ISSN 2071-789X

RECENT ISSUES IN ECONOMIC DEVELOPMENT

ECONOMICS
& Sociology

Maknickienė, N., Maknickas, A., & Tvaronavičienė, M. (2026). Choosing approaches towards investment decisions: A case study of artificial intelligence (AI) based method use. *Economics and Sociology, 19*(1), 276-291. doi:10.14254/2071-789X.2026/19-1/13

CHOOSING APPROACHES TOWARDS INVESTMENT DECISIONS: A CASE STUDY OF ARTIFICIAL INTELLIGENCE (AI) BASED METHOD USE

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ABSTRACT. Intensive development of digitalisation tools and digital financial services significantly increases the range of societal actors who are interested and can make financial decisions about using available funds. Since there is a wide range of approaches towards investment making, choosing a method from the available menu has become a partly sociological decision. Institutional investors, SMEs and individual investors are increasingly using artificial intelligence algorithms. The paper offers an analysis of a specific AI investment decision method, i.e., the Cuckoo Selection algorithm. It is based on the logic of cuckoo breeding and was applied to stock selection and portfolio optimisation for three data sets in different markets. The goal of minimising risk was to reduce risk, but at the expense of profitability. When the Cuckoo Selection algorithm was applied to maximise the Sharpe ratio, both stock selection and portfolio optimisation showed an increase in diversification efficiency. The algorithm proved to be particularly useful when it was used for selection, and optimisation was performed by other known algorithms. This research can be useful in automating financial decisions and developing recommendation systems for investors who are interested in efficient allocation of available funds, whether it is financial fund management, investment of underused funds, or financial project management.

Received: April, 2025
1st Revision: January, 2026
Accepted: March, 2026

DOI: 10.14254/2071-789X.2026/19-1/13

JEL Classification: D02, O17, P31

Keywords: AI, investment decisions, Genetic algorithms, Cuckoo Search, swarm intelligence, nature-inspired, stock selection, portfolio optimization, diversification, recommender system, financial funds management

Introduction

Society constantly faces the challenge of balancing very opposite things: rapid growth and sustainability, benefits and social welfare, work and leisure, etc. The most studied is investing, where portfolio optimisation aims to balance risk and return. However, it is not enough to use the tools of modern portfolio theory; every investor also faces the challenge of selecting suitable investment instruments. Earlier, the instrument selection method was particularly relevant for institutional investors, who had broader portfolio diversification opportunities than individual investors. Nowadays, the development of digitalisation (Peclinovský et al., 2024; Haurovi & Chilunjika, 2024; Ondrík & Jankal, 2025; Zhang et al., 2025), financial literacy and availability of investment tools have allowed a broader range of society, representing earlier unconventional investors, such as SMEs, non-financial organisations or individuals to become active investors with a purpose to employ underused financial resources with the highest possible return (Hui et al., 2025; Tang & Zhou, 2025).

Investment decisions can be made using a broad menu of available and newly emerging approaches. Currently, AI is increasingly used to make financial decisions. In this paper, the authors, taking into account the increasing use of AI, suggest a novel approach towards investment decision analysis and introduce an investment decision method which has not been used previously. Hence, the “so-called” Cuckoo's reproductive logic radically differs from that of other birds, which care for and raise their young in their nests. The Cuckoo must choose a foreign nest that has enough resources to raise a foreign bird, but also enough resources to raise its own chicks; otherwise, both bird species may become extinct. This optimisation of natural phenomena inspired Yang and Deb (2009) to create a learning algorithm, which has been successfully applied in various fields; however, we could not find any research where this algorithm has been utilised in the financial market.

This study aims to investigate whether Cuckoo's Search algorithm (CS) can serve as an alternative portfolio optimisation algorithm, whether it can be utilised as an instrument selection tool, and whether it can be integrated with other known optimisation algorithms.

1. Literature review

Developing an investment strategy starts with the investor's goals, which usually depend on the investor's individual characteristics, such as experience, risk tolerance, and the time and resources available to devote to this process. Chosen investment strategies, as a rule, yield different results (Feng et al., 2024; Peternel & Bukvič, 2024; Bukvič, 2025). Detzel & Howard (2024), after examining three groups of investment fund strategies, found that consistency, to which fund managers invest in similar stocks, not only allows for greater-than-average returns but also helps identify a latent characteristic of the manager's skill.

