Selection and multi-objective optimization of stock portfolio using a combination of machine learning methods and meta-heuristic algorithms

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ABSTRACT
The main goal the model and optimal investment portfolio selection to maximize stock portfolio returns based on the forecasted price and minimize investment portfolio risk based on the Markowitz model. This paper presents is to select the optimal stock portfolio based on data training through Markov decision-making and ensemble learning. To teach data from the data of five years (2011-2016), 85 active stock exchange companies in Iran that have been filtered based on technical, fundamental, and time series variables have been used. Therefore, the stock sets are first filtered based on optimizing trading rules based on technical analysis, Markov decision-making and ensemble learning that issued the buy signal. Data for the next 5 years (2020-2016) were also used to test NSGA II and MOPSO algorithms. According to the obtained results, if the shares are bought equally among 85 companies and maintained for five years, the average return on the total stock portfolio is equal to 13.08%, with a risk of 0.946%. While using the MOPSO algorithm has achieved an average of 43.54% with an average risk of 1.102% . The rate of return on capital for the NSGA II algorithm was also the highest in 5 years. Therefore, it can be said that based on the obtained indicators, NSGA II algorithm is the best combination of the stock portfolio.

Keywords:
Markov decision making, portfolio optimization, machine learning, ensemble learning.

1. Introduction

Financial markets have undergone extensive changes over the past decade. In line with these changes and the widespread advancement of computer science and technology, the methods and algorithms of modeling and decision-making regarding the formation and monitoring of stock portfolio and trading have also moved towards electronicization (Bolton et al., 2013). The extreme sensitivity of the stock market to political and economic changes and the unstable and nonlinear properties of financial time series has made market forecasting challenging (Ballings et al., 2015; Kara et al., 2011; Tan et al., 2007). Also, drastic changes in prices and markets at different times require more attention and quick reactions to these changes (Patel et al., 2015). Today, financial institutions such as investment companies, investment funds, banks, and individuals invest in the capital and stock markets to increase their capital or cover risk. In Iran, the capital market penetration index has grown significantly in recent years. This index, obtained from the total number of shareholder codes and the number of owners of fund investment units, has increased from approximately 6.5 million in 2013 to more than 55 million by the end of March 2016. The higher the capital market penetration, the more likely it is that people unfamiliar with the concepts of capital market and stock trading will increase their presence in the capital market. Therefore, expanding the optimization and design of the automated method of selecting and forming a portfolio seems necessary. Also, people who are present in the capital market with sufficient knowledge and information and buy and sell in the stock market, use technical and fundamental analysis and various tools to find a suitable investment opportunity. These analyzes are often done manually and only for one share, and therefore investment opportunities are examined slowly. To solve this problem, there is a need for the emergence of algorithms and methods for automatic selection so that they can analyze more data more quickly (Khedmati & Azin, 2020). New research on market scheduling has used the buy-and-hold method to achieve higher returns in times of market fluctuations (Mascio et al., 2021), which requires an accurate tool, performance and more speed for market forecasting. Nowadays, machine learning models can achieve this by considering their high computational ability.

Transaction risk also refers to the risk arising from the trader's order scheduling. This timing is due to an error in estimating future price movements, which causes the trader to place his order at the desired price based on his predictions, and faces the risk of not fulfilling the order at the desired price. In this case, it has to trade at a more unfavorable price than the market price when ordering (Andersson et al., 2020). Therefore, in executing an order, there is always an exchange between cost and ordering risk. This is what has been described as a trade-off (Glantz & Kissell, 2013). Therefore, balancing the market reaction cost and opportunity cost risk requires the design of trading strategies. In choosing a trading strategy, the investor, in addition to adjusting his preferences, must be prepared to change and adapt the strategy to changing market conditions. The task of designing an optimal transaction strategy is complex because it requires decisions about the best way to split the order, the investor's entry point in order execution, the choice of order type, and how to measure transaction performance. In the past, designing a trading strategy was usually the responsibility of experts (humans), but with the increase in the number of decisions, an automated approach is needed. Therefore, the method must be dynamic and responsive to market conditions in real-time (Fischer & Krauss, 2018).

In the financial markets today, the volume and speed of transactions have increased significantly, which with manual analysis, can hardly keep pace with market changes. The main methods used for manual analysis of investment opportunities in financial markets are technical and fundamental analysis. Fundamental analysts calculate the intrinsic value of a stock based on its financial statements and ratios, compare it to the market price of the stock, and decide whether to buy or sell the stock. Instead of calculating the intrinsic value of a share, technical analysis approaches believe that the past performance of each share is a sufficient criterion for predicting its future performance (Ghahremani Nahr et al., 2021). Instead of calculating the intrinsic value of a share, technical analysis approaches believe that the past performance of each share is a sufficient criterion for predicting its future performance (Ghahremani Nahr et al., 2021). In general, fundamental and technical analysis tools simultaneously analyze a stock. Today, however, investors prefer to form a portfolio of various financial assets and examine and analyze a set of assets in an integrated manner. On the other hand, as noted, the speed of fundamental and technical analysis tools is very low relative to the speed and frequency of trades in financial markets, and these methods cannot meet the needs of investors in financial markets (Hsiao & Shen, 2003; TW et al., 2012). Therefore, the use of algorithmic trades in financial markets seems inevitable. Selection and formation of the investment portfolio is one of the algorithmic trading methods that uses statistical tools and machine learning and Markov chain and, by combining these concepts with economic theories, tries to maximize the return on investment in the long run (Khedmati & Azin, 2020). Financial markets are complex systems that are non-linear and dynamic in nature with high internal dependence, high noise with high turbulence, and influenced by political, economic, social, and psychological factors. One of the problems for investors in the stock market is the inability to predict market turmoil and choose the right trading strategy to make a profit with minimal risk (arsskarsson, 2021). Therefore, choosing a suitable strategy in the stock market is very important when you are faced with increasing and decreasing trends or fluctuations, and by choosing the right strategy, in addition to reducing the level of risk, you can focus your power on achieving higher returns. More generally, like other financial markets, the most important factor in stock market success is the ability to accurately predict the future movement of the market and the appropriate time for a trader to enter. In this way, he buys a share that has a low price and sells it after the price increases, and earns a profit equal to the difference between the purchase and sale price. There are various methods for predicting the market trend in order to use stock portfolio returns or reduce investment risk, in which methods such as; Timing, Markov decision-making process (Chang & Lee, 2017), machine learning or meta-innovative methods are employed. Each of them alone cannot lead to the desired result. Ensemble learning is a field in machine learning in which techniques have been proposed that use several models in combination and simultaneously to make decisions to increase the model's ability to estimate data output (Dietterich, 2002; Zhou, 2021). Extra-innovative methods are prone to error due to the randomness of their prediction process, or the machine learning method has problems such as ignoring external conditions on the market trend (Fallah and Nozari, 2021). In addition, all economic factors and indicators should be taken into account in forecasting the market, because ignoring any of these indicators causes the market trend to not be determined correctly, and the investment risk increases (Ghahremani Nahr, 2020). Recently, hybrid methods have been considered because they can improve the limitations of single method (Malik et al., 2021). The results of most studies show that hybrid models have higher accuracy and sensitivity than other models (Jahed Armaghani et al., 2021; Strader et al., 2020). The efficient market theory states that investors cannot predict stock prices and market conditions based on past information (FAMA, 2021). According to efficient market theory, information rapidly affects stock prices and prices themselves according to the modify this information. As a result, stock price changes in the efficient markets must also be random. Recent studies show that by studying and identifying the time-series patterns of past data, it is possible to predict some markets (Lo et al., 2000; Maikeil, 2003; Mandelbrot & Hudson, 2004). The efficient market theory does not rule out the possibility of repetitive and short-term patterns. If these hidden patterns can be identified before they occur, the market's future can be accurately predicted. Many projects have been undertaken to forecast financial markets. Some of these studies have used soft computing techniques such as genetic algorithms, neural networks and fuzzy systems. Researchers, therefore, use sophisticated methods to reduce prediction error.

