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Comparison of Portfolio Optimization for Investors at Different Levels of Investors' Risk Aversion in Tehran Stock Exchange with Meta-Heuristic Algorithms

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ABSTRACT

The gaining returns in line with risks is always a major concern for market players. This study compared the selection of stock portfolios based on the strategy of buying and retaining winning stocks and the purchase strategy based on the level of investment risks. In this study, the two-step optimization algorithms NSGA-II and SPEA-II were used to optimize the stock portfolios. In order to determine the winning algorithm, the performance indexes, set coverage and the Mean Ideal Distance were used. Finally, the active shares of 50 Tehran Stock Exchange companies were analysed (2007-2016). The results indicate that the SPEA-II algorithm can perform optimization and achieve a better performance than the NSGA-II. This algorithm could achieve better outcomes than the winning strategy during the selection period based on the risk-taking strategies in different months.

1 Introduction

Optimization models are used for decision making purposes in conditions of uncertainty in order to allocate risky assets. A modern portfolio selection theory based on the average variance model was presented by Markowitz [25]. Since then, most authors have tried to make optimal solutions to portfolio selection issues by balancing between the return maximization and investment risk minimization. Given the assumption of normal or abnormal return of assets, two different theories have been proposed. In modern theory, the distribution of return is assumed to be normal. Accordingly, standard deviation is introduced as a risk measure. However, the research shows that the distribution of the assets return is not normal. Given the assumption, risk measures vary from standard deviation to values at risk. Since there is no doubt about multi-objective nature of portfolio selection optimization, the use of multi-objective optimization techniques has attracted a lot of attention. Although, stock portfolio optimization is one of the most important stages of portfolio, stock selection is the most important stage of a proper investment [12]. The efficient market hypothesis (EMH) claims that it is impossible to overcome the market by choosing the underlying stock and yielding higher return than the average market. Changes in stock prices are random, and in fact follow the random walk process. Therefore,

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abnormal return cannot be achieved with historical information. The hypothesis also claims that there is no trend in the market price and return, and it is not possible to profit from market trends [12]. Over the past two decades, many studies have seriously challenged the credibility of the efficient market hypothesis. Fama [8], one of the major efficient market theorists, acknowledged in an article that stock market prices could be somewhat irrational. In a situation where the market loses its return relatively, the return can be increased through the use of appropriate investment strategies. Therefore, this paper aims to solution the question that which one of the algorithms of NSGA-II (Non-dominated Sorting Genetic Algorithm II) and SPEA-II (strength Pareto evolutionary algorithm) is more efficient in the stock market in different months. It also aims to determine which of the two optimized portfolios can achieve better results based on the strategy of stock selection strategy based on investor risk-taking and momentum.

2 Overview of the Research Background

One of the most important theories in the field of investment is the theory of capital market return. In the efficient market hypothesis, Scientists take into account two very important hypotheses: firstly, investors have a rational behavior in their decision-making on the market. Secondly, according to the latest information and news, investors buy and sell securities and show a good reaction to the news and information on the market. Thus, investors cannot get good return using investment strategies. However, various studies focusing on the efficient market hypothesis are indicative of conflicting results with these hypotheses. The evidence shows that investors over-react or under-react to the information published by companies in the short, mid and long term [4].
Contrary to the efficient market hypothesis and given the different reactions of investors towards information disclosure the horizons of time, the following strategy can be taken into account

2.1 Momentum Strategy

Several research suggest that the market reacts very slowly to information and news. Unlike the efficient market, whose stock prices react within a few hours or minutes to new information, in many cases, it has taken weeks, months, and even years for the price of securities to be adjusted to existing information. Hall [26] found evidence that analysts from the Value Line Institute, as an important group of market participants, under-react to three-month profits in their forecasts. Bernard and Thomas [27] also found that analysts of securities exhibited under-react to the corporate profits. According to the initial acceleration of motion, the object continues to move, even if the force is stopped. Furthermore, they predict the future with a kind of conservatism and follow the old habits. Edwards called this phenomenon " Conservatism Heuristic." According to this phenomenon, the future is like the past, and winners will remain winners and losers will remain losers [13].

