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Investigating the Effects of New Corporate Liquidity and Market Operational Performance Indicators on the Markowitz Model Portfolio Returns Using Genetic Algorithm: A Case Study on Refineries and Petrochemical Companies Listed on Tehran Stock Exchange

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ABSTRACT

The research on the Markowitz model and optimization of its portfolio using a variety of evaluation indicators and metaheuristic-algorithms has always been the focus of attention of accounting and finance researchers. The results of studies carried out by various types of optimization method are different in the Markowitz modified models. The purpose of this study is to measure the optimal portfolio and its corresponding return with respect to the portfolio in the traditional Markowitz model as well as comparing the position of the refining and petrochemical companies versus stock market outperformers through integrating the operational criteria and the new indicators of liquidity by using the genetic algorithm in the Markowitz model. Therefore, financial data related to the research variables of 35 cases of refinery and petrochemical companies listed on Tehran Stock Exchange (TSE) from 2012 to 2016 fiscal years were extracted from Rahavard Novin database software and simulated by the genetic algorithm. The results show that returns on the stock portfolios optimized using the genetic algorithm without considering the liquidity limitations and filters are significantly and positively different from the returns on the stock portfolios optimized with regarding the liquidity limitations and filters. Furthermore, the application of liquidity limitations and filters to the formation of the optimal stock portfolios leads to a conservative increase in the choice of stocks (portfolio formation), which results in a reduction in the risk and return of investment in such portfolios.

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1. Introduction

Increasing growth in financial markets has resulted in some complications, uncertainties, and risks which make it difficult for investors to make decisions about asset types. In such markets, stockholders are constantly looking for high returns which have a lower corresponding risk exposure (Ebrahimi, 2014). The creation of a portfolio, the investment policy, the expected risk-return level, and other limitations, according to which the portfolio should be formed, shall be determined, essentially, before selecting a stock or determining the composition of a portfolio (Mendes, etal.,2016). Generally speaking, the fluctuations in returns and stock prices are influenced by many systematic and unsystematic risks, and the sensitivity of the stocks varies according to these factors; hence, one of the main proposed solutions in financial discussions is the asset portfolio formation to eliminate fluctuations caused by unsystematic risks. In fact, one of the tools for managing the risk of investment portfolios is the diversification approach presented by Markowitz. This model is based on expectations of return performance and portfolio risk diversification, which is essentially a theoretical framework for analyzing risk and return criteria.

Investment management involves two main issues of security analysis and portfolio management. An analysis of securities involves estimating the benefits of a single investment, while portfolio management deals with analyzing the composition of investments and managing the holding of a set of investments. In the last decade, the trend of investment topics has changed from stock selection (portfolio analysis) into portfolio management. What has been done in the field of financial calculations, stock selection, and investment portfolio has been to prioritize existing investments in terms of risk and return in order to enable investors to take into account their financial resources and their risk appetite for making up their preferred portfolio. Therefore, an investment should lead to a maximum return potential, and this return must be constant and stable. Measuring this stability shows the risk of investing (Strong, 2009). Assigning and allocating different assets to a profitable portfolio is one of the most interesting and common issues in managing each market, especially the energy market. Considering the importance of investing in financial markets and the impact of various financial and nonfinancial indicators on profitability and increasing the value of a stock, which leads to the impact on choosing the type of stock in the optimal investor portfolio, the issues of using new indicators for measuring the level of corporate liquidity and stock liquidity, obtaining the operational efficiency of market, considering the type of industry and market studied, and using hyper-burst algorithms to assess the stock fitness in a portfolio are of particular importance in maximizing shareholder wealth. Further, due to the position of the refineries and petrochemical companies in the stock exchange as the top listed companies in recent years, the importance of investing in these sectors, and the economic dependence of the country on chemical products, it seems necessary to select refineries and petrochemical companies as the main point of focus.

In the investment market, there is a wide range of assets which have varying degrees of quality from bad to good. With regard to information asymmetry, the selection of good-quality assets (valuable assets) in practice faces particular difficulties. The Markowitz mean-variance model is considered to be the optimal combination of portfolios, so that the risk of that portfolio is minimized with respect to a certain return. Considering that portfolio selection is based only on two factors of risk and return, it has always been questioned whether in choosing the optimal portfolios all the selected assets have a desirable quality, or low quality assets may also be included in the optimized portfolio (Sarean, 2007). Investors usually use controversial goals such as returns, risk, and liquidity in portfolio selection issues (Abdul Aziz et al., 2011). Therefore, it can be stated that blindly following the Markowitz theory of optimal portfolio selection, regardless of the quality of assets, may lead to the selection of portfolios embedding low-quality assets (Lee et al., 2006). This study tries to review the effects of new indicators of corporate liquidity and operational efficiency (stock liquidity) on the portfolio returns of the Markowitz model. The purpose of this study is to first determine the position of petrochemical companies and refineries in the optimal portfolios with respect to the outperformers. Then, we will be able to use genetic algorithm for fitting stocks data and financial ratios representing new indicators of corporate liquidity and operational efficiency (stock liquidity) to be included in the portfolio. The results of this research can be used by financial analysts and other investors to increase their portfolio returns. The remaining parts of the paper are devoted to review of literature, research methodology, empirical findings, conclusions, and policy implications respectively.

2. Theoretical Foundations and Hypothesis Development

The field of investment is usually divided into two sections: "security analysis" and "investment management." The valuation of financial assets as a function of risk and return is the major task of analyzing securities. Return on investment (dividend and capital gains) is a driving force which motivates and rewards investors, but risk is a future phenomenon which cannot be accurately predicted because of uncertainty (Rae & Pouyanfar,2012). The higher uncertainty will result in a greater risk (Dianati, et al., 2010). Due to the volatility and fluctuation of prices and returns on stocks, returns on future periods are not cautious. If the securities are risky, the main issue of each investor is to determine the portfolio of securities with the maximum utility, which is equivalent to selecting the optimal portfolio from a portfolio group; this model is well known as portfolio selection problem, and was presented by Markowitz in March 1952. Markowitz states that investors must estimate the expected returns and standard deviations of each portfolio and then choose the best combination. Based on Markowitz approach, investors should focus on increasing their final wealth when deciding to buy a portfolio of their initial investment wealth (the first period) and assess their investment portfolio with criteria such as expected returns and risk (standard deviation).