Isidore & Arun (2022) identified five dimensions of investor personality (Extraversion, Agreeableness, Conscientiousness, Neuroticism, Openness), which correlate with popular decision-making tools such as economic analysis, sector analysis, technical analysis, company ratio analysis, and expert recommendations. Other authors agree that human factors affect performance results irrespective of the combination of other factors (Body et al., 2024; Mishchuk et al., 2021; Yang et al., 2025). It is unanimously agreed that investment returns are affected by other non-financial factors too, e.g., as corporate sustainability can appear very important (Blajer-Gołębiewska, 2024; Saminem et al., 2024; Sedlák & Veber, 2024; Lu et al., 2025). Anyway, financial results cannot be underestimated (Lendelová et al., 2024; Sedlák & Veber, 2024; Víghová et al., 2024; Bureš et al., 2024). Many authors examined the key aspects of the choices made by the millennial generation (e.g., Ahuja & Kumar 2025; Mabungela et al., 2025; Manchidi, 2025). Kim et al. (2023) investigated the impact of social media interactions on stock selection. Pandey et al. (2025) and Gimmelberg et al. (2025) studied the influence of influencers on the choice of investment instruments and the five main factors that strengthen that influence. De Oliveira et al. (2022) investigated the importance of diversification in reducing losses in mutual funds, while Marfatia (2022) examined diversification at both the domestic and international levels. When developing investment strategies, investors are first faced with the choice of financial instruments. Cheong et al. (2021) investigated the impact of advertising on share prices and found that companies that advertise more are less dependent on market or sector trends. Generational differences determine investors' evaluation of information.

Selective use of information leads to representativeness bias in choosing stocks for investment. Meanwhile, investor familiarity bias leads to geographical restriction of the stock portfolio. Lei & Mathers (2024) examined the profile of investors with familiarity bias. A comparison of the success factors of foreign and local investors is presented in Kim et al. (2021). Investors also select stocks using various analysis methods: technical and fundamental (e.g., Katina et al., 2024; Wang et al., 2024). AI is increasingly used for decision-making in numerous business areas, irrespective of geographical location (e.g., Banaitiene et al., 2025; Mugunzva & Manchidi, 2024; Temerbulatova et al., 2025; Yeşil, 2025; Čižo et al., 2025; Mohammed & Ahmad, 2025).

Financial decisions are being dominated by AI use, frequently using unconventional approaches towards investment decision making. The Cuckoo search algorithm (Yang & Deb, 2009) compares new solutions (cuckoo eggs) with existing solutions (eggs in the nest) and selects better ones that better match the multimodal objective function. In this way, searching occurs, and the degree of correspondence to the ideal solution allows optimising the solution set. The Cuckoo Search algorithm employs two search systems, local and global, which, combined with probability estimation, make the algorithm highly efficient (Yang & Deb, 2014). The popularity of the algorithm led to the creation of several modifications of the Cuckoo algorithm, which Yang & Deb (2017) classify into binary cuckoo search, chaotic cuckoo search, modified cuckoo search, self-adaptive cuckoo search, and multi-objective cuckoo search. In the Tsipianitis and Tsompanakis (2020) article, the optimisation efficiency, reliability, and speed achieved by improving the Cuckoo's algorithm through the combination of other evolutionary algorithms and the use of dynamic penalties are discussed. Yang et al. (2023) proposed a multi-objective cuckoo optimisation algorithm, which, when applied to nine functions and five datasets, showed better results in solving the studied problems. The latest trends, methods, efficiency, and application possibilities of the CS algorithm are detailed in the article by Safdar et al. (2023).

The application of the CS algorithm to solve various problems has spread not only to engineering but also to the social sciences since its development. Yang et al. (2012) tested the CS algorithm in the areas of bankruptcy prediction and business project schedule optimisation. Kurdi et al. (2018) improved the classic CS by creating the "MultiCuckoo" algorithm and applied it to the Internet of Things by combining the services of various suppliers and addressing user needs. Various artificial intelligence algorithms are also often integrated into recommendation systems. Singh and Solanki (2019) searched for the best algorithm for a movie recommendation system and combined the K-means clustering algorithm with bat, firefly, cuckoo, and modified cuckoo search algorithms. The best fit for the movie recommendation system was a combination of K-means clustering and a modified CS algorithm. Zhang and Yang (2022) modified the Cuckoo algorithm to solve the Travelling Salesman problem and found that the stability and accuracy of the CS are superior to those of state-of-the-art optimisation algorithms. To solve the problem of influence maximisation in social networks, Meena et al. (2024) applied the CS algorithm and statistically proved the effectiveness of CS compared to reference algorithms.

