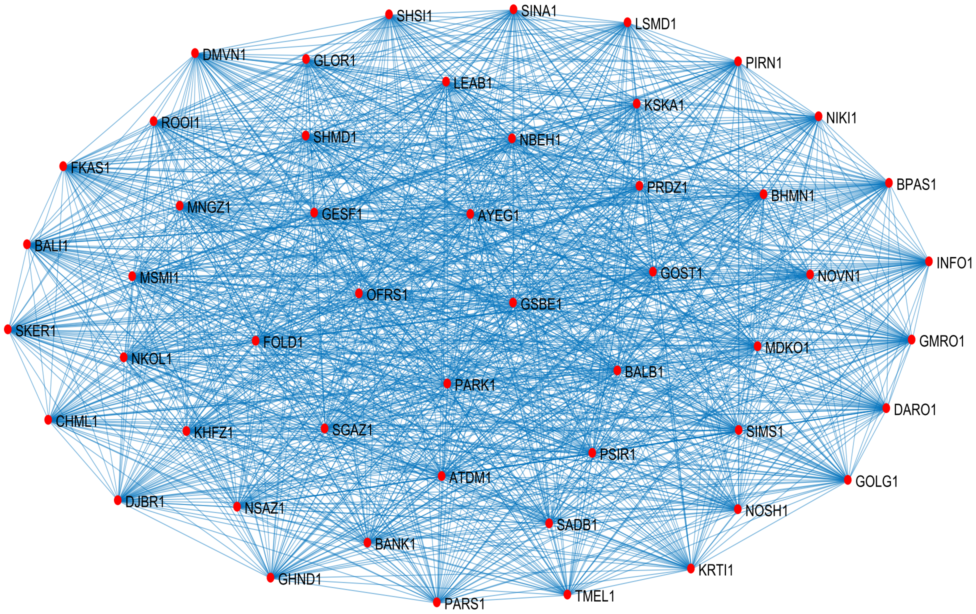

Fig. 6: Graph Distance Matrix

The minimum spanning tree visualization is shown as follows in Fig 7 as follows:

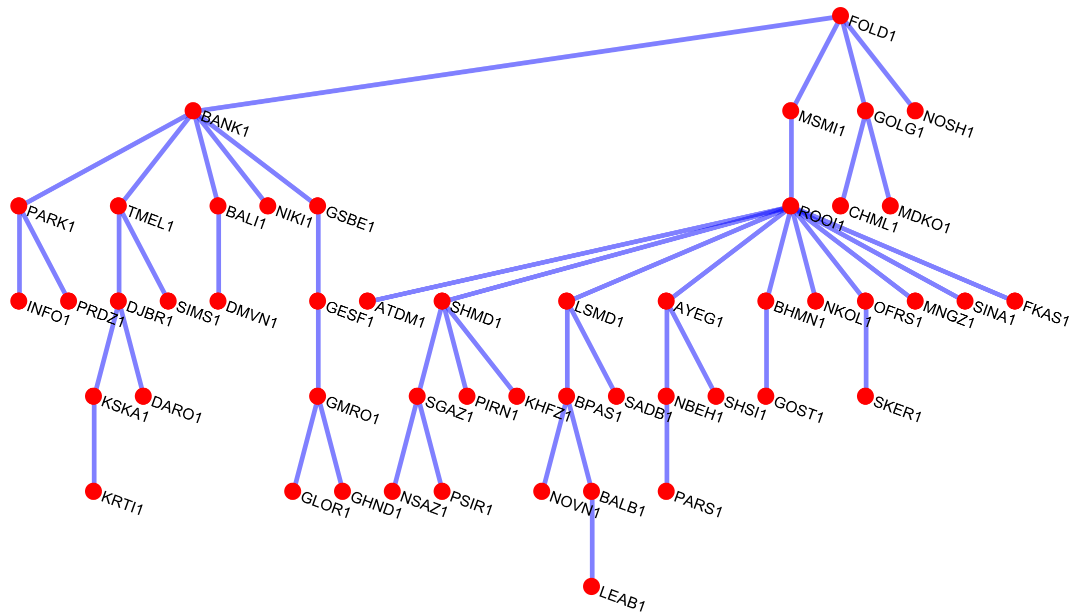

Fig. 7: Minimum Spanning Tree of 50 Stocks in the TSE

The minimum spanning tree visualization with the distance between the stocks is shown in Fig 8 as follows:

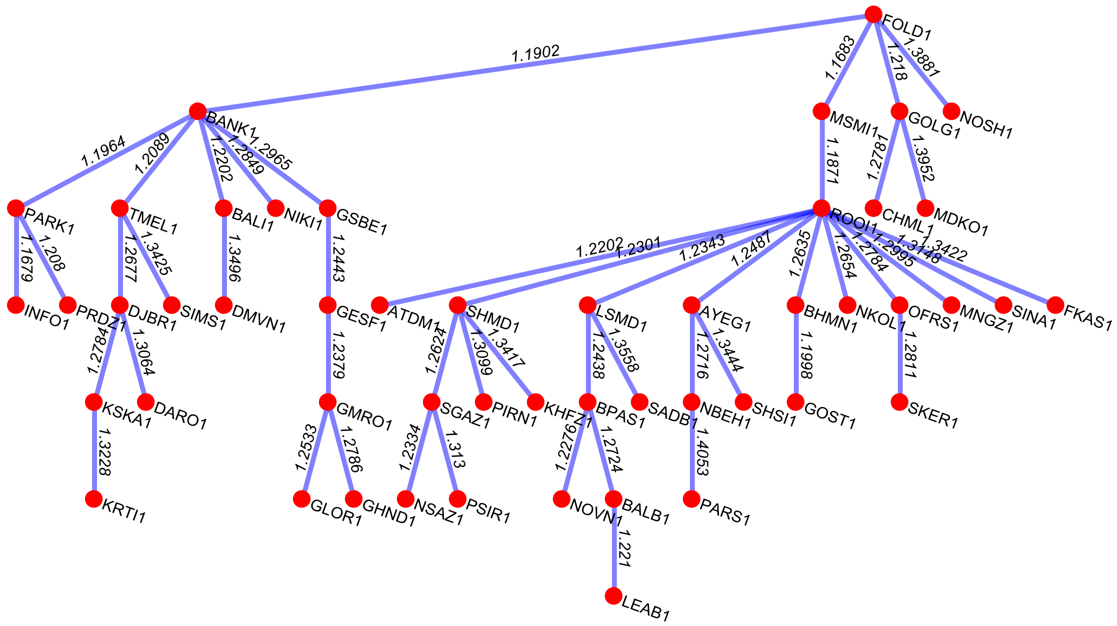

Fig. 8: Minimum Spanning Tree of 50 Stocks in the TSE

The filtering approach based on the MST can also be used to consider aspects of portfolio optimization and to do a correlation-based classification. In short, the study of correlation-based financial networks is able to filter out economic information from the correlation coefficient matrix of a set of financial time series [29]. A visualization of the MST shows the existence of well-characterized clusters. The minimum spanning tree presents a few clusters composed of stocks working in the same part and many stocks having a single link [30]. Examples are the cluster of basic metals. Most of these stocks connect with a reference stock that, in the present network, is ROOI1.

3 Results

In this section, the results of stock portfolio optimization with the Markowitz'mean-variancece method are presented. Finally, the efficient frontier curve of the portfolio is determined for 50 stocks in the TSE .Creating optimal portfolio allocation is very important, which guarantees the main goals of the investor in the form of maximizing returns or minimizing the degree of investment risk. In the analysis, first, we're minimizing the risk degree of the investments.An optimal portfolio allocation that provides an average expected return with the lowest risk level is shown in Table 1 as follows. According to Table 1, it is observed that MDKO1 has the highest return with 0.016964821, on the other hand, it has also the highest standard deviation. PARS1 is ranked as the 2nd highest stock in return with 0.009569826 and 0.456611305 standard deviations. NOSH1 is ranked as the 3rd highest stock in return with 0.005335935 and 0.211941463 standard deviations. After solving the optimizing equation to minimize risk level and get an average return, Table 1 is obtained.

