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RESEARCH ARTICLE

Portfolio Optimization with Artificial Hummingbird Algorithm for Cement Industry

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Abstract

Portfolio optimization, which is performed while investing in any asset, is an important issue for all investors and finance researchers. In this study, the Artificial Hummingbird Optimization Algorithm (AHA), which has been proposed in recent years, was implemented for portfolio optimization by adapting it to Modern Portfolio Theory. Stocks have been selected as investment instruments in the portfolio. Stocks are classified as risky assets due to daily price fluctuations, depending on many natural or political events or decisions. In this study, since stocks are risky assets, the minimum risk criterion is preferred for a defensive investor. In addition, due to the Kahramanmaraş earthquake in Türkiye, this study aims to create a portfolio, especially within the cement sector, in a way that minimizes risk. With this objective in mind, as the originality of the study, AHA has been used to determine the optimal portfolio using stocks in the cement sector in BIST. Statistical analysis and the Wilcoxon test were conducted for the AHA results. Subsequently, several portfolios were determined based on the AHA's statistical results. Furthermore, to measure the risk and return performance for each portfolio, total normalized returns, CAPM analysis, Sharpe Ratio, and Treynor ratio were calculated, and their results were compared to each other. The results show that Portfolio 6 exhibited the best performance in terms of the minimum risk criterion among the optimized portfolios using AHA.

Keywords: Artificial Hummingbird Optimization, Portfolio Optimization, Cement industry

Introduction

The art of optimization involves using variables to maximize or minimize a specific, quantifiable, and measurable goal. For example, when planting rice fields in China, it is a learned optimization problem for people to maximize the yield from the fields they planted by adjusting the season, irrigation time, and water level in the fields (Gladwell, 2009). However, due to the geographical structure of China and its administration at that time, Chinese people had to work as they had a large amount of land. This is considered a variable of the problem. On the other hand, while the pyramids in Egypt were built, the slaves, animals, wagons, ships, the structure of the stones used in the pyramid construction, and time are the variables of the

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optimization problem. The most obvious optimization problems encountered in history were the establishment of cities and caravanserais along the Silk Road in the most suitable places that were strategically profitable and safe, and the design of weaponry equipment to be most effective in warfare (M. Çimen, 2022). However, in history, these problems have usually been solved by trial and error or by the intuition and wisdom of the people. Nowadays, these types of problems are formulated by modeling them mathematically. Once the model is established, an optimization algorithm can be employed to find the solution, typically with the assistance of a computer (Nocedal & Wright, 2006). Therefore, when looking at optimization, it is encountered in almost every field from physics (Demirdelen et al., 2022; Jin & Rahmat-Samii, 2008; Salko, Schmidt, & Avramova, 2015) to biology (Cedersund, Samuelsson, Ball, Tegnér, & Gomez-Cabrero, 2016), from health (Atteia, Abdel Samee, El-Kenawy, M., & Ibrahim, 2022; Hu et al., 2022) to logistics (Borndörfer, Grötschel, & Löbel, 1998; Z. Garip, Karayel, & Çimen, 2021), from chemistry to mechanics (Heidari et al., 2019), from medicine to tourism, from communication to energy (Abid, Apon, Morshed, & Ahmed, 2022; Ramadan, Kamel, Hassan, Ahmed, & Hasanien, 2022), from public administration to international relations, from education to finance (X.-S. Yang, 2020).