Price forecasting in financial markets is an attractive topic of interest for market participants, both personal and institutional investors. Investment in today's world faces major challenges that the methods of selecting and forming the appropriate portfolio algorithmically can address these challenges. Given the importance of investing in portfolio optimization and the existence of different methods for doing so, each has its own characteristics. In this paper, based on technical indicators, fundamental variables, stock price time series, collective machine learning and Markov chain, portfolio optimization is performed in order to maximize stock portfolio returns based on forecast price and minimize investment portfolio risk. In this paper, new and combined methods for filtering stocks of listed companies for training and prioritizing stock portfolio based on machine learning are discussed. Hence the use of filters used to select companies' stocks to teach a combination of trading rules optimization methods based on technical analysis as the first filter (Trading Rule Filter), optimizing a strong trading system using the Markov chain as a filter The second (Markov Model Filter) and optimization based on machine learning methods is the third (Predict Model Filter). Therefore, companies are selected for training that have issued a purchase signal in all three methods. The use of a learning machine based on six different learning models also filters companies and, more importantly, predicts stock returns. The combination of using heterogeneous and homogeneous base models as a collective learning model helps to determine stock portfolio returns in the coming days. Of the six simplification models, five are related to heterogeneous base models, including support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), MLP neural network, and Bayesian network (NB) and a base model. Homogeneity includes the weighted average. These six classification classes are the most important part of predicting stock price returns in the issue under consideration. For this purpose, data related to companies listed on the stock exchange in Iran during the years 1390 to 1399 were examined and the mentioned tools for training data in the first 60 months (1390 to 1394) and the NSGA II and MOPSO algorithms. Also, the investment method based on purchase and maintenance has been used to test data in the second 60 months (2016 to 2016).

The structure of the paper is as follows. In the second part, the background of research related to stock portfolio optimization and stock portfolio risk is discussed. In the third part, a multi-objective stock portfolio selection and optimization model based on the Markov decision-making process and ensemble learning algorithms is presented, and a two-objective model for stock portfolio optimization is presented. In the fourth section, the results of the implementation of the approach on the data of listed companies operating in Iran are analyzed and presented. The fifth section concludes and suggests future research recommendations.

2- Literature review

Research conducted in foreign markets using a combination of different strategies to support foreign market optimization algorithms shows promising results. On the other hand, there are different approaches to evolutionary computing strategies, and machine learning algorithms, which include neural networks, genetic algorithms, and support vector machine algorithms. Kimoto et al. (1990) combined genetic algorithms and other methods, such as technical analysis, regression, and support machining, to identify optimal stock market trading opportunities through experiments that demonstrate good returns. Shoaf and Foster (1998) provide a forecasting model that combines genetic algorithms integrated with Ruff set theory to improve the accuracy of stock price forecasting. This model can achieve higher efficiencies than general purchasing or maintenance strategies or genetic algorithms. Gold and Lebowitz (1999) selected a number of investment opportunities to select the appropriate strategy, taking into account the investment objectives according to the return and risk of investing stocks, and then identifying the optimal portfolio. Lazo et al. (2000) proposed the use of genetic algorithms for stock selection and capital allocation strategies. They were among the researchers who used neural networks to select stocks and genetic algorithms to solve the problem of capital allocation. Ng et al. (2003) considered identification and scheduling using genetic algorithms to optimize portfolio and achieve sustainable profit. Ghezzi and Piccardi (2003) used Markov's decision-making process to analyze continuous data with good results. Using the analysis of historical stock market data and using these results, the investment process was designed. Oh et al. (2006) stated the combination of artificial intelligence and fundamental analysis to optimize and diversify the portfolio and to examine the possibility of using artificial intelligence for investments. Ko et al. (2007) developed a combination of genetic algorithms with technical indicators and considering the return on investment and risk of a stock trading system. Genetic algorithms can help identify the best combination of technical indicators and have better results. Lipinski (2008) developed a smart stock trading system using neural networks to predict stock prices and stock market trends. Quek et al. (2009) proposed the use of fuzzy neural network as a tool to balance the portfolio. Hsu et al. (2009) used Markov chains and fuzzy theory to create a stock market index forecasting model. Following the validation of the data, the results show not only the ability to improve the return on investment, but also the prevention of losses. Versace et al. (2004), Khan et al. (2008), and Du et al. (2010) stated that the use of genetic algorithms to optimize the stock index forecasting model is ineffective. Chiu and Chian (2010) designed new functional genetic algorithms to select investment targets based on stock price regardless of declining stock market index. This method can achieve sustainable returns. Cheng et al. (2010) proposed a combination of genetic algorithms, regression, and technical analysis to design stock selection models and identify high-yield, high-yield stocks as investment goals for accurate stock price forecasting.