As stated above, the original model proposed by Markowitz (1952) to solve the problem of choosing the optimal asset portfolio was a quadratic planning model and selected a portfolio of assets based on the minimum risk in compensation for a predetermined return. Because of the difficulties in quadrature planning and the vast scale of asset portfolio issues, researchers have tried to solve the problem employing other mathematical programming techniques (Chan et al., 1990). The model presented by Markowitz is theoretically solvable by linear models, but it encounters problems in practice. First, the nature of risk metrics precludes a general solution, and quadratic optimization techniques are not usable due to the convexity of the shape of the objective function. In addition, the typical size of real-world asset selection problems includes tens or hundreds of asset types, and the expected returns and risks of these assets are calculated using time series derived from hundreds of historical yield information. The selection of assets with the least return variance is another problem this model suffers from, which leads to choosing low-return assets because low variance requires low expected returns. Markowitz model also considers nonnegative constraints for decision variables to prevent asset sales. The above problems has led researchers to introduce new methods for solving the problem (Larsci and Tetamanzi, 1995). The extensive investigations, some of which are mentioned in the following, have all emphasized the importance of meta-heuristic algorithms in optimizing portfolios and the position of stock liquidity indicators in evaluating and selecting outperformer stocks for entering the portfolios under review.

Liquidity has long been recognized as one of the most important areas for financial innovation, and it can be used to describe firm or stock situations which are both regarded in this study. When we use "liquidity" along "corporate", we refer to a measure of whether a firm has enough cash flow to cover the cost of its operations and the payment of its bills. A firm is liquid if it has plenty of money to meet its expenses and illiquid if it does not, but liquidity of assets such as stock is referred to the ability to trade a large volume of low-cost securities at a low price effect. The ability of the market to absorb huge volumes of transactions without excessive fluctuations in prices is another definition for liquidity. In addition, the main feature of spot markets with high liquidity is the small spreads between the quotas on bid and ask, that is, the trades have the ability to convert assets into cash in an economically viable way. In general, financial liquidity is the same price of the closing transaction, assuming no new information has been received since the last transaction (Yahyazadefar, 2008). Fichter (1995) utilized genetic algorithm to manage asset portfolios, including oil and gas industry projects.

In this study, genetic algorithm with different fit functions is investigated, and the results have been compared with other methods of optimization. The results show that genetic algorithm outperforms other optimization methods. Schlottmann and Seese (2000) also employed a genetic algorithm, along with credit risk estimation, to solve the portfolio optimization problem with an emphasis on default risk. Their results showed that the hybrid genetic algorithm used in a reasonable time yielded better results than other models. This difference can be seen even in comparison with the approach of using the genetic algorithm solely.

Lazo et al. (2003) applied a genetic algorithm to selecting and managing asset portfolios. To this end, firstly, by using a genetic algorithm, 12 assets were selected from 137 assets traded on the Brazilian Stock Market of Sao Paulo (BOVESPA) between July 1994 and December 1998, and then, by using neural networks, return on each of the selected assets was predicted for the next period. Further details of the survey indicate that in the dominant position of the temporary recession of the market, the return on the selected portfolio is higher than the return on the market index, and its risk is less than market risk. Islami Bidgoli et al. (2007) optimized portfolios by completing Markowitz model. One of the criticisms of Markowitz model was that the model only considers two measures of mean and standard deviation of return, while investors practically regard different criteria when creating portfolios. Liquidity is one of the most important criteria of investors when creating portfolios. Therefore, they select optimal portfolios using three criteria of return, risk, and liquidity. In other words, in this research, the liquidity criterion has been integrated into the proposed Markowitz model with a comprehensive portfolio of investors to formulate portfolios. The results of the research show that liquidity at high levels influences investors' decisions and thus affects the effective boundaries. The results of the filter approach and the limitation of liquidity state that optimizing liquidity-based portfolios can have many benefits of reducing the risk of liquidity of investors' portfolio without losing a significant amount of expected returns per unit risk. Chang et al. (2009) introduced a heuristic approach to portfolio optimization problems in different risk measures by employing genetic algorithm (GA) and compared its performance to mean-variance model in terms of cardinality constrained efficient frontier. They collected three different risk measures based upon mean-variance by Markowitz, namely semi-variance, mean absolute deviation, and variance with skewness. The results indicated that these portfolio optimization problems can now be solved by genetic algorithm if mean-variance, semi-variance, mean absolute deviation, and variance with skewness are used as the measure of risk. The robustness of the heuristic method was verified by three data sets collected from main financial markets. The empirical results also demonstrated that the investors should include only one third of their total assets in the portfolio which outperforms those containing more assets. Soleimani et al. (2009) developed a portfolio selection model based on Markowitz portfolio selection problem including three of the most important limitations; their results could make Markowitz model more practical. Minimum transaction lots, cardinality constraints, and market (sector) capitalization were also considered in the extended model. To solve this mixed-integer nonlinear program (NP-Hard), a corresponding genetic algorithm (GA) was utilized, and the results showed the outperformance of Markowitz model when using three limitations.