2.2 Investment Strategy Based on Levels of Risk-Taking

According to theoretical literature, investors tend to choose the stock with an acceptable level of risk-taking. Given the personality traits, one who takes big risks is a bold individual and is willing to take more risks in order to obtain high profits. He/she is willing to be involved in risky investments. Conversely, with regard to personality traits, one who avoids taking risks seeks profit with minimal risk because fears of risk and failure overcomes pleasure in his/her perspective. Therefore, he/she invests in low-risk assets. The risk-taking person creates a high-risk portfolio with the hope of generating high profits [11,12]. The ultimate goal of the portfolio optimization process is to increase the investor's utility. Thus, choosing a portfolio based on the level of risk-aversion can improve the investor's utility in choosing the optimal portfolio. Given the level of risk-aversion of an investor and due to its association with the level of risk-taking, the investor can assess the appropriate returns and risks for the same level.

2.3 Multi-Objective Optimization Algorithms

One of the important issues in the capital market which should be taken into consideration by investors, whether natural or legal, is the choice of a set of stocks. This process requires a fundamental and technical analysis because each set has its own complexity. In some cases, each method comes up with contradictory predictions and makes it difficult for the investor to choose. For this reason, investing in stock portfolios and diversifying the stock selection can be a good option for investment and risk reduction [9]. The unfavourable risk index represents a clear distinction between favourable and unfavourable volatility. Conditional value at Risk (CVaR) which is also called Expected Shortfall (ES) and Average Value at Risk (AVaR), is more conservative than value-at-risk.
Given that some risk measures add complexities to the problem, the search region of the optimization problem turns into a non-convex region. Therefore, meta-heuristic algorithms are referred to as population-based search methods which have proved successful in solving complex multi-objective problems in the real world. The main advantage of meta-heuristic optimization algorithms is the ability to simultaneously match the candidate solutions. Therefore, they can estimate the entire set of optimal solutions. Over the past decade, many have attempted to develop multi-objective evolutionary algorithms (MOEA). These algorithms have been applied in various fields, including engineering, economics, etc. [14]. The question is, what algorithm is suitable for solving this problem among available meta-heuristic algorithms? Zitzler and Hohm [24] introduced the Strength Pareto Evolutionary Algorithm II and compared this algorithm and the most widely used and most powerful algorithms. They highlighted the superiority of the Strength Pareto Evolutionary Algorithm II and the Pareto Envelope-Based Selection Algorithm. Accordingly, Park et al. [28] compared Genetic Algorithm II and the Strength Pareto Evolutionary Algorithm II. They reported that Multi-Objective Genetic Algorithm was superior. Meghwani and Thakur [13] compared the NSGA-II, SPEA-II, PESA-II and GWASFGA algorithms for the seven indices in the Indian market. In this paper, the three criteria of generational distance (GD), inverted generational distance (IGD), hyper volume (HV) were used to measure the distance from Pareto optimization. According to the results, the Strength Pareto Evolutionary Algorithm II was a much diversified method which created more solutions. Meanwhile, Non dominated Sorting Genetic Algorithm II could achieve better results. This algorithm is used to optimize stock portfolios. In this study, these two algorithms were used for optimization to show which ones are more efficient.

Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is one of the most popular algorithms. Meanwhile, genetic algorithm is one of the exploratory algorithms for problem solving that is derived from the biological modelling of the animal population. In this algorithm, the characteristics of the generations are similar to those in which target functions and improvements in generational characteristics occur in the course of time, and the emergence of new generations is likened to improvements in the value of target functions. In other words, this algorithm uses the principles of Darwin's natural selection to find a formula or an optimal solution to predict or adapt the pattern [1]. The difference between the algorithm and the single-objective genetic algorithm is in the sorting method of the solutions. In fact, in multi-objective mode, solutions are ranked according to the distance from the swarm. In each replication of this algorithm, the new population is obtained by selecting the parent from the members of the main population and applying the operators [2].

Zitzler and Hohm [24] introduced the Strength Pareto Evolutionary Algorithm as a technical report on a multiple objective optimization algorithm with elitism and clustering along the Pareto. The technical report was later published [20]. The Strength Pareto Evolutionary Algorithm was developed as a part of Zitzler's PhD thesis [24]. He used it to find solutions to the optimal Pareto collections by combining several new methods and techniques. It was based on the genetic algorithm. In the SPEA algorithm, like many other evolutionary algorithms, solutions from another population were used to maintain optimal solutions over generations of algorithms [5]. The clustering approach was used to maintain the dispersion and elimination of additional solutions, but this algorithm had obvious weaknesses in parental selection. Zitzler and Hohm [24] improved the Strength Pareto Evolutionary Algorithm (SPEA) and came up with SPEA-II. Unlike the SPEA, this algorithm used a new approach to define fitness, in which both the set of concave solutions and the set of non-dominant solutions play a role. SPEA is a multiple objective optimization algorithm, and it also belongs to the field of evolutionary multiple objective algorithms. SPEA is an extension of the original genetic algorithm [3], for multiple objective optimization problems. Strength Pareto has an important role in SPEA because this shows how solutions close to the first rank. The objective of the algorithm is to identify and preserve a set of non-dominated solutions, ideally a set of Pareto optimal solutions. All the Pareto optimal solutions are called the Pareto optimal set [5].