Leu and Chiu (2011) described integrated genetic algorithms and pattern search methods for capital allocation and stock selection. Such experiments with the usual selection methods lead to good results with the roulette wheel method. Dastkhan et al. (2011) used fuzzy time series to predict return on investment and then genetic algorithms to identify the optimal investment strategy. Experimental results showed this method for the performance of 60 Taiwanese market indices. Sefiane and Benbouziane (2012) in a paper entitled Portfolio Selection Using Genetic Algorithm, used the genetic algorithm on a simple example consisting of 6 shares. They note that the results are interesting and confirm the efficiency of the genetic algorithm for its rapid convergence to a better solution, as well as the computational time. Abounoori et al. (2016) in a study entitled Predicting Fluctuations in the Tehran Stock Exchange with the Markov GARCH approach, evaluated several GARCH models in relation to their ability to predict fluctuations in the Tehran Stock Exchange. Chen and Hao (2017) provide a technical analysis of a set of technical features such as moving average and moving average and mean convergence-divergence motion and volume ratio and relative power index and volume level and acceleration index for prediction with learning algorithms. Basak et al. (2019) presented a stock market forecast using random forest. An experimental classification framework for predicting stock prices with respect to price increases or decreases n the day before, random forests and decision trees facilitate this relationship. Anwar and Rahman (2019) proposed a stock market price forecasting model using advanced machine learning tools that examines past price trends through technical analysis using open, closed, up and down prices. From the stock chart, they predict the probable direction of its price in the future. The performance of this research is evaluated using Dhaka Stock Exchange data. Huang (2019) presented a share index prediction model using machine learning tools using fundamental indicators. They reviewed quarterly stock financial data for 11 years with three machine learning algorithms including neural network, random forest and adaptive neural fuzzy inference system. Jiang et al. (2020) proposed a stock index forecasting model using deep learning algorithms. This input model of technical indicators along with macroeconomic indicators were used to forecast the stock price index on a monthly basis. Chowdhury et al. (2020) presented stock price forecasting using the Black Scholes pricing model and machine learning. Different algorithms such as decision tree, machine learning method and neural network have been used. Pungetmongkol et al. (2020) examined the performance of a balanced basket and a shopping cart for five different market trends: top, bottom, top, bottom, and side aspects of the market. They considered three asset classes: equity, bonds, and gold, determined the initial weight of the portfolio using the Markowitz method, and used geometric Brownian motion to simulate prices. Salman et al. (2020) examined the relationship between portfolio investment and banking financial performance in Nigeria. Andersson et al. (2020), in a study aimed at advancing theory and practice for portfolio management in cities and destinations, conducted an experiment with professionals in a city to develop their ideas and strategies for balancing value and risk in the collection. Determine your basket. Bigerna et al. (2021), considering the amount of oil imports and the risk associated with this amount, introduced a new approach to the concept of energy security, which from the perspective of the portfolio theory to examine these issues, from the perspective of four major Asian energy importers; Used by China, Japan, Korea and Taiwan.

Wang et al. (2021) proposed a reinforcement learning method for optimizing investment policy. To address the problem of balance of risk and return, they proposed a model that uses macro market conditions as a dynamic indicator to adjust the ratio between short and long funds to reduce the risk of market fluctuations. Arsskarsson (2021) A study aimed at retesting theories and analyzing the impact of risk management tools on different collections, focusing on investing in Iceland, where stock price fluctuations and foreign exchange rates can change portfolio returns over time. And affect investor profitability. dos Santos et al. (2021) conducted a study to identify which tools and techniques are more appropriate for the strategic selection and alignment of projects and the balance of the project portfolio.

According to the research background, it can be said that different methods have been used to optimize the stock portfolio and reduce the investment portfolio risk. However, there is no comprehensive model that uses the collective learning machines and Markov decision-making process for training and the NSGA II and MOPSO algorithms to test the data simultaneously.

3- Methodology

This section presents a multi-objective stock portfolio selection and optimization model based on Markov decision-making process and collective learning algorithms. Accordingly, the main purpose of selecting stocks of listed companies in the investment portfolio is to increase the return of the portfolio based on the projected profit and reduce the investment risk in the stock portfolio. Due to the existence of different listed companies, it is not possible to study all companies due to the lack of continuity of the activities of listed companies in all time periods. Therefore, according to the activities of listed companies in different years, not all listed companies have been selected to analyze and optimize the stock portfolio and have been filtered based on various characteristics such as technical variables, fundamental variables, and time series. Based on Figure (1), the companies that are based on the filter are selected to be open for at least one business day per month. Variables used to filter listed companies include 8 technical variables (final price, number of buyers, number of trades, trading volume, daily trading value, company day value, P / E ratio and number of shares of each company), seven basic variables (price Old design coins, new design coins, dollars, indices, gold, oil, euros) and time series are the prices of the last 10 days per month. According to the three decision variables, the following methods have been used to filter the studied stocks of listed companies based on the buy signal and eliminate low-yield companies:

- Optimization of trading rules based on technical analysis as the first filter (Trading Rule Filter)
- Optimizing a robust trading system using the Markov Model Filter as a second filter
- Optimization and forecasting of stock returns based on machine learning methods as a third filter (Predict Model Filter)

Whether the stock market is bullish, bear, or modified, the new model can be used in the stock market to achieve a high return portfolio and be used in the further optimization parameter settings. Investors in the stock market are looking for maximum returns and minimum risk. But investors' goals have different levels of risk and return based on their desirability. To diversify risk and increase returns, investors need to diversify. The goal is to maximize the expected return on the portfolio. In this study, the Markov chain integrates technical indicators, machine learning, and genetic algorithms to propose a stock investment decision support system, as shown in the figure below. Then the filtered companies are presented through these three models in three ways. Thus, the signal to buy the share of a company is confirmed either through all three filters, or the majority vote, or only from one filter. To avoid the risk of abusing a single signal, using multiple signals may reduce the risk of the model.

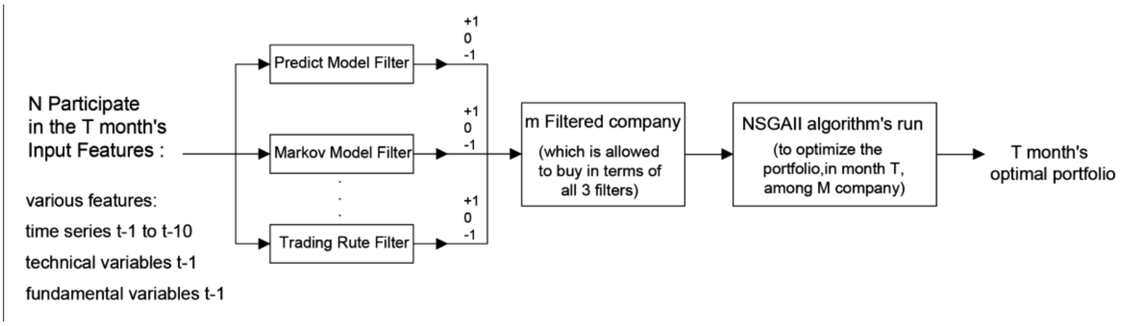

Figure 1- Proposed Model for General Market Timing

The following is a description of each of the filters based on the receipt of the buy signal and the elimination of low-yield companies:

Technical: Technical analysis is a tool that analyzes the future prices of financial assets based on past pricing information. There are various technical methods for predicting the future status of a stock.

