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Research Article

Achieving an Optimal Stock Portfolio using Gray Wolf, Particle Swarm, and Hybrid Gray Wolf and Particle Swarm Algorithms

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ABSTRACT

In this research, portfolio optimization using Gray Wolf Optimizer (GWO), Particle Swarm, and a combination of Gray Wolf and Particle Swarm algorithms is presented. The main goal of this model is to maximize the return and minimize the risk of the portfolio, in a way that helps investors choose the best combination of available assets.The metaheuristic algorithm has been used to solve the multi-objective optimization problem in this study due to its high ability to search for optimal solutions and escape from local optima. The models used in this study include models developed from the Markowitz mean-variance model, the mean-half-variance model, the mean absolute deviation model, and the conditional mean value-at-risk model, to which some restrictions have also been added.

Keywords: *Stock Optimization, Gray Wolf Algorithm, Financial Constraint, Stock Portfolio*

Introduction

Investing in the stock market as a financial instrument has always attracted the attention of many investors (Ganjan et al., 2023). This choice not only has a great impact on the investor's financial performance, but can also help in better risk management and optimizing returns. Therefore, understanding the principles and methods of investment portfolio optimization is of particular importance.

Among the methods that have been effective in solving many optimization problems in recent years and have responded to human ambiguities are the methods and algorithms known as metaheuristics. These methods have become a successful approach in dealing with complex problems and can help improve the performance of investment systems (Lee et al., 2022).

Metaheuristic methods, which have been introduced to overcome the shortcomings of classical optimization methods, largely guarantee the possibility of achieving better results by comprehensive and random search. Since the stock portfolio selection problem, as a resource allocation problem, considers diverse and often conflicting constraints, it is naturally considered an NP-complete problem. This problem can usually be solved approximately (not exactly) on existing computers. Many studies have shown that the use of intelligent computational techniques, such as various algorithms, leads to improved solution of such problems (Mazraeh et al., 2022). In this study, the application of gray wolf algorithms will be examined to optimize the set of active stocks listed on the Tehran Stock Exchange. This approach can help investors make better choices in their investment portfolio and minimize risk.

Financial Markets

Financial markets provide the necessary facilities for the transfer of savings from individuals and legal entities and other persons who have productive investment opportunities and financial resources. The transfer of said funds, in almost all cases, results in the creation of a financial asset, and is in fact a claim to the future income of the personal assets (legal entities) that have issued and distributed the securities (Rahnamee Roudpeshti, 2018). With this interpretation; financial markets are a formal and organized market in which the transfer of funds from individuals and units requesting financial resources to individuals and units requesting funds takes place. Obviously, in this market, the majority of lenders are households and the majority of applicants for funds are economic enterprises and

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the government. In developed economies, financial markets help to optimally allocate excess funds (from savers) to individuals and organizations that need funds for investment or consumption. The more efficient the process of transferring cash flows is, the more efficiency will be created and included in the economic system with respect to factors such as production and financing.

One of the main features of financial markets is their dynamism and creativity, so that new financial instruments are always designed and investors are faced with a diverse range of instruments. The investor also chooses them based on financial strength, expectations of future financial resources for investment, and the level of risk tolerance. Financial funds are transferred between savers and borrowers in two ways: direct and indirect. In the direct case, there is no intermediary between the buyer and seller of a financial asset. In the indirect case, the transfer is carried out through investment banks and financial intermediaries (mutual investment funds and brokerage firms, etc.) (Rai et al., 2014).

Financial markets have three important economic functions:

1. The mutual relations of the buyer and seller in the financial market determine the price of the exchanged asset. In other words, these relations determine the expected return on the financial asset.
2. Financial markets provide a mechanism for investors to sell financial assets. Given this feature, it is said that the financial market provides liquidity.
3. It reduces transaction costs, which have two types of costs: search costs and information costs.

Search costs represent obvious costs, such as the money spent on advertising that a person wants to buy or sell a financial asset, as well as hidden costs, such as the time spent on finding a counterparty. The existence of organized financial markets reduces search costs. Information costs are the costs associated with estimating the investment characteristics of a financial asset, that is, the probability of cash flows expected from the asset (Abdo Tabrizi et al., 1997).

Investment

Investment has a wide range of activities that include investing in certificates of deposit, bonds, common stocks, warrants, stock options, convertible bonds, and tangible assets such as gold, land, precious metals, etc. "Investment is the purchase of a real or financial asset whose rate of return is commensurate with the expected risk" (Jahankhani, 1995). In simpler terms, investment is any negotiation of value now in the hope of obtaining value in the future. The investment process is a series of activities that ultimately result in the purchase of real assets or securities. Saving the excess of investment income over one's cost is an estimate that must be taken in the first way, and the next step is to recognize and be aware of the risk. An investor must be able to calculate and predict the amount of return and acceptable risk. In the next stage, awareness and recognition of the types of securities available in the market. After this stage, it is necessary for the investor to calculate the risk and return of the securities of the companies in which he wishes to invest. One of the pillars of the investment process is access to the information system in this field through specialized newspapers, financial sites, etc. (Jabari, 2012).

Understanding the structure of the securities market is another part of the investment process. The investor must know how these securities are traded and how to trade and establish a relationship with the broker. The last step is to select a set of securities that, from the investor's point of view, has acceptable returns and risks (Jahankhani, 2015).

