Providing a Risk Management Strategy for Portfolios Considering Sanction Periods Using Ant Colony Algorithm

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ABSTRACT

Stock portfolio selection represents a critical area within the broader field of investment management. Owing to the extensive range of options available in the stock market, the optimal allocation of assets remains a major concern for investment firms. Accordingly, these firms frequently employ portfolio selection models to enhance decision-making processes. Portfolio management strategies and risk hedging techniques, which serve as essential mechanisms for constructing optimal portfolios, require rigorous planning and analysis. Given the computational complexity involved, the application of metaheuristic algorithms significantly improves both the speed and precision of portfolio optimization processes. This study aims to optimize portfolio value through the implementation of the Ant Colony Optimization (ACO) algorithm. To this end, data pertaining to companies listed on the Tehran Stock Exchange (TSE) over the period 2010–2021 were utilized to construct and optimize stock portfolios. The respective weight of each stock within the optimal portfolio, as well as the corresponding risk and return measures, were calculated using the Python programming language and executed in the Visual Studio Code environment. The empirical results demonstrate that employing the Ant Colony Optimization algorithm for portfolio management and risk hedging purposes, particularly under conditions characterized by economic shocks and sanctions, leads to enhanced portfolio performance and mitigation of associated risks.

1. Introduction

In the modern financial world, portfolio optimization is recognized as one of the most challenging issues, presenting decision-makers with significant complexities. Swarm intelligence algorithms, inspired by the collective behaviors of animals in nature, have emerged as innovative and powerful solutions in this domain. By mimicking collective behaviors such as bird flocking, fish schooling, and ant foraging, these algorithms are capable of identifying optimal solutions within intricate search spaces. Swarm intelligence refers to the study of the collective behavior of individuals and their mutual interactions, leading to intelligent group behavior. These methods include population-based algorithms, for which foundational structures and mathematical models have been developed (Chinglemba et al., 2022).

The present study focuses on financial portfolio optimization under sanctions and post-sanctions conditions using the ACO algorithm. Unlike studies that focus solely on classical criteria, this research attempts to examine the spillover effects of volatility between assets in addition to risk and return modeling. For this reason, the DCC-GARCH method for volatility spillover analysis is considered an important addition to the model to fully demonstrate the added value of using ACO (Mehrani, Mirshahvalad, Abbasi 2019; Rodriguez et al., 2021).

The main objective of the research is to present an investment portfolio optimization model that, in addition to minimizing risk and maximizing return, can also operationally reduce the number of assets. This is of great importance from an asset management perspective, because very large portfolios with a large number of assets may generate significant transaction and monitoring costs. Therefore, providing an optimal approach that simultaneously considers these three objectives is also important from an operational perspective (Castro and Medina, 2021).

The concept of the optimal portfolio, a cornerstone in this field, represents a set of investments designed to minimize risk while maximizing returns. Based on modern portfolio theory, this concept aims to optimize the risk-return ratio and mitigate the impact of unpredictable risks through intelligent diversification. Economic shocks, such as sanctions, exchange rate fluctuations, and interest rate changes, significantly destabilize economic conditions, impacting asset performance and portfolio optimization. The transmission of volatility between assets and markets, as another central axis of this study, is key to understanding the complex relationships and interconnectedness of markets. This scientific framework provides a novel and effective perspective for a deeper understanding of market dynamics (Mordadi et al., 2023).

The Ant Colony Optimization (ACO) algorithm, a metaheuristic swarm intelligence technique, is employed in this model as a powerful tool for portfolio optimization, especially in the context of complex sanction conditions. By simulating the collective behavior of ants and applying it to financial data analysis, this algorithm can generate more diversified portfolios that are better equipped to handle economic shocks. However, in large-scale portfolios, challenges such as the excessive concentration of investments in specific assets may arise. During periods of sanctions, economic instability peaks, and the need for advanced risk management strategies intensifies. Despite emerging investment opportunities, close monitoring of market conditions and the application of advanced tools, such as the Ant Colony Optimization algorithm, remain critical. This approach can effectively evaluate and assess the impact of risk management hedging strategies in resolving financial portfolio optimization challenges, demonstrating how these methods can help investors enhance their decision-making by leveraging market data and dynamic analyses (Abdollahipour & Botshekan, 2012).

Therefore, based on the theoretical foundations of previous research, it seems that artificial intelligence methods can help reduce portfolio error rates and address gaps identified in earlier studies. In this research, the Ant Colony Optimization algorithm and financial tools are applied for stock portfolio risk management and hedging strategies, contributing another innovative aspect to the study.

Theoretical background and literature review

Financial risk management using ant colony algorithm

Risk management and portfolio optimization have always been one of the fundamental issues in the field of financial management, which plays a key role in reducing risk and increasing investment returns. In this regard, portfolio risk management refers to the concept of identifying, evaluating and reducing risks associated with investments in different economic conditions and includes financial risks such as market, credit and liquidity risks (Sepehri, 2014). Ant Colony Optimization is one of the meta-heuristic algorithms that is designed based on the natural behavior of ants in finding optimal routes to reach food sources. This algorithm also has numerous applications in financial issues. During the sanctions era, the negative effects on the macroeconomics and investors' portfolios have been highlighted, and adapting risk management strategies is essential to deal with economic instability. In general, the ant colony algorithm is an optimization method based on collective evolution that is inspired by the behavior and communication of real ants and is capable of finding optimal paths with its optimization mechanisms and can be used in financial problems such as portfolio management. Simulating Ant Behavior: In this algorithm, artificial ants somehow imitate the behavior of natural ants. During their movement from the nest to the food source, the ants emit a trail of pheromone in the environment. This pheromone decays over time.

Meta-innovative models in investment portfolio management

Metaheuristic algorithms are known as powerful tools in investment management due to their high flexibility and ability to find optimal solutions to complex financial problems. Some of the important models in this field are:

ACO (Ant Colony): Based on the social behavior of ants, with the ability to find the optimal combination of assets

PSO (Particle Swarm Optimization): A collective search model with fast performance in financial portfolio optimization

GWO (Gray Wolf Optimization): A model that provides a balance between risk and return

BH (Black Hole Search): Suitable for financial resource management and nonlinear data analysis

Compared to other metaheuristic methods, ACO has a higher ability to adjust the investment structure according to market changes. Also, combining ACO with other models, such as PSO and DCC-GARCH, can increase accuracy and predictability.