To adapt the cuckoo selection algorithm for trading in financial markets, it is necessary to consider modern investors' needs and the challenges investment funds face. Mutual funds also define investment objectives, developing strategies that are particularly useful during economic instability. However, this is often the next step after selecting a set of stocks. Cho et al. (2021) have developed a stock selection strategy based on the text classification of corporate reports. They have succeeded in making the "buy and hold" strategy with various horizons work not only in a rising but also in a dynamically fluctuating market.

Xidonas et al. (2010) demonstrate the necessity of employing multi-criteria decision-making methods before constructing an investment portfolio. Multi-criteria decision-making methods enable investors to consider multiple aspects of the market or investor expectations, whereas modern portfolio theory focuses solely on expected return and risk. Hargreaves and Mani (2015) sought to reduce the set of stocks by evaluating four indicators: return on investment, return on equity, book value per share, and earnings per share. Principal component analysis is a statistical technique that allows for stock selection and achieves portfolio efficiency and profitability. Attempts to apply nature-inspired algorithms to optimise a stock portfolio are described and compared with known methods in the Liu et al. (2021) article. In this article, the Grey Wolf Optimisation algorithm, together with support vector regression, is applied to stock selection. In wolf behaviour, hierarchy and its consolidation are crucial for achieving the group's goal. Stocks selected using the Grey Wolf algorithm showed better returns than those selected using other algorithms. Mazraeh et al. (2022) applied the Multi-Objective Grey Wolf Optimiser and Machine Learning Preselection Methods to optimise a stock portfolio and obtained high portfolio optimisation efficiency. Persio et al. (2023) combined stock price predictions using various AI tools with portfolio construction, demonstrating that a forward-looking risk parity portfolio strategy is effective. Investors' desire to automate stock selection is being realised through the use of artificial intelligence. Singh et al. (2023) developed a model that combines the advantages of a convolutional neural network (CNN) and a long-term short-term memory network (LSTM), selecting stocks that, when combined with the mean-variance portfolio optimisation method, outperform not only random stock selection but also the separate CNN and LSTM models. Ashrafzadeh et al. (2023) developed a model that uses a convolutional neural network (CNN) with optimised hyperparameters obtained using particle swarm optimisation (PSO) to select clustered stocks, and applies mean–variance (MV) with forecasting to the optimisation. Although the proposed model did not exceed conventional methods in accuracy, the portfolio nevertheless yielded good financial results. The variety of investment instruments in financial markets makes automated stock selection for trading a crucial step, especially in algorithmic trading.

2. Methodological approach

A case study of Cuckoo Search will utilise back testing portfolios in the investment decision-making process under real market conditions. To compare the results under the same conditions, portfolios will be tested using the Monte Carlo (MC) simulation method. Mean-Variance (MV) and Sequential Least Squares Programming (SLSP) methods are also used for optimisation evaluation and comparison. The sequence of using the methods is illustrated in Figure 1.

Cuckoo algorithm adoption. The "Metaheuristic-Cuckoo_Search" Python script developed by Pereira (2018) was applied, and the "Cuckoo Search Algorithm" minimises objective functions with continuous variables. In short, the cuckoo search algorithm is based on the behaviour of the Cuckoo in the natural environment, which has an analogy with the Cuckoo Search algorithm for moving in steps (Chechkin, 2008) of a distribution of randomly generated parameters. These randomly generated parameters were used to calculate the objective function values. Next, the objective function values were combined with the list of best-found objective function values obtained in the previous step. The resulting list of objective function values should be sorted so that the values are replaced by the newly generated top list of identified objective values. The search process continues until the number of repeated iterations reaches a maximum given value or the convergence criterion for the accuracy of the objective function is reached. A specific objective function was created for algorithm adaptation by using the implementation of modern portfolio optimisation functions' source code (Pichka, 2021). The input variables in the objective function were the portfolio return weights, which were used for the portfolio return, variance values and Sharpe ratio calculations. Again, the triple comparison of return, variance, and sharp index max values was determined during the portfolio quality evaluation process in each step. Finally, the following initial parameters were used for the cuckoo search during the study: birds = 1000, discovery rate = 0.02, alpha value = 0.15, lambda value = 1.5, iterations = 500.

Steps of investigation. The research process is illustrated in Fig. 1 and comprises four steps that enable us to evaluate and compare the back-testing results of 53 portfolios.