2.4 Performance Evaluation of Optimization Algorithms

Given the fact that meta-heuristic algorithms are regarded as optimal algorithms for solving optimization problems and have a random nature, solving a problem through different methods may lead to different solutions. Therefore, the evaluation of algorithms and the selection of suitable algorithms with the help of various indices has attracted the attention of the researchers. However, convergence in Pareto's solutions and diversity in the set of solutions are two distinct and somewhat contradictory goals in multi-objective evolutionary algorithms. Accordingly, there is no absolute criterion for evaluation [7]. The nearness or closeness between Pareto solutions and the ideal point is measured by Mean Ideal Distance (MID criterion. The ideal value is equal to the best possible value for each objective function in all algorithms [7]. The lower the value of this index means better performance of the algorithm. For this purpose, the ideal points are calculated for the objective function. The coordinates of the ideal point are identified as $({f_2}^{best},{f_1}^{best})$ and the points of the algorithms are calculated by (1) [6].

$$\mathbf{MID} = \frac{\mathbf{1}}{\boldsymbol{N}}\sum_{\boldsymbol{i}=\mathbf{1}}^{\boldsymbol{n}}\sqrt{(\mathrm{f}_{1\mathrm{i}} - \mathbf{f_1}^{\mathbf{best}})^{\mathbf{2}} + (\mathrm{f}_{2\mathrm{i}} - \mathbf{f_2}^{\mathbf{best}})^{\mathbf{2}}} \tag{1}$$

Another index is set coverage index. This index, presented by Zitzler et al. [29], can be used to compare the relative density of the two sets. C (A, B) represents the percentage of solutions from B, which are obtained by at least one solution from A and defined by the following:

$$C\,(A, B) = |\,\{U \in B \mid \text{such that } \nu \in A \text{ and } \nu \text{ dominates } U\}\,| / (|B|) \tag{2}$$

2.5 Literature Review

In a research paper entitled “Momentum and reversal strategies in Chinese commodity futures markets”, Yang et al. [21] investigated the profitability of a momentum and reversal strategy in different time intervals in the upcoming Chinese commodity market. First, momentum and reversal trading strategies can generate robust and consistent returns over time; however, the intra-day strategies used cannot generate sufficiently enough high excess returns to cover the excessive costs due to the higher frequency of trading. Secondly, at lower trading frequencies and longer holding periods momentum and reversal strategies can generate excess returns, but with higher maximum drawdown risk. Finally, the double-sort strategies statistically improve the performance of the trading strategies. Vu and Taung [20], in a study showed that momentum effects exist in Vietnamese stock market. Specifically, we find that the strategy in which investors select a portfolio based on previous 6 months and hold for 9 months, generating significant profit. The finding from this paper does not support the hypothesis of stock market efficiency, which clearly characterizes the distinct features of emerging markets.

Rezaei and Elmi [18] showed that the reaction of stock price in the stock market was modelled by the behavioural finance approach. The population of this study included the companies listed on the Tehran Stock Exchange. In order to forecast the stock price, the final price data of the end December, March, June, and September 2006-2015 and the stock prices of 2014 and 2015 were analysed as the sample. In this study, Bayes' rule was used to estimate the probability of the model change. Through this rule, the probability of an event can be calculated by conditioning the occurrence or lack of occurrence of another event. The results of model estimation showed that there is the probability of being placed in high-fluctuated regimes (overreaction) and low- fluctuated (under-reaction of stock price despite the shocks entered to the stock market. In modelling with the -month final prices, it was proved that the real stock price had no difference from the market price. Miryekemami et al. [12] using a genetic algorithm in an issue aimed at maximizing returns and stock liquidity, they show that selected model provides a good performance for selecting the optimal portfolio for investors with specific goals and constraints.