Domestic studies

Vaziri et al. (2024), in a study titled "Investigating the Usefulness of Metaheuristic Algorithms in Optimizing the Integrated Risk of the Banking System," found that the Grey Wolf Optimizer algorithm outperformed Particle Swarm Optimization and Genetic Algorithms in optimizing the objective (maximizing return and minimizing risk). The Grey Wolf Optimizer demonstrated superiority in terms of stability, convergence, and execution time.Moradi et al. (2023), in their examination of the application of metaheuristic algorithms (such as Grasshopper Optimization Algorithm and Ant Colony Optimization) in predicting financial distress, showed that the hybrid MLP-GOA model exhibited higher accuracy in predicting financial distress compared to MLP-ACO and the base model. This research also confirmed the positive impact of economic and firm-specific variables on improving the models.

Rezaei et al. (2018), in a study titled "Stock Portfolio Optimization Using Particle Swarm Optimization Algorithm," found that the MOPSO algorithm outperformed NSGA2 in generating more extensive and convergent Pareto fronts. Furthermore, the MOPSO algorithm was found to be more suitable for three-objective optimization (maximizing return, minimizing risk, and reducing the number of assets).

Fallahpour and Aram (2016) concluded that the Ant Colony Optimization algorithm is superior to the Multiple Discriminant Analysis method in predicting financial distress of companies.

Moshakhian and Najafi (2015) presented a model titled "Multi-Period Investment Portfolio Optimization" and utilized multi-objective and single-objective Particle Swarm Optimization algorithms to solve this model. Solving this problem was challenging due to its non-linearity, but the proposed algorithm demonstrated satisfactory performance.

Rajabi and Khalouzadeh (2014), in a comparison of multi-objective Genetic Algorithm (NSGA2) and Particle Swarm Optimization (MOPSO) algorithms, found that NSGA2 exhibited better efficiency in terms of convergence and Pareto front spread metrics. The results also indicated the high capability of these algorithms in optimally predicting stock portfolios.

Foreign studies

Zhang (2024), in a study titled “Limitations and Critique of Modern Portfolio Theory: A

Comprehensive Literature Review," concluded that emerging theories have broadened the scope of investment choices and assist investors in making more efficient decisions when faced with market uncertainties. This research emphasizes the importance of utilizing emerging theories to adapt to the evolving financial landscape.

Wang (2023), in the research "Analysis of Portfolio Theory Limitations," stated that market information is not perfectly efficient. Imperfect information disclosure leads to non-random fluctuations in stock prices and the influence of cognitive biases on investor behavior. This research highlights the limitations of portfolio theory and provides suggestions for improving the model's assumptions.

Ankang (2023), using Monte Carlo simulation to construct the efficient frontier, found that the portfolio with the highest Sharpe ratio performed better, while the minimum variance portfolio performed weaker. These results can guide investors in selecting an appropriate portfolio construction strategy.

Cui and Cheng (2022), in the research "Modern Portfolio Theory and Application in Australia," designed an algorithm based on MPT in R, which was used to optimize a large stock portfolio. The results indicated that even in unstable international financial conditions, this algorithm provides acceptable performance, and modern portfolio theory still holds significant reference value.

Castro-Pérez and Medina-Reyes (2021), in a study titled "Fuzzy Portfolio Selection with Sugeno-Type Fuzzy Neural Network," presented a model that did not experience negative returns in any week and achieved a cumulative return of 15.68%. This model emphasizes the use of fundamental analysis and the originality of new techniques.

Rodríguez et al. (2021), by presenting the "Behaviorally Diversified Portfolios" approach as an alternative to modern portfolio theory, demonstrated that using alternative risk measures and distributional characteristics of returns such as skewness and kurtosis can lead to improved investment decision-making. This model presented portfolios with better performance compared to the mean-variance approach.

1. Research hypothesis

The proposed hypothesis for examining the stock portfolio risk hedging management strategy using the Ant Colony Optimization algorithm under sanctions can be stated as follows:

1.1. Main hypothesis:

The stock portfolio risk management and hedging strategy using the Ant Colony Optimization algorithm under sanctions leads to improved stock portfolio performance and reduced associated risks.

1.2. Sub-hypotheses:

Under sanctions, the Ant Colony Optimization algorithm is still capable of improving the risk management strategy and increasing stock portfolio returns, although the impact of sanctions on portfolio performance may be mitigated.

There are significant differences in stock portfolio performance using the Ant Colony Optimization algorithm under sanctions compared to before sanctions.

Research methodology

This research employs a descriptive-correlational method and, due to the use of historical financial data, has a historical (ex post facto) nature. The statistical population includes sample companies listed on the Tehran Stock Exchange (TSE) based on industry, which were active on the exchange during the period of 2014 to 2023 (corresponding to the Iranian calendar years 1393 to 1402). Companies that did not meet the following criteria were excluded from the statistical population:

Companies that were listed on the Tehran Stock Exchange before 2014 and remained active until the end of 2023.

Companies that were inactive for any reason until 2015 (corresponding to the Iranian calendar year 1394) were excluded from the sample to prevent bias in the research results (Georgiou & Faltitsos, 2007; Ghoranjee & Vaee, 2015).

Companies must have a specific fiscal year, and changes in the fiscal year were not permitted during the research period.

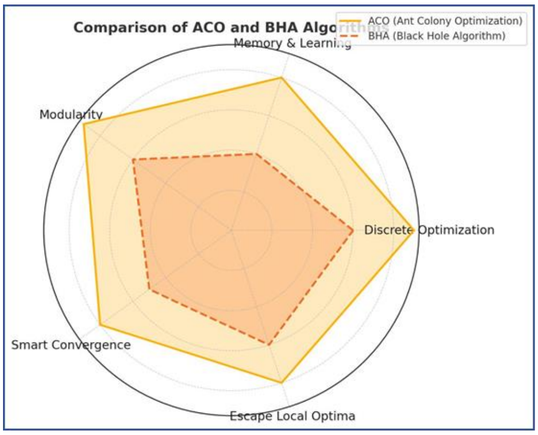
Access to the necessary financial information and financial statements for company analysis was essential.