Table 1: Optimal Portfolio Allocation That Shows Average Expected Return with Lowest Risk Level

Symbol	Full name	Average Return	Standard Deviation	Weight
FOLD1	S*Mobarakeh Steel	0.000634835	0.027490140	0.025451187
PIRN1	Pumpiran	0.001167464	0.028462601	0.041536271
MSMI1	S*I. N. C. Ind.	0.000470769	0.028514980	0.025446990
MDKO1	Khavarmianeh Ins.	0.016964821	0.816649823	0.000362996
GOLG1	Gol-E-Gohar.	0.000818267	0.036815288	0.014370200
CHML1	Chadormalu	0.001409756	0.064795228	0.000000000
BPAS1	S*Pasargad Bank	0.000781521	0.021877630	0.068251542
DMVN1	Damavand Min.	0.001829559	0.037914915	0.032853042
NOSH1	Noush Maz.	0.005335935	0.211941463	0.001128301
SHSI1	Sina Chem. Ind.	0.001343076	0.036642185	0.031497281
KRTI1	Iran Carton	0.001157948	0.035976352	0.026902693
KSKA1	Kaveh Paper	0.001030610	0.037971784	0.011947358
KHFZ1	Hafez Tile	0.001360247	0.034445157	0.051238428
SINA1	Sina Tile	0.001475497	0.035697371	0.018191831
GSBE1	S*Sabet Khorasan	0.001100571	0.039257442	0.008590815
SGAZ1	Glass and Gas	0.001398848	0.032367836	0.007841389
NSAZ1	Azar Refract.	0.001403544	0.040471042	0.000000000
PRDZ1	Pardis Petr.	0.001162554	0.026283206	0.036035238
GMRO1	Marvdasht Sugar	0.000753084	0.037088055	0.017971814
DJBR1	Jaber Hayan P.	0.000826543	0.028152671	0.027357348
LEAB1	Loabiran	0.000920999	0.038283793	0.004372321
PSIR1	Iran Glass Wool	0.001613339	0.040593419	0.013542975
PARS1	PARS Petrochemical	0.009569826	0.456611305	0.000569637
AYEG1	Pardis Investment	0.000686203	0.028055767	0.015796606
OFRS1	Fars Dev.	0.001079131	0.029406048	0.023213990
BALI1	Buali Inv.	0.001051918	0.027236084	0.002757575
NIKI1	Iran N. Inv.	0.000870253	0.027164513	0.040838408
NOVN1	S*EN Bank	0.000375910	0.027357668	0.010715896
BANK1	Bank Melli Inv.	0.000973894	0.028283938	0.000000000
SHMD1	Hamadan Glass	0.001266110	0.031654296	0.000000000
NBEH1	Behran Oil	0.000583673	0.030999924	0.027567130
PARK1	Shazand Petr.	0.001160479	0.029525221	0.000000000
NKOL1	NiroCholor	0.000932952	0.033167129	0.006540718
ATDM1	Atye Damavand	0.001318406	0.034597556	0.000000000
SKER1	Kerman Cement	0.001018504	0.030123724	0.024523573
BHMN1	Bahman Group	0.000944734	0.034423779	0.000000000
LSMD1	Ind. & M. L.	0.000681585	0.028029014	0.004746398
DARO1	Daroupakhsh	0.000995533	0.025342841	0.063891668
ROOI1	Iran Zinc Mines	0.001059548	0.028173917	0.000000000
GESF1	Isfahan Sugar	0.001625476	0.037742167	0.000000000
SADB1	Ardebil Cement	0.001266883	0.050932183	0.017621110
TMEL1	Tosee Melli Inv	0.000733132	0.026703669	0.016423295
GOST1	Iran Kh. Inv.	0.001506039	0.044675801	0.000000000
GHND1	Khoy Sugar Co.	0.000804069	0.033054518	0.049838121
FKAS1	Khorasan Steel Co.	0.000704230	0.020336541	0.160261367
GLOR1	Lorestan Sugar	0.001241364	0.040981226	0.011399377
SIMS1	Shomal Cement	0.001794054	0.056037386	0.007745395
INFO1	Inf. Services	0.000226005	0.029763713	0.037854360
BALB1	S*Alborz Bimeh	0.000578690	0.033655504	0.000000000
MNGZ1	Iran Mn. Mines	0.001114845	0.042336068	0.012805356