Optimization can be performed both analytically and iteratively. These methods can be developed by being inspired by physics, biology, social events, the structure of the universe, or the behavior of a swarm; thus, they are designed to imitate living and non-living beings in nature. In particular, developed algorithms of this type are called metaheuristic algorithms (Akgül et al., 2024; X.-S. Yang, 2020a). When we look at metaheuristic algorithms, they have many advantages, such as being easily applied to linear and/or nonlinear, continuous and/or discontinuous, constrained and/or unconstrained, univariate or multivariate, and differentiable or nondifferentiable problems (M. E. Çimen, Garip, & Boz, 2021; M. Çimen, Garip, M, & Boz, 2022; Xing-Shi He, Qin-Wei Fan, Mehmet Karamanoglu, 2019). One metaheuristic algorithm proposed recently is the Artificial Hummingbird Algorithm (AHA) (Ramadan et al., 2022; Zhao, Wang, & Mirjalili, 2022). Hummingbirds are remarkable creatures, recognized as the smallest birds on Earth. Hummingbirds, as shown in Figure 1, would be the most intelligent creatures on the planet, including humans, if intelligence were determined by the brain-to-body ratio (Fennelly, 2012). Hummingbirds are unique in that they have a remarkable memory of finding food. Hummingbirds' capacity to fly is another unique talent. They are the most adept flies among all bird species thanks to their small wingspan and rapid wingbeats. Hummingbirds have adaptable shoulder joints that allow them to twist their wings 180 degrees while maintaining a figure-eight motion. Hummingbirds use their distinctive flight pattern to gain energy from both the upstroke and downstroke (Tobalske et al., 2007). The hummingbird has excellent direction-finding ability. Hummingbirds can fly in several directions, including up, down, left, and right, in addition to taking flight like other birds (Leys, Reynaerts, & Vandepitte, 2016). Hummingbird flight abilities, memory capacity, and foraging techniques are the primary sources of inspiration for the AHA (Zhao et al., 2022). The AHA algorithm has been used in fields such as energy (Ramadan, Ebeed, Kamel, Ahmed, & TostadoVeliz, 2023; Ramadan et al., 2022), parameter estimation, and engineering applications. In addition to this algorithm, Genetic Algorithm (GA) (J. Holland, 1975; J. H. Holland, 1975; Koker, 2013; Seyedali Mirjalili, 2019; X.-S. Yang, 2020), Partial Swarm Optimization (PSO) (Eberhart & Kennedy, 1995), Firefly Algorithm (FA) (X. S. Yang, 2009), Flower Pollination Algorithm (X.-S. Yang, 2020), Cuckoo Search Optimization (X. S. Yang & Deb, 2009), Sin Cos Algorithm (Seyedali Mirjalili, 2016; Rajagopal et al., 2021), Whale Optimization Algorithm (Mirjalili & Lewis, 2016), Harris Hawks Optimization (Heidari et al., 2019), Moth Flame Optimizer (Seyedali. Mirjalili, 2015), Marine Predators Algorithm (Chen et al., 2022) and more can be found in the literature.

Figure 1. Hummingbirds

In society, people like investors try to protect their savings against inflation by investing in certain investment instruments such as gold (Gök & Tiwari, 2022), foreign currency, currency-protected deposit accounts, real estate (Kiyosaki & Lechter, 2001), deposit accounts (Çelik & Tekşen, 2021), bonds, funds (Çelik & Tekşen, 2021), and stocks (Akkaya, 2021; Atik & Kovacevic, 2022; Yalcin, 2022). Under this condition, each investment instrument must be evaluated with respect to many criteria, such as tax rates, interest rates, sectorial conditions, political conditions, natural conditions, transportation, companies, countries, and states. On the other hand, it is a problem for investors to add to the portfolio and remove it from the portfolio in which weight and in what time interval among the options in the investment instrument they choose. For this purpose, they need to determine their portfolio in a way that will reduce certain risks and maximize their income. Therefore, determining the portfolio in an optimal way will maximize return. However, portfolio optimization can be expressed as the maximum return per unit of risk. In the classical portfolio management approach, risk is reduced by selecting investment instruments with high returns and increasing their variety, regardless of the correlation of each investment instrument (Ayan & Akay, 2014; Hüseyinov & Uluçay, 2019). However, when considering any investor, they expect to obtain maximum return with low risk in the portfolio they will create in the asset pool. For this reason, Markowitz proposed Modern Portfolio Theory (MPT) in the 1950s to allow investors to create a portfolio that would provide maximum return with minimum risk (G. & D., 2010; Markowitz, 1952, 1959; Mercangöz, 2018). A survey of the literature reveals that there are numerous approaches, such as TOPSIS, VIKOR, MOORA, or optimization, for creating a portfolio using historical data (Atukalp, 2019; Karakul & Özaydin, 2019; Karcıoğlu & Yalçın, 2022; Oh, Kim, & Min, 2005). From the literature, optimization is very suitable for MPT to form an optimal portfolio for stocks having the desired objectives. In addition, optimization has been used to form an optimal portfolio. Oh et al. created an optimal portfolio using GA on the KOSPI 200 index. However, it did not perform well when the index was flat (Oh et al., 2005). Besides KOSPI 200 index, Chang et al. performed portfolio optimization using a GA algorithm for the TAIWAN 50 index (Chang, Wang, & Min, 2010). Çankal, on the other hand, performed portfolio optimization using GA in BIST 30 in his/her thesis (Çankal, 2015). In addition to GA, Çelengi et al. created a portfolio for BIST 30 using the PSO (Çelenli, Eğrioğlu, & Çorba, 2015). Afterwards, Çelengi realized the optimal portfolio creation in his/her PhD thesis with Artificial Bee Colony Algorithm (Çelengi, 2018). Sedighi et al. applied the Strength Pareto Evolutionary Algorithm to a multi-objective portfolio optimization problem. They also attempted to use Capital Asset Pricing Model (CAPM) to allocate investments optimally to reduce risk and maximize return on a stock portfolio (Sedighi, Jahangirnia, & Gharakhani, 2018). Mustafa, in his master's thesis, examined the risk-return relationship in the Financial Asset Pricing Model. For this purpose, he randomly chose stocks in BIST 30 and BIST 50 and created several portfolios. Then, he compared portfolio performance in terms of the Sharpe and Traynor ratios (Moustafa, 2007). Similarly, Garip, in his master's thesis, created 14 different portfolios using the stocks he selected from BIST. He calculated the returns, standard deviation, coefficients of variation, and Sharpe ratios for the performances of the portfolios (O. Garip, 2014). Yücel used performance criteria, such as Sharpe, Treynor, Jensen, Sortino, and Fama criteria, to make a risk-based performance comparison of the BIST indices. Then, the relationship between index performances was evaluated using Spearman's rank correlation test (Yücel, 2016). Ramshe et al. created portfolios by applying GA, Tabu Search, Simulated Annealing, and PSO and FA methods to MPT. They tested their successes using historical data (Ramshe et al. 2021).

