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Application of artificial intelligence algorithms in stock market forecasting

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Abstract

New methods of machine learning in Artificial Intelligence (AI), changing the parameters and naturally finding the most logical and optimal solution possible based on what has been learned in the past, reducing the search space, reduce decision error. The use of these new methods of calculation, mathematics, and artificial intelligence has increased in recent years in the capital market, but most of the methods of portfolio construction are based on the traditional methods of the past and, of course, more in the category of asset classification. In this paper, most algorithms that had been used in other research are implemented and tested. The results of this research show that PSO (Particle Swarm Optimization) and GWO (Grey Wolf Optimizer) are the best algorithms for forecasting financial markets. Both algorithms have the same capability and show good results.

Keywords: Artificial Intelligence, Machine Learning, Training Algorithms, Stock Market Forecasting.
2020 MSC: 68T05, 91B54, 91G15

1 Introduction

It is very difficult to predict financial time series because they are influenced by various dimensions and factors. Portfolio management can quickly become a gamble if the models used to predict future returns are not understood and the complexity of their dependent variables and, of course, their impact on risk are underestimated. Optimizing securities requires an awareness of matching expected market returns with predicted investment risk. The modern portfolio theory (MPT) proposed by Markowitz is an investment theory that emphasizes the extent to which risk is an integral part of stock portfolio returns and the idea of optimizing expected portfolio returns based on an asset's risk level. Transition and consideration of market risk provide [1]. Markowitz's theory shows the importance of selecting the right securities to build an egg basket and explains that investment management is not a simple game of selecting multiple stocks from the market. The price fluctuations of multiple assets in a portfolio are correlated, which is usually the source of market risk [15]. According to capital market theories, the risk of holding a single stock is much greater than the risk of holding a portfolio with minimal correlation. With a limited number of securities in a portfolio, the most common source of volatility in stock prices is market risk, also known as the general factor. Typically, the assets

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in a portfolio fluctuate less when they are separated from market risk, while the assets that are exposed to market risk are not only highly volatile but also generate a lot of profit or loss. In portfolio risk management, risks are divided into two categories: systematic risks and non-systematic risks. Market risk or systemic risk is an inherent risk to the market as a whole and its impact is not specific to a particular industry or sector. Non-systematic risk, on the other hand, has almost nothing to do with systematic risk and is an industry or sector-specific risk. It is therefore a good context for exploring the identification of new techniques to diversify and optimize portfolio risk.

Financial time series are very difficult to predict and are inherently affected by a high degree of governance. If the models used to predict future returns are not understood and the complexity of correlation and its impact on risk is underestimated, portfolio management can quickly become a gamble.

The analysis of securities is discussed in two general contexts:

- analysis and selection of individual stocks.
- formation of a systematic portfolio of stocks.

In the second framework, the new portfolio theory, capital market theory, efficient market hypothesis, index models, and performance evaluation scales are used. The optimization of securities requires the awareness of balancing the return and measuring the expected investment risk. Modern portfolio theory (MPT), proposed by Markowitz in [9], is an investment theory that emphasizes how risk is an integral part of stock portfolio returns and the idea of optimizing expected portfolio returns based on desirability and risk orientation of a portfolio. The investor proposes and determines market risk. Markowitz's theory illustrates the importance of selecting the right securities to build a portfolio and explains that managing investments is not a simple game of putting multiple stocks on the market.

The price fluctuations of the individual assets in a portfolio (portfolios), which are exposed to a common source of market risk, affect each other and are therefore correlated [15]. Therefore, the risk of holding each security individually is much higher than the risk of holding a portfolio that contains different assets with minimal correlation. With a limited number of securities in a portfolio, the most common source of price volatility is market risk and is therefore also referred to as the total capital factor. Assets in a portfolio tend to fluctuate less when they are separated from market risk. Assets exposed to market risk, on the other hand, are not only highly volatile but also involve large gains or losses [11].

Since there are so many meta-heuristic methods, the question always arises as to which is the best method. In this research, we need to compare the different meta-heuristic methods to find the best method for our work. In the following, we present the works related to this research and in the next section, we present the general algorithms used.