It should be highlighted that to attain this target, 11 out of 50 stocks are excluded from the portfolio and FKAS1, BPAS1, DARO1, and KHFZ1 will have the most shares (weights) the in portfolio by 0.160261367, 0.068251542, 0.063891668 and 0.051238428 respectively.

Table 2: Portfolio Optimization at The Minimum Point

Portfolio Return	0.000956657
Portfolio Variance	0.00009222
Portfolio Standard Deviation	0.009602922

The best solution for the overall portfolio can be outlined as an average return is 0.000956657 with a minimum standard deviation is 0.009602922, which is shown in Table 2.

Another main objective is to maximize the return with the average standard deviation of the investment portfolio. Similar to the first optimization process, the results are shown in the table below. The portfolio optimization that provides the maximum expected return with a given average level is shown in Table 3.

Table 3: Optimal Portfolio Allocation That Provides Maximum Expected Return with Average Risk Level

Symbol	Full name	Average Return	Standard Deviation	Weight
FOLD1	S*Mobarakeh Steel	0.000634835	0.027490140	0.00000000
PIRN1	Pumpiran	0.001167464	0.028462601	0.00000000
MSMI1	S*I. N. C. Ind.	0.000470769	0.028514980	0.00000000
MDKO1	Khavarmianeh Ins.	0.016964821	0.816649823	0.99999284
GOLG1	Gol-E-Gohar.	0.000818267	0.036815288	0.00000071
CHML1	Chadormalu	0.001409756	0.064795228	0.00000000
BPAS1	S*Pasargad Bank	0.000781521	0.021877630	0.00000087
DMVN1	Damavand Min.	0.001829559	0.037914915	0.00000000
NOSH1	Noush Maz.	0.005335935	0.211941463	0.00000000
SHSI1	Sina Chem. Ind.	0.001343076	0.036642185	0.00000000
KRTI1	Iran Carton	0.001157948	0.035976352	0.00000094
KSKA1	Kaveh Paper	0.001030610	0.037971784	0.00000000
KHFZ1	Hafez Tile	0.001360247	0.034445157	0.00000000
SINA1	Sina Tile	0.001475497	0.035697371	0.00000000
GSBE1	S*Sabet Khorasan	0.001100571	0.039257442	0.00000093
SGAZ1	Glass and Gas	0.001398848	0.032367836	0.00000000
NSAZ1	Azar Refract.	0.001403544	0.040471042	0.00000000
PRDZ1	Pardis Petr.	0.001162554	0.026283206	0.00000000
GMRO1	Marvdasht Sugar	0.000753084	0.037088055	0.00000000
DJBR1	Jaber Hayan P.	0.000826543	0.028152671	0.00000000
LEAB1	Loabiran	0.000920999	0.038283793	0.00000000
PSIR1	Iran Glass Wool	0.001613339	0.040593419	0.00000000
PARS1	PARS Petrochemical	0.009569826	0.456611305	0.00000000
AYEG1	Pardis Investment	0.000686203	0.028055767	0.00000000
OFRS1	Fars Dev.	0.001079131	0.029406048	0.00000000
BALI1	Buali Inv.	0.001051918	0.027236084	0.00000000
NIKI1	Iran N. Inv.	0.000870253	0.027164513	0.00000000
NOVN1	S*EN Bank	0.000375910	0.027357668	0.00000000
BANK1	Bank Melli Inv.	0.000973894	0.028283938	0.00000000
SHMD1	Hamadan Glass	0.001266110	0.031654296	0.00000000
NBEH1	Behran Oil	0.000583673	0.030999924	0.00000000
PARK1	Shazand Petr.	0.001160479	0.029525221	0.00000000
NKOL1	NiroCholor	0.000932952	0.033167129	0.00000072
ATDM1	Atye Damavand	0.001318406	0.034597556	0.00000061
SKER1	Kerman Cement	0.001018504	0.030123724	0.00000000
BHMN1	Bahman Group	0.000944734	0.034423779	0.00000000