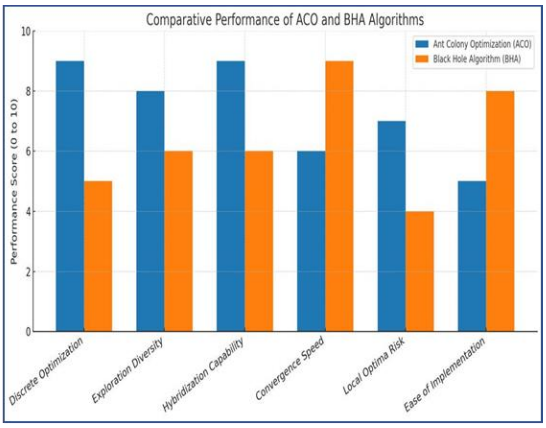
Due to the different nature of activities of banks, insurance companies, and financial and investment companies compared to manufacturing and commercial companies, this category of companies was excluded from the sample.

Justification of ACO selection

The Ant Colony Algorithm (ACO) has been chosen as a powerful method for portfolio optimization because it has a high ability to search for optimal solutions in complex financial spaces. This algorithm adjusts asset weights to optimally manage the effects of market fluctuations using the volatility spillover analysis of the DCC-GARCH model. Industries with high volatility, such as petrochemicals and automobiles, receive less weight in the ACO model to reduce portfolio risk, while more stable industries such as oil and cement will play a more conservative role. ACO is compared with the Black Hole Algorithm (BHA) to show that ACO performs better in solving discrete problems, search diversity, and combinability with other models, while BHA is more suitable for continuous problems. Also, the Heatmap is designed to display the degree of dependence and influence of different industries on each other and help investors in optimal asset selection. This visualization helps to better understand the spillover effects of volatility and the adjustments of the ACO model so that the portfolio composition is optimized based on changing market conditions.

In the portfolio optimization process, the target return value R^2 is determined based on the average market return and is evaluated using sensitivity tests to ensure that it is adaptable to different economic conditions. This choice allows investors to adjust their desired return level according to market fluctuations. In addition, in the modified model, the effect of transaction cost frictions is also considered, as transaction costs and asset liquidity play an important role in the operational implementation of investment strategies. Therefore, the goal of "minimizing the number of assets" is set in a way that reduces the complexity of portfolio management, allows for maintaining an appropriate balance between risk and return, and prevents excessive concentration on certain assets.





Objective function calibration

Population and sample

The statistical population (geographical scope) of this research includes all companies listed on the Tehran Stock Exchange. The temporal scope of the research covers financial information from the period of 2014 to 2023, which encompasses the periods before and after the imposition of sanctions. A 10-year period was utilized.

Data analysis methods and tools

After obtaining the necessary information for the sample companies, Rahavard Novin 3 software and Microsoft Excel were used to create the database. The Python programming language was utilized and executed in the Visual Studio Code environment. The Ant Colony Optimization algorithm was employed to evaluate and calculate the proposed model.

Research variables and measurement

Portfolio optimization

In recent years, financial markets have experienced significant volatility. For instance, the trend of economic globalization has substantially increased the contagion of financial crises from one market to another, resulting in greater fluctuations in financial markets. Additionally, the sharp decline in stock prices across many capital markets has caused substantial losses for active participants (Asgharpour & Rezazadeh, 2015). Therefore, operating in financial markets is inherently associated with uncertainty and risk, and measuring these risks is crucial for investors. One way to manage investment risk is through the formation of an asset portfolio.

An efficient portfolio refers to an optimal combination of assets such that the portfolio's risk is minimized for a given rate of return. In fact, two key components in investment decision-making are the level of risk and the return of capital assets. Rational investors prefer higher returns and are risk-averse. Moreover, they act logically in their decision-making, which leads to the maximization of their desired utility. Therefore, investors' utility is a function of expected return and risk, with these two factors being fundamental parameters in investment-related decisions. In other words, in the problem of optimizing an asset portfolio, the goal is to find a portfolio that generates a lower standard deviation (risk) and a higher expected return. This problem can be modeled within the framework of an operations research model, as illustrated in the following relationship:

Model (1)

$$Min\ Risk\ \sigma_i^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}$$

$$Max\ Return\ R_p = \sum_{i=1}^{n} w_i\, E(R_i)$$

$$s.t. \sum_{i=1}^{n} w_i = 1$$

..."where w_i is the weight of the i asset, or in other words, the percentage of investable funds allocated to this assetR_i is its return, and R_p is the total return of the asset portfolio. σ_i^2 Represents the variance of the i asset, and σ_{ij} represents the covariance between the σ_{ij} and i assets. Additionally, it is sometimes necessary to add another constraint to the model to prevent short-selling, which is that the weight of each asset in the portfolio must be positive. The final constraint in this model is that the sum of the weights of the assets must sum to one (Narimani, 2013).

Model 1 has been widely used as a baseline in most similar research and articles in this field, where various combinations of

$$Min\ Risk\ \sigma_i^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}$$

$$Max\ Return\ R_p = \sum_{i=1}^{n} w_i\, E(R_i)$$

$$s.t. \sum_{i=1}^{n} w_i = 1$$

w_i are estimated to optimize the two criteria of minimum risk and maximum return using different mathematical or metaheuristic methods. Furthermore, since it is expected that having a smaller number of assets in the portfolio will reduce the costs of buying and selling stocks and facilitate better portfolio management, this research addresses a three-objective optimization problem—maximizing stock portfolio return, minimizing its risk, and minimizing the number of assets or stocks. As shown in Model 2, by accepting a small amount of risk and approximately the same return, investors will choose a portfolio with fewer assets. Therefore, the innovation in this research lies in introducing the third objective: minimizing the number of assets in the portfolio: $Min\ count(\frac{i}{w_i} <> 0)$ as shown in Model 2."