Hosseini et al. (2010) investigated the relationship between the business unit performance and the liquidity of shares of the companies listed on Tehran Stock Exchange. They investigated and compared the relationship between performance and stock liquidity based on representations and feedback theories using multivariate regression. Findings of the research show that there is a meaningful relationship between the liquidity and performance criteria of the company. Garchek et al. (2010) took the various definitions of risk into account to select and optimize stock portfolios. Since the selection of portfolios to maximize return is one of the main concerns of investors in financial markets, ultra-innovative algorithms are efficient in portfolio selection and therefore have been used to solve this problem. The results of the research show that the genetic algorithm designed at different repetitions has a high level of optimality and stability, and the use of genetic algorithm enables investors to select the optimal portfolios. Demurry et al. (2011) used the algorithm of flying birds to predict stock price index, and the designed model was compared with traditional patterns suggesting the better prediction of the model of flying birds. Garkaz et al. (2011) conducted a study to optimize the stock portfolio based on semivariance risk criterion. They designed a genetic algorithm and mean-semivariance and then added some of the real world limitations to the model. Their findings indicated the optimum and high stability of genetic algorithm at different frequencies. Zarranezhad et al. (2015) evaluated the optimum portfolio selection using particle swarm algorithm and genetic algorithm. They collected financial information on companies listed on Iran Stock Exchange during years 2007 to 2012 and used genetic algorithm based on Markowitz model, mean-variance model, and client risk model to generate optimal portfolio from the stocks investigated. The results showed that using this algorithm can provide solutions close to optimality and gives investors the confidence to make decisions about investment. Also, they concluded that Markowitz and mean-variance models can provide most optimal portfolio, and particle swarm algorithm performs best in client risk model. Venturelli and Kondratyev (2019) developed a hybrid quantum-classical solution to the mean-variance portfolio optimization problems. They examined several options to run the quantum computation optimally and ultimately discovered that the best results in terms of expected time-to-solution as a function of the number of variables for the hardest set of instances are obtained by seeding the quantum annealer with a solution candidate found by a greedy local search and then performing a reverse annealing protocol. The optimized reverse annealing protocol is found to be more than 100 times as fast as the corresponding forward quantum annealing on average.

The central hypothesis of this research is based on the weakness of Markowitz model because it limits the portfolio optimization to only expected return and risk criteria despite its essential features. However, many researches have criticized the ignorance of other investor preferences in this model because the investor applies conflicting objectives such as returns, risks, and liquidity simultaneously. For this reason, Markowitz model has been attempted to be integrated into one of the other essential criteria (liquidity) to which investors are paying particular attention when buying stocks. Therefore, part of the additional return on equity is expected to compensate for the lack of liquidity in the stock market; in other words, it is expected to be a negative relationship between the level of liquidity and expected return on investment (Wimin Leo et al., 2013). Therefore, using genetic algorithms, we attempt to establish a portfolio that achieves higher liquidity levels without losing a lot of returns. Generally, the main hypothesis of the research states that the portfolio optimized using the genetic algorithm and without considering the liquidity constraints outperforms the optimized stock portfolios which consider the liquidity limitations and filters significantly. This hypothesis can be broken down into two sub-hypotheses, and the results are analyzed using analysis of variance (ANOVA) test in the form of the Scheffe test.

- First sub-hypothesis: The return on the optimal portfolios using the genetic algorithm and without considering the liquidity indicators is higher than the return on the stock portfolios optimized by considering liquidity limitations significantly.
- Second sub-hypothesis: The return on the optimal portfolios using the genetic algorithm and without considering the liquidity indicators is higher than the return on the stock portfolios optimized by applying liquidity filters significantly.

The distinction between the present study and internal research can be found in two new financial ratios due to the importance of assets and associated depreciation costs, which have a significant impact on profitability and the first class of cash flows: during weighting and classifying the initial stocks of companies and during using new liquidity indicators for liquidity limitation and filters which have replaced traditional indicators. However, the difference between the current work and foreign research can be attributed to the lack of information disclosed in the financial statements, due to the type of financial statement structure, to use other new indicators of liquidity to optimize portfolios. The indicator of liquidity include debt maturity index, current debt, and receivables matching index, etc. because of the disclosure of liquidity surplus and cash payments in the financial statements and the Lambda index owing to the lack of disclosure of information such as the amount of credit in the current account and the amount of cash flow dispersion.

3. Methodology

The present work is applied research in terms of the purpose and quantitative research in terms of research choice. The strategy of this research is a kind of archival study that uses a deductive approach to generalizing the results. The data used in this study were extracted from Rahavard database software and, after initial processing in Microsoft Excel, were imported into lite software for subsequent processing. The theoretical scopes of the study can be limited to financial management, investment management, or risk management, and, in particular, to modern portfolio theory. The spatial scope (statistical population) of the research is limited to the refineries and petrochemical companies listed on Tehran Stock Exchange (traded stocks at TSE as well as over the counter (OTC) market). The time horizon of the research ranges from 2012 to 2016. All the companies possessing the following features have been investigated as the final sample (biased sampling):

- Companies that do not stop stocks trading for more than three months because investors never buy the stocks of the companies which stop the symbol for a long time. Thus, this condition was used to capture investors' preferences.
- Companies the financial information of which was available for the five years of time scope. Obviously, lacking financial information will remove the corresponding company from the process.

Regarding the above filters, the statistical sample of the research contained 35 refineries and petrochemical companies along with eight best-seller companies the main activities of which are similar to those of refining and petrochemical companies. Markowitz model was compared with the modified Markowitz model in two ways using the new indicators of liquidity and operational efficiency of the capital market. Once using three new indicators of valuation and two capital market operating efficiency indicators (a total of five indicators), a 10-stock portfolio was created and compared with a portfolio including 10 stocks which were generated using six primary financial indicators (liquidity filter approach). Once again, using a total of 11 indicators, including six financial indicators and five new indicators of liquidity and operational efficiency of the capital market, a 10-stock portfolio was created and compared with a portfolio including 10 stocks which were generated using six primary financial indicators (liquidity constraint approach). In order to test the research hypotheses, to answer the questions, and to estimate variance-covariance matrix, the genetic algorithm model was used along with the Eviews 10 software; MATLAB software and SPSS were also utilized for linear programming and the Scheffe post hoc test respectively.