In fact, the disability-oriented view that exists in technical methods, as well as the existence of numerous disabilities that exist in the discussion of the capital market, and especially stocks, causes many innovative methods to be proposed in this category. However, the success of technical methods is quite relative. In technical methods, disabilities can be considered as signposts for a route. In this paper, using the information of the previous month, the RSI indicator can be used to identify the saturation zone of buying and selling, so that when the RSI value is less than 90, it means that we are witnessing extreme sales in the market and therefore the possibility of reducing There is selling pressure and rising prices and we receive a buy signal. The MACD trading rule is based on the sell signal occurring when the MACD is below its signal line and vice versa buying occurs when the moving average of the convergence / divergence moving above the signal line. Only price information is used in the ROC indicator. In fact, in this indicator, the ratio of price changes to past changes is displayed as a curve. This indicator fluctuates between negative and positive intervals around the zero axis. Moving ROC above zero is usually accompanied by an upward trend in prices. The strategy used is the moving average dimension. This strategy gives a buy signal when the short-term moving average breaks the medium-term moving average and moves above it. In PDEMA, which is the percentage difference of the average price expression. This index is saturated when it is less than 10%, and when it is above zero, it is accompanied by an upward trend in prices. After estimating the technical indicators, the market shares that buy the signal are determined; And by using the technical filter, a number of market shares that are suitable for buying are determined. Figure (2) shows how to apply the technical filter.

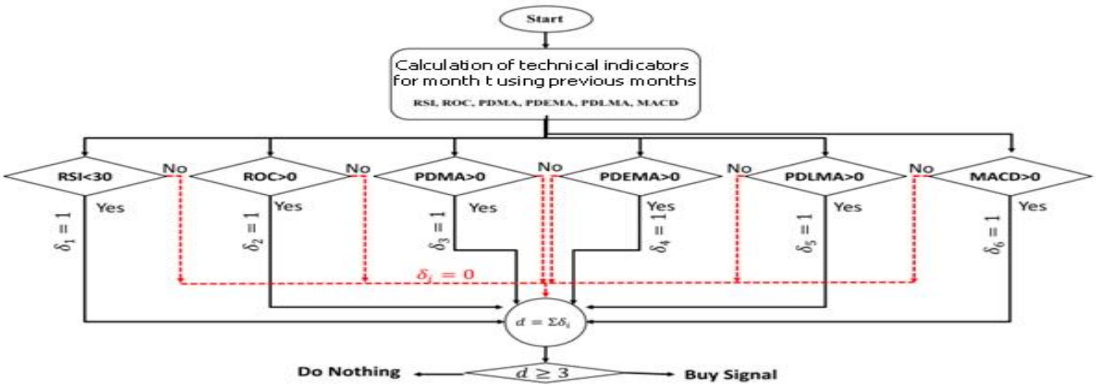

Figure 2. Performance of the technical rule in providing a buying signal

Markov chain: A Markov chain is a special type of probabilistic process in which the next state of the system depends only on the current state of the system and is not dependent on its previous states. The Markov chain is a memoryless random process, meaning that the conditional probability distribution of the next state depends only on the current state and is independent of its past. This type is Markov property without memory. A sequence of random variables is called a random process, and if the state space is discrete and the future position of the process depends only on its current position, it is called a Markov chain. In these processes, the future position of the process depends only on its current position, and knowing the previous positions of the process does not provide additional information. A discrete-time Markov chain is a Markov process whose state space, that is, the set of values that the random variables that make up the process can take, is a countable or finite set. According to this method, groups of data similar to today's data are examined based on the time series of the data in question and the amount of increase or decrease of the average price is calculated. Therefore, based on the current day price and the next day price forecast, a buy signal is issued.

Machine learning: Machine learning methods, inspired by pattern learning and computational learning theory, study the study and construction of algorithms that can learn and predict based on data. Such algorithms do not follow program instructions and make predictions or decisions by modeling sample input data. Machine learning makes it possible for software development to derive some rules of a software system that cannot be extracted through analysis and design by analysts and designers from past data—using a learning machine based on six different learning models to filter companies and most importantly, predict stock returns. The combination of using heterogeneous and homogeneous base models as a collective learning model helps to determine stock portfolio returns in the coming days. Of the six simplification models, five are related to heterogeneous base models, including support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), MLP neural network, and Bayesian network (NB) and a base model. Homogeneity includes the weighted average. These six classification classes are the most important part in predicting stock price returns in the issue under consideration.

According to the use of the above methods for filtering listed companies based on receiving the purchase signal and eliminating low-yield companies from among the active active listed companies, the m N of the listed company is selected to train and test the data. After selecting the listed company, the trend and return of each company's share to participate in the stock portfolio is predicted through collective machine learning methods. Collective learning methods are divided into homogeneous and inhomogeneous categories based on whether the basic learning models are homosexual or heterosexual. In heterogeneous methods, different learning models from L (support vector machine (SVM), decision tree (DT), K-nearest neighbor (KNN), neural network (NN), Bayesian network (BN, etc.) as learning models The base is used. Homogeneous methods, on the other hand, use the same type of basic wind deflector (eg, a support vector machine) with an L number of models, and Sample Bagging methods are often used to teach basic learning models. In this method, the whole set of training is divided into a number of distinct categories and only a percentage of the total set of data is used to teach each basic learner. In this way, L models of the same basic learning model are trained using different datasets, and as a result, aggregating their results can reduce prediction error.

Finally, after the data training, the Markowitz model has been used to optimize the stock portfolio based on maximizing returns and also minimizing stock portfolio risk. Equations (1) to (4) show the Markowitz model for optimizing the stock portfolio m of a selected listed company.

$$max\ \mu p = \sum_{i=1}^{m} R_i^{t(predict)} . W_i \tag{1}$$

$$min\ Risk = \sum_{i=1}^{m} \sum_{j=1}^{m} cov_{ij} W_i\, W_j \tag{2}$$

$s.t.$:

$$\sum_{i=1}^{m} W_i = 1 \tag{3}$$

$$W_i \geq 0 \tag{4}$$

In the above relations, $R_i^{t(predict)}$represents the forecast profit per share of the company, cov_{ij} is the covariance between the two shares of the company i and j, and W_i is a decision variable that determines the amount of investment in each stock portfolio.

According to the definitions, Equation (1) maximizes the return on the total portfolio through the ratio of different investments in the shares of listed companies based on projected profits. Equation (2) seeks to reduce portfolio risk based on the ratio of different investments made on the shares of listed companies. Equation (3) ensures that the total amount of investment made on the companies' share should not exceed 1. Equation (4) also ensures that the investment ratio should not be a negative number. According to Markowitz model, NSGA II and MOPSO algorithms have been used to optimize the stock portfolio based on the two mentioned objective functions. In the following, the mentioned solution methods are presented.