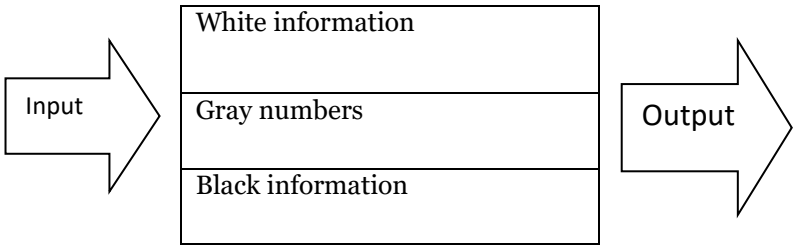
Gray System Theory

In the real world, there are many different systems, each of which and its components have their own subsystems. If the clear and transparent information of a system is visualized as white and the completely unknown information of a system is visualized as black, then the information related to most systems in nature is not white or black information, but a mixture of the two, that is, gray. Such systems are called gray systems, the main characteristic of which is the incompleteness of the information related to it. The goal of gray systems theory and its applications is to create a bridge between social sciences and natural sciences, where grayness means lack of information and uncertainty (Mohammadi et al., 1401).

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Flowchart 1- "Conceptual representation of a gray system"

Gray numbers

Every gray system is described by gray numbers, gray equations, and gray matrices, where gray numbers are the atoms and cells of this system. A gray number can be defined as a number with uncertain information.

For example, the ranking of criteria in a decision-making process is expressed as linguistic variables that can be expressed with numerical intervals. These numerical intervals will contain uncertain information. In general, it can be said that a gray number refers to a number whose exact value is unknown but the interval that includes its value is known. Gray numbers can be with only a lower bound in the form $[\infty, {}^{a}]\varepsilon$ or with only an upper bound in the form $({}^{a}, \infty\text{-})\varepsilon$ or written as a number in the form $[25, 20]\varepsilon$ (Jabari, 1379).

Gray Research Result

In addition to examining the relationships between different factors and options, the Gray Relationship Analysis method for multi-criteria decision-making considers inputs as interval numbers, which in fact displays both the uncertainty in the system structure and the uncertainty in the inputs to the decision-making system; in addition, it is a simple and practical model that covers the above methods simultaneously. In this method, firstly, there is no requirement for accurate information, and Gray theory has provided the ability to accept and use uncertain information by using the concept of Gray numbers. Secondly, in this method, multiple criteria are considered simultaneously and the relationships between them are also applied in the model. Thirdly, information related to consecutive years of a company is compared with the financial information of other companies in a model, which actually includes a combination of two conventional methods of financial evaluations (horizontal and vertical).

Research Method

The present study is classified as applied research in terms of purpose. From a methodological perspective, this study is descriptive. In the portfolio optimization problem, the goal is to invest our capital in a number of assets to achieve desirable characteristics of the total investment return.

Research Findings

One of the most important and challenging decisions that every investor faces is the formation of an optimal investment portfolio or basket. In the process of selecting a portfolio, the investor is faced with a diverse and extensive set of assets and stocks, each of which has different characteristics, risks, and returns. In such circumstances, making a decision to select the best combination of assets requires careful analysis, comprehensive evaluation and considering various financial criteria.

The investor must recognize which stocks have a more favorable position than others and deserve to be in his investment portfolio by understanding the market situation, company characteristics, economic trends and macro conditions. In addition to choosing the most suitable stocks, the optimal allocation of capital among the selected assets is also of great importance, because this can directly affect the final return and the level of investment risk. For this reason, the process of selecting and forming an optimal portfolio is a sensitive and complex issue that requires mastery of financial concepts and the use of appropriate analytical tools.

In order to form an optimal portfolio, various models based on the relationship between return and risk have been used. These models include: the mean-variance model with constrained components, the mean-half-variance model with constrained components, the mean-absolute deviation model and the mean-value-at-conditional-risk model.

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Each of these models By considering specific characteristics and constraints, it allows for optimization and analysis of portfolio composition with different approaches.
It is worth noting that in order to achieve optimal and more efficient solutions in this study, the use of meta-heuristic methods has been proposed. Among the proposed and selected algorithms in this study are the Gray Wolf Algorithm (GWO), Particle Swarm Optimization (PSO), Gray Wolf-Particle Swarm Hybrid Algorithm. These algorithms have been proposed for optimizing the portfolio models used in this study due to their high ability to search a large response space and avoid being trapped in local optima. As is clear, the use of the algorithms used in this thesis, in addition to achieving an optimal combination of stock portfolios, has also provided the possibility of comparing different definitions of risk, which could not be done directly in the normal case. In order to examine and compare the risk in the proposed models, the graphs presented in Figures 1 to 3 show the efficiency frontier of the three algorithms used in this study. Each of these graphs has drawn the efficiency frontier of the algorithms in the face of different definitions of risk. It should be noted that all graphs are drawn based on percentages; in such a way that the horizontal axis indicates the amount of risk and the vertical axis indicates the amount of efficiency obtained from the optimization. These graphs allow for a more detailed analysis of the relationship between risk and efficiency in the form of different models.

Table1: Stocks and stock ratios in portfolios. Using the Gray Wolf algorithm and models for research.

Company	CVaR	MAD	CCMSV	CCMV
Persian Gulf Petrochemicals	0.04155	0.04967	0.04623	0.04730
Ghadir Investment Company	0.00022	0.00045	0.00076	0.00054
Tamin Oil, Gas and Petrochemical I	0.04174	0.04582	0.04756	0.04385
Bank of Sina	0.00875	0.00932	0.00845	0.00970
Khorasan Steel	0.00001	0.00025	0.00051	0.00092
Mobarakeh Steel Isfahan	0.07692	0.07463	0.07811	0.07815
Omid Investment Management Group	0.00002	0.00001	0.00009	0.00014
MAPNA Group	0.07281	0.07345	0.07453	0.07312
IranKhodro	0.04476	0.03512	0.03729	0.03765
IranKhodro Diesel	0.00003	0.00007	0.00002	0.00005
Iran Transfo	0.03242	0.03389	0.03480	0.03603
Islamic Republic of Iran Shipping	0.03290	0.03851	0.03762	0.03185
Informatics services	0.75854	0.07099	0.07483	0.07811
Rayan Leasing Saipa	0.03745	0.04276	0.04613	0.04823
Golgohar Mining and Industrial	0.07810	0.08105	0.08376	0.08642
Chadormaloo Mining and Industries	0.09370	0.08867	0.08879	0.08771
National Iranian Copper Industries	0.07612	0.07688	0.07325	0.08645
Isfahan Oil Refining	0.05747	0.05389	0.05528	0.05634
Pars Khodro	0.00010	0.00004	0.00000	0.00000
Khark Petrochemicals	0.13276	0.08123	0.09810	0.09901
SAIPA	0.00007	0.00030	0.00035	0.00044
National Development Group Investment	0.05612	0.05668	0.05497	0.05523
Rena Holding Investment	0.00021	0.00007	0.00012	0.00020