3.1. Corporate Liquidity Measures

Considering the implications of traditional liquidity indicators of corporations, the speed of repayment of current debts, and most notably the unmatched levels of liquidity of current assets, financial researchers have sought to introduce indicators that provide details of the liquidity situation in companies while addressing these issues. The financial ratios used for the new liquidity indicators are derived as follows:

Cash Conversion Cycle (CCC) has been mentioned as a vital component of working capital management. Cash conversion cycle is the net period between the payment of debts and cash receipts from the sources where the receivables are collected. A shorter period denotes that the company has better liquidity. The formula for calculating the CCC index is given by (Equation 1):

$$\begin{aligned} CCC &= OC - PP \\ OC &= INVP + RP \\ PP &= PA / DCOGS \end{aligned} \tag{1}$$

where, OC is operating cycle, and RP stands for time to collect receivables; INVP, PA, and DCOGS represent inventory held period, account payables, and daily cost of goods sold (which is equal to cost of goods sold (COGS) divided by 365, i.e. COGS/365) respectively.

Inclusive Liquidity Index addresses the problem of not considering the degree of liquidity of current assets and the time of repayment of current debt by calculating the weighted average of the current ratio. The index is calculated as follows (Equation 2):

$$ACR = ACA / LCA \tag{2}$$

Where, ACA denotes adjusted current assets and LCA stands for adjusted current liabilities. Under this indicator, a certain weight is assigned to each current asset and liability, depending on their liquidity (maturity) status, and their adjusted amounts are calculated. The weight of each asset/liability is related to the following conditions:

- It is the inverse turnover of each asset.
- In cash, due to the fact that it is essentially the most liquid asset, a coefficient equal to one is allocated and it does not need to be adjusted (multiplied by one).
- Because the company's receivables will be outstanding for at least one period, it is adjusted as $AR = R \times [1 - (1/TR)]$. Where, R is account receivables and TR represents account receivable turnovers.
- Inventory, due to the fact that it should be converted first into receivables and then into cash flows, is adjusted as $AINV = INV \times [1 - (1 / TR) - (1 / TINV)]$. Where, TINV stands for inventory turnovers.
- Account payables are adjusted as $APA = PA \times [1-(1 / TPA)]$ and $PA = PUR / PA$. Where, PUR denotes purchased during period, and PA and TPA are account payables balance and account payable turnovers respectively. Other components of debt can also be adjusted on the basis of this method.

As can be seen, the main drawbacks of the current ratio, including the degree of liquidity of current assets and the time of repayment of current liabilities have been eliminated by applying the adjustment coefficient to a large extent.

Net Cash Balances is another new indicator introduced to determine the liquidity status of companies. It take the cash and securities balance sheet into account to show the liquidity situation of the company. This index shows the company's real cash savings in relation to unforeseen needs. Net cash balances are calculated by (Equation 3):

$$NLB = (CASH + MKT - AP) / TA \tag{3}$$

Where, MKT, AP, and TA are marketable securities, account payables, and total assets respectively.

3.2. Stock Liquidity Measures (Operational Efficiency)

We used a number of trading days in a year and the average current value of transactions to capture the operational efficiency of market (stock liquidity). An increase in the number of trading days is a sign of stock liquidity and means ticking the bid-ask spreads in quotas (Gholami et al., 2019). For liquid stocks, the value of transactions is tended to be high, while illiquid stocks experience a low transaction volume and values (Brogaard et al., 2017).

3.3. First-Stage Optimization

At the beginning, the stocks of companies were examined using six financial ratios, including the current ratio, earning per share (EPS), price-to-earnings ratio (P/E), return on investment (ROI), operating profit, and cash coverage ratio. At first, according to their 5-year process, stocks are averaged and then ranked in 11 classes from 0 (the lowest rank) to 10 (the highest rank). Because the importance of the extraction rankings of each of the financial ratios varies, by using the genetic algorithm each one was given a weight, depending on their fluctuation and extraction rates, derived from the conversion of daily returns to the annual returns by the geometric mean. The objective function of the first step is expressed in (Equation 4):

$$\text{RMSE} = \sqrt{\frac{1}{M}\sum_{i=1}^{M}(R\,derived\ - Ractual)2} \tag{4}$$

Where, Rderived = aX + bY + cZ + dS + eT + gU and Ractual =11 × (N – r)/(N – 1); Rderived is the derived ranking of stock. Also, a, b, c, d, e, and g are the coefficients of the above indices, and X, Y, Z, X, T, and U represent the corresponding ranking of each index. Ractual also stands for the standardized rank of return on stocks in each of the 11 portfolios. In this function, the six ratios are multiplied in a manner that the extracted rank of each stock differs least from the real rank of the same stock. When this function reaches its lowest position, the coefficient of each index is determined. Therefore, the objective function of this stage is optimized when it is minimized. A geometric mean obtained from the coefficients is calculated by this function for 35 stocks, and a coefficient basis is considered for each of the financial ratios. After this ranking, first 10 stocks are selected to be entered into the desired portfolio. One can use the same approach to select the top ten portfolios in the first hypothesis, which combines the initial financial ratios and the new indicators of liquidity and operational efficiency (liquidity constraint approach), as well as the top ten portfolios examined in the second hypothesis, which is based only the new indicators of liquidity and operational efficiency (the liquidity filtering approach).