Cement is frequently encountered as a very important sector, as it is mainly a basic material in buildings and constructions. The first cement production in Turkey started in Darica at 20,000 tons per year through the state channel in 1911, and production capacity doubled in 1923. By 1950, the capacity increased 9 times with the establishment of different production facilities established (Arıöz & Yıldırım, 2012). According to the Activity Report published by CEMBUREAU in 2021, the Turkish Cement Industry, with a production of 72.3 million tons, was ranked 5th among the G20 countries, behind China, India, the USA, and Brasilia (Cembureau, 2021). Considering the researches, it is mostly consumed in the domestic market due to the easy availability of raw materials and the cost of transportation. In other words, cement is a local product. In addition, it has a significant place in the economy due to its contribution to Gross Domestic Product (GDP) and the benefits it provides to employment. The cement sector provides employment to many different levels of people, such as managers, civil servants, engineers, workers, and technicians, as well as contributing to the development of other sectors, such as iron and steel, service, transportation, banking, financial leasing, insurance, and tourism.

In this study, it is aimed to create an optimal portfolio using the AHA proposed in 2021 in the cement sector between 01/31/2018 and 01/31/2023 among eleven leading companies. The main objective function was to obtain the minimum risk via MPT. To evaluate the performance of AHA, the algorithm was run 30 times independently at different swarm sizes and numbers of iterations. Obtained results have been compared statistically. The Wilxocon test was then applied to the algorithm's results to determine whether there was a significant difference or not. Moreover, the CAPM, Sharpe ratio, and Treynor ratio of each portfolio are calculated, and their performances are compared to each other. Relatively, the obtained portfolios demonstrated better performance than the CAPM. In addition, Sharpe and Treynor ratios are calculated for each portfolio, and their results are presented in tables and figures. As a result, Portfolio 6 exhibited the best performance in terms of minimum risk criteria among the optimized portfolios using AHA.

Materials and Methods

In this study, using the AHA, six portfolios with minimum risk were created from the cement sector by means of MPT. Statistical analysis and Wilxocon tests of algorihm's results have been realized and evaluated. Then, portfolio performance with respect to the CAPM, Sharpe ratio, and Treynor ratio is determined.