Meghwani and Thakur compared the algorithms NSGA-II, SPEA-II, PESA-II, GWASFGA in the Indian market. The paper is based on three criteria (GD, IGD, HV), which are used to measure distance from Pareto optimization. Proposed methods can easily be incorporated into existing evolutionary algorithms. To evaluate their effectiveness, four MOEAs namely Non-Dominated Sorting Genetic Algorithm-II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2), Global Weighting Achievement Scalarizing Function Genetic Algorithm (GWASFGA) and Pareto Envelope-based Selection Algorithm-II (PESA-II) have been adapted and their capability of approximating unconstrained efficient frontier are discussed. Zeng & Liu [23] used the stock market data since April 2010, this paper sets focus on the existence of the momentum effect and reversal effect on Chinese stock market. From the empirical research results, we find that there exist the short-term momentum effect and the mid-term reversal effect on Chinese stock market. Based on the BSV model, this paper makes an effective explanation of the momentum and reversal effect on Chinese stock market.

In an article entitled "Comparing NSGA-II and SPEA-II in Multi-Objective Economic and Environmental Dispatch", Park et al. [28] argued that the environmental/economic dispatch problem is a multi-objective nonlinear optimization problem with constraints. Until recently, this problem has been addressed by considering economic and emission objectives separately or as a weighted sum of both objectives. Multi-objective evolutionary algorithms can find multiple Pareto-optimal solutions in one single run and this ability makes them attractive for solving problems with multiple and conflicting

objectives. They used an elitist multi-objective evolutionary algorithm based on the non-dominated sorting genetic algorithm-II (NSGA-II) for solving the environmental/economic dispatch problem. Elitism ensures that the population best solution does not deteriorate in the next generations. Simulation results are presented for a sample power system.
Anagnostopoulos Konstantin and Mamanis [3] used three multi-objective evolutionary algorithms including PESA, NSAGA-II and SPEA-II to solve the capital portfolio optimization problem. The results showed that by using the mean-variance model, all of the above algorithms have a very near approximation to Pareto's optimal level. Badri and Fathollahi [4] investigated the stock return momentum in Tehran Stock Exchange. Their study included 6438 stock portfolios and the average portfolio return test was carried out in a 10-year period. The results indicate that in a sample of 94 companies, momentum-based trading strategies are profitable until mid-term. Various studies have investigated the issue of strategy. Some studies have examined the effects of momentum and reversal strategies. In this research, both the simple average return and the weighted average return have been used by the meta-heuristic-algorithm. These methods, and in particular the two methods used in this research, can provide better results. Accordingly, several studies conducted in Iran have neglected these two strategies. This study intends to compare these two methods and the choice of stocks proportional to risk taking using NSGA-II and SPEA-II in the Iranian Stock Exchange.

3 Methodology and Analysis

The data includes the adjusted prices over the last 7 years for companies in the Tehran Stock Exchange (2008-2015). After calculating the return of stocks for the first three months, each strategy was selected and stocks with low negative fluctuations were identified. In order to select the momentum strategy, the shares of 50 companies (2008-2015) which have been able to earn more returns than other stocks were integrated. Those with less standard deviation were chosen as a portfolio. With the help of NSGA-II and SPEA-II algorithms, the stock portfolios were optimized. Then, an algorithm that performs optimization better was selected as an efficient algorithm. Having selected the appropriate algorithm, the portfolio of strategies was optimized by the algorithm over different intervals (three months, six months, nine months and twelve months). Finally, the results of the two strategies were compared. In this research, the portfolios were optimized by two SPEA-II and NSGA-II algorithms with a risk-based approach. The results and the comparison of the strategies are presented below.

3.1 Efficient Boundaries

After identifying the momentum strategies and low-risk stocks, the portfolios were optimized by NSGA-II and SPEA-II algorithms to determine which algorithms were more efficient in the first step. For this purpose, efficient boundaries were obtained. Figure 1 represents an optimized portfolio of low-risk strategies with NSGA-II and SPEA-II algorithms. It managed to yield a return up to 11% in three months. The same applied for the value is at risk. As shown in Figure 2, the portfolios of optimized by NSGA-II and SPEA-II algorithms could earn a return up to 14% in a three-month period. Moreover, the value in the conditional risk reached 9%-13% in the same interval. As shown in Figures 1 and 2, the SPEA-II algorithm was able to achieve more efficient strategies in comparison to the NSGA-II algorithm. To better illustrate this, the SPEA- II and NSGA-II were compared using the performance indicators (set coverage and mean ideal distance).