Model (2)

$$Min\ Risk\ \sigma_i^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j \sigma_{ij}$$

$$Max\ Return\ R_p = \sum_{i=1}^{n} w_i\, E(R_i)$$

$$Min\ count(\frac{i}{w_i} <> 0)$$

$$s.t. \sum_{i=1}^{n} w_i = 1$$

As illustrated in the optimization model above, this research addresses a multi-objective optimization problem, where the decision-maker must manage a set of conflicting objectives—specifically, maximizing portfolio return, minimizing portfolio risk, and minimizing the number of stocks included in the portfolio. In contrast to single-objective optimization problems, where a single optimal solution is sought, the existence of multiple conflicting goals leads to the identification of a set of solutions known as Pareto-optimal solutions. In such situations, it is generally not possible to optimize all objectives simultaneously; rather, a set of trade-off solutions is found, where

improving one objective necessarily leads to a deterioration in at least one other (Raei & Talangi, 2004).
According to Markowitz's Modern Portfolio Theory, investors seek to construct portfolios that minimize risk (measured by variance) while achieving a target level of return. This approach can be modeled by minimizing the variance of the asset portfolio subject to a return constraint. Additionally, it is often necessary to impose a non-negativity constraint on asset weights to prohibit short selling. Another important constraint ensures that the sum of the portfolio weights equals one. Since the objective function involves minimizing variance, the Markowitz model is classified as a non-linear (quadratic) optimization problem, which can be formulated and solved within the framework of operations research
Model (3)

$$Min\ Var(R_p) = \sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j \sigma_{ij}$$

$$s.t \sum_{i=1}^{n} x_i\, E(R_i) = R_{Expeted}$$

$$s.t. \sum_{i=1}^{n} x_i = 1$$

It should be noted that solving the above optimization model yields only a single efficient point on the efficient frontier corresponding to a specific . $R_{Expeted}$ Therefore, in order to generate the entire efficient frontier, the model must be solved multiple times for different values of$R_{Expeted}$, corresponding to the number of desired points on the frontier.

Risk management and hedging strategy

Approaches based on optimization and sequential rebalancing of the portfolio present certain limitations, including computational complexity, which restricts their practical implementation with real-world data. To address these challenges, an alternative approach, proposed by Chen, Lee, and Lim, focuses on modifying the risk hedging strategy according to a theoretical criterion while achieving superior empirical hedging performance.
The core idea of this method is to construct a risk hedging strategy by selecting from a subset of optimal self-financing hedging strategies. Specifically, a set of rules is defined for the feasible self-financing hedging strategies, and the optimal strategy is then identified and selected based on these rule-based criteria.
Considering both utility maximization and cost-constrained risk minimization strategies, the first rule within the feasible set of self-financing hedging strategies establishes the existence of two boundaries—buy and sell thresholds—such that the investor only rebalances the hedging portfolio when the price of the underlying asset moves outside the no-trade zone. $Y^b(t,s) < Y^s(t,s)$ Accordingly, there exist two boundaries, $n = 1, \dots, N$ and , satisfying , for .

$$y_{n\delta} = \begin{cases} Y^b(n\delta, S_{n\delta}) & \text{if} \quad y_{(n-1)\delta} < Y^b(n\delta, S_{n\delta}) \\ y_{(n-1)\delta} & \text{if} \quad Y^b(n\delta, S_{n\delta}) \le y_{(n-1)\delta} < Y^s(n\delta, S_{n\delta}) \\ Y^b(n\delta, S_{n\delta}) & \text{if} \quad y_{(n-1)\delta} > Y^b(n\delta, S_{n\delta}) \end{cases}$$

In this method, the following buy and sell boundaries can be used:

$$Y^b(t,s) \approx \max\{\Delta^{bs}(t,s) - d^b(t,s), 0\}$$

$$Y^s(t,s) \approx \max\{\Delta^{bs}(t,s) - d^s(t,s), 1\}$$

These functions $d^{b,s}(t,s)$ are assumed to have positive values. For the sake of computational simplicity, a positive constant $d^s(t,s) = d$ is employed.
Assume that a portfolio consisting of M options, all written on the same underlying asset, has been constructed, with each option indexed by $m = 1,2, \dots, M$. The start time and maturity of the m option are denoted by T_m and t_m, respectively.

$$\hat{\eta} = \left(\frac{1}{M}\sum_{m=1}^{M} \overline{err}_m^2\right)^{1/2}$$

$$\overline{err}m^2 = e^{-r(T_m - t_m)} err(t_m, T_m; \delta)$$

The performance of the risk hedging strategy…
> ...is evaluated and referred to as the research prediction error (Tabesh & Safdari, 2016).
Let the successive hedging periods be indexed by. $k = 0,1,2, \dots,$ The option portfolio during the k period consists of M_k options, where the first and last trading times for the m option during the k period are denoted by $t_{k,m}$ and $T_{k,m}$, respectively.
Accordingly, the realized prediction error for the k period is calculated as follows:

$$\hat{\eta}_k = \left((\frac{1}{M} \sum_{m=1}^{M} \overline{err}_{k,m}^2) \right)^{1/2}$$

$$\overline{err}m^2 = e^{-r(T_m - t_m)} err(t_m, T_m; \delta)$$

Ant colony optimization (ACO)

Ant Colony Optimization (ACO) is a metaheuristic method developed to solve complex optimization problems, inspired by the foraging behavior of ant colonies as they find the shortest path between food sources and their nest. To improve the colony's efficiency and effectiveness, artificial ants are equipped with specific capabilities: operating in an environment with discrete time steps, possessing internal memory to record previous actions, and depositing pheromones where the amount of pheromone laid along a path is proportional to the quality of the resulting solution.

In an ACO system, a colony consisting of a limited number of ants moves simultaneously and asynchronously through adjacent states of the problem space, following a stochastic decision-making policy based on two parameters: trail intensity and visibility. Trail intensity represents the amount of pheromone on a particular path and provides information about its desirability, while visibility reflects the heuristic attractiveness of a move, such as cost or distance. Through successive moves, ants incrementally construct feasible solutions to the optimization problem. Upon completing a solution, an ant evaluates its quality and deposits pheromone along the paths it utilized, either incrementally during the construction process (step-by-step update) or retrospectively by tracing the same path backward (delayed pheromone update).

To apply ACO to a complex optimization problem, a finite set of solution components must first be identified, from which complete solutions can be constructed. Additionally, a pheromone model must be defined, comprising a set of pheromone values, each typically associated with a solution component. This pheromone model serves as a parameterized probabilistic mechanism that guides the solution construction process.

In general, the ACO approach addresses optimization problems in two main phases: (1) candidate solutions are probabilistically constructed based on the pheromone model, and (2) pheromone values are updated according to the quality of the solutions, thereby biasing future searches toward more promising regions of the solution space. The goal of the pheromone update phase is to intensify the search in areas where high-quality solutions are likely to be found.