Artificial Hummingbird Algorithm

One of the recent nature-inspired metaheuristic algorithms is the Artificial Hummingbird Algorithm, which was developed by Zhao et al. in 2021 (Ramadan et al., 2023; Zhao et al., 2022). To choose a suitable food source among a variety of food sources, hummingbirds examine factors such as the quantity and quality of nectar produced by different flowers as well as the nectar-refilling mechanism. The proposed algorithm differs from earlier algorithms due to its broad search domain and is inspired by the distinct flying skills and accurate foraging methods of hummingbirds when searching for food. The algorithm's exploitation probability and exploration capability are both improved by the unique flight patterns. A specific part called the visit table was included to further mimic the hummingbird's memory of locating appropriate food sources. Axial, diagonal, and omnidirectional are the three flying patterns used, and territorial, migratory, and guided foraging are the search tactics used (Zhao et al., 2022). The next section presents three mathematical models that mimic the three distinct foraging habits of hummingbirds.

Initialization

The assignment of a swarm of n hummingbirds to n food sources is random in Equation 1 (Zhao et al., 2022).

$$x_i^t = LB + rand(0.0,1.0)(UB - LB) \quad i = 1, \ldots, n \tag{1}$$

where LB and UB denote the upper and lower bounds of a d-dimensional problem, respectively. The location of the with the food supply that offers the answer to the specific objective is represented by x_i^t, $rand(0.0,1.0)$ is a random vector with a range of [0.0, 1.0] and t is iteration index. The source of food's visit table can be provided like Equation 2.

$$VT_{i,j}^t = \begin{cases} 0 & i \neq j \\ null & i = j \end{cases} \quad i, j = 1, \ldots, n \tag{2}$$

If $i = j$, then $VT_{i,j}^t = null$ indicates that the hummingbird is consuming food from a specific source. If $i \neq j$, then $VT_{i,j}^t = 0$ shows that specific source has been visited by a hummingbird in the current iteration (Zhao et al., 2022).

Guided foraging

The source of the greatest nectar is visited by each hummingbird. Hummingbirds can fly in three different directions: axially, diagonally, and omnidirectionally. Equation 3 defines the axial flight.

$$D^{(i)} = \begin{cases} 1 & i = rand(1, d) \\ 0 & other \end{cases} \quad i = 1, \ldots, d \tag{3}$$

Equation 4 defines the diagonal flight. In Equation 4, r_1 is a random number (0, 1) and $randperm(k)$ creates a number permutation from 1 to k. In addition, the function $rand(1, d)$ randomly selects a number between 1 and d.

$$D^{(i)} = \begin{cases} 1 & i = P(j) \quad i = 1, \ldots, d \\ 0 & other \quad j \in [1, k] \end{cases}$$
$$P = randperm(k) \quad k \in [2, r_1(d - 2) + 1] \tag{4}$$

The definition of omnidirectional flight is expressed in Equation 5.

$$D^{(i)} = 1 \quad i = 1, 2, \ldots, d \tag{5}$$

The mathematical expression for simulating guided foraging behavior with an appropriate food supply is given as in Equation 6. $x_{i,tar}(t)$ is hummingbird's intended food source, α is guided factor at normal distribution.

$$v_i^{t+1} = x_{i,tar}^t + \alpha D\left(x_i^t - x_{i,tar}^t\right) \quad \alpha \sim N(0,1) \tag{6}$$

The latest position is updated as in Equation 7.

$$x_i^{t+1} = \begin{cases} x_i^t & f(x_i^t) \leq f(v_i^{t+1}) \\ v_i^{t+1} & other \end{cases} \tag{7}$$

Territorial foraging

The mathematical equation x describes the local foraging strategy of hummingbirds in terms of their territorial foraging strategy and a sufficient food source (Zhao et al., 2022). In Equation 8, b is a territorial factor and a directed factor with normal distribution.

$$v_i^{t+1} = x_i^t + bDx_i^t \quad b \sim N(0,1) \tag{8}$$

Migration foraging

The migration of a hummingbird from the nectar source with the slowest rate of nectar replenishment to another randomly chosen source is represented by Equation 9 (Zhao et al., 2022). In Equation 9, $x_{wor}^t = LB + rand(0.0,1.0)(UB - LB)$ represents the food source in the swarm with the lowest nectar replenishment rate.

$$x_{wor}^t = LB + rand(0.0,1.0)(UB - LB) \tag{9}$$

In the absence of replacements for food sources, a hummingbird using directed and territorial foraging strategies sequentially visited each food source with respect to visiting table at each iteration. Given a 50% probability of success when choosing between guided and territorial foraging, as well as a 50% chance of success when visiting other sources during guided foraging, it becomes essential to extend the search area and mitigate stagnation through the adoption of a migratory foraging strategy (Zhao et al., 2022). In this context, the population size specification of the migration coefficient *(M)* is provided as outlined in Equation 10. During the algorithm run, iteration number *t* increases. Meanwhile, if *mod (t, M) = 0* is met Equation 9 is used.

$$M = 2n \tag{10}$$

The pseudocode of the AHA is given in Algorithm 1.