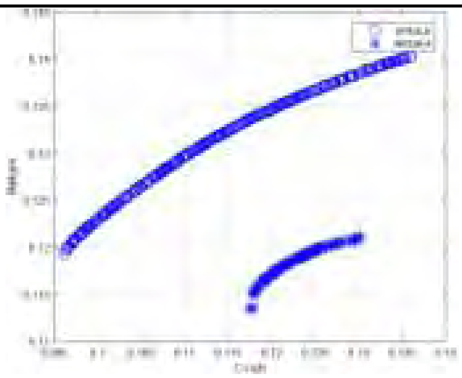

Fig 2: Drawing an efficient boundary for the winning stock strategy using nsga2 and spea2 algorithms

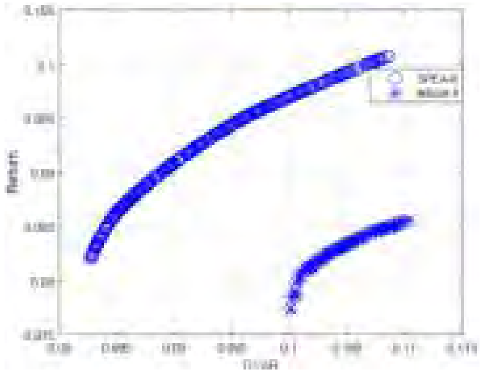

Fig 1: Drawing an efficient boundary for low-risk portfolio strategy using nsga2 and spea2 algorithms.

According to the mean ideal distance calculated in Table 2, the SPEA-II algorithm had a lower mean ideal distance than the NSGA-II algorithm in both strategies, suggesting the superiority of SPEA-II. This algorithm was able to simultaneously achieve solutions with higher return and low risks. According to the set coverage index presented in Table 3, the SPEA-II algorithm was able to obtain better results than the NSGA-II algorithm in both strategies, indicating that the SPEA-II was able to provide the NSGA-II solutions, which indicates the superiority of the SPEA-II algorithm.

Table 1: Calculating the MID

Optimization Method	MID-metric	
	Low-risk strategy	Momentum strategy
SPEA-II	0.186	0.156
NSGA-II	0.324	0.289

Table 2: Calculating the set coverage index

Optimization Method	Momentum strategy	Low-risk strategy
C(NSGA-II, SPEA-II)	0	0
C(SPEA-II,NSGA-II)	1	0.94

Table 3: Comparison of momentum and selection strategies based on risk taking

Strategy		3 months	6 months	9 months	12 months
Winning portfolio return	Mean return with equal weight	0.0164	0.0328	0.0873	0.0657
	Mean return with optimal weight	-0.0043	-0.0085	0.0552	-0.017
Low-risk portfolio return	Mean return with equal weight	0.0397	0.0739	0.14	0.1478
	Mean return with optimal weight	0.0544	0.1135	0.2018	0.2271

3.2 Comparison of Momentum and Selection Strategies

According to the results, the SPEA-II is the winning algorithm. This is why the weights obtained from this algorithm are used for different periods (three months, six months, nine months and twelve months) in both strategies.

In Table 3, the average portfolio returns for different periods (three months, six months, nine months and twelve months) are presented. The results show that momentum strategy was able to achieve better results in optimal weight. Moreover, low-risk could obtain better outcomes than the weight. The low-risk strategies could obtain better results in all maintenance periods compared to momentum strategy which is indicative of the superiority of the low-risk strategy.

4 Conclusions

In this paper, the two NSGA-II and SPEA-II algorithms were first compared using the value at conditional risk. According to the set coverage index and the mean ideal distance, SPEA-II algorithm was able to obtain better solutions than NSGA-II algorithm. The reason for the superiority of the SPEA-II algorithm is that it combined genetic algorithm and the particle swarm algorithm. Having determined the winning algorithm, the weights obtained from the winning algorithm were used as the optimal weights. The results indicate that the selection strategy based on the risk-taking level of the investor could obtain a return up to 9.5% in the three-month period. It could also achieve an annual return of 22%. The results show that it could obtain better returns in the recession. This can be attributed to many complex factors, but it may be argued that standard deviation made the stock selected with a minimum of negative fluctuations. During the recession, these stocks have the least loss and can get proper return. During the boom period, they can have proper and low-risk return. However, in the winning strategy, portfolios with high returns were selected. Thus, high risks and fluctuations were expected. During the recession, the probability of stock loss was much higher. In this research, given the fact that the stock exchange experienced a recession, one could expect that the low-risk portfolio selection strategy would have a better return than the winning portfolio. According to the results, it can be suggested that the investment funds for an investor would optimize portfolios with a lower half-standard deviation using the SPEA-II algorithm. If a stock market downturn is predicted, the maintenance of a low-risk portfolio can be a suitable investment option. It is also suggested that investment funds generally use the SPEA-II algorithm to gain optimal stock weight.

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