NSGA II Algorithm: The NSGA II algorithm starts by randomly creating an initial population of chromosomes, while satisfying the boundaries or limitations of the problem. In other words, chromosomes are strings of proposed values for problem-solving variables, and each represents a possible answer to the problem. Chromosomes are inferred from consecutive replications called generation. During each generation, these chromosomes are evaluated according to the goal of optimization, and the chromosomes that are the better answer to the problem are more likely to reproduce the answers to the problem. It is important to formulate the evaluation function of chromosomes in a way that helps speed up the convergence of calculations towards the optimal general answer. Because in the genetic algorithm, the value of the evaluation function must be calculated for each chromosome, and since we usually encounter a significant number of chromosomes in many problems, the time consuming calculation of the evaluation function can make it practically impossible to use the genetic algorithm in some problems; Therefore, based on the obtained values of the objective function in the population of strings, each string is assigned a fit number. This fitness number will determine the probability of selection for each discipline. Based on this selection probability, a set of strings is selected first. To produce the next generation, new chromosomes, called offspring, are created by linking two chromosomes from the current generation using the combination operator or by modifying the chromosome using the mutation operator. The new strings then replace the strings from the original population so that the number of strings in the various computational iterations is constant. Random mechanics that act on the selection and removal of strings are such that strings that are more fitting are more likely to combine and produce new strings and are more resilient than other strings in the replacement phase. Thus, the population of sequences in a competition based on the objective function is completed over different generations and increases by the value of the objective function in the population of the strings, so that after several years, the algorithm converges to the best chromosome, which hopefully represents the optimal solution or below. Optimal for the problem at hand. In general, in this algorithm, while in each computational iteration, new points of the response space are searched by genetic operators by the selection mechanism, it explores the process of searching for areas of space in which the statistical average of the objective function is higher. Usually the new population that replaces the previous population is more appropriate. This means that the population is improving from generation to generation. The search will be fruitful when we have reached the maximum possible generation, or convergence has been achieved, or the cessation criteria have been met, and as a result the best chromosome obtained from the last generation is selected as the optimal solution or optimal solution to the problem. Figure (3) shows the pseudocode of the NSGA II algorithm.

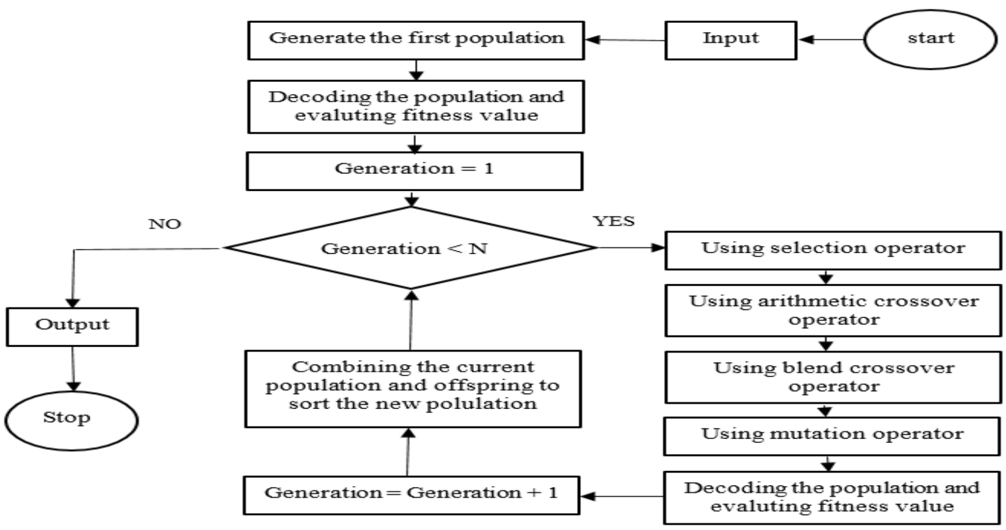

Figure 3: Pseudocode of NSGA II algorithm in stock portfolio optimization

MOPSO Algorithm: Cumulative particle motion algorithm has many similarities with algorithms such as ants or genetics, but there are serious differences with them that make this algorithm different and simple. For example, this algorithm does not use operators such as intersection and mutation, so the algorithm does not require the use of number strings and decryption steps, so it is much simpler than algorithms such as genetics. This algorithm divides the solution space into several paths using a quasi-probabilistic function, which are formed by the movement of individual particles in space. The motion of a group of particles consists of two main components (definite and probable). Each particle is interested in moving in the direction of the best current answer x^* or the best answer obtained so far g^*. Equations (5) and (6) show the equations of velocity and motion in the MOPSO algorithm.

$$V_i^{t+1} = wV_i^t + c_1 rand(pbest_i - X_i^t) + c_2 rand(gbest_i - X_i^t) \quad (4)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (5)$$

Where velocity V_i^{t+1} particle velocity i in the new iteration t, V_i^t particle velocity i in the current iteration t, X_i^{t+1} the current position of the particle $t+1$, X_i^tparticle position in the new iteration, $pbest_i$ The best position the particle i has ever taken and $gbest_i$ the best position the best particle (the best position all particles have ever taken). $Rand$ is a random number between zero and one that is used to maintain group diversity. C_1 and $C_2$are cognitive and social parameters, respectively. Selecting the appropriate value for these parameters leads to accelerating the convergence of the algorithm and preventing premature convergence in local optimizations. Recent research shows that choosing a larger value for the C_1 cognitive parameter is more appropriate than the C_2 social parameter. The w parameter is called weight inertia, which is used to ensure convergence in the particle group. Gravitational inertia is used to control the effect of previous velocity records on current velocities. Accordingly, Figure (4) shows the pseudo-code of the MOPSO algorithm.