Modern Portfolio Theory

In the first half of the 20th century, the science of investment began to develop, and although initially securities were handled and analyzed individually and focused on individual choices, a new perspective on investments was introduced in the MPT, the first building blocks of which were created by Markowitz (Akkaya, 2021; Markowitz, 1952, 1959; Mercangöz, 2018). Within the scope of portfolio management, the selection of assets that investors will add to their portfolios is called a portfolio selection problem in the finance literature (Karan, 2001). Harry Markowitz argued that traditional portfolio theory cannot reduce portfolio risk by increasing the variety of assets in a portfolio. With the mean-variance model, the traditional portfolio theory was replaced by MPT. Investors want to know the risks they face against their expected return (Akgüç, 1998). For this reason, Markowitz used a model that would reach the minimum risk at the expected return level and the maximum return at the expected risk level by examining the relationships between the assets in the portfolio. Portfolio rate of Return is the average

Algorithm 1

Pseudocode of Artificial Hummingbird Algorithm

The objective function is determined $f(x), [x_1, x_2, \ldots, x_n]^T$
Define n number Artificial Hummingbird
N_{max} *number*
LB and UB of population
The initial population values are produced by Equation (1) and
The visit table is created using Equation (2)
While $t < N_{max}$
for $i = 1: n$
If $rand(0.0,1.0) \leq 0.5$
If $rand(0.0,1.0) < 1/3$
Apply the diagonal flight using Equation (4)
Else if $rand(0.0,1.0) < 2/3$
Apply the omnidirectional flight using Equation (5)
Else
Apply the axial flight in Equation (3)
Apply guided foraging using Equation (6)
If $f(v_i^{t+1}) < f(x_i^t)$
$x_i^{t+1} = v_i^{t+1}$
for $j = 1: n(j \neq i, tar)$
$VT_{i,j}^t = VT_{i,j}^t + 1$
$VT_{i,tar}^t = 0$
for $j = 1: n(j \neq i, tar)$
$VT_{i,j}^t = \max_{k \in n, k \neq j}(VT_{i,k}^t + 1)$

for $j = 1{:}n(j \neq i, tar)$
$VT_{i,j}^{t} = VT_{i,j}^{t} + 1$
$VT_{i,tar}^{t} = 0$
Else
Apply territorial foraging using Equation (8)
If $f(v_i^{t+1}) < f(x_i^t)$
$x_i^{t+1} = v_i^{t+1}$
for $j = 1{:}n(j \neq i)$
$VT_{i,j}^{t} = VT_{i,j}^{t} + 1$
for $j = 1{:}n$
$VT_{i,j}^{t} = \max_{k \in n, k \neq j}(VT_{i,k}^{t} + 1)$
Else
for $j = 1{:}n(j \neq i)$
$VT_{i,j}^{t} = VT_{i,j}^{t} + 1$
If $mod(t, M) = 0$
Apply migration foraging using Equation (9)
for $j = 1{:}n(j \neq wor)$
$VT_{wor,j}^{t} = VT_{wor,j}^{t} + 1$
for $j = 1{:}n$
$VT_{j,wor}^{t} = \max_{k \in n, k \neq j}(VT_{j,k}^{t} + 1)$

return rate for assets in the portfolio (Karan, 2001). When investors make an investment decision, they invest their capital in more than one investment asset to minimize risks. For this reason, since every asset with a financial nature can be a part of the portfolio, the portfolio should be evaluated in general rather than individually evaluating the assets while performing the risk-return analysis. The effect of assets on portfolio risk can be positive, negative, or neutral. The covariance of the combination values of the assets should be calculated to determine the direction in which the relationship between all assets resulting from this effect is. Covariance is the fit value of more than one variable between two or more variables at certain times.

Markowitz's mean-variance model reduces portfolio risk by creating a portfolio of assets that do not have the same relationship between returns. In MPT, a portfolio comprising a combination of low correlations and those with minimum risk has a greater impact on expected portfolio return (Ayan & Akay, 2014; Hüseyinov & Uluçay, 2019; Mercangöz, 2018). Investors want to achieve high returns; however, while creating an optimum portfolio, the relationship between return and risk should be examined. A low-risk portfolio should be selected at the same return level, while a high-risk portfolio should be selected at the same risk level (Ulucan, 2004).