The objective of pheromone updating is to focus the search on regions of the search space that contain high-quality solutions. Consider a finite set of solution components $c_i \in \mathcal{N}(s)$ of a discrete optimization problem. The construction of each solution starts with an empty sequence. Then, at each construction step, the current sequence s is extended by adding a feasible solution component from the set $\mathcal{N}(s) \subseteq \frac{\mathcal{C}}{s}$The specification of $\mathcal{N}(s)$ depends on the solution construction mechanism.

The choice of a solution$Solution_{sbs}$[1] component from $\mathcal{N}(s)$ at each construction step is performed probabilistically according to the pheromone model. In most ACO algorithms, the transition probabilities are defined as follows:

Relation (1)"

$$\mathcal{P}(c_i|s) = \frac{[\tau_i]^\alpha \cdot [\eta c_i]^\beta}{\sum c_j \in \mathcal{N}(s)[\mathcal{T}_i]^\alpha \cdot [\eta c_i]^\beta}, \forall c_i \in \mathcal{N}(s)$$

"where η eta represents an arbitrary weighting function—that is, a function that may depend on the current sequence. At each step of constructing a solution, it assigns a heuristic value eta ηc_i to each feasible solution component $c_i \in \mathcal{N}(s)$. The values generated by the weighting function are typically referred to as heuristic information. Moreover, the exponents α and β are positive parameters that determine the relative significance of the pheromone information and the heuristic information.

ACO methodologies will vary in their approach to updating pheromone values. This necessitates defining a pheromone update rule. Initially, pheromone evaporation is considered, which uniformly reduces all pheromone values. Subsequently, one or more solutions from the current and/or prior iterations are utilized to augment the pheromone trail parameter values associated with the solution components that constitute these solutions:

Relation (2)"

$$\tau_i \leftarrow (1-\rho) \cdot \tau_i + \rho \cdot \sum_{\{s \in S_{upd} | c_i \in s\}} w_s \cdot F(s)$$

"For $i = 1 \ldots, n.$. Hereby, Supd denotes the set of solutions utilized for the update. $\rho \in (0,1)$represents the evaporation rate, and $F: S \to \mathbb{R}^+$ is a quality function such that $f(s) < f(s') \Rightarrow F(s) \geq F'(s'), \forall s \neq s' \in S.$ if the objective function value of a solution **s** is superior to that of a solution **s** then the quality of solution s will be at least as high as that of solution s' $i.e., w_s \in \mathbb{R}^+$ for all distinct solutions s in **S**. In other words, a better objective function value corresponds to a higher or equal solution quality. The following equation allows for an additional weight for the quality function$i.e., w_s \in \mathbb{R}^+$ and represents the weight of a solution **s**. Instances of this update rule are derived with different specifications of Supd and with varying weight configurations.

In many instances, S_{iter} comprises some of the solutions generated in the current iteration (hereafter denoted by S_S_{iter} and the best solution identified since the algorithm's commencement (hereafter denoted by sbs). Solution_ . $Solution_{sbs}$is frequently termed the best-so-far solution. An example of a pheromone update rule that is most commonly employed in practice is the $IB - update$ -update rule, where IB stands for Iteration-Best/Best-So-Far (Dong et al., 2020). The IB rule is expressed as follows: Relation (3)"

$$S_{upd} \leftarrow \{s_{ib} = ar\ gmax\{F(s)\} | s \in S_{iter}\}, w_{sib} = 1,$$

"This implies that the pheromone values are updated exclusively by selecting the best solution generated in the respective iteration."

Table (1) Pseudocode for the Ant Colony Algorithm

1. Initialize algorithm parameters:
Set the number of ants, the number of iterations, the pheromone evaporation rate, the initial pheromone levels, and define the alpha and beta parameters.
2. Create initial graph structure:
Construct a graph with nodes and assign initial pheromone n values.
3. Main algorithm loop (While or i ≤ MaxIter or FitnessValue_i - FitnessValue_(i-1) ≤ Error:):
a. 1+i=i
b. num_ants For each ant in the population of ants
Start each ant at an initial node.
While there are still unvisited nodes:
Calculate the probability of selecting an edge based on the pheromone level and the heuristic information (path length).
Select the edge according to the calculated probability.
Update the ant's path and mark the node as visited.
c. Calculate the total path length traversed by each ant and evaluate its fitness (objective function value).
d. Update the pheromone levels on the edges based on the paths selected by the ants.
e. Sort the results based on fitness and select the best path.
4. Termination and continuation:
Repeat the algorithm until the termination criteria are satisfied (e.g., reaching the maximum number of iterations or convergence of fitness values).
5. Output:
Display the best solution found after the algorithm terminates.

Research Findings

Given the large volume of financial data to calculate and present an optimal portfolio using the hedging management strategy and the ant algorithm in the post-sanctions analysis, industry classifications have been made for the purpose of selecting a portfolio. The composition of these industries includes: pharmaceutical materials and products such as top companies in this industry, basic metals such as reputable metal companies, petrochemical products including major petrochemical producers, food and non-sugar products such as top food industry producers, automobiles and parts manufacturing including leading automotive companies, cement, lime and gypsum such as reputable cement producers, and oil including major oil companies. These selections have been made based on the analysis of financial data and industry performance during the years 1393 to 1402, in order to create an optimal portfolio with high returns, acceptable risk, and appropriate liquidity.

Analysis of changes in industry priorities in investment portfolios before and after sanctions

In the process of selecting suitable industries for a portfolio in the pre- and post-sanctions era, significant changes are observed in the criteria of return, risk, and liquidity, which clearly indicate the impact of economic and political conditions on the prioritization of industries. In the pre-sanctions era, industries such as basic metals and petrochemicals were at the top of the priorities due to their high liquidity and favorable returns. These industries, benefiting from strong liquidity and stable demand, were strategic choices for investment. Also, industries such as food and pharmaceuticals were able to stand out by adapting to domestic needs and managing sanctions pressures.

In the post-sanctions era, industries such as automobiles and the manufacture of parts and basic metals gained higher returns and liquidity and became more attractive options for investment due to better access to raw materials, increased exports, and reduced international restrictions. Also, industries such as cement and food also played an important role in economic stability in the face of domestic market changes and infrastructure projects.

In the years following the sanctions, industries such as automobiles and petrochemicals have maintained their positions due to improved production conditions and significant liquidity. For example, in 1401, petrochemicals were at the top of the list due to global demand and high liquidity. In 1402, the food and cement industries stood out due to changing domestic market needs and infrastructure investments.