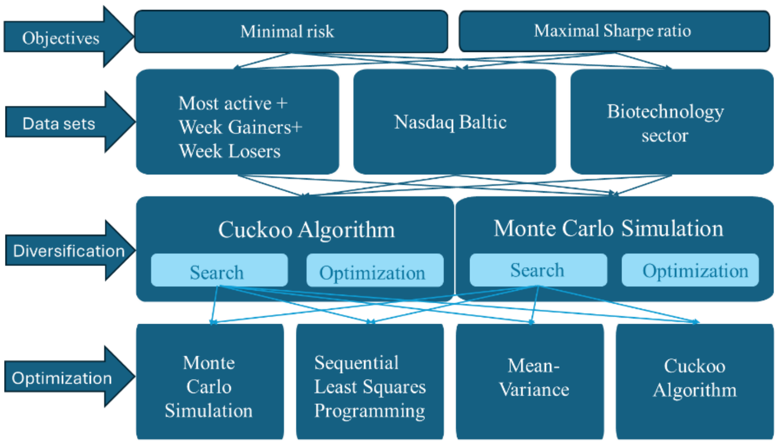

Figure 1. Diagram of research

Objectives. All financial decisions begin with the investor's goals. The most common goals are maximising return, minimising risk, and striking a balance between return and risk. Inexperienced market newcomers usually seek maximum return. Minimum risk is attractive to investors who are sensitive to losses, often in various funds. The maximum return per unit of risk, expressed through the Sharpe ratio, reflects the investor's more profound knowledge of the market. This paper will examine two options: minimal risk and maximum Sharpe.

Data. Process automation in the modern world is gaining momentum, so the data for the study is selected without considering the individual characteristics of stocks, historical price chart trends and financial indicators of companies. The data is taken from three different lists:

MA +WG+WL. 20 stocks from the Most Active in 2024 list, 20 stocks from the 52 Week Gainers list, and 20 stocks from the 52 Week Losers list (citeYahooFinance). This composition of stocks includes different investor attitudes towards stocks. Most active stocks are often very popular and representative. Gaining stocks excites investors seeking maximum results, and losing stocks is interesting because a rise usually follows a price drop.

Nasdaq Baltic stock portfolio includes all stocks of the small Baltic stock market. Sector diversity covers all vital areas of Lithuania, Latvia, and Estonia. The full list consists of 72 stocks (cite NasgaqBaltic).

60 Biotechnology sector stocks from the list sorted by market capitalisation (citeYahooFinance).

The evaluation and testing periods for all datasets are the same: 2022/04/22 - 2024/04/22 for portfolio construction and 2024/04/22 - 2025/04/22 for testing. Some stocks were excluded from all datasets due to a lack of data.

Diversification. The simplest distribution of investment funds is equal. We will use this distribution as a basis for comparison and calculating the efficiency of diversification. The other two distributions of investment funds meet the investor's goals: minimal risk and maximum Sharpe ratio. The formula used to evaluate the efficiency of diversification is:

$$\frac{\boldsymbol{b-a}}{\boldsymbol{a}} * 100\% \tag{1}$$

where a is the indicator of the base portfolio, profitability, or standard deviation describing risk, and b is the corresponding indicator of the portfolio under study.

Stock selection is performed using the Cuckoo algorithm for both minimal risk and maximal Sharpe. To compare the results, we apply the same approach using the Monte Carlo algorithm. Selection means that only those stocks remain in the portfolio that the algorithm has assigned at least 1% of the funds. When optimising using the same methods, the funds are distributed according to the weights provided by the algorithm.

Searching+optimization methods. If the Cuckoo algorithm works as a stock selection tool, it may be worth using it in conjunction with well-known optimisation algorithms: Monte Carlo (MC), Sequential Least Squares Programming (SLSP), Mean Variance (MV).

The Monte Carlo method is a stochastic approach that randomly selects stock price data from a dataset and calculates the optimal solution that aligns with the investor's objectives by evaluating the probability of various possible combinations. Monte Carlo simulation takes into account the many possibilities in financial markets and helps reduce uncertainty.

Sequential Least Squares Programming (SLSP) is a mathematical algorithm for nonlinear optimisation applied to stock price datasets. It works by approximating a nonlinear risk minimisation or Sharpe maximisation objective and constraints using quadratic models, solving a sequence of quadratic programming problems, and iteratively updating the solution to account for the constraints directly.

The Mean-Variance portfolio is the best-known model of Modern Portfolio Theory, which seeks to balance an investor's desire to minimise risk and maximise return. The solutions to the system of equations form an efficient line, and a set of stocks on it corresponds to either the lowest possible risk with a sufficiently good return or the best return-to-risk ratio. The algorithm allows you to choose an expected return; in our study, it is 15% for the minimum risk portfolio and 30% for the maximum Sharpe portfolio.