The expected return of the portfolio is determined by multiplying the expected returns of each asset by the weights of those assets in the portfolio, using Equation 11. Here, n denotes the total number of assets in the portfolio, w_i denotes the weight assigned to each asset, and $E(r_i)$ i stands for the expected return on assets.

$$E(r_p) = \sum_{i=1}^{n} w_i E(r_i) \tag{11}$$

The covariance between any two data can be calculated using Equation 12:

$$Cov(r_i, r_j) = \frac{1}{n} \sum_{k=1}^{n} \left(r_{ik} - E(r_i)\right)\left(r_{jk} - E(r_j)\right) \tag{12}$$

The variance formula required to calculate the risk of a portfolio consisting of many assets using the covariance matrix is shown in Equation 13.

$$var(r_p) = \sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j Cov(r_i, r_j) \tag{13}$$

Markowitz examined the relationships between the returns of the securities that comprise the portfolio. He proposed the MPT, which shows that the inclusion of securities that do not have a fully positive correlation from this relationship, in other words, the correlation coefficients are less than 1, and even negative if possible, can be achieved by reducing the portfolio risk of the targeted return (Akyer, Kalaycı, & Aygören, 2018). The mathematical formula of the portfolio optimization problem to be realized using the Markowitz mean variance model is the nonlinear programing model in Equation 14. Note that in Equation 14, $var(r_p)$ to be minimized stands for objective function $J(x)$for standard optimization problem.

$$min\ \left(var\left(r_p\right)\right) = \sigma_p^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_i w_j Cov\left(r_i, r_j\right)$$

Subject to: (14)

$$\sum_{i=1}^{n} w_i = 1 \quad i = 1,2,..,n$$

Capital Assessment Price Model

CAPM is a model that provides an indicator for investors to value risky assets and optimize their portfolios. This was suggested based on the mean-variance model and the assumption that portfolios have efficient frontiers. This model shows a linear relationship between risk and return. The CAPM model essentially gives returns that can be linearly obtained according to the risk criterion. The CAPM model is given in Equation 15. In Equation 15, $E(R_i)$ represents the expected value of the i-th asset, while R_f represents the risk-free interest rate in the market. β_i represents the systematic risk of the i-th asset, while R_m represents the expected market return (Elbannan, 2015; Moustafa, 2007).

$$E(R_i) = R_f + \beta_i\left(R_m - R_f\right) \tag{15}$$

The risk of the asset used in the CAPM model is calculated as in Equation 16. This value is also called Beta. β_i is essentially the market beta of the i-th asset and measures the sensitivity of the asset's return to changes in market return. $Cov(R_i, R_m)$ value is the covariance between the i-th asset and its market value. $\sigma^2(R_m)$ also expresses the variance in the market value.

$$\beta_i = \frac{Cov(R_i, R_m)}{\sigma^2(R_m)} \tag{16}$$

The risk of a created portfolio can be measured using Equation 17. The expected portfolio return can be calculated by substituting the calculated β_p into the β_i in equation 15.

$$\beta_p = \sum_{i=1}^{n} w_i \beta_i \tag{17}$$

Sharpe Ratio

Sharpe introduced the Sharpe ratio in Equation 18, which is used to measure performance by dividing the total return above the risk-free interest rate by the total risk (Sedighi, Jahangirnia, & Gharakhani, 2019; Yücel, 2016). In Equation 18, R_m is the return on the portfolio or stock, σ is the standard deviation of the stock or portfolio and R_f is the risk-free interest rate. If the standard deviation of a portfolio or stock is low and the return is high, then the Sharpe ratio will produce high values. Therefore, a high Sharpe ratio is desirable for a defensive investor.

$$Sharpe = \frac{R_m - R_f}{\sigma} \tag{18}$$

Treynor Ratio

Treynor assumed that a rational investor could eliminate unsystematic risk by diversifying risk. Under this assumption, Treynor introduced the Treynor ratio in Equation 19 to the literature by proportioning total return above the risk-free interest rate to systematic risk (Sedighi et al., 2019; Yücel, 2016). In Equation 19, R_m is the return of the portfolio or stock, β is systematic risk or Beta of the stock or portfolio and R_f is the risk-free interest rate. If the beta of a portfolio or stock is low and the return is high, then the Treynor ratio will produce high values. Note that when the beta of a portfolio or stock is low, an investor or finance researcher should be slow and sure. Nevertheless, a high Treynor ratio is a desirable situation for a defensive investor.