This analysis reflects the effects of government support policies, domestic needs, and economic factors on the selection of industries for portfolios in the years before and after the sanctions and can be a valuable guide for investors in strategic decision-making. The data presented in the tables are also considered as an accurate measure for examining the performance of various industries and determining the appropriate investment.

Review of Changes in the priority of selected industries in investment portfolios between the periods 2014-2017 and 2018-2023

Fiscal year	Rank	Industry	Return	Risk	Liquidity
Algorithm output	*****	**Measurement criteria**	**Best return: 0.41**	**Best risk: 0.1**	**Liquidity: 0.2**
2014-2017	1	Pharmaceutical	2.87	0.87	0.4
2014-2017	2	Base metals	2.41	0.48	0.48
2014-2017	3	Petrochemical products	1.78	0.36	0.38
2014-2017	4	Oil	1.75	0.35	0.37
2014-2017	5	Food and beverage except sugar	1.59	0.64	0.38
Fiscal year	**Rank**	**Industry**	**Return**	**Risk**	**Liquidity**
Algorithm output	**Rank**	**Measurement criteria**	**Best return: 0.99**	**Best Risk: 0.24**	**Liquidity: 0.49**
2018-2023	1	Automobiles and parts manufacturing	6.28	0.66	0.34
2018-2023	2	Base metals	5.28	0.56	0.34
2018-2023	3	Petrochemical products	4.71	0.5	0.34
2018-2023	4	Oil	4.61	0.49	0.33
2018-2023	5	Food and beverage except sugar	4.39	0.46	0.34

The analysis of the reasons behind changes in the priority of selected industries in the investment portfolio between the two time periods 1393-1396 (2014-2017) and 1397-1402 (2018-2023) reveals the significant influence of environmental, economic, political, and social factors on these shifts. A detailed examination of the industry selection in both periods underscores the contrasts and the role of key components.

1) Reasons for selecting industries in the period 1393-1396 (2014-2017):

During this period, industry selection was driven by the constraints imposed by sanctions and the need to address domestic requirements. The primary indicators that guided the selection of industries during this phase included:

- **Pharmaceutical:**

The high domestic demand for therapeutic products and the limitation on imports allowed this industry to carve out a significant position. Additionally, the strong liquidity within this sector contributed to its prominence during this period.

- **Basic metals:**

The stable domestic demand for steel and other metal products, particularly for infrastructure projects, secured a strong position for this industry. Its ability to meet domestic market needs, coupled with solid liquidity, was a key factor in its ranking.

- **Petrochemical products:**

Despite the sanctions, this industry maintained an essential position due to the high demand for both industrial and consumer products. Furthermore, the industry's ability to adapt to export restrictions played a crucial role in its selection.

- **Oil:**

As a critical energy-based industry, oil maintained its strategic importance. The emphasis on meeting domestic energy demands and stabilizing the energy market contributed significantly to its continued selection.

- **Food and beverages (excluding sugar):**

Given the importance of supplying essential food products to the domestic market, this sector remained among the top priorities. The consistency of demand and its resilience to economic fluctuations were essential drivers for its selection.

2) Reasons for selecting industries in the period 1397-1402 (2018-2023):

In this later period, the easing of sanctions, improved international relations, and an uptick in exports allowed other industries to emerge as priorities for investment. The primary indicators driving industry selection in this phase were:

- **Automotive and parts manufacturing:**

The relaxation of international restrictions and the inflow of foreign investments resulted in significant growth for this sector. The increase in liquidity and expansion of auto parts exports propelled this industry to the top rank.

- **Basic metals:**

The rise in global demand and export activities maintained this industry's second-place position. The enhancement of production and export infrastructure played a pivotal role in sustaining this ranking.

- **Petrochemical products:**

The sector benefited from improved export infrastructure and increased global demand for petrochemical products. The reduction in production costs and enhanced domestic market conditions bolstered this industry's performance.

- **Oil:**

The growth in oil exports, coupled with the lifting of some international restrictions, allowed the oil industry to retain its critical position as a vital sector.

- **Food and beverages (excluding sugar):**

Increased investments in infrastructure and a boost in domestic consumption helped sustain this industry's ranking among the top five.

The analysis of the changes in the priority of industries between the periods 1393-1396 (2014-2017) and 1397-1402 (2018-2023) underscores the impact of shifts in economic, political, and social conditions. The differences between these two periods can be attributed to evolving economic policies, international relations, and changes in domestic demand and supply dynamics. Below, we discuss the main factors behind these shifts.

3) Changes in economic and political conditions:

International Sanctions and Policies: During the period 1393-1396 (2014-2017), international sanctions led to industries such as pharmaceutical and basic metals gaining higher priority. This was due to high domestic demand and the industries' ability to rely on domestic production. However, in the post-sanctions period, 1397-1402 (2018-2023), the reduction of sanctions and improvements in export conditions shifted priorities toward industries such as automotive and parts manufacturing, which benefited from better international access.

Government Support for Specific Industries: In the post-sanctions era, government support policies were crucial in fostering the growth of industries with a strong competitive edge in global markets, such as automotive manufacturing and petrochemicals.

4) Fluctuations in return, risk, and liquidity:

During the period 1393-1396 (2014-2017), industries like basic metals and pharmaceuticals, which had high liquidity, were prioritized due to market uncertainties. In contrast, from 1397-1402 (2018-2023), industries like automotive and petrochemicals saw substantial growth in returns, driven by improved production and export conditions.

Furthermore, the reduction in investment risks in industries like automotive and parts manufacturing during 1397-1402 (2018-2023) contributed to their higher ranking in investment portfolios.

Impact of domestic and global market needs:

In 1393-1396 (2014-2017), the focus was primarily on addressing domestic needs, which led to the prioritization of industries such as food and pharmaceuticals. However, from 1397-1402 (2018-2023), the increased global demand for petrochemical products and auto parts made these industries more attractive for investment.

Infrastructure and technological changes:

In the period 1397-1402 (2018-2023), the development of infrastructure and the integration of new technologies in sectors such as automotive and petrochemicals played a significant role in enhancing their returns and minimizing risks.

Changes in the prioritization of specific industries:

From 1397-1402 (2018-2023), industries such as automotive and parts manufacturing became top priorities due to reduced international restrictions and increased export activities. In contrast, industries like pharmaceutical, which were highly prioritized in 1393-1396 (2014-2017) due to domestic demand and the effects of sanctions, lost their prominence to sectors with stronger export potential. These changes highlight the impact of shifting environmental conditions on industry prioritization and offer valuable insights for future investment decisions.