The Cuckoo algorithm, adapted for minimal risk and maximum Sharpe ratio.

All of these methods will be used to answer the research questions. (RQ):

RQ1: Is the Cuckoo algorithm suitable for selecting stocks for investment?

RQ2: Is a portfolio of equal shares of stocks selected by the Cuckoo algorithm more profitable than a portfolio of equal shares of all stocks in the set?

RQ3: Is a portfolio optimised by the Cuckoo algorithm more profitable than a portfolio of equal shares of all stocks in the set?

RQ4: Does the Cuckoo algorithm select/optimise better than one selected/optimised by a Monte Carlo simulator?

RQ5: Are portfolios selected/optimised by the Cuckoo algorithm efficient compared to the basic and Monte Carlo selected/optimised portfolios?

RQ6: Does optimising stocks selected by the Cuckoo algorithm according to minimal risk by various algorithms result in lower risk efficiency compared to corresponding Monte Carlo portfolios?

RQ7: Does optimising stocks selected by the Cuckoo algorithm according to the maximal Sharpe ratio by various algorithms result in stable diversification efficiency compared to corresponding Monte Carlo portfolios?

3. Conducting research and results

Investigation

The multi-step research process begins with the selection of data sets. Many trading platforms offer a specific set of stocks for trading. The data for the study was taken automatically based on tickers and by selecting the start and end dates. The data collection and testing periods simulate the investor's ability to make decisions under uncertainty. The data used for portfolio construction (2022/04/22 - 2024/04/22) is not used for testing (2024/04/22 - 2025/04/22). The financial markets were relatively calm during the period of portfolio data compilation, with an upward trend. However, this cannot be said about the testing period, especially at the beginning of 2025. Due to changes in customs policy in the United States, stock prices fluctuated significantly. The Cuckoo algorithm is tested under natural investment conditions.

Cuckoo search? First, we tested whether the Cuckoo algorithm can select less risky and more profitable stocks compared to a baseline equal-share portfolio and a Monte Carlo simulation (Table 1). The table also provides a comparison with indices. The MA+WG+WL portfolio is compared to the S&P 500 (^GSPC), Nasdaq Baltic to OMX Baltic Benchmark GI, and the Biotechnology stocks portfolio to NASDAQ Biotechnology (^NBI). Changes in the indices during the testing period reflect stock market trends.

Table 1. Profitability results of searching by the Cuckoo algorithm and Monte Carlo simulation

Market	Number of shares	Equal weights	Minimal volatility	Maximum Sharpe	Benchmark
Cuckoo search					
MA+WG+WL	60	19.70%	20.93%	23.22%	14.55%
Nasdaq Baltic	52	11.10%	7.54%	12.14%	10.18%
Biotechnology	56	26.54%	20.11%	33.77%	-2.09%
Monte Carlo search					
MA+WG+WL	60	19.70%	22.02%	19.91%	14.55%
Nasdaq Baltic	52	11.10%	7.39%	13.15%	10.18%
Biotechnology	56	26.54%	18.04%	36.96%	-2.09%

The results presented in Table 1 show that using only selection without optimisation for the maximum Sharpe ratio, both for the Cuckoo algorithm and the Monte Carlo simulator, yields better results than allocating funds equally across the entire set of stocks. However, the results are worse for achieving minimum-risk profitability.

Cuckoo optimisation? The profitability results obtained by optimising with minimum risk and maximum Sharpe ratio using the Cuckoo algorithm are compared with those of the baseline equal shares portfolio and with the profitability results obtained using the Monte Carlo simulator (Table 2).

Table 2. Profitability results of optimisation by the Cuckoo algorithm and Monte Carlo simulation

Instruments market	Number of shares	Equal weights	Minimal volatility	Maximum Sharpe	Benchmark
Cuckoo optimisation					
MA+WG+WL	60	19.70%	30.38%	40.67%	14.55%
Nasdaq Baltic	52	11.10%	8.34%	11.09%	10.18%
Biotechnology	56	26.54%	35.73%	34.49%	-2.09%
Monte Carlo optimisation					
MA+WG+WL	60	19.70%	26.86%	16.31%	14.55%
Nasdaq Baltic	52	11.10%	12.92%	19.68%	10.18%
Biotechnology	56	26.54%	32.90%	34.53%	-2.09%

Portfolios optimised by the Cuckoo algorithm in two ways yielded excellent profitability results for two datasets: MA+WG+WL and Biotechnology stocks. However, the profitability of the Nasdaq Baltic portfolio for minimum risk decreased, while for maximum Sharpe it remained the same. Portfolios optimised by the Monte Carlo simulator for minimum risk yielded good profitability results for all portfolios. However, for maximum Sharpe optimisation, the results were significantly different.