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Company	CVaR	MAD	CCMSV	CCMV
Pension Fund Investment	0.05290	0.05613	0.05383	0.05652
Mining and Metals Developmen	0.00174	0.00367	0.00304	0.00232

Table 2: Stocks and stock ratios in portfolios based on particle swarm optimization (PSO) algorithm and models used in research.

Company	CVaR	MAD	CCMSV	CCMV
Persian Gulf Petrochemicals	0.04010	0.05374	0.04818	0.04821
Ghadir Investment Company	0.00296	0.00313	0.00374	0.00421
Tamin Oil, Gas and Petrochemical I	0.04225	0.04720	0.04213	0.04816
Bank of Sina	0.01188	0.00665	0.00571	0.00648
Khorasan Steel	0.00196	0.00025	0.00013	0.00111
Mobarakeh Steel Isfahan	0.07794	0.07201	0.07625	0.07690
Omid Investment Management Group	0.00044	0.00285	0.00300	0.00014
MAPNA Group	0.07358	0.06983	0.07536	0.07027
IranKhodro	0.04002	0.04041	0.04283	0.04043
IranKhodro Diesel	0.00195	0.00402	0.00184	0.00060
Iran Transfo	0.02890	0.03408	0.03058	0.04059
Islamic Republic of Iran Shipping	0.03024	0.04130	0.03486	0.03183
Informatics services	0.75909	0.06850	0.07938	0.08087
Rayan Leasing Saipa	0.04128	0.04740	0.04735	0.05301
Golgohar Mining and Industrial	0.07452	0.07942	0.07858	0.08470
Chadormaloo Mining and Industries	0.09234	0.08595	0.09155	0.08614
National Iranian Copper Industries	0.07407	0.07688	0.06940	0.08935
Isfahan Oil Refining	0.05340	0.05856	0.05796	0.05345
Pars Khodro	0.00494	0.00315	0.00207	0.00229
Khark Petrochemicals	0.13430	0.07696	0.09722	0.09579
SAIPA	0.00374	0.00149	0.00138	0.00400
National Development Group Investment	0.05490	0.05440	0.05667	0.05716
Rena Holding Investment	0.00387	0.00028	0.00370	0.00233
Pension Fund Investment	0.05495	0.05631	0.05641	0.05669
Mining and Metals Developmen	0.00182	0.00287	0.00150	0.00136

Table 3: Stocks and stock ratios in portfolios based on the Gray Wolf and Particle Swarm Hybrid Algorithm (HGWOPSO) and the models used in the research

Company	CVaR	MAD	CCMSV	CCMV
Persian Gulf Petrochemicals	0.04165	0.04958	0.04612	0.04717
Ghadir Investment Company	0.00031	0.00039	0.00072	0.00057

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Company	CVaR	MAD	CCMSV	CCMV
Tamin Oil, Gas and Petrochemical I	0.04150	0.04567	0.04723	0.04374
Bank of Sina	0.00882	0.00941	0.00867	0.00956
Khorasan Steel	0.00002	0.00023	0.00047	0.00089
Mobarakeh Steel Isfahan	0.07703	0.07482	0.07821	0.07828
Omid Investment Management Group	0.00003	0.00001	0.00008	0.00013
MAPNA Group	0.07296	0.07374	0.07493	0.07342
IranKhodro	0.04448	0.03558	0.03761	0.03785
IranKhodro Diesel	0.00004	0.00006	0.00002	0.00004
Iran Transfo	0.03275	0.03394	0.03485	0.03611
Islamic Republic of Iran Shipping	0.03299	0.03836	0.03741	0.03178
Informatics services	0.75845	0.07086	0.07455	0.07803
Rayan Leasing Saipa	0.03727	0.04232	0.04602	0.04812
Golgohar Mining and Industrial	0.07820	0.08134	0.08388	0.08637
Chadormaloo Mining and Industries	0.09382	0.08851	0.08864	0.08778
Persian Gulf Petrochemicals	0.07635	0.07688	0.07315	0.08650
Ghadir Investment Company	0.05742	0.05376	0.05511	0.05626
Tamin Oil, Gas and Petrochemical I	0.00008	0.00003	0.00001	0.00002
Bank of Sina	0.13252	0.08116	0.09803	0.09887
Khorasan Steel	0.00006	0.00028	0.00033	0.00041
Mobarakeh Steel Isfahan	0.05604	0.05659	0.05489	0.05512
Islamic Republic of Iran Shipping	0.00018	0.00005	0.00010	0.00018
Informatics services	0.05272	0.05601	0.05371	0.05642
Rayan Leasing Saipa	0.00168	0.00353	0.00313	0.00234

The final converged value of the objective function for the proposed algorithms in different patterns is as follows:
• For the Gray Wolf algorithm:
o In the mean-variance model with constrained components: 0.005829
o In the mean-half-variance model with constrained components: 0.005445
o In the mean-absolute deviations model: 0.003959
o In the mean-conditional value-at-risk model: 0.003469

• For the particle swarm algorithm:
o In the model model – variance with constrained components: 0.005811
o In the model model – half-variance with constrained components: 0.005445
o In the comparison model – absolute deviations: 0.003959
o In the model model – conditional value at risk: 0.003469

• For the combined Gray Wolf and Particle Swarm algorithm:
o In the mean-variance model with constrained components: 0.005931
o In the mean-half-variance model with constrained components: 0.005509
o In the mean-absolute deviations model: 0.003997

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o In the mean-conditional value-at-risk model: 0.003494

These final values indicate the performance of each algorithm in reaching the most optimal value possible for each model used.