2 Literature and Theoretical Foundations of the Study

In 1952, the Journal of Finance published an article entitled "Portfolio Selection" by Harry Markowitz. The ideas presented in this article formed the basis for what is now commonly referred to as Modern Portfolio Theory (MPT). At first, MPT was met with relatively little interest, but over time the financial world embraced the thesis. Today, 50 years later, financial models based on same principles are constantly being reinvented to incorporate any new insights that emerge from this seminal work [5].

One important result of the research that has emerged from the ideas formulated in MPT is that today's investment professionals and investors are very different from those of 50 years ago. Not only are they more sophisticated financially, but they also have many more tools and concepts at their disposal. This allows both investment professionals to better meet the needs of their clients and investors to monitor and evaluate the performance of their investments [5].

Portfolio optimization is primarily concerned with the optimal selection of assets and securities that can be allocated a given amount of capital. Although minimizing risk and tracking returns may seem straightforward, in practice there are several methods for building an optimal portfolio. Cesaron and Tardella [17] state that the key to building an efficient portfolio is to balance risk and return and to decide on an asset allocation strategy. Optimal portfolios achieve this balance using several characteristics that measure risk and return. For example, the risk is measured as the standard deviation of return or using the Sharp ratio [16], and return can be measured using expected or absolute, or average returns. The calculation of expected returns is complex and therefore financial experts focus on controlling (or minimizing) risk using various diversification strategies. Markowitz's [10] portfolio theory states that the portfolio is optimally diversified if the variance of a given portfolio cannot be further reduced at a given level of expected return. According to this definition, the degree of diversification of any portfolio can be interpreted as a proxy-based on its variance.

Pedersen et al. [14] in an article aimed at investigating the weaknesses and problems of using the standard mean-variance model in practice presented an improved mean-variance model for portfolio optimization. The model, Enhanced Portfolio Optimization (EPO) model, which is an optimization based on the standard variance standard model, uses an additional input, the correlation shrinkage parameter, which has been selected to maximize risk-based returns on past data. EPO improves port-folio performance by calculating investor risk assessment noise and expected returns.

Kriksciunieneet al. [8] directly estimated the weight of portfolio assets optimally intending to optimize the portfolio by using deep learning models and modulating the model parameters. In the above study, the indicators of different asset classes show strong correlations and their adopted framework significantly reduces the range of available assets for selection. The results of sensitivity analysis, compared to a wide range of algorithms, show that the research model has the best performance during the test period, from 2011 to the end of April 2020, including the financial fluctuations of the first quarter of 2020.

Khan et al. [7] presented the quantum beetle antenna search (QBAS) algorithm to examine the optimal portfolio determination models based on artificial intelligence and determine the optimal stock set with the aim of minimizing the risk factor and maximizing the average portfolio return. Quantum computing is very popular in the scientific community because it surpasses conventional computers in terms of efficiency and speed. The proposed algorithm was applied to real stock market data and the results were compared with other meta-heuristic optimization algorithms. The results show that QBAS surpasses congestion algorithms such as particle congestion optimization (PSO) and genetic algorithm (GA). In their study for portfolio optimization, Kuraza et al. [4] propose a hybrid meta-heuristic algorithm based on particle swarm optimization algorithm. The results indicate that the modified hybrid metaheuristic algorithm performs better than the particle swarm optimization solver with fixed parameters. This operation is performed similarly with two-particle swarm optimization solvents corresponding to the parameters based on REVAC and IRACE.

Meng et al. [12] by studying the two-criteria portfolio optimization model and the interaction be-tween the expected portfolio rate of return and the maximum uncertainty measured by variance for all portfolio investments, specify and present an efficient portfolio and its structure such as dimensions and distribution. They paid for it. In his research, first by converting the model into a set of piecemeal linear convex programs, and then analyzing their optimization conditions, an efficient portfolio is estimated and created. The results also show that portfolio components are approximately equal in terms of risk; This means that the risks are evenly distributed among the investments.

Chaouki et al. [3] aimed to investigate the use of deep learning enhancement algorithms as optimal strategy solvers and showed that such reinforcing learning factors can successfully retrieve the basic features of optimal strategies and achieve near-optimal rewards.

portfolio return is the weighted average of each type of portfolio

$$r_p = w_1 r_1 + w_2 r_2 + ... + w_n r_n = \sum_{j=1}^{n} w_j r_j$$

r_j is the expected return on each asset and w_j is the ratio of the total resources invested in each asset.