The diversification efficiency, calculated according to formula (1), for all examined portfolios is presented in Figure 2. Light green and blue areas are marked where the diversification efficiency is positive for all investigated data sets.

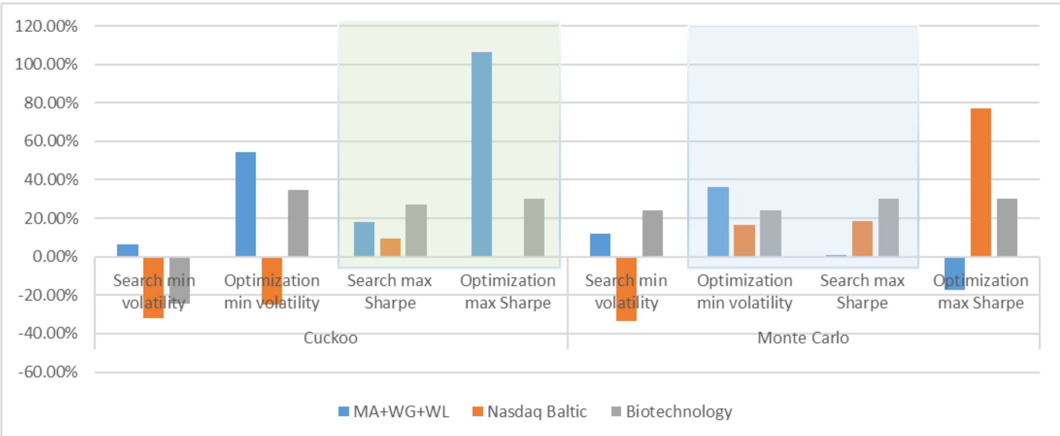

Figure 2. Comparison of the efficiency of diversification by the Cuckoo algorithm and Monte Carlo simulation

When evaluating the efficiency of the Cuckoo algorithm, it can be seen that both selection and optimisation, according to the maximum Sharpe ratio, are efficient within the limits of 0% and 106%. However, when using risk minimisation, only half of all results exhibit positive efficiency. When evaluating the efficiency of the Monte Carlo simulator, the results are less unambiguous. The total number of efficient portfolios is larger, but only optimisation with a minimum risk objective and selection based on the maximum Sharpe ratio demonstrated positive results within the limits of 1% to 36%

Cuckoo search+optimisation for risk reduction. When the investor chooses minimal risk as his goal, the return and profitability of portfolios are no longer a priority, although the goal of having a positive return remains. To determine whether the Cuckoo algorithm reduces risk, we will first apply the Cuckoo algorithm to select stocks that minimise risk, and then utilise known portfolio optimisation methods on the remaining stocks: Monte Carlo (MC), Sequential Least Squares Programming (SLSP), Mean-Variance (MV), and Cuckoo. The number of stocks in all portfolios has almost halved. Table 3 presents the results of the profitability of the obtained portfolios during the testing period.

Table 3. Results of searching for minimal volatility and optimisation for minimal risk

Instruments market	Number of shares	MC	SLSP	MV	Cuckoo
Cuckoo searching and optimisation for minimal risk					
MA +WG+WL	32	24.76%	14.57%	-2.99%	19.19%
Nasdaq Baltic	32	-0.63%	-3.51%	12.01%	-2.18%
Biotechnology	32	27.22%	21.69%	20.08%	37.72%
Monte Carlo searching and optimisation for minimal risk					
MA +WG+WL	36	26.86%	43.65%	32.69%	21.94%
Nasdaq Baltic	32	8.06%	-2.40%	7.02%	2.07%
Biotechnology	35	32.90%	23.27%	22.96%	35.73%

The profitability indicators of low-risk portfolios are not favorable, with many negative results. Using the Cuckoo algorithm, all portfolios are profitable only for the data related to Biotechnology companies. The Monte Carlo simulator generated profits for two data sets: MA + WG + WL and Biotechnology.

The risk reduction efficiency, calculated according to formula (1) by comparing the standard deviations of the portfolios with the base portfolio, is presented in Figure 3.