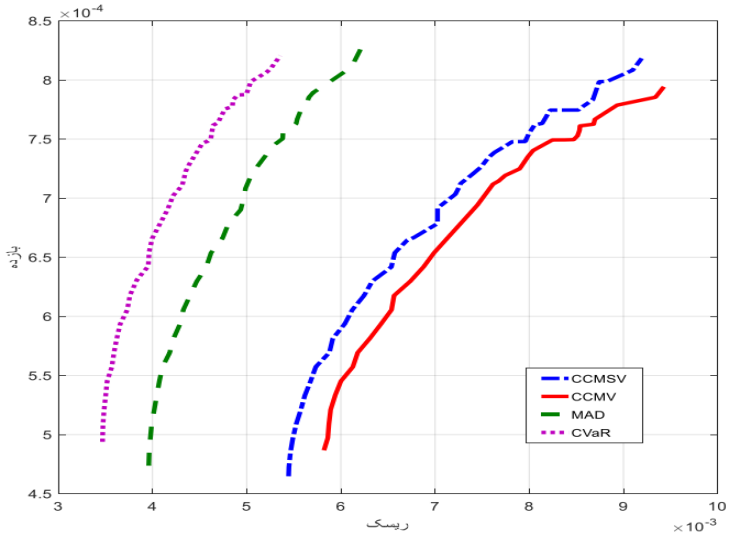


Figure 1- Efficient frontier of CCMV-CCMSV-MAD-CVaR models – GWO algorithm

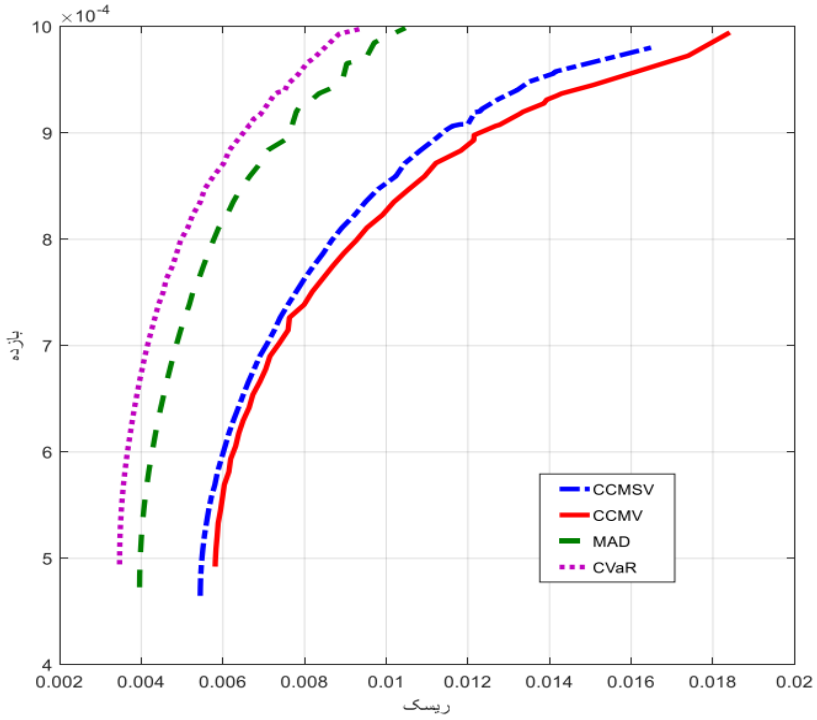


Figure 2- Efficient frontier of CCMV-CCMSV-MAD-CVaR models - PSO algorithm

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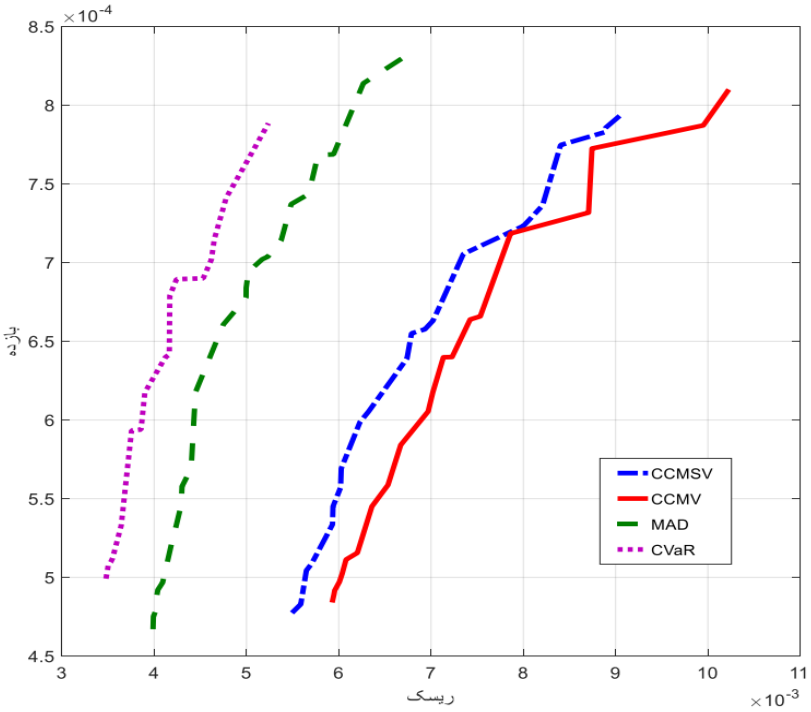


Figure 3- Efficient frontier of CCMV-CCMSV-MAD-CVaR models –GWO&PSO algorithm

In Figures 1 to 3, the different graphs represent different types of risk definitions with different colors. Specifically, the red graph represents variance as one of the risk measures, the blue graph represents half-variance, the green graph represents the absolute value of deviations, and finally the purple graph represents the conditional value at risk. Each of these graphs separately represents one of the different aspects of risk-taking for each of the algorithms used in the present study and helps to more accurately analyze the relationship between risk and return within the framework of different models.