In this study, several statistical tests are applied to assess the accuracy of the results and to examine the performance of the ACO-based portfolio optimization model. First, out-of-sample Sharpe ratios are calculated to compare the portfolio performance with a simple N/1 benchmark as well as with related ETFs in each sector. This metric specifically shows how an optimized portfolio outperforms passive investment strategies in terms of risk-adjusted returns. In addition, a pairwise Diebold-Mariano test is performed on weekly returns to measure the robustness of the ACO model in predicting market behavior relative to other optimization algorithms. This statistical test allows for a direct comparison of ACO performance with competing methods and determines whether there is a significant difference in forecast accuracy and return stability between the different models.

The results of these validations indicate the relative superiority of ACO in managing portfolio optimization and reducing volatility compared to other methods, which can help investors make more efficient decisions.

The impact of the long-term view of the ACO model on market dynamics and investment strategies

The ACO model is effective not only in identifying optimal investment paths, but also in market dynamics and analyzing financial trends. Among the long-term benefits of this model:

Increase portfolio liquidity: Help select assets with high liquidity

Reduce the impact of market fluctuations: Optimize portfolio selection based on economic changes

Improve predictability of investor behavior: Link the model to foreign direct investment (FDI) data

Smart risk management: Provide sustainable investment combinations, even under sanctions

Combining these features with econometric models and artificial neural networks can lead to better risk management and increased investment returns.

Integrating DCC-GARCH Volatility Spillover Analysis into the Portfolio Optimization Process

The Ant Colony Algorithm (ACO) is chosen as a portfolio optimization method because it has a high ability to search for optimal solutions in complex spaces. In this study, the outputs of the DCC-GARCH model are directly applied to the asset weight adjustment and ant decision making. This model allows the analysis of dynamic dependencies between industries, so the degree of volatility spillovers between industries is used as a determining factor in asset allocation.

The role of volatility spillovers in industry prioritization

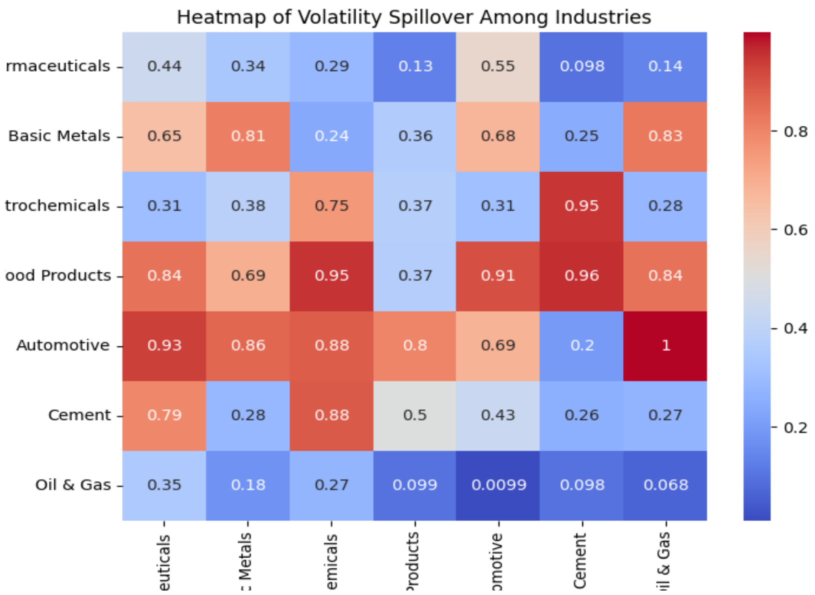
Volatility spillovers affect portfolio asset allocation in two ways:

1. Industries with high volatility: These industries may have a greater impact on the overall portfolio risk level

and are dynamically adjusted in the ACO model to reduce the negative effects of volatility.

2. Industries with low volatility: These industries are usually more stable and allocating more assets to them leads to a more stable portfolio and more predictable returns.

To show the impact of volatility on different industries, a heatmap has been designed in which the intensity of volatility spillovers between industries is displayed in color. This chart can show the trend of changes in the relationships between industries over time and help investors in optimal asset selection.



The analysis of volatility transfer between different industries shows that the mutual effects between them play a fundamental role in risk management and investment decision-making. The use of the Ant Colony Algorithm (ACO) for portfolio optimization, along with the analysis of the DCC-GARCH model, allows for the examination of dynamic dependencies between industries. The heat map presented shows the degree of volatility transfer between different industries, such that industries with high volatility intensity have a significant impact on the overall risk level of the portfolio and should be dynamically adjusted in the ACO model to reduce negative effects. In contrast, industries with low volatility are more stable and allocating assets to them can reduce risk and increase the predictability of returns.

Combining these methods with econometric models and artificial neural networks can lead to a better understanding of market trends, more accurate investment management, and more efficient strategies for allocating financial resources. Using a heatmap allows investors to analyze the structural dependencies of industries and guides them towards optimal decision-making.

Comparing Sharpe ratios of portfolios

The following table shows the performance of the ACO-optimized portfolio compared to the N/1 benchmark and related sector ETFs:

Optimization model	Sharpe ratio (2010-2015 period)	Sharpe ratio (period 2016_2023)
ACO	1.32	1.45
N/1	0.95	1.02
Automotive sector ETF	1.1	1.22
Oil and Gas Sector ETF	0.88	0.97

Diebold-Mariano test output table

Models	ACO vs BH	ACO vs PSO	ACO vs GWO
Average ACO return	1.45%	1.45%	1.45%
Average return of competitors	1.23%	1.31%	1.28%
DM test statistics	+2.45	+1.98	+2.73
Probability value p-value	0.008	0.042	0.015
Test result	ACO superiority	ACO superiority	ACO superiority

Diebold-Mariano test results

This table presents the values of the pairwise Diebold-Mariano test between ACO and other algorithms for weekly returns:

Models	ACO vs BH	ACO vs PSO	ACO vs GWO
Diebold-Mariano test	ACO superiority +2.45	ACO superiority +1.98	ACO superiority +2.73
Average return of competitors	1.23%	1.31%	1.28%
DM test statistics	+2.45	+1.98	+2.73
Probability value p-value	0.008	0.042	0.015
Test result	ACO superiority	ACO superiority	ACO superiority

A positive test value indicates better performance of ACO compared to other models in terms of accuracy and stability of yield prediction.