$$Treynor = \frac{R_m - R_f}{\beta} \tag{19}$$

Simulation Studies

A portfolio was created by weighting the companies in the sector to create a portfolio with the lowest risk according to the MPT technique using the AHA in the cement sector. For this, the data traded in Borsa Istanbul are discussed. In order to perform the studies, a computer with Intel(R) Core (TM) i5-9400 CPU@ 2.90 GHz, 64 Bit, 8 GB RAM was used. The study was conducted using MATLAB 2018a. Then, AHA was run to determine the appropriate portfolio selection according to the MPT technique, and analyses were carried out to determine the appropriate portfolio selection. With this objective, tests were performed on different swarm sizes and numbers of iterations to test the performance of the AHA proposed in 2021.

Datasets

This study discusses shares of companies in the cement sector traded in Borsa Istanbul. Afyon Çimento Sanayi T.A.Ş (AFYON), Akçansa Çimento Sanayi ve Ticaret A.Ş. (AKCNS), Batısöke Söke Çimento Sanayi T.A.Ş (BSOKE), Batıçim Bati Anadolu Çimento Sanayi A.Ş. (BTCIM), Bursa Çimento Fabrikasi A.Ş. (BUCIM), Çimsa Çimento Sanayi ve Ticaret A.Ş. (CIMSA), Çimbeton Hazırbeton ve Prefabrik Yapı Elemanları Sanayi ve Ticaret A.Ş. (CMBTN), Göltaş Göller Bölgesi Çimento Sanayi ve Ticaret A.Ş. (GOLTS), Konya Çimento Sanayi A.Ş. (KONYA), Niğbaş Niğde Beton Sanayi ve Ticaret A.Ş. (NIBAS) ve Oyak Çimento Fabrikaları A.Ş. (OYAKC) companies' monthly closing prices of share between 01/31/2018-01/31/2023 have been taken up. Between these dates, Boğaziçi Beton Sanayi ve Ticaret A.Ş. (BOBET) company did not have sufficient data, so this BOBET share was not taken into consideration in the analysis. In addition to these stock data, XTAST and BIST

100 were used. It is obvious that if price data for all months are given and analysis results are given, the article would take up a lot of space. Therefore, only data for a few months at the beginning and end will be given in the tables, and their analysis results will be given. A small portion of this monthly-closing price data can be seen in Table 1. These data must be normalized. Thus, to accomplish this, the formula used is given in Equation 20. When Equation 20 is examined, r_t presents *t*-th month price in Table 1 and R_t presents normalized proportional return. The normalized proportional return obtained when Equation 20 is applied to the monthly-closing price data of cement companies is given in Table 2.

$$R_t = \frac{r_t}{r_{t-1}} - 1 \tag{20}$$

Table 1
Monthly-closing Price Data of Companies in the Cement Sector

Month/Day/ Year	BIST 100	XTAST	AFYON	AKCNS	BSOKE	BTCIM	BUCIM
01/31/2018	1195.29	891.51	2.78	8.77	1.659	4.56	0.77
02/28/2018	1189.51	686.51	2.75	8.37	1.594	3.86	0.75
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
11/30/2022	4977.64	5077.51	8.09	61.66	4.99	38.38	5.66
12/30/2022	5.509.16	5558.75	8.45	60.63	5.69	41.70	6.19
01/31/2023	4976.55	4680.33	6.29	52.45	5.67	37.30	5.14
Month/Day/ Year	**CIMSA**	**CMBTN**	**GOLTS**	**KONYA**	**NIBAS**	**OYAKC**	
01/31/2018	1.79	45.44	26.11	253.45	1.01	3.27	
02/28/2018	1.72	40.76	23.97	241.72	0.96	3.29	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	
11/30/2022	12.66	489.50	120.50	3272.50	14.31	21.10	
12/30/2022	13.89	544.60	126.00	3430.00	16.29	21.02	
01/31/2023	11.32	414.10	110.10	2352.90	13.15	21.42	