As can be seen in the graphs in Figures 1 to 3, the algorithms used in this study have been able to effectively simulate optimal responses at all levels of risk and return, and the results have shown acceptable performance. By using more complex models that include precise mathematical and computational analyses, these algorithms have been able to draw the investment efficiency frontier with considerable accuracy. In this way, investors will be able to make the best choices in their stock mix and resource allocation by observing this frontier. In the graphs presented, the values obtained clearly indicate the differences between different levels of risk and return, and using this information, the optimal stock portfolio can be effectively determined. One of the important aspects of this research is the examination of different risks in investment portfolios. As can be seen from these graphs, we can accurately simulate different types of risks, including systematic risk, unsystematic risk, and market volatility risks, and examine their impact on the optimal mix of stocks. In fact, this research allows us to better understand how these risks affect the overall portfolio return.

According to economic theories, portfolios that are below the efficient frontier are not considered optimal. This is because such portfolios do not provide the highest possible return for a given level of risk. In other words, if a portfolio is below the efficient frontier, it means that there are other portfolios that can provide higher returns at the same level of risk. This indicates that the investor can achieve further optimization of his/her return by choosing a different portfolio and, as a result, can have better options for allocating capital in the financial markets.

This is of particular importance because it shows that accurate and up-to-date analysis in the field of selecting the optimal portfolio of stocks can significantly improve investment decisions. As a result, portfolios that are built based on non-optimal models actually lose a higher potential for better returns. This is especially important for investors

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with different risk appetites, because they can use this analysis to optimize their investments according to specific market conditions and their financial goals.

Given that the functions examined in this study differ only in the objective function and in the risk minimization part, in this study, the effectiveness of the optimization algorithms used is evaluated based on the risk measurement criterion. Specifically, in the mean-variance model, the effectiveness of the algorithms is measured using variance-constrained components, which indicate the amount of deviations and dispersion of the data. In the mean-half-variance model, the risk measurement criterion is carried out by means of half-variance-constrained components, which focuses more on reducing unsystematic risks and minimizing risks. Also, in the mean-absolute deviation and mean-conditional value-at-risk models, adverse risk factors are measured using the absolute deviation and conditional value-at-risk criteria. This means that in the mean-absolute deviation model, the main goal is to minimize deviations from the mean, while in the mean-value-at-risk model, risk assessment is carried out specifically with a focus on estimating risks in specific and risky situations. As a result, each of these models analyzes and optimizes risk and return according to its own approach and examines the efficiency of optimization algorithms using different risk-taking criteria.

In general, the most important results from Figures 1 to 3 are as follows:

•The mean-half-variance algorithm with constrained components, unlike the variance criterion, defines risk as the probability of loss. In this model, favorable changes (i.e., an increase in the rate of return of a financial asset) are not considered as risk. In other words, this model focuses more on reducing negative risks and possible losses. By reducing the risk in this model, the indicators related to the portfolio performance increase with fewer deviations. This causes all the algorithms proposed in the research to act similarly in the mean-half-variance model with constrained components and shift the efficient frontier to the left. This shift of the efficient frontier indicates an improvement in the performance of the investment portfolio, in which the same risk is met with a higher rate of return. Finally, due to these features, the use of the mean-half-variance model with constrained components allows investors to obtain higher returns by accepting the same risk.

•All portfolios that are on the efficient frontier offer the highest expected return for a given and identical level of risk or have the lowest risk for a given and identical level of expected return. In other words, these portfolios are the most optimal investment options, because no other portfolio can achieve a higher return with the same level of risk. In contrast, portfolios that are below the efficient frontier are not optimal, because these portfolios do not offer the highest possible return for a given level of risk. That is, there are other portfolios that will have a higher return with the same level of risk. In particular, the best efficient frontier resulting from the four proposed approaches for the algorithms used in this thesis belongs to the conditional mean-value-at-risk, mean-absolute deviation, mean-half-variance with constrained components, and mean-variance with constrained components models, respectively. These results indicate that models based on conditional value-at-risk and absolute deviations provide the best performance in optimizing the composition of investment portfolios compared to other models and are able to draw the efficient frontier effectively.

•According to the results obtained from the application of the four proposed algorithms, the efficient frontier obtained from the mean-value-at-risk approach is significantly better than that of other models. This means that the portfolio obtained using the mean-value-at-risk method has a higher efficiency than when the portfolio is obtained using the mean-absolute deviation, mean-half-variance with constrained components, and mean-variance with constrained components models. These results indicate that the conditional mean-value-at-risk method is more efficient than other methods, because this model has been able to effectively shift the efficient frontier and bring investors higher returns with the same risk. In other words, the conditional mean-value-at-risk approach has performed better than other models in terms of optimizing returns under different risk conditions.

To compare the efficiency of the algorithms used, the efficient frontier of the four proposed algorithms with the three algorithms used in this thesis is shown in Figures 6 to 9. These figures clearly show the performance differences between the different algorithms in terms of optimizing portfolio combinations at different levels of risk and return. This comparison allows for a more detailed analysis of which algorithms provide the best results in achieving the efficient frontier and helps investors achieve the best possible portfolio composition by choosing the most appropriate algorithm.