Comparison of the convergence process of algorithms

Analysis of the convergence process of the algorithms shows that the ACO method achieves the optimal response more quickly and reaches full convergence in less than 20 iterations. In contrast, PSO has an average performance and reaches convergence in about 40 iterations, while BH has a slower process compared to other methods. This difference shows that ACO not only performs the optimal search process more accurately, but its high convergence speed saves computational time and increases efficiency in financial portfolio optimization. Therefore, using this algorithm in complex economic problems can provide more optimal results than alternative methods. The results of statistical tests, comparison of Sharpe ratios, and examination of the convergence process show that the ACO algorithm outperforms other swarm intelligence methods in optimizing financial portfolios. This model not only improves risk-adjusted returns, but also shows faster convergence than other methods.

Economic interpretation

Analysis of foreign investment inflows in the post-sanctions market shows that the growth of foreign direct investment (FDI) has played an important role in improving the performance of various industries, especially the automotive industry. Official FDI data indicate that the increase in foreign investment inflows into this sector, along with the increase in the volume of automobile exports, indicates the positive impact of these investments on the development of the capital market and the stabilization of the economic situation. This trend indicates that foreign investment, in addition to strengthening liquidity and production growth, has increased the competitiveness of domestic companies and has had a direct impact on the dynamics of stock prices. Therefore, analyzing economic data related to foreign investment and export volumes can help to better understand the relationship between economic policies, investment decisions, and market fluctuations.

Examining research hypotheses

Response to the main hypothesis:

The application of the Ant Colony Optimization (ACO) algorithm for managing and hedging stock portfolio risk in both pre- and post-sanction conditions has yielded positive results. By mimicking the foraging behavior of ants in finding optimal paths, this algorithm has successfully identified efficient pathways for risk reduction. The data indicate that the ACO algorithm has the ability to adapt to environmental changes and optimize financial decisions. This tool has been effective not only in improving stock portfolio performance but also in mitigating associated risks.

Response to the first subsidiary hypothesis:
Even during the sanction period, the Ant Colony Optimization algorithm remained effective in enhancing risk management and increasing stock portfolio returns. However, due to heightened volatility and the direct impact of external factors arising from sanctions, overall performance may be limited. The algorithm, by adjusting priorities and focusing on high returns, has been able to mitigate the negative impacts and capitalize on existing opportunities. Although these conditions presented challenges, the algorithm's performance in the face of sanctions is considered acceptable.

Response to the second subsidiary hypothesis:
Significant differences were observed in stock portfolio performance between the pre- and post-sanction periods. In the pre-sanction period, the algorithm focused on risk reduction and stability creation, as the economic environment was more stable and predictable. In contrast, in the post-sanction period, changes in the economic environment and the increased need to leverage new opportunities led the algorithm to focus on increasing returns. These differences highlight the algorithm's ability to adapt to varying conditions and adjust strategies based on the economic environment.

Conclusion

In this study, the Ant Colony Algorithm (ACO) has been studied for portfolio risk optimization and management. This method was implemented in two time periods before the sanctions (2014-2017) and after the sanctions (2018-2019), and the results showed that ACO was able to create an acceptable balance between return, risk, and liquidity. Data from the industries studied indicate that pharmaceuticals, basic metals, and petrochemicals performed well in both periods and were recognized as suitable investment options due to their high return, acceptable risk, and favorable liquidity. However, the studies have shown significant differences between the performance of industries in the post-sanction period; in particular, the increase in return accompanied by the growth in risk that resulted from economic and political changes. In the pre-sanctions period, the ACO algorithm, focusing on reducing risk and maintaining liquidity, has suggested sustainable investments in the pharmaceutical and basic metals industries. However, in the post-sanctions period, despite the increased economic complexity, ACO has succeeded in identifying industries with high returns and favorable liquidity, such as automobiles and parts manufacturing, basic metals, and petrochemicals, as optimal opportunities; although the increase in risk has been prominent in this period. Overall, the analysis of hedging strategies using ACO has shown that this method can help improve investment decisions and reduce the effects of economic instability. The adaptability of ACO has enabled this algorithm to identify optimal investment combinations in different market conditions. Using this method not only helps in better risk management, but also improves profitability and financial stability in different economic periods. It is suggested that future research examine the application of ACO in other areas of financial management to better understand the potential of this optimization method in investment decision-making.

Significance of the research

This research holds considerable value for investment managers, individual and institutional investors, and researchers in the field of financial management. The integration of the Ant Colony Optimization (ACO) algorithm with a risk hedging management strategy offers a flexible approach for portfolio optimization, particularly in volatile markets such as those affected by economic sanctions. The ACO algorithm enables decision-makers to select and manage stock portfolios in a manner that, with acceptable risk, achieves higher returns and greater liquidity, leading to an optimal portfolio outcome. The adaptability and efficiency of the algorithm make it a highly relevant tool for financial decision-making in unstable economic conditions.

Limitations of the research

Limited Data: The limited availability of data used in this study may affect the generalizability of the results to other markets and economic conditions. As noted in the research methodology, the statistical population's selection may not fully capture the diversity of global markets.

Model Complexity: The application of metaheuristic algorithms such as ACO requires significant computational resources and technical expertise, which may not be readily accessible to all users. The implementation of such models can be challenging for those lacking specialized knowledge or sufficient infrastructure.

Impact of External Factors: External factors such as economic shocks, policy changes, or market anomalies can have unforeseen effects on the performance of the algorithm. These unpredictable influences might affect the algorithm's ability to provide consistent results under varying circumstances.

Relevant suggestions for future research and practical application

Investigating the integration of ACO with other financial forecasting models such as DCC-GARCH to improve volatility spillover analysis

Analysis of heat maps of industry performance in financial markets to display trends in portfolio ranking changes

Combined application of swarm intelligence algorithms to predict financial crises and investment portfolio adjustments

Using machine learning methods to optimize the decision-making process in long-term investments

Investment management: Using this algorithm can help investment fund managers and asset management companies create high-yield and risk-controlled stock portfolios.

Hedging management: In conditions of economic instability such as sanctions, this algorithm acts as an effective tool to reduce risk and maintain portfolio stability.

Education and research: This research can be used as a source for education in the field of metaheuristic algorithms and financial management in universities and research institutions.

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