3.4. Second-Stage Optimization

a. Optimal portfolio formation

The second step is to choose the best portfolio among the outperformed stocks. Outperforming stocks of the firm are considered as inputs in the second stage. According to the hypotheses of the research, two categories of portfolios should be formed through genetic algorithm:

- The first category is devoted to the optimal portfolios that have the maximum expected return and the minimum risk.
- The second one is assigned to the optimal portfolios with the maximum expected return, the minimum risk, and the maximum level of liquidity.

b. Optimization of genetic algorithm portfolio: without liquidity and liquidity filter

The objective function used to form the portfolios for achieving the maximum returns and the minimum risk is as follows (Equation 5):

$$\text{Fitness} = \sum_{i=1}^{n}\sum_{j=1}^{n} QijXiXj - \sum_{i=1}^{n} E(Ri)Xi \tag{5}$$

Where, Q_{ij} is the covariance between the pairs of the stocks in the portfolio, and Xi represents the weight of stock *i* in the portfolio; E(Ri) stands for the average weight of portfolio returns (the expected return on portfolio). The expected returns on the portfolio should be the maximum, and the sum of the covariance between each pairs of the stocks should be also minimized. Therefore, by including the negative expected returns on the portfolio in the above function, the function is optimized when it takes the minimum value.

c. Genetic algorithm portfolios formation: an alternative approach to liquidity limitation

In this method, the portfolio optimization process is used only for those securities the liquidity of which is more significant than the liquidity level lO. If U is regarded as the reference set, all the securities considered in the portfolio optimization process will be considered, and UO subset portfolios are set at U so that the standard mean-variance optimization process is now applicable to the set and is useful for obtaining medium-variance-efficient filtered portfolios. Thus, regarding level lO, only the securities are participated in the optimization process in which their liquidity is greater than or equal to level lO. To this end, the companies are ranked regarding the level of liquidity in the ten classes using the below formula (Equation 6):

$$l = 11 \times \frac{N-r}{N-1} \tag{6}$$

An alternative solution for obtaining a portfolio in a liquidity constraint is to create an additional constraint on the mean-variance optimization problem (Andrew et al., 2003). The objective function of this approach is more complete, and, in addition to risk and return, the liquidity level is also considered. The objective function of the second stage in this approach is defined by (Equation 7):

$$\text{Fitness} = \sum_{i=1}^{n} \sum_{j=1}^{n} QijXiXj - \sum_{i=1}^{n} E(Ri)Xi - \sum_{i=1}^{n} E(\ell i)Xi \tag{7}$$

Where, Qij is the covariance between each pairs of the stocks in the portfolio, and Xi represents the weight of stock i in the portfolio; E (Ri) indicates the average weight of portfolio returns (the expected return on portfolio), and E (li) describes the expected level of portfolio liquidity. It is worth noting that covariance is a measure of portfolio risk. Naturally, by reducing covariance between two stocks in the portfolio, the risk decreases.

3.5. Scheffe Post Hoc test

After the formation of the optimal stock portfolios using the genetic algorithm, in the next step, it is necessary to compare the returns on each of the optimized portfolios, i.e. without considering stock liquidity, with considering liquidity limitations, and finally with considering liquidity filters, in order to test the research hypotheses. To do such a comparison, there are different methods such as the distribution of t-student and Z-test; however, due to the small volume of the research sample (5 years), their use is associated with a great deal of error. On the other hand, according to statisticians, if more than two statistical samples are compared simultaneously (two by two), and distributions of t-student and Z-test are used, the probability of rejecting the null hypothesis increases. One of the ways to overcome these problems is to use the analysis of variance and subsequently the Scheffe post hoc test, which provides the most accurate and conservative results and shows how much the statistical populations differ from the samples. Therefore, due to its accuracy and compatibility, Scheffe test is chosen instead of comparing the mean of the samples with the distribution of t-student. This test was performed in SPSS® software version 24. The execution of the Scheffe test requires calculating the critical *t* of the following equation (Equation 8) and comparing it with the observed t.

$$t'_{critical} = \sqrt{(k-1)F_{critical(\alpha,d.f.b,d.f.w)}} \tag{8}$$

Where, k is the standard deviations between the groups, and $F_{critical}$ (α.df.b.d.f.w) represents the critical value of F in the main test of analysis of variance of the intergroup and intragroup; α is the level of error.

4. Empirical Results

4.1. Descriptive Statistics Results

Tables 1 tabulates the intervals between the financial indices of the initial ranking of companies' stocks.

Table 1. Initial ranking based on the five year financial indices of the companies surveyed.

Stock Initialization on Financial Indicators						
N	**P/E**	**Average Current Value**	**Net Liquidity Balance Index**	**Cash Conversion Cycle**	**Return**	**Comprehensive Liquidity**
0	(-∞ , 0)	(-∞ , 0)	(-∞ , 0)	(-∞ , 0)	(-∞ , 0)	(-∞ , 0)
1	(1 , 5)	(1 , 10)	(1 , 50)	(1 , 10)	(0.01 , 0.05)	(0.1 , 0.5)
2	(6 , 10)	(11 , 20)	(51 , 100)	(11 , 25)	(0.06 , 0.10)	(0.6 , 1)
3	(11 , 15)	(21 , 30)	(101 , 150)	(26 , 40)	(0.11 , 0.15)	(1.1 , 1.5)
4	(16 , 20)	(31 , 40)	(151 , 200)	(41 , 55)	(0.16 , 0.2)	(1.6 , 2)
5	(21 , 25)	(41 , 50)	(201 , 250)	(56 , 70)	(0.21 , 0.25)	(2.1 , 2.5)
6	(26 , 30)	(51 , 60)	(251 , 200)	(71 , 85)	(0.26 , 0.3)	(2.6 , 3)