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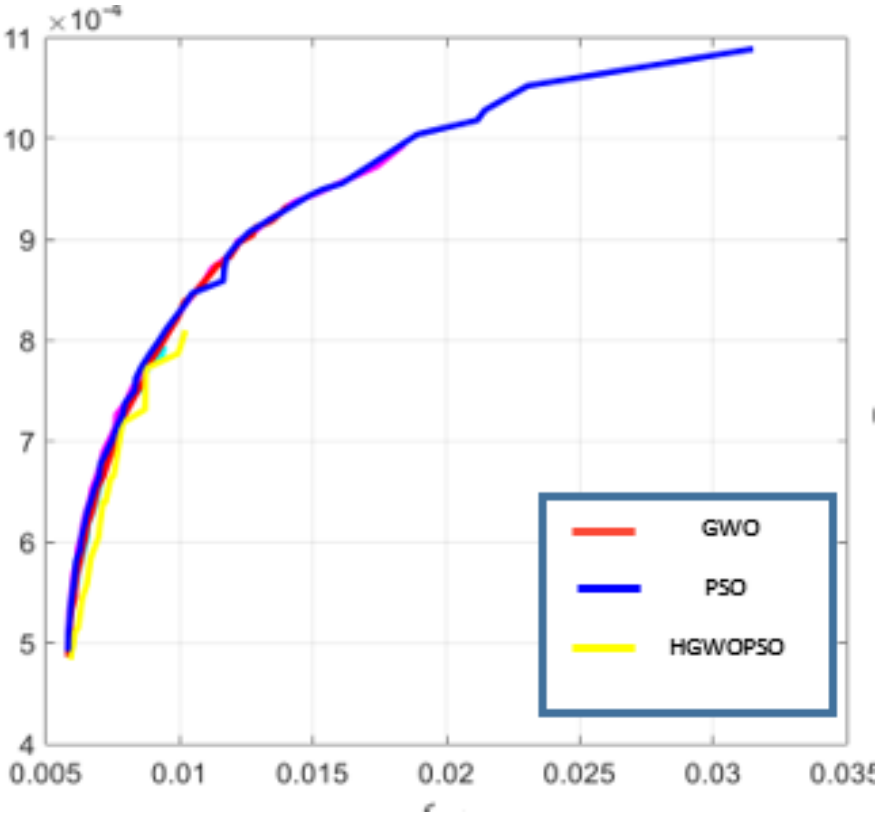


Figure 6- Efficient frontier of GWO algorithms -PSO-HGWOPSO -CCMV model

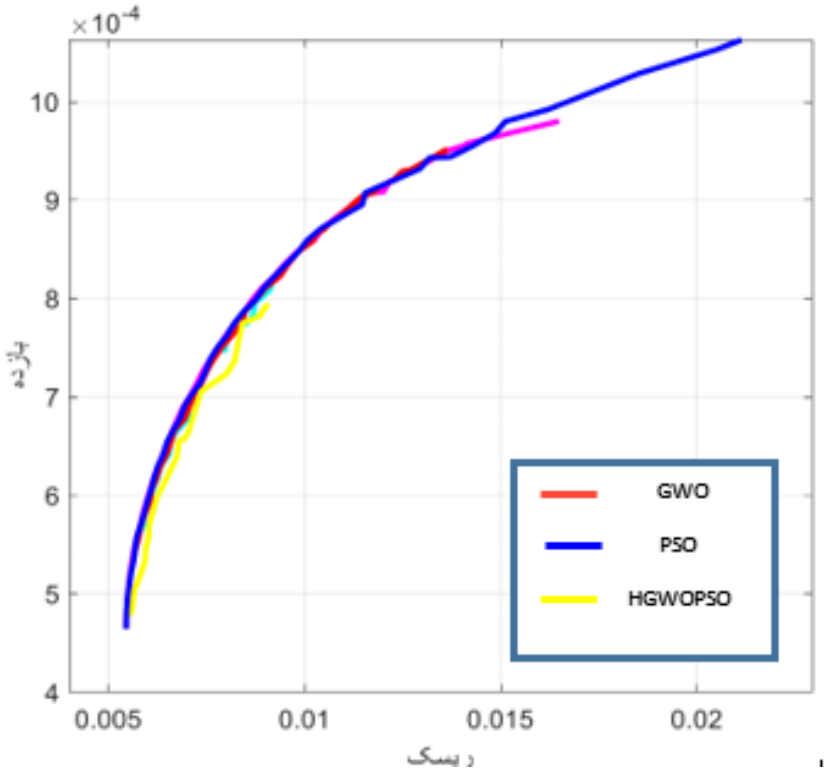


Figure 7 - Efficient frontier of GWO algorithms, PSO - HGWOPSO - CCMSV model

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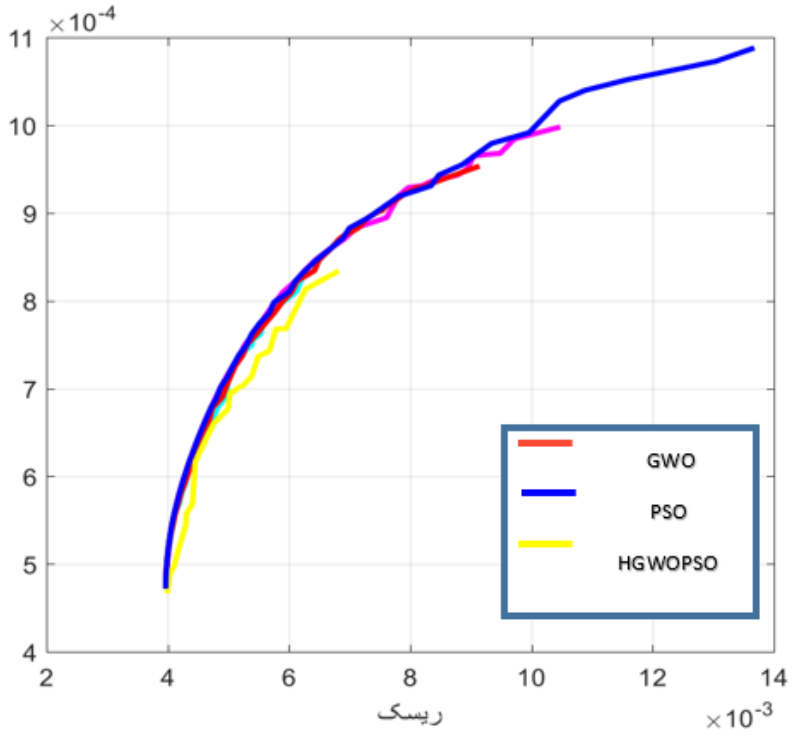