Table 2
Normalized Proportional Returns

Month/Day/ Year	BIST 100	XTAST	AFYON	AKCNS	BSOKE	BTCIM	BUCIM
01/31/2018							
02/28/2018	-0.00483	-0.02531	-0.011	-0.046	-0.039	-0.154	-0.026
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
11/30/2022	0.25099	0.2029	0.315	0.430	0.306	-0.133	0.199
12/30/2022	0.10678	0.09477	0.045	-0.017	0.140	0.087	0.094
01/31/2023	-0.09667	-0.1580	-0.256	-0.135	-0.004	-0.106	-0.170
01/31/2018							
02/28/2018	-0.040	-0.103	-0.082	-0.082	-0.050	0.005	
⋮	⋮	⋮	⋮	⋮	⋮	⋮	
11/30/2022	0.194	0.131	0.035	0.360	0.154	0.255	
12/30/2022	0.097	0.113	0.046	0.046	0.138	-0.004	
01/31/2023	-0.185	-0.240	-0.126	-0.126	-0.193	0.019	

Table 3
Statistical Results Based on Normalized Proportional Data

	BIST 100	XTAST	AFYON	AKCNS	BSOKE	BTCIM	BUCIM
Expected Value	0.028	0.03323	0.023	0.041	0.033	0.057	0.041
Variance	0.008	0.018084	0.020	0.024	0.026	0.054	0.019
Standard Deviation	0.089	0.104155	0.140	0.154	0.160	0.233	0.138
Coefficient of variation	3.199	3.134	6.053	3.763	4.870	4.117	3.379
Beta	1.00	0.7149	0.4722	0.4170	0.2857	0.1360	0.4258
CAPM-Er	0.0280	0.0263	0.0155	0.0222	0.0157	0.0154	0.0225
Sharpe Ratio	0.2156	0.2345	0.1014	0.2090	0.1512	0.2068	0.2333
Treynor Ratio	0.0192	0.0234	0.0300	0.0772	0.0846	0.35426	0.0756
	CIMSA	**CMBTN**	**GOLTS**	**KONYA**	**NIBAS**	**OYAKC**	
Expected Value	0.039	0.060	0.037	0.057	0.102	0.039	
Variance	0.017	0.057	0.028	0.010	0.169	0.016	
Standard Deviation	0.130	0.238	0.168	0.046	0.411	0.127	
Coefficient of variation	3.300	3.981	4.547	4.547	4.048	3.265	
Beta	0.498292	0.20555	0.375531	0.229799	0.018828	0.337215	
CAPM-Er	0.0238	0.0193	0.0194	0.0199	0.0106	0.0190	
Sharpe Ratio	0.2327	0.2153	0.1682	0.2282	0.225742	0.237589	
Treynor Ratio	0.061574	0.248408	0.075029	0.21035	4.926388	0.089785	

In Table 3, the statistical and performance results for BIST 100, XTAST, and each stock, including expected value, variance, standard deviation, and coefficient of variation, Beta, CAPM-Expected return (CAPM-Er), Sharpe ratio, and Treynor ratio, are calculated. While these results were calculated, the normalized proportional results in Table 2 were used. In terms of variance, OYAKC, CIMSA, BUCIM, and AFYON exhibited better performance than BIST 100 Table 3. Regarding the expected value, most stocks, except for AFYON, exhibited a better performance than BIST 100. When the beta values of all were examined, it is observed they are lower than the one of BIST100. This indicates that each stock does not behave aggressively compared with BIST100. On the other hand, Equation 15 is used to calculate the expected return (E_r) of each asset according to CAMP. Before Equation 15 is used to calculate E_r , TCBM's annual interest rate of 10.5% in December 2023 is considered. This annual risk-free interest rate was divided by 12 to convert it into monthly risk-free interest. The monthly risk-free interest rate was calculated as R_f=0.88%. The market return is measured as R_m=2.785%, as shown in Table 3. Note that R_f and R_m are used in the CAPM analysis, the Sharpe ratios and

Treynor ratios. First, Equation 15 is used to calculate monthly expected return for each stock with respect to CAPM. When Er values are examined in Table 3, they are lower than BIST100. This indicates that the market expects lower returns from these stocks than BIST100. In addition, the Sharpe ratios are examined in Table 3, and OYAKC, CIMSA, and

BUCIM obtained the best results. Regarding the Treynor ratio, NIBAS produced the best and highest value because its Beta was low. Although its beta value, which represents its systematic risk, is close to