The objective function of maximizing the expected range of the stock portfolio is as follows:

$$E_{\Omega}^{m} = \max \sum_{i=1}^{n} w_i \bar{r}_i$$

$$st: \sum_{i=1}^{n} w_i = 1 \quad w_i \geq 0$$

The following model, which is an edition of the above model, is defined as a $1 - \gamma$ percentage of the maximum expected possible return.

$$V_{\Omega} = \min \sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{l=1}^{n} \sum_{l \neq i} w_i w_l \psi_{il}$$

$$st: \sum_{i=1}^{n} w_i \bar{r}_i \geq (1-\gamma) E_{\Omega}^{m}$$

$$\sum_{i=1}^{n} w_i = 1$$

$$w_i \geq 0$$

PORTFOLIO RISK is defined as follows:

$$\sigma_P = \sqrt{W_A^2 \sigma_A^2 + W_B^2 \sigma_B^2 + 2\rho_{AB} W_A W_B \sigma_A \sigma_B}$$

3 Methodology

We compare five algorithms that spouse to be faster and better algorithms than others. We implement them and check the result on the same data.

The algorithms studied in this research have been implemented using Matlab Simulator version 2019. In the next section, entitled Implementation and Experiments, the tools are examined and introduced in detail. The following table also shows the specifications of the system in which the proposed method is implemented and the results are evaluated.

Table 1: System specifications for simulation and evaluation of results

Hardware / Software	**Specifications**
operating system	Windows 10
Operating system type	64-bit
RAM	8GB - 7.12 GB usable
Processor	Intel Processor - Number of Cores 7 ($Core^{TM}$) i7 CPU) - Q 720 @ 1.60GHz 1.60 GHz

Data that we used are the same in every test and they are Tehran price stocks index(TEPIX) from2011-March-01 to 2020-March-01. We check the capacity of the algorithm with data and forecasting.

3.1 PSO

The PSO method is a universal method of minimization that can be used to deal with problems whose answer is a point or surface in n-dimensional space. In such a space, hypotheses are made and an initial velocity is assigned to them, as well as channels of communication between the particles. These particles then move in the response space, and the results are calculated based on a "competency criterion" after each period. Over time, the particles accelerate towards particles that have a higher competency standard and are in the same communication group. Although each method works well in a range of problems, this method has shown great success in solving continuous optimization problems [6]. We get good results on PSO, the timing was 86.3s.

3.2 Imperialist Competitive Algorithm (ICA)

The colonial competition algorithm is a method in the field of evolutionary computation that finds the optimal answers to various optimization problems. This algorithm provides an algorithm for solving optimization mathematical problems by mathematically modeling the process of socio-political evolution. In terms of application, this algorithm is in the category of evolutionary optimization algorithms such as genetic algorithms, particle swarm optimization method, ant colony algorithm, simulated refrigeration algorithm, etc. Like all algorithms in this category, the colonial competition algorithm is a basic set of possible answers. These initial answers are known in the genetic algorithm as

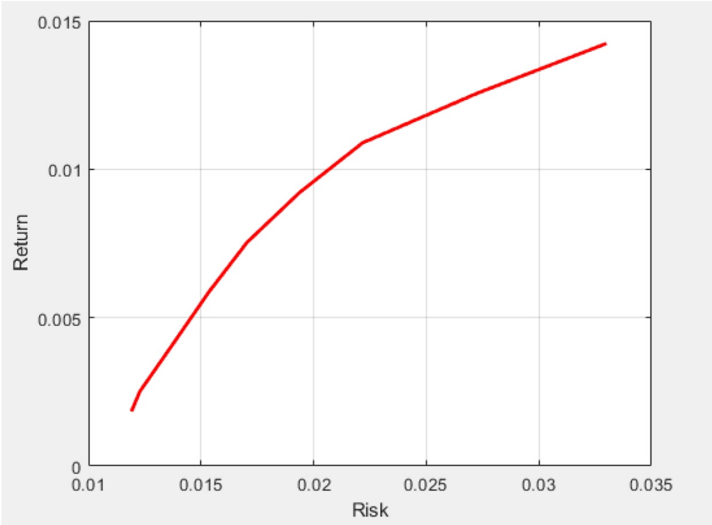

Figure 1: results of PSO on sample data

chromosomes, in the particle swarm algorithm as particles, and in the colonial competition algorithm as countries. The algorithm of colonial competition with the special process that follows gradually improves these initial answers and finally provides the appropriate answer to the optimization problem, the desired country. The main foundations of this algorithm are the policy of assimilation, colonial competition, and revolution. By emulating the process of social, economic, and political development of countries and by mathematically modeling parts of this process, this algorithm provides operators in regular form as algorithms that can help solve complex optimization problems. This algorithm looks at the solutions of the optimization problem in the form of countries that tries to improve these answers overtime during a repetitive process and finally reach the optimal solution of the problem [2]. We get normal results on ICA, the timing was 148.3s.