Figure 8 - Efficient frontier of GWO algorithms -PSO -HGWOPSO -MAD model

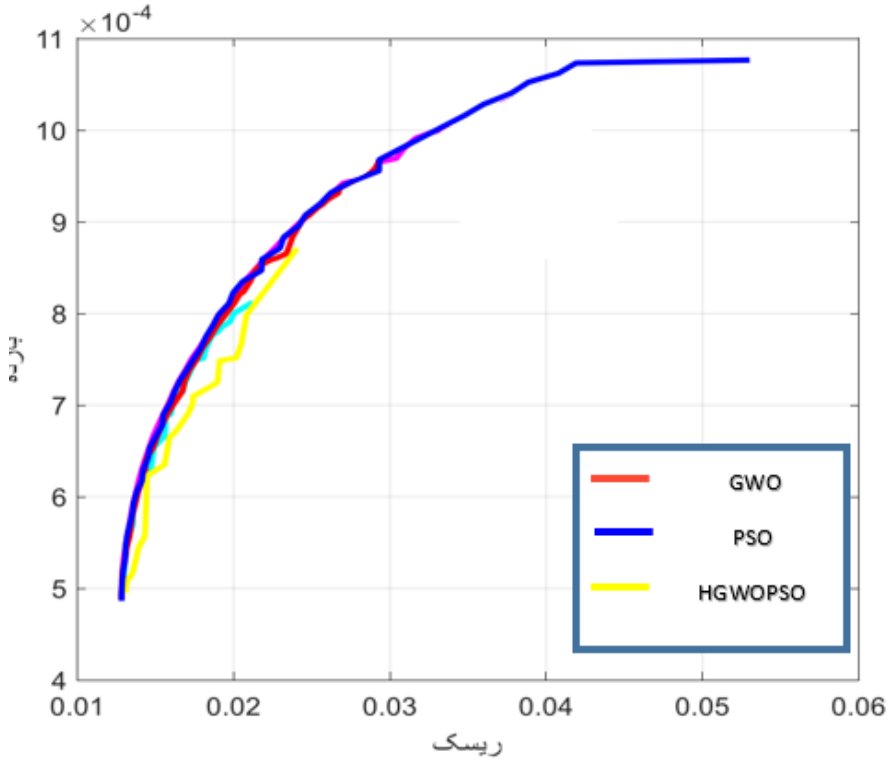


Figure 9 - Efficient frontier of GWO algorithms -PSO -HGWOPSO -CVR model

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As can be seen, in these forms there is no significant difference in the use of algorithms in the models of mean-variance with constrained components, mean-half-variance with constrained components, mean-absolute deviations and mean-value at conditional risk. In fact, as can be seen, the efficient frontier of these algorithms overlap and the optimal portfolio coefficients are very close to each other. This indicates that in these methods, the algorithms have almost similar performance and effectively achieve a similar efficient frontier. Therefore, considering the similarities of these algorithms in optimizing the portfolio composition, it can be concluded that these models perform equally in achieving the best results for different levels of risk and return. As a result, generally similar results have been obtained from both methods, which indicates their acceptable efficiency and effectiveness in the process of portfolio optimization. To make a precise comparison and comprehensive assessment of the accuracy and performance of these models, two basic criteria are considered: time and variance. The time criterion is used to measure the execution speed and efficiency of the algorithms in finding the best portfolio combination, and the variance criterion is used to measure the volatility and stability of the results.
These two criteria have been carefully calculated and analyzed for each of the different models and algorithms used in this study. The results obtained from these analyses are presented in full and in detail in Table 1. In addition to displaying the numerical results, this table allows for a precise comparison of the performance of each model and algorithm and helps researchers and decision makers to choose a more optimal algorithm for portfolio optimization.

Table 1- Comparison of proposed algorithms in the models used in the study using the time (in seconds) and variance criteria

Gray Wolf Algorithm (GWO)							
CCMV		CCMSV		MAD			CVaR
Time	Variance	Time	Variance	Time	Variance	Time	Variance
9159.6	2.09 E -11	17480.7	2.00 –E 12	10790.2	3.81 –E 14	12848.2	2.09 E -37
Particle Swarm Optimization (PSO) algorithm							
CCMV		CCMSV		MAD			CVaR
Time	Variance	Time	Variance	Time	Variance	Time	Variance
959.9	4.26 E -14	1943.5	7.10 E -15	1115.8	3.00 E -16	1365.6	8.36 E -37
Gray Wolf and Particle Swarm Hybrid Algorithm (HGWOPSO)							
CCMV		CCMSV		MAD			CVaR
Time	Variance	Time	Variance	Time	Variance	Time	Variance
1064.3	4.94 E -09	2257.2	1.80 E -09	1307.4	1.10 E -09	1544.07	2.09 E -37