Stock Initialization on Financial Indicators						
N	**P/E**	**Average Current Value**	**Net Liquidity Balance Index**	**Cash Conversion Cycle**	**Return**	**Comprehensive Liquidity**
7	(31 , 35)	(61 , 70)	(201 , 350)	(86 , 100)	(0.31 , 0.35)	(3.1 , 4)
8	(36 , 40)	(71 , 80)	(351 , 400)	(101 , 115)	(0.36 , .4)	(4.1 , 4.5)
9	(41 , 45)	(81 , 90)	(401 , 450)	(116 , 130)	(0.41 , 0.45)	(4.6 , 5)
10	(46 , +∞)	(91 , +∞)	(451 , +∞)	(131 , +∞)	(0.46 , +∞)	(5.1 , +∞)

Stock Initialization on Financial Indicators						
N	**ROE**	**EPS**	**Operating Profit to Assets**	**Current Ratio**	**Cash Coverage Cost Interest**	**Number of Trading Days**
0	(-∞, 10%)	(-∞ , 0)	(-∞ , 0)	(-∞ , 0)	(-∞ , 0)	(-∞ , 0)
1	(11%, 120%)	(1 , 500)	(1%, 5%)	(0.1 , 0.5)	(1 , 15)	(1 , 50)
2	(121%, 230%)	(501 , 1000)	(6%, 10%)	(0.6 , 1)	(16 , 30)	(51 , 70)
3	(231%, 340%)	(1001 , 1500)	(11%, 15%)	(1.1 , 1.5)	(31 , 45)	(71 , 90)
4	(341%, 450%)	(1501 , 2000)	(16%, 20%)	(1.6 , 2)	(46 , 60)	(91 , 110)
5	(451%, 560%)	(2001 , 2500)	(21%, 25%)	(2.1 , 2.5)	(61 , 75)	(111 , 120)
6	(561%, 670%)	(2501 , 3000)	(26%, 30%)	(2.6 , 3)	(76 , 90)	(121 , 140)
7	(671%, 780%)	(3001 , 3500)	(31%, 35%)	(3.1 , 4)	(91 , 105)	(141 , 160)
8	(781%, 890%)	(3501 , 4000)	(36%, 40%)	(4.1 , 4.5)	(106 , 120)	(161 , 180)
9	(891%, 1000%)	(4001 , 4500)	(41%, 45%)	(4.6 , 5)	(121 , 135)	(181 , 200)
10	(1001% , +∞)	(4501 , +∞)	(46% , +∞)	(5.1 , +∞)	(136 , +∞)	(201 , +∞)

Source: The findings of the current research

Since the rankings are not equally important, the genetic algorithm is used to weight them and to determine the final rank based on Equation 4. Table 2 represents the weights derived from the genetic algorithm for identifying the final rank of the stocks for classification and entry into the portfolio

Using the weights obtained, the final rank of each stock is determined based on the financial indicators assessed, and then the first 10 stocks of this classification are selected to enter the three portfolios examined. In the next step, by employing the genetic algorithm based on the minimum risk and the maximum return (and in the case of the third portfolio, based on the most liquid stocks), the optimal weights are assigned to each of these 10 stocks, and the final returns of their portfolios are obtained. Table 3 presents the parameters of the genetic algorithm in the stage of stock selection

Figures 1 and 2 provide the weighting function of returns on each of the stocks in stock portfolios in the form of liquidity constraints (the second portfolio) and liquidity filters (the third portfolio) respectively.

Table 4 also lists the weights and return on each of the 10 stock portfolios obtained from the genetic algorithm in the three examined states.

Table 2. The weight of each financial index for the final ranking of stock companies in each of the portfolios examined.

The weight of financial ratios in optimized first	
P/E	0.047
EPS	0.285
Operating profit to assets	0.238
Cash coverage interest rate	0.142
Current ratio	0.095
ROE	0.193
Total	1

Second hypothesis

The weight of financial ratios in liquidity filter mode	
Net liquidity balance index	0.334
Comprehensive liquidity	0.266
Cash coverage cost interest	0.133
Number of trading days	0.066
Average current value	0.201
Total	1

First hypothesis

The weight of financial ratios in liquidity limitation mode	
P/E	0.136
EPS	0.03
Operating profit to assets	0.09
Cash coverage interest rate	0.167
Current ratio	0.045
ROE	0.015
Net liquidity balance index	0.064
Comprehensive liquidity index	0.151
Cash coverage cost interest	0.075
Number of trading days	0.121
Average current value	0.106
Total	1

Source: The findings of the current research

Table 3. Parameters of the genetic algorithm in the stage of stock selection.

Description	Parameter Level
Primary population	35 (chromosomes)
Type of integration	single point
Mutation rate	0.1
The number of repetitions	1000 times
Limit and time delay (stop condition)	unlimited
Generation limit (stop condition)	unlimited
Limit of delay accuracy in objective function (stop condition)	0.001

Source: The findings of the current research

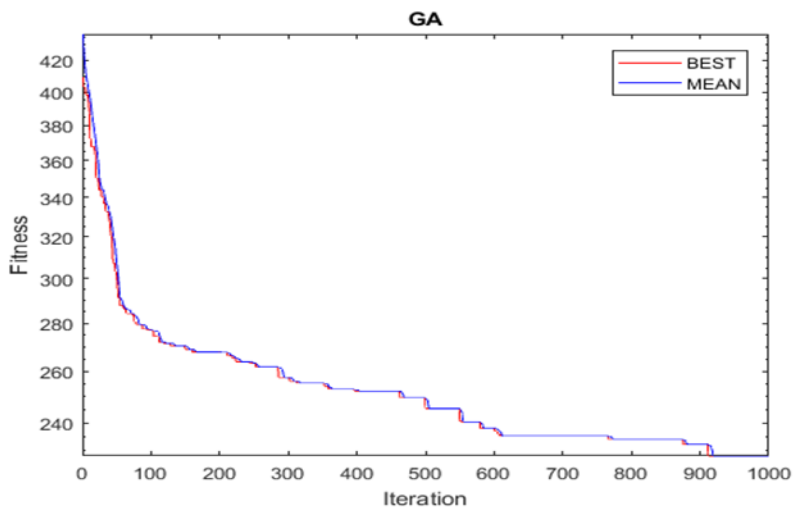

Figure 1. Weighting function of returns on each of the stocks in stock portfolios in the form of liquidity constraints