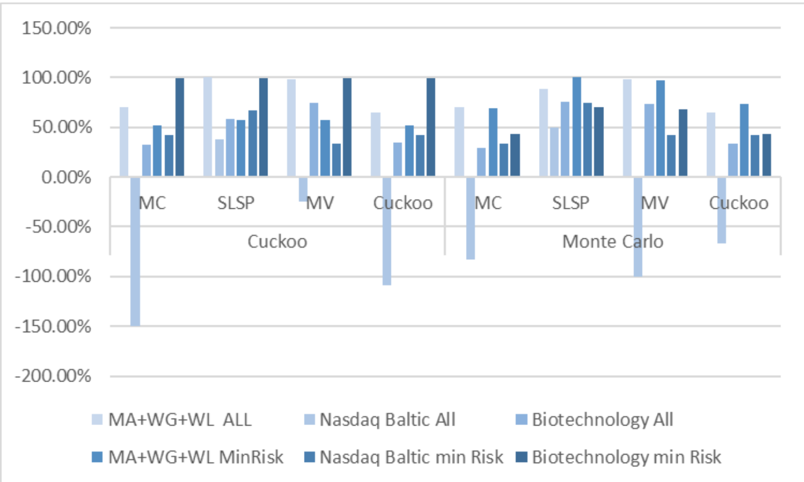

Figure 3. Risk reduction efficiency of search by Cuckoo, Monte Carlo, and four optimisation algorithms

By taking data without risk selection and optimising in different ways, it turns out that almost all optimisation algorithms increased the risk for Nasdaq Baltic data, while reducing it for the other two. Meanwhile, for data selected by both the Cuckoo and Monte Carlo algorithms, the risk reduction for all tested data ranges from 33% to 99%. The results show that minimal risk selection effectively reduces the risk of various portfolios, but portfolios optimised using the SLSP method stand out the most.

Cuckoo search+optimisation for Sharpe maximisation. The investor's goal of balancing the return per unit of risk is realised using algorithms that maximise the Sharpe ratio. First, stocks are selected using the Cuckoo and Monte Carlo algorithms to maximise the Sharpe ratio, and then four additional optimisation algorithms are employed to enhance this optimisation further. The results of portfolio profitability are presented in Table 4.

Table 4. Results of searching for maximum Sharpe and optimisation for maximum Sharpe

Instruments market	Number of shares	MC	SLSP	MV	Cuckoo
Cuckoo searching and optimisation for maximum Sharpe					
MA +WG+WL	37	29.31%	82.72%	68.00%	26.74%
Nasdaq Baltic	30	14.20%	30.33%	19.67%	11.09%
Biotechnology	28	30.22%	11.17%	32.35%	24.18%
Monte Carlo searching and optimisation for maximum Sharpe					
MA +WG+WL	41	16.31%	-15.19%	-11.59%	10.25%
Nasdaq Baltic	32	18.11%	-1.65%	10.71%	16.41%
Biotechnology	34	45.33%	8.77%	12.11%	44.24%

When testing selected and optimised portfolios based on the maximum Sharpe ratio, the portfolios selected by the Cuckoo and Monte Carlo algorithms showed significant differences. Portfolios selected by the Cuckoo algorithm achieved profitability ranging from 11% to 82%, without incurring losses, when optimised using different optimisation algorithms. The Monte Carlo selection was not as effective and was scattered within the interval of -15% to 45%.

The diversification efficiency of portfolios selected according to the maximum Sharpe ratio and optimised using four different optimisation methods is presented in Figure 4, comparing the final results with the base portfolio of equal shares.

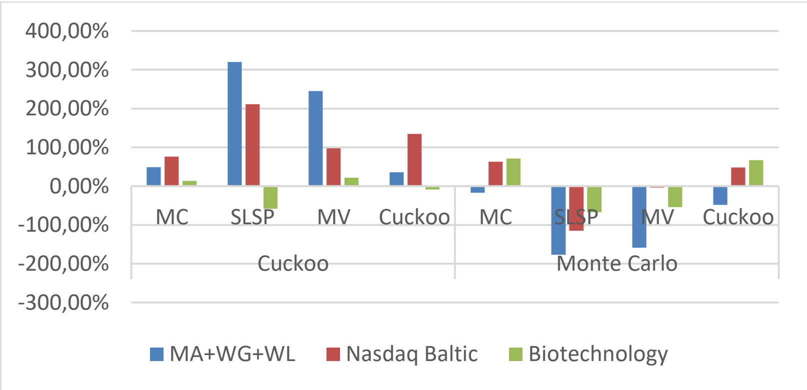

Figure 4. Comparison of the efficiency of diversification using Cuckoo and Monte Carlo algorithms for max Sharpe

A study on the efficiency of portfolio optimisation using four different methods, selected based on the maximum Sharpe ratio, revealed that the Cuckoo algorithm for stock selection is significantly more efficient than selection with a Monte Carlo simulator, especially when combined with the SLSP and MV optimisation methods.