According to economic theories, in general, the smaller the value of the best variance criterion, the shorter the convergence speed and the time to reach the optimal solution, the higher the forecast accuracy of the estimated models. According to the results obtained in Table 1, it is clear that for a data set of 25 stocks, the particle swarm algorithm has provided the best variance compared to other algorithms used in the research. This algorithm has been able to show better performance than other algorithms with different application models. In addition, in this algorithm, the mean-value-at-risk model has a lower variance than other models, which indicates higher accuracy in predictions and reduced volatility. On the other hand, the highest convergence speed belongs to the combined gray wolf and particle swarm algorithms, respectively, and then the gray wolf algorithm is in third place. According to the research results, the mean-variance model with constrained components in the algorithms has a higher convergence speed than other models, which indicates the ability of these models to reach the optimal solution in a shorter time.
In fact, as can be seen, the combined Gray Wolf and Particle Swarm algorithms are able to achieve better solutions in less time, which is especially important in environments requiring fast and optimal decision-making.
Due to the reasons mentioned, in this article, all the algorithms used are able to find solutions close to the global optimal solution, and it seems that the Particle Swarm algorithm converges faster than other algorithms. This feature of the Particle Swarm algorithm is of great importance, especially in optimization problems with large and complex

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dimensions, because the high convergence speed can help reduce the calculation time and improve the overall efficiency of the system.

Another important criterion for evaluating the efficiency of algorithms in the portfolio optimization process, which has been used in this research, is the MPE (Mean Percentage Error) criterion. This criterion actually acts as a criterion for measuring the accuracy of the forecasting method in portfolio optimization and expresses the accuracy as a percentage. The MPE value indicates the average percentage of the model's forecasting error compared to the actual values. In other words, the MPE numerically displays the deviation of forecasts from actual data and is used as a criterion for measuring the accuracy of forecasts and evaluating the efficiency of algorithms in achieving more accurate results. The lower the MPE value, the higher the accuracy of the model in forecasting and optimizing the portfolio, which is defined for each of the proposed approaches in the research as the following relationship:

(1)$MPE = \frac{100\%}{n}\sum_{t-1}^{n}\frac{a_t - f_t}{a_t}$

In this regard, it is considered as the best value of the objective function in the iterations and at is considered as the value of the objective function in the iteration. To solve this problem, it is recommended to use a large number of iterations to achieve more optimal results. In this study, the number of iterations is considered to be 50 so that the optimization process can be carried out accurately and in a sufficient time. The results of these iterations are presented comprehensively in the form of Table 2, which allows for the analysis and comparison of the results obtained from this process. This table includes different values of the objective function during different iterations and the best value obtained at each stage, which will be examined in detail in subsequent analyses.

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Table 2- Results of calculating the MPE criterion for the proposed algorithms in the models used in the study

Proposed algorithm	CCMV			CCMSV				MAD		CVaR		
	Objective function		Number of iterations until convergence	Objective function		Number of iterations until convergence		Objective function	Number of iterations until convergence	Objective function		Number of iterations until convergence
	Optimality value of the objective function	Average error percentage value in 50 iterations of the objective function		Optimality value of the objective function	Average error percentage value in 50 iterations of the objective function		Optimality value of the objective function	Average error percentage value in 50 iterations of the objective function		Optimality value of the objective function	Average error percentage value in 50 iterations of the objective function	
GWO	0.005829	0.06134%	96	0.005445	0.0729%	84	0.003959	0.00643%	64	0.003469	0.003919%	157
PSO	0.005811	0.0598%	14	0.005445	0.0674%	43	0.003959	0.00286%	16	0.003469	0.00313%	47
GWO-PSO	0.005931	0.0474%	1	0.005509	0.00315%	1	0.003997	0.002871%	1	0.003494	0.0278%	1

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In a general conclusion, it can be stated that by considering all three criteria for assessing the accuracy of portfolio optimization simultaneously, the particle swarm algorithm has a higher accuracy in the optimization process. This algorithm has been able to achieve the best results compared to other algorithms used in this study and has shown better performance than other methods, especially in complex conditions and big data. Since the accuracy of portfolio optimization requires considering various criteria such as convergence time, variance, and prediction accuracy, the particle swarm algorithm has achieved the best results in all these areas. Also, according to the discussions raised in the upcoming study, it can be concluded that in this algorithm, the conditional mean-value-at-risk model has a higher optimization accuracy than other models. This model is able to effectively manage the risks in the portfolio and provide accurate predictions about the future behavior of assets. In situations where decision makers need to accurately predict and optimize the performance of their portfolios, this model can be a powerful tool for reducing risk and improving the overall portfolio return. Especially in financial markets where there are many fluctuations and risks, using such a model can bring more favorable results.

The results obtained in this study are all consistent with the theoretical foundations of the present study and are consistent with the results of most research studies conducted in the field of portfolio optimization. This alignment between the results of the study and previous findings emphasizes the accuracy and validity of the models and algorithms selected in portfolio optimization. Also, this consistency with previous studies is a testament to the reliability of the research results and the applicability of these methods in the real world. In general, the results of this study can be used as a new basis for developing portfolio optimization models in various financial and economic fields.

Conclusion

According to the main objective of the research, this research is designed based on four different algorithms in the field of portfolio optimization. These algorithms include the mean-variance model with constrained components, mean-half-variance with constrained components, mean-absolute deviations and mean-value at conditional risk. In this process, various constraints such as the number of stocks in the portfolio and determining the ceiling and floor for each asset are also considered. In order to predict and analyze accurately, various algorithms such as gray wolf, combination of gray wolf and particle swarm algorithms were used to extract daily return and risk information. The main goal was to identify the best combination and ratio of stocks in the portfolio by using these algorithms so that the selected stock portfolio has the highest return and the lowest possible risk simultaneously.

According to the findings of this study, it can be concluded that these results confirm the effective use of meta-heuristic algorithms in portfolio optimization and selection.Based on the analyses, the use of these algorithms can significantly help in improving the accuracy and efficiency of portfolio optimization processes and therefore it is recommended that these algorithms be considered as the main tools in portfolio optimization.

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