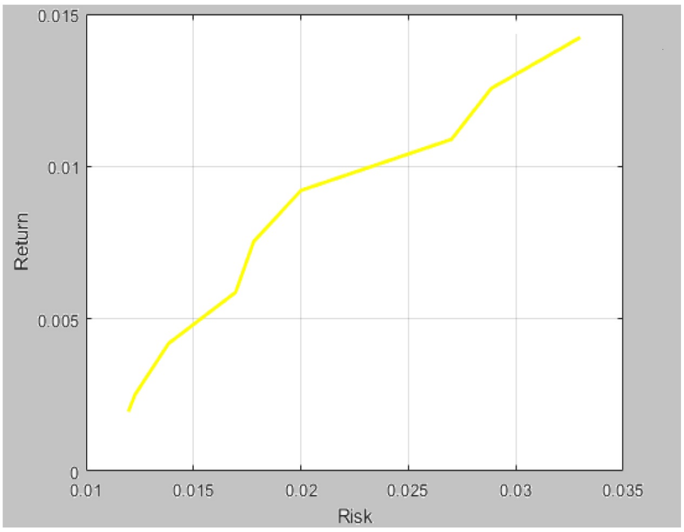

Figure 2: results of ICA on sample data

3.3 Non-dominated Sorting Genetic Algorithm II (NSGA-II)

The concept of a robust optimal solution is integrated with multi-objective optimal reactive power dispatch (MORPD) to account for uncertain load disturbances during system operation. Robust MORPD searches for solutions that are immune to parameter drift and load changes. It uses information about load increase directions to promote stability of optimal solutions in the presence of load disturbances. The genetic algorithm II (NSGA-II) with non-dominated sorting is used to search for robust Pareto solutions on a standard IEEE 118-bus system. Simulation has confirmed the effectiveness of NSGA-II for robust MORPD. NSGA-II obtained Pareto solutions over the trade-off space [18]. We did get not good results on NSGA-II, the timing was 474.9s.

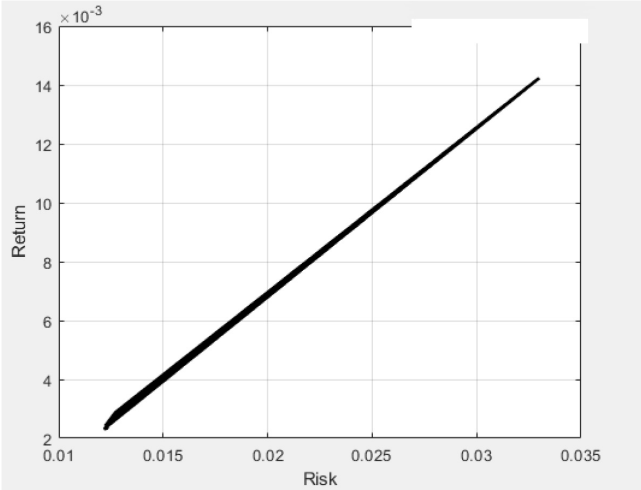

Figure 3: results of NSGA-II on sample data

3.4 The Strength Pareto Evolutionary Algorithm 2 (SPEA2)

The Strength Pareto Evolutionary Algorithm (SPEA) is a relatively new technique for finding or approximating the Pareto-optimal set for multi-objective optimization problems. In various studies, SPEA has shown very good performance compared to other multi-objective evolutionary algorithms and has therefore been a reference point in various recent studies, e.g. It has al-so been used in various applications, e.g. Authors propose an improved version, namely SPEA2, which, unlike its predecessor, includes a fine-grained fitness assignment strategy, a density estimation technique, and an improved archive truncation method [19]. We get unstable results on SPEA2, there is no pattern on results and we cannot see if it works or not, the timing was 332.9s.