Discussion

The obtained research results allow us to answer the research questions raised (RQ) in the introduction.

RQ1: The cuckoo algorithm is not new, but it has yet to be applied to financial decision-making. The logic of cuckoo reproduction, encoded in an evolutionary artificial intelligence algorithm, can help solve the problem of automating stock selection for investment. Selection with the cuckoo algorithm for minimal risk reduces portfolio risk, while selection for maximum Sharpe increases profitability.

RQ2, RQ3: Equal-part portfolios are often used for comparison in optimisation studies. It is typically challenging for established portfolio optimisation methods to outperform basic equal-weight portfolios, as financial markets are highly dynamic and unpredictable. The Cuckoo algorithm in this study achieved positive efficiency in 8 out of 12 portfolios, both in selection and optimisation.

RQ4, RQ5: Monte Carlo simulation was chosen for comparison with the Cuckoo algorithm due to the similarity of the results to sampling in both cases, funds are distributed into many small parts, clear favourites are not distinguished, and the number of stocks is reduced by about half. Perhaps this is why the risk reduction results of these two algorithms are very similar, but the pursuit of maximum Sharpe revealed a significant advantage of the Cuckoo algorithm.

RQ6, RQ7: Stock selection and optimisation using algorithms may seem redundant, especially when the same algorithm is used twice. However, both of these actions occur one after the other during each investment. An investor or investment fund selects financial instruments using fundamental, technical, or sentiment analysis, or simply relying on the representativeness of stocks. After that, the method of fund allocation is chosen. The Cuckoo algorithm for stock selection automates the selection process quite easily and efficiently. For optimisation, using SLSP or MV yields better results for stocks selected using the Cuckoo algorithm.

To mitigate data limitations, the process should be more automated and collect larger amounts of data. Three data sets were used during the study, from which 75 portfolios were compiled and summarised. Another limitation is that the results may change in subsequent periods. The testing period covers one year of investment; for future research, it would be possible to test investment for 2-4 years.

Conclusions

The Cuckoo selection algorithm was applied to stock selection and optimisation. A multi-step study, choosing the minimum risk and maximum Sharpe objectives, using three very different data sets and comparing it with the Monte Carlo method, revealed that the Cuckoo selection algorithm can be successfully applied in making investment decisions. By selecting stocks with this algorithm, it is possible to reduce risk and increase portfolio profitability.

The algorithm obtained better profitability results for both selection and optimisation when maximising Sharpe was chosen. When choosing the risk reduction objective, the risk reduction efficiency was high, but not all portfolios managed to obtain a positive return. When using selection together with optimisation algorithms, the Cuckoo selection algorithm significantly outperformed the Monte Carlo simulator, especially in combination with the SLSP and MV optimisation algorithms. The double use of CS for selection and optimisation yields no significant results.

In the future, it will be necessary to automate the process by taking a larger number of stocks, adapting the cuckoo algorithm to the needs of investment funds, and creating a recommendation system. Another way is to use the logic of the cuckoo algorithm more and adapt it to integrate sustainable development stocks into investment portfolios while maintaining profitability and risk level

Theoretical part of this paper explains that the transitional crisis is influenced by different institutional, economic, political, cultural, and the following factors: conflicts of formal and alternative institutions, global processes, liberalization of economy, domination of politics, etc. Characteristically, they had a multiple impact through several independent variables which we have analyzed in three countries in transition (Montenegro, Serbia, and Bosnia and Herzegovina). During the socialist period, these countries had centrally-planned economies, limited economic growth, and spiral reproduction of the crisis. However, they are a typical example of the general situation in the Eastern Europe. Therefore, the results of this research are expected to contribute to the understanding the transitional crisis in the most Eastern European countries. Apart from some positive processes and improvements (in business environment, tourism, liberalization, civil society, civil and political rights, democracy, freedom of the media, the development of a knowledge society, environment for investments, etc.) the observed countries experienced the intensification of the social, political and economic crisis for the last 25 years. Conducted Empirical research has verified it. A number of negative factors provoked the transitional crisis. The most important of them (from my perspective) are selectively identified and explored in this research.

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