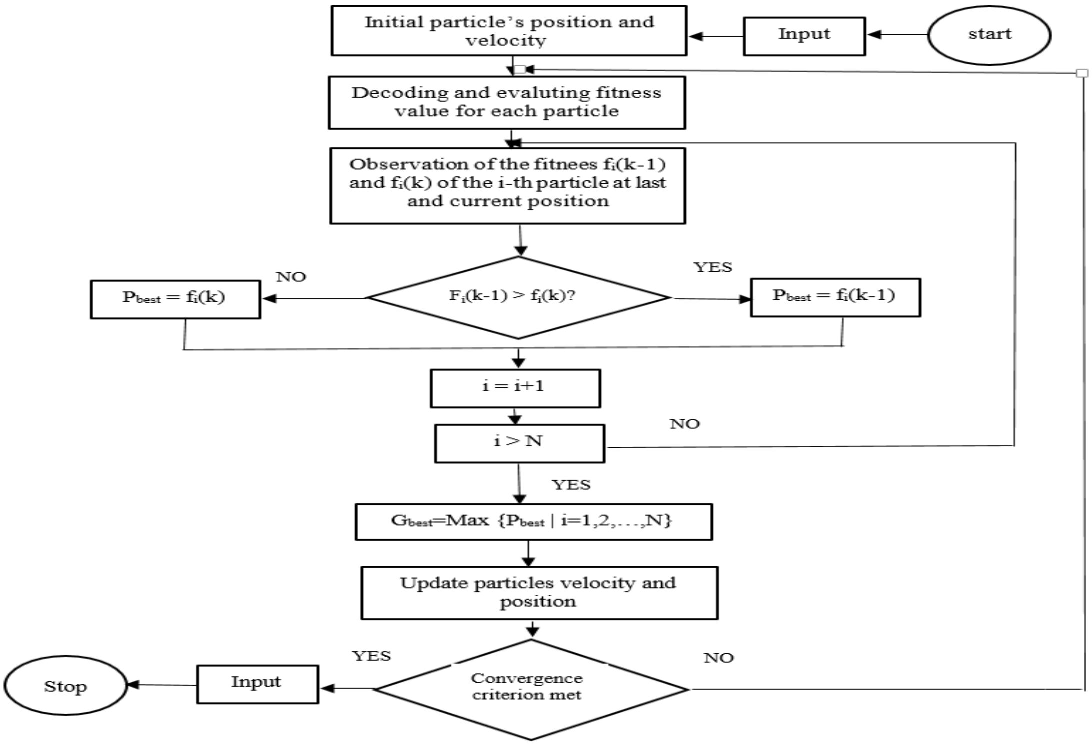

Figure 4- Pseudocode of MOPSO algorithm in stock portfolio optimization

4- results

Considering the presentation of a collective machine learning method for data training and the use of the Markowitz model to optimize the stock portfolio, the results of Iranian stock exchange companies during the years 2011 to 2020 are analyzed. The case study in this article is 480 companies listed on the Iranian Stock Exchange in the period from 2011 to 2020, including various industries. The data required for the research have been collected through network and annual financial statements reports along with explanatory notes and new savings software and trading board data through the information site of Tehran Stock Exchange Technology Management Company (tsetmc). Data collected for the selection of stock exchange companies active from 2011 to 2020 based on 8 technical variables (final price, number of buyers, number of transactions, trading volume, daily trading value, company day value, P / E ratio and number of shares of each company), 7 fundamental variables (old design coin price, new design coin, dollar, index, gold, oil, euro) and the time series of the price of the last 10 days each month.

Based on the use of Predict, Markov and Trading Rule filters, 85 active listed companies have been selected for data training based on receiving a buy signal and eliminating low-yield companies. The basis for selecting companies is that companies' transactions are open for at least one business day per month. After selecting 85 active stock exchange companies, collective machine learning methods between 2011 and 2015 have been used to teach the data. In this study, the thresholds for determining the uptrend and downtrend are 2% profit and 2% loss, respectively. Figure (5) shows the machine learning error based on 3 sets of input data.

Due to the volume of input data, the data is well trained and machine learning also provides very accurate results. Its error is about zero symmetric and also the correlation between trained and predicted data obtained from machine learning is approximately equal to 0.925.

Table 1- The input characteristics of each data sample

technical variables	fundamental variables	time series
final price	index	the time series of the price of the last 10 days each month
number of buyers	dollar	
number of transactions	gold	
trading volume	oil	
daily trading value	euro	
company day value	old design coin price	
number of shares	new design coin	
P / E ratio		

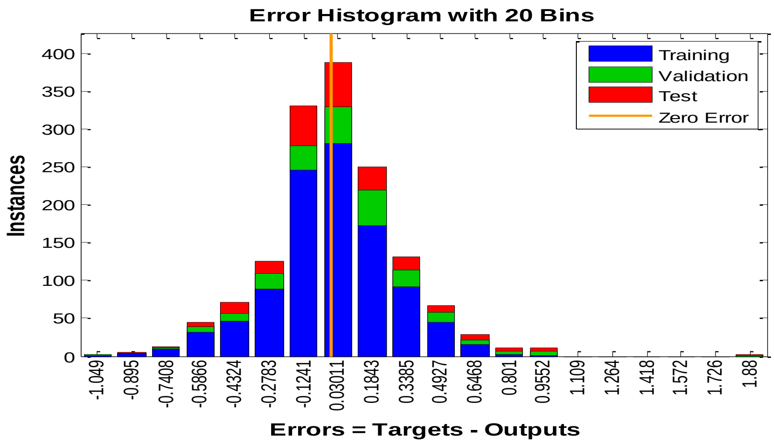

Figure 5 - The best machine learning performance in successive learning repetitions

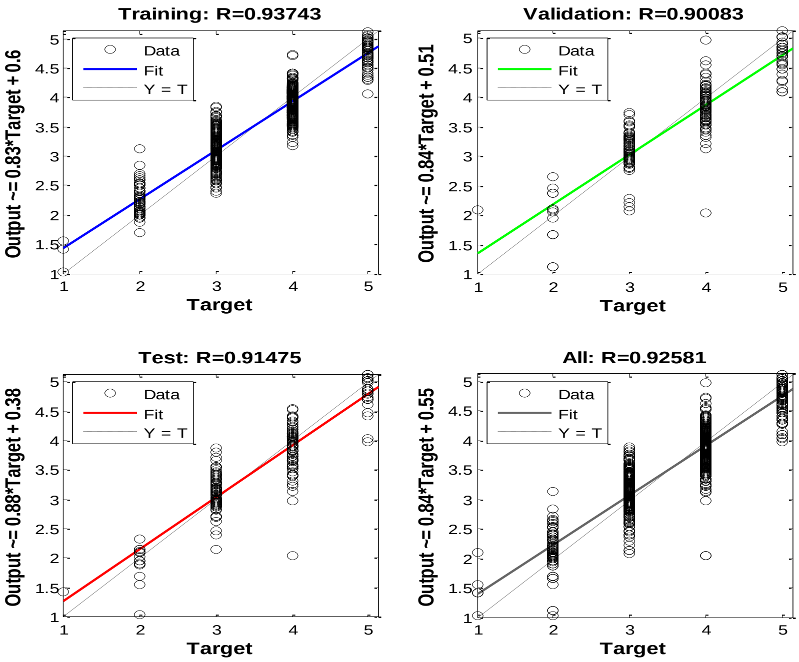

Figure 6. Relationship between tested and predicted data

After training the data using mass learning machine methods, to test the data based on stock portfolio optimization in accordance with maximizing stock portfolio returns and minimizing investment portfolio risk in listed companies, data from 85 selected companies between 2016 and 2020 have been used. Therefore, using the Markowitz model with the two objectives of maximizing the return of the portfolio and minimizing the risk of the invested stock portfolio, the stock portfolio has been optimized. In this section, three methods are used to optimize the stock portfolio, including the same investment method between stock portfolio (Buy & Hold), NSGA II algorithm and MOPSO algorithm. First, Table (1) shows the parameterization of meta-heuristic algorithms to increase their efficiency in obtaining optimal values of objective functions.

After setting the optimal parameters of NSGA II and MOPSO meta-heuristic algorithms, the Markowitz model is solved. Due to the dual purpose of the model, Figure (7) shows the Pareto front resulting from stock portfolio optimization in three different ways.

Table 2- Parametric adjustment of meta-heuristic algorithms by Taguchi method

Algorithm	Parameter	Best Level	Best Value
NSGA II	$N\ pop$	3	200
	$Max\ it$	3	300
	P_c	2	0.5
	P_m	1	0.2
MOPSO	$N\ particle$	3	200
	$Max\ it$	3	300
	C_1	2	1.5
	C_2	1	1
	w	3	0.7

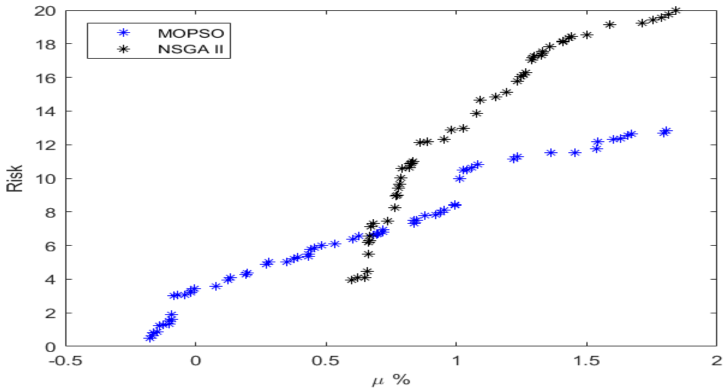

Figure 7- Pareto front resulting from stock portfolio optimization

According to Figure (7), 65 efficient answers are obtained by NSGA II algorithm and 53 efficient answers are obtained by MOPSO algorithm. Each of the efficient answers involves a set of investments in the stock portfolio of listed companies. Since the two objective functions are optimized simultaneously, it can be seen that as the stock portfolio returns increase, the investment portfolio risk also increases. This is if the NSGA II algorithm uses the leap and combine operators to obtain the best portfolio mix based on maximizing stock portfolio returns. However, the MOPSO algorithm has obtained the best combination of the portfolio based on the lowest investment risk. Table (2) compares the indices obtained from different efficient answers obtained by two algorithms for stock portfolio optimization.

Table 3- Comparison indicators of efficient solutions in stock portfolio optimization

Index	MOPSO	NSGA II
Mean of μp	43.54%	107.63%
mean of risk	1.10%	1.419%
NPF	65	53
MSI	12.47	16.04
SM	6.09	9.02
MID	0.581	0.483

Comparing the above indicators, it can be seen that NSGA II algorithm has obtained the best combination of investment portfolio with the highest return on portfolio. Also, this algorithm has performed better than MOPSO algorithm in obtaining MSI and MID indices. On the other hand, MOPSO algorithm has obtained the best combination of investment portfolio with the lowest risk, highest NPF and lowest SM, which has been more efficient than NSGA II algorithm in obtaining these indicators.

In the following, due to the high number of efficient answers, the average of efficient answers obtained from stock portfolio optimization is examined by two algorithms, NSGA II and MOPSO. To balance the results of these methods, a balancing method has been used. In this method, it is assumed that at the beginning of the data test, 85 companies of the same size were purchased from each share and maintained it for 5 years. Accordingly, Table (3) shows the total return on the stock portfolio, the total risk created and the amount of return on investment. The amount of rate of return on capital is obtained based on relationships (7) and (8) per day of investment.

$$ROI_t = \frac{(1+\mu_t)}{100}, \quad \forall\, t = 1 \tag{7}$$

$$ROI_t = \frac{ROI_{t-1}(1+\mu_t)}{100}, \quad \forall\, t > 1 \tag{8}$$

According to the obtained results, if the shares are bought equally among 85 companies and maintained for 5 years, the average return on the total portfolio is 13.08% with a risk of 0.946%. While using the MOPSO algorithm has achieved an average of 43.54% with an average risk of 1.102% and the highest return of 91.49% with a risk of 2.668%. The best value of the stock portfolio obtained in the lowest, average and highest mode is obtained by NSGA II algorithm.

Accordingly, the highest return of the stock portfolio was 151.54% with a risk of 2.935%. The rate of return on capital for the NSGA II algorithm was also the highest in 5 years. Therefore, it can be said that based on the obtained indicators, NSGA II algorithm is the best combination of stock portfolio. Figures (8) and (9) show the lowest, highest and average returns of the total stock portfolio in each month between the years (2020-2016) with different solution methods.

Based on the results obtained from Figures (8) and (9), it can be stated that due to sharp price fluctuations in late 1398 to mid-1399, investment risk has increased in these months and also the average total return on investment has increased. So that the NSGA II algorithm had the highest return on the portfolio with the highest risk.

In general, the return on investment portfolio, investment risk and rate of return on investment in each year can be seen in Figure (10).

Since a combination of three different methods has been used to filter companies in the optimization process. In the following, the stock portfolio return trend and also the stock portfolio risk are examined by considering different methods of filtering the stocks of listed companies and comparing them with each other. Therefore, each of the filtering methods including Trading Rule Filter, Markov Model Filter and Predict Model Filter alone and in combination is compared and the results are shown in Figure (11).

According to Figure (11), it can be seen that in case of using each of the filters individually, the stock portfolio profit was less than the combined method (using three filters simultaneously) due to the high error of stock selection in each period. However, the risk of this process is less. Also, by comparing different filtering methods, it is observed that the machine learning method has achieved the best efficiency in stock portfolio optimization among the individual filtering methods. Subsequent methods of the Markov chain and technical are the next categories. However, on average, the risk of technical filtering was lower than all other methods.

Table 4 - Stock portfolio return, investment risk and return on investment

Solution	1/N	MOPSO	NSGA II
Mean of μp	13.08%	43.54%	107.63%
Mean of risk	0.946%	1.102%	1.419%
Mean of ROI	100.77	103.11	109.87
Mean of μp	-27.71%	3.55%	67.29%
Mean of risk	0.365%	0.349%	0.547%
Mean of μp	61.89%	91.49%	151.54%
Mean of risk	1.801%	2.668%	2.935%

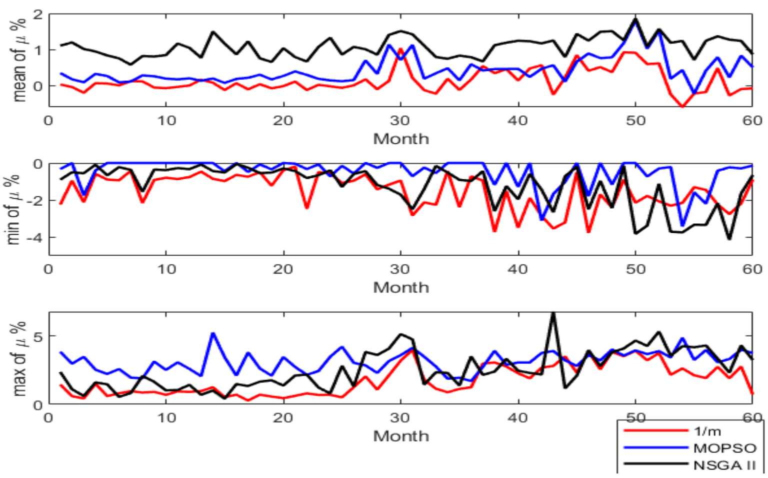

Figure 8- Total return on investment per month (2020-2016)