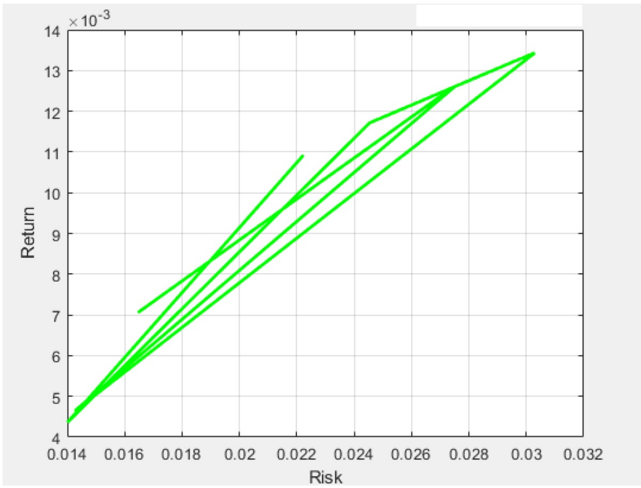

Figure 4: results of SPEA2 on sample data

3.5 Grey wolf optimizer (GWO)

The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. Four types of grey wolves such as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. In addition, the three main steps of hunting, searching for prey, encircling prey, and attacking prey, are implemented. The algorithm is then bench-marked on 29 well-known test functions, and the results are verified by a comparative study with Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), Differential Evolution (DE), Evolutionary Programming (EP), and Evolution Strategy (ES). The results show that the GWO algorithm can provide very competitive results compared to these well-known meta-heuristics [13]. We get good results almost as same as PSO on GWO, timing was 87.5s.

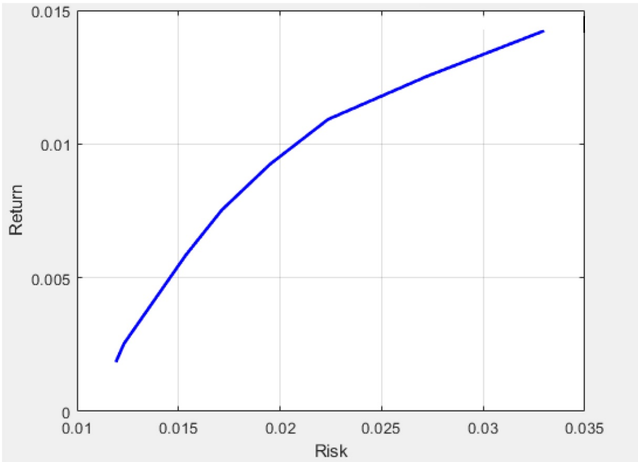

Figure 5: results of GWO on sample data

4 Conclusion

In this paper, we test some sample data on five algorithms introduced before. Timing of almost same PSO and GWO the results on these two algorithms is as same as spending time on computing. ICA is not bad but as we can see in figure 6 return and risk of investment were less than PSO and GWO. PSO and GWO are synchronized in all aims. The time of NSGA-II was worst in all tests, but still, we can see some forecasting which is not trustworthy. We have no comment on SPEA2 and its results, it seems this algorithm misses the purpose of this test.

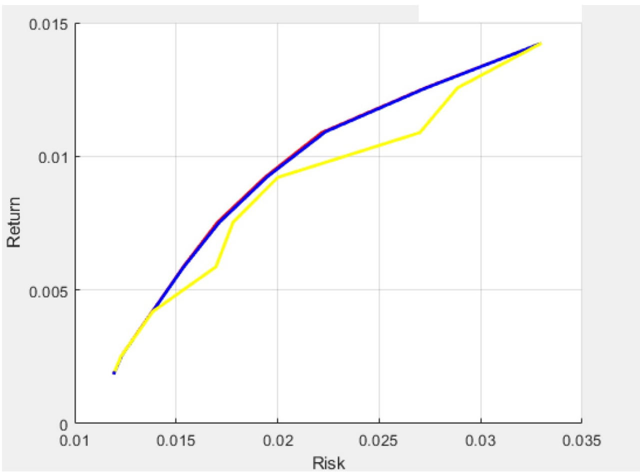

Figure 6: results of PSO, ICA, and GWO on sample data

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