Table 3: Continu

LSMD1	Ind. & M. L.	0.000681585	0.028029014	0.00000000
DARO1	Daroupakhsh	0.000995533	0.025342841	0.00000000
ROOI1	Iran Zinc Mines	0.001059548	0.028173917	0.00000000
GESF1	Isfahan Sugar	0.001625476	0.037742167	0.00000000
SADB1	Ardebil Cement	0.001266883	0.050932183	0.00000000
TMEL1	Tosee Melli Inv	0.000733132	0.026703669	0.00000081
GOST1	Iran Kh. Inv.	0.001506039	0.044675801	0.00000000
GHND1	Khoy Sugar Co.	0.000804069	0.033054518	0.00000095
FKAS1	Khorasan Steel Co.	0.000704230	0.020336541	0.00000000
GLOR1	Lorestan Sugar	0.001241364	0.040981226	0.00000000
SIMS1	Shomal Cement	0.001794054	0.056037386	0.00000000
INFO1	Inf. Services	0.000226005	0.029763713	0.00000000
BALB1	S*Alborz Bimeh	0.000578690	0.033655504	0.00000000
MNGZ1	Iran Mn. Mines	0.001114845	0.042336068	0.00000062

Table 4: Portfolio Optimization at The Maximum Point

Portfolio Return	0.016964707
Portfolio Variance	0.66690739
Portfolio Standard Deviation	0.816643979

After solving the optimization equation to maximize the expected return level based on a given level of average standard deviation, Table 3 is obtained. It should be highlighted that to attain this target, nearly all stocks are excluded from the portfolio except for MDKO1. MDKO1 has all shares (weights) in the portfolio by 0.99999284 by providing 0.016964821 return and 0.816649823 standard deviations. The best solution for the overall portfolio can be outlined as an average return is 0.016964707 with a minimum standard deviation is 0.816643979, which is shown in Table 4.

Based on all these results, the efficient frontier curve of the portfolio is calculated and shown in Fig 9 as follows:

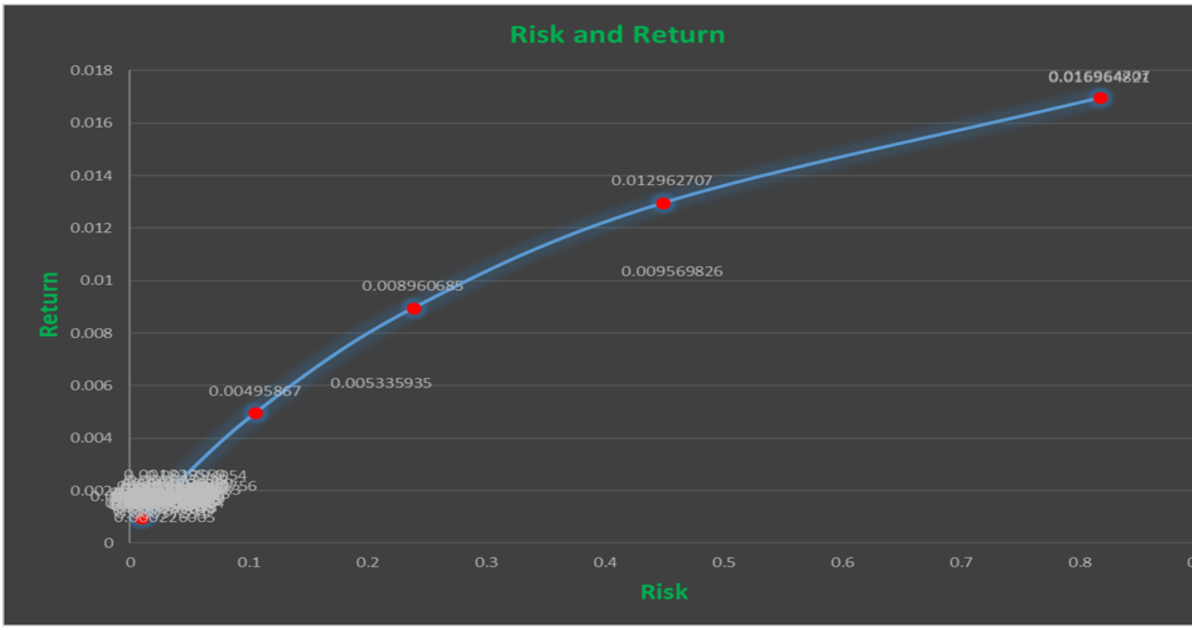

Fig. 9: The Efficient Frontier Curve of the Portfolio

The efficient Frontier Curve underpins portfolio theory. This curve shows the best rate of return an investor can obtain against the risk. The Efficient Frontier Curve shows the portfolio with the highest return at a given risk level or the portfolio with the lowest risk against a specific return target. Points above the curve in the graph represent optimal portfolio returns.

The variance matrix of stocks according to coding in MATLAB is shown below:

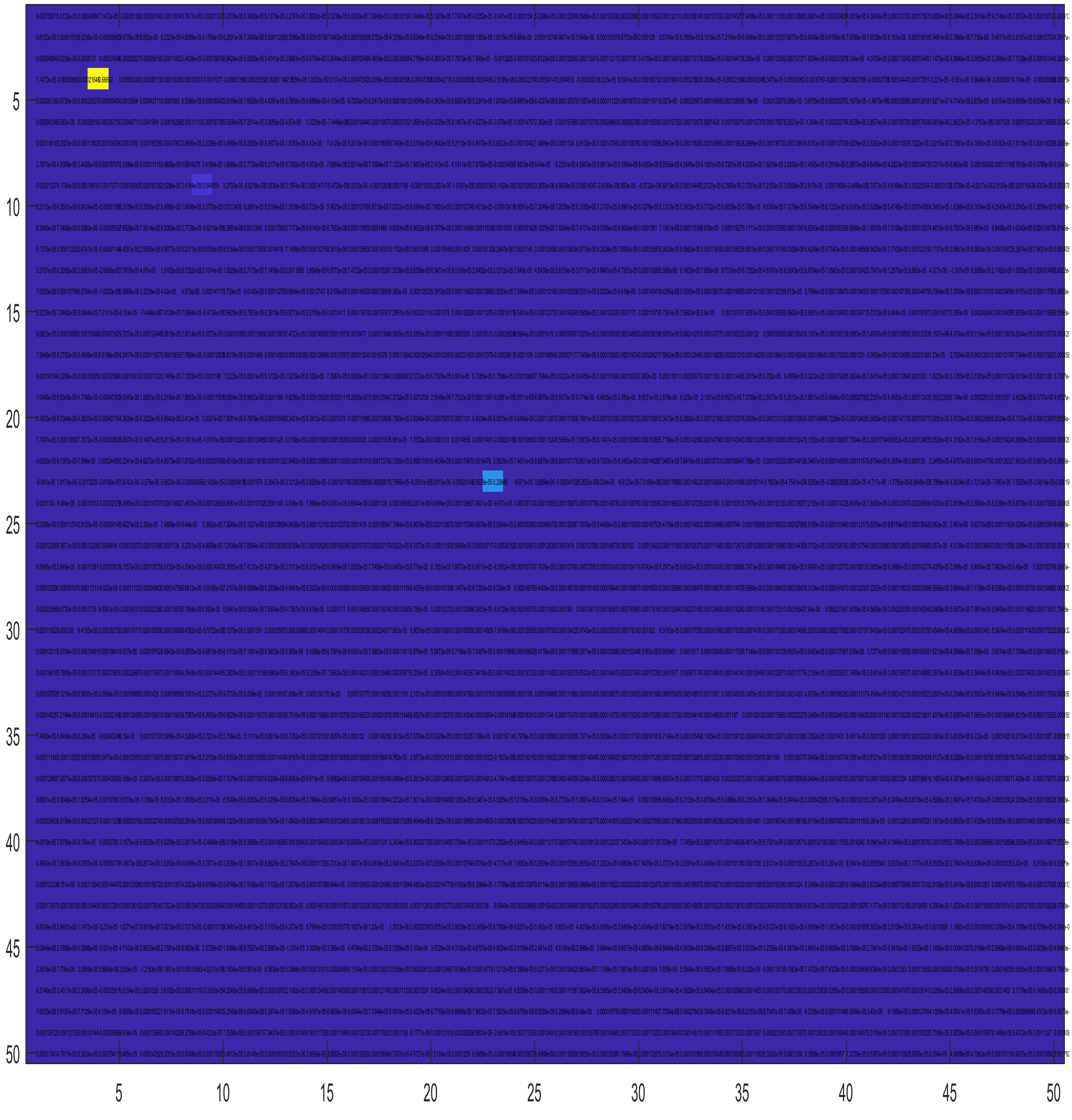

Fig. 10: Variance Matrix between Stocks

4 Conclusion

Today, one of the major concerns of investment managers is optimal decisions in a large volume of information and data on stocks and capital markets. Especially when investment diversification increases, optimal decision-making is very important given the limits of expected returns and the level of risk [21]. The two basic criteria of portfolio management are risk and portfolio return, respectively. Modern portfolio optimization led by Markowitz establishes a quantitative relationship between return and risk. An investor can obtain the average expected return at the minimum risk level or the maximum return at the average risk level In this paper, we studied the Markowitz model to optimize the stock portfolio in the period from January 2012 to October 2022 period. The stock price return was calculated daily basis, and the variance and standard deviation of the stock return were calculated based on the calculated return. The main objective of this study is to create a portfolio allocation that provides the average expected return at the minimum risk level and the maximum expected return at the medium risk level. When the analysis is performed to obtain the average expected return at the minimum risk level of the portfolio of stocks, 11 stocks are not included in the optimal portfolio. FKAS1, BPAS1, DARO1, and KHFZ1 shares have the highest shares in the optimal portfolio with 0.160261367, 0.068251542, 0.063891668, and 0.051238428, respectively. The average return of the portfolio that fulfills the minimum risk level average return requirement was determined as 0.000956657 and its standard deviation as 0.009602922. When the analysis is made to obtain a maximized expected return at the average risk level of the portfolio, only MDCO1 stock is included in the optimal portfolio. In other words, the optimal portfolio has only MDCO1 stock and its expected return is 0.016964707. The expected return of the portfolio that fulfills the average risk level with maximized return requirement was determined as 0.016964707 and its standard deviation as 0.816643979.

In the next section, we identified the minimum spanning tree (MST) structure in the portfolio consisting of 50 stocks traded in the Iranian stock market. To detect the minimum spanning tree (MST) of the stock, we used the simultaneous correlation coefficient of the daily difference of the logarithm of the closure price of stocks. According to the minimum spanning tree structure, the stock network is divided into several clusters, and each cluster contains approximately one industry. In conclusion, the main target of this paper is to link stocks traded in a financial market, which has associated with a meaningful economic taxonomy. The present study shows that it is possible to determine an MST starting from the distance matrix of equation (4). The detected MST might be useful in the theoretical description of financial markets and the search for economic factors affecting specific groups of stocks. The classification associated with the MST structure is obtained by using information present in the time series of stock prices only. This result shows time series of stock prices are carrying valuable economic information.

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