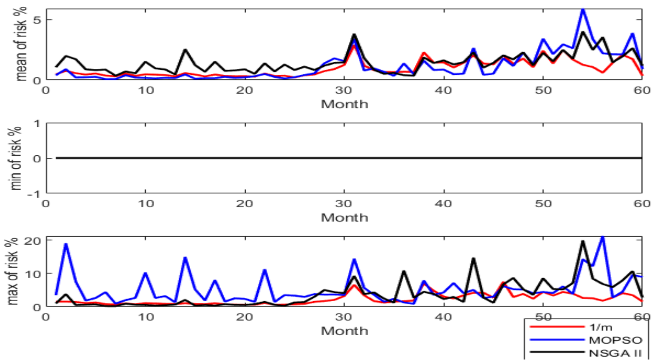

Figure 9 - Investment risk per month (2020-2016)

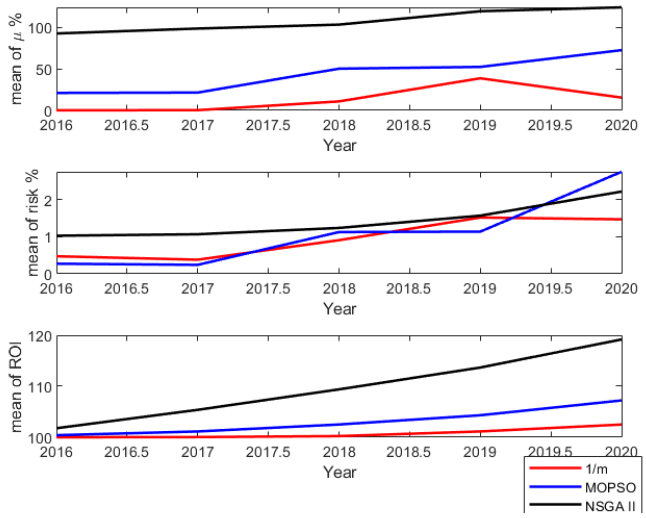

Figure 10 - Average indicators and objective functions studied in each year (2020-2016)

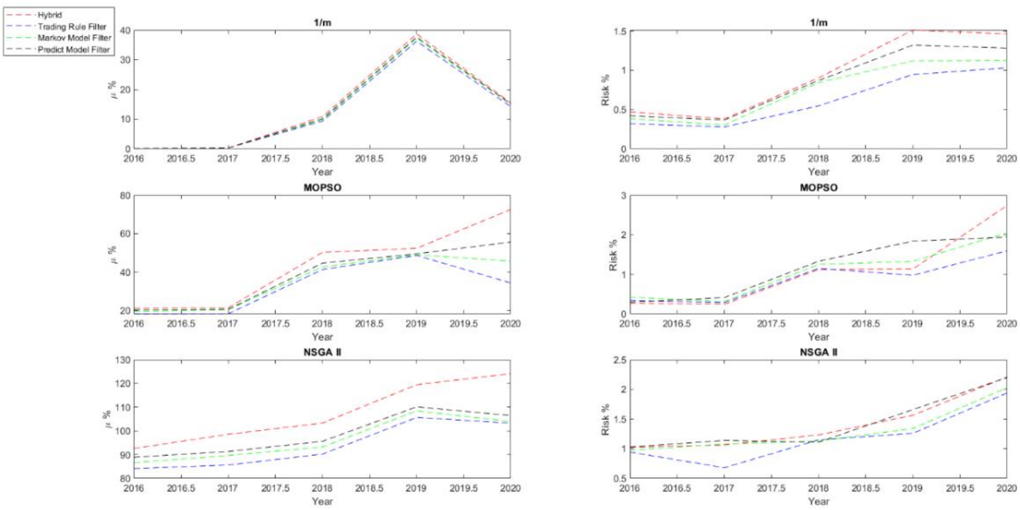

Figure 11 - Average performance of filters in stock portfolio optimization

5- Discussion and Conclusions

With the increase in the volume and speed of exchanges in the capital markets in recent years, manual techniques for market analysis have lost their effectiveness. In this regard, algorithmic trading techniques have emerged, which help investment activities through computational techniques. Today, with the help of computational techniques, machines can analyze various tools and more companies more quickly than humans and make decisions without human error. Algorithmic trading is used to both sell and buy assets. Machine learning and algorithmic trading can also be used if an individual or firm intends to purchase an asset. In purchasing, intelligent decisions are made to achieve the desired goal, such as maximizing profits or minimizing risk, or both, using machine learning to analyze and search for patterns. The selection of the investment portfolio is one of the main and important issues in the field of purchasing, which allocates capital between several shares in order to maximize the return on investment in the long run. In selecting the investment portfolio, algorithms are presented that combine economic theories and different machine learning methods to maximize the return on investment over several periods. The importance of optimizing the stock portfolio of listed companies led to this article to provide a model and optimal selection of investment portfolio to maximize stock portfolio returns based on the forecast price and minimize investment portfolio risk based on the Markowitz model. For this purpose, data from 480 companies listed on the stock exchange for ten years were used. Data were trained using a combination of Markov decision-making methods and learning machines for 85 active stock exchange companies filtered based on technical, fundamental, and time-series variables. Therefore, the stock sets are first filtered based on optimizing trading rules based on technical analysis that issued the buy signal. Also, the second type of filter uses a strong trading system using Markov chain and the third type uses a learning machine based on six classification models (SVM, DT, NB, KNN, MLP neural network as heterogeneous base models and weighted average method. As a homogeneous base model). Using a learning machine, in addition to filtering stocks based on buying signals and eliminating low-yield companies, also predicts stock returns. Hence, a set of stocks has been selected, which has been issued through all three methods of the buy signal. Accordingly, the data collected for the first five years (2015-2016) were trained and used for testing in the data for the next five years (2020-2016).

Two NSGA II and MOPSO algorithms were used to optimize the stock portfolio. According to the results, it was observed that if the shares are bought equally among 85 companies and maintained for 5 years, the average return on the total portfolio is 13.08%, with a risk of 0.946%. While using the MOPSO algorithm has achieved an average of 43.54% with an average risk of 1.102% and the highest return of 91.49% with a risk of 2.668%. The best value of the stock portfolio obtained in the lowest, average, and highest mode is obtained by NSGA II algorithm. Accordingly, the highest return of the stock portfolio was 151.54%, with a risk of 2.935%. The rate of return on capital for the NSGA II algorithm was also the highest in 5 years. Therefore, it can be said that based on the obtained indicators, NSGA II algorithm is the best combination of the stock portfolio. For future activities, the use of new meta-innovative algorithms such as Wall or Gray Wolf optimization for stock portfolio optimization is suggested.

Sensitivity analysis on different filtering methods in stock portfolio optimization was observed, if filtering methods are used individually, the stock portfolio will decrease. If all three methods provide a buy signal simultaneously, the probability of earning a portfolio profit and the risk of an investment portfolio will increase.

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