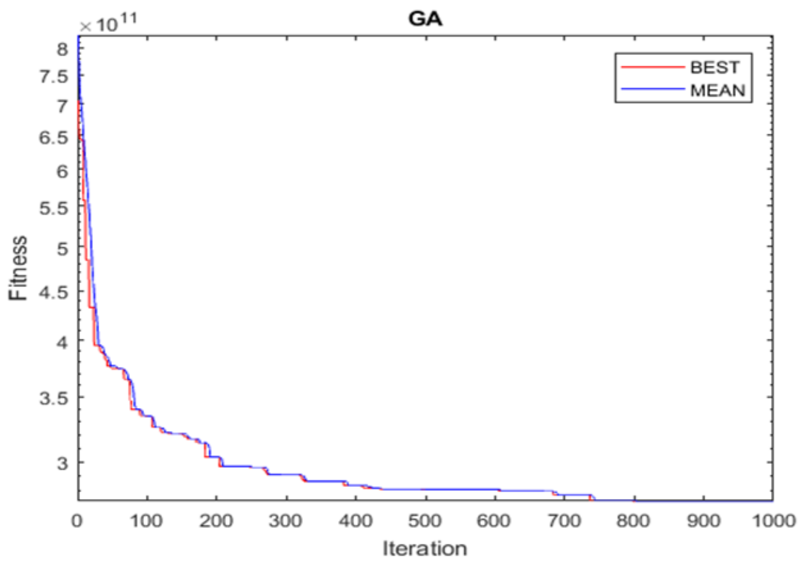

Figure 2. Weighting function of returns on each of the stocks in stock portfolios in the form of liquidity filters.

Table 4. The optimum weight and the final returns obtained from the genetic algorithm in each portfolio.

Selected Stock returns in Different Optimal Modes					
Without Liquidity		With Liquidity Filtering		With Liquidity Limitation	
Name	Return	Name	Return	Name	Return
Maroon Petrochemical Co.	2.31%	Khorasan Petrochemical Co.	109.83%	Shazand Petrochemical Co.	6.65%
Khark Petrochemical Co.	1.64%	Jahrom Petrochemical Co.	0.32%	Maroon Petrochemical Co.	4.35%
Pardis Petrochemical Co.	0.01%	Darab Petrochemical Co.	0.51%	Khark Petrochemical Co.	2.99%

Selected Stock returns in Different Optimal Modes					
Without Liquidity		With Liquidity Filtering		With Liquidity Limitation	
Name	Return	Name	Return	Name	Return
Zagros Petrochemical Co.	23.57%	Kazerun Petrochemical Co.	0.76%	Khorasan Petrochemical Co.	43.55%
Fanavaran Petrochemical Co.	4.10%	Pardis Petrochemical Co.	0.05%	Bandar Abbas Oil Refining	6.78%
Tehran Oil Refining	205.75 %	Fanavaran Petrochemical Co.	7.95%	Pardis Petrochemical Co.	0.03%
Shazand Petrochemical Co.	3.56%	Kermanshah Petrochemical Industries	1.20%	Fanavaran Petrochemical Co.	4.13%
Jam Petrochemical Co.	28.04%	Mamassani Petrochemical Co.	0.01%	Lavan Oil Refining	22.26%
Isfahan Oil Refining	0.98%	Fajr Petrochemical Co.	0.01%	Isfahan oil refining	1.84%
Khorasan Petrochemical Co.	23.18%	Khark Petrochemical Co.	2.77%	Shiraz Oil Refining	7.27%
Total	269%	Total	123%	Total	99.84%
Stock Weights Selected in Different Optimal Modes					
Without Liquidity		With Liquidity Filtering		With Liquidity Limitation	
Name	Weight	Name	Weight	Name	Weight
Maroon Petrochemical Co.	0.0609	Khorasan Petrochemical Co.	0.4208	Shazand Petrochemical Co.	0.118683802
Khark Petrochemical Co.	0.05839	Jahrom Petrochemical Co.	0.03535	Maroon Petrochemical Co.	0.114445094
Pardis Petrochemical Co.	0.00471	Darab Petrochemical Co.	0.10184	Khark Petrochemical Co.	0.106815422
Zagros Petrochemical Co.	0.17081	Kazerun Petrochemical Co.	0.04743	Khorasan Petrochemical Co.	0.166872456
Fanavaran Petrochemical Co.	0.08726	Pardis Petrochemical Co.	0.01737	Bandar Abbas Oil Refining	0.049854365
Tehran Oil Refining	0.35291	Fanavaran Petrochemical Co.	0.23373	Pardis Petrochemical Co.	0.009035139
Shazand Petrochemical Co.	0.06362	Kermanshah Petrochemical Industries	0.02558	Fanavaran Petrochemical Co.	0.121597913
Jam Petrochemical Co.	0.08988	Mamassani Petrochemical Co.	0.00673	Lavan Oil Refining	0.121622836
Isfahan Oil Refining	0.02273	Fajr Petrochemical Co.	0.0121	Isfahan oil refining	0.042718221
Khorasan Petrochemical Co.	0.08879	Khark Petrochemical Co.	0.0991	Shiraz Oil Refining	0.148354752
Total	1	Total	1	Total	1

Source: The findings of the current research

To sum up the descriptive results, the findings are summarized in Table 5, which tabulates the descriptive statistics obtained using the genetic algorithm in the triple states and compares the return on the optimized stock portfolios.

Table 5. Descriptive statistics results.

	Value Label	Mean	Standard Deviation	Number of Portfolios (N)
Return	GA Without Liquidity	269%	1.03425	5
	GA With Liquidity Constraints	99%	0.24422	5
	GA With Liquidity Filters	123%	0.21495	5

As shown in the Table 5, during the studied years, the average return on the portfolio optimized using the genetic algorithm, regardless of liquidity indices (based solely on financial indicators), is greater than the average return obtained from the average return on stock portfolios optimized using the genetic algorithm while taking into account the liquidity constraints as well as liquidity filters, and, according to the ruling relationship between risk and return on investments, the risk (deviation) is higher. Similarly, during the research years, the risk and returns on the stock portfolio optimized using the genetic algorithm while considering liquidity constraints is greater than the risk and the return on the portfolio while liquidity filters are regarded. Generally, the results of comparing the performance of stock portfolios, optimized using the genetic algorithm, follow the relationship between risk and return on investment since by limiting and filtering liquidity, conservatism in the portfolio and subsequently investment risk decreased, which has led to a drop in returns on portfolios. However, inferential statistics should be used to rely on and generalize the results.

4.2. Inferential Statistics Results

Considering the initial results obtained from the returns on the portfolios optimized by the genetic algorithm, it can be inferred that there seems to be a significant difference among the returns on the portfolios. Therefore, for more accurate analysis, more powerful statistical tests are utilized to identify the significant difference among the returns on the portfolios and its severity. As previously mentioned, the research hypothesis was broken down into two sub-hypotheses, and the results were analyzed using an analysis of variance (ANOVA) test in the form of a Scheffe post hoc test. The results of the hypothesis test are presented in Table 6.

Table 6. Results of Scheffe multiple comparison test.

Dependent variable	(I) portfolio number	(j) portfolio number	Mean Difference (I-J)	Standard Error	Significance
Return	GA With Liquidity Filters	GA With Liquidity Constraints	2.61	1.969	0.019
		GA Without Liquidity	3.08	1.969	0.001
	GA With Liquidity Constraints	GA With Liquidity Filters	2.61	1.969	0.019
		GA Without Liquidity	1.12	2.291	0.000
	GA Without Liquidity	GA With Liquidity Filters	3.08	1.969	0.001
		GA With Liquidity Constraints	1.12	2.291	0.000

* The significant level of the mean difference is 0.05.

Table 6 compares the returns on the equity portfolios optimized using the genetic algorithm without liquidity indicators (GA Without Liquidity), with liquidity limitations/constraints (GA with Liquidity Constraints), and with liquidity filters (GA with Liquidity Filters) have been compared. Considering that the observed significant levels in all the cases are less than the significant level of 5%, with 95% confidence, it can be inferred that the returns on the stock portfolios optimized using the genetic algorithm without considering the liquidity limitations and filters significantly and positively differ from the returns on the optimized stock portfolios which consider the liquidity limitations and filters. It should be noted that the significance level in the first and second hypotheses is 0.000 and 0.001 respectively. Therefore, since there is no reliable evidence for rejecting research hypotheses, it can be stated that research hypotheses are out of rejection region and thus confirmed. To justify the above results, it should be noted that the application of liquidity limitations and filters in the formation of optimal stock portfolios leads to a conservative increase in the choice of stocks (portfolio formation), which leads to a reduction in the risk of investment in such portfolios. However, the reduction in the risk causes the expected returns on the portfolios to decline, which also supports the hypotheses test results.

5. Conclusions and Suggestions

Given the newness of the liquidity indicators used in this work and the fact that no financial information on studied companies computes the relevant financial ratios, obtaining these ratios for all companies to be compared with those of petrochemical companies and refineries was effectives in terms of time and cost. Further, precise indicators of identifying operational efficiency in the Iranian capital market have not been evaluated and cannot be identified due to factors such as transaction costs, fair competition of stockholders and brokers, etc. However, many studies have utilized some algorithms. We can use the new indicators of liquidity and indices to identify the operational efficiency of the capital market in a particular industry as a relatively useful contribution, which has not previously been used to optimize portfolios. This contribution has several advantages, including the investment analysis and technical and fundamental analyses, which are related to the analysis of the price trend and the volume of capital market transactions and the analysis of the ratios of financial statements to identify the inherent value of each stock; the contribution of the current work can also be linked to stock valuation. Moreover, the main focus on the refineries and petrochemical companies and the comparison of their position with the top companies in the same field (the activities of which are related to the refining and petrochemical industry) can be considered as other contribution of the current study. Other indicators of liquidity measurement such as Lambda index, debt maturity, the bid-ask quoted price spreads, etc., can be used to measure liquidity variables. In other words, considering that liquidity is a multi-dimensional criterion, it is suggested that the present study should be redesigned with alternative liquidity variables. Future studies can concentrate on new models such as ant colony algorithm, honey beehive algorithm, and other meta-methods or other mechanisms. In addition, it is expected that changes in the model, including how to make initial solutions, how to deal with irrelevant, and how to simultaneously control risk with the semi-variance of the stock will achieve better and more reliable results. Adding other investor preferences such as transaction costs into models based on multivariate genetic algorithms can also be very desirable. Given that the investment process is complex and many possible variables are involved, investors should use these approaches to consider all of these requirements as well. Therefore, the expansion and completion of this model can be of great help to investors' portfolio selection. A wide-ranging debate on the use of genetic algorithms and other exploratory methods is proposed to solve problems with multiple variables. In researches conducted in other disciplines, especially in the field of computer science and engineering, more genetic algorithms are employed to solve three-variable issues to achieve desirable results. However, to solve more than three variables, i.e. four or five variables, the application of neural networks is recommended. On the other hand, when the data input is bulky, using neural networks has several significant problems such as the time spent on training neural networks and possible errors due to the use of inputs variables which do not affect the output. Thus, the problem of portfolio optimization when considering four variables of return, risk, liquidity, and transaction costs will require paying full attention to the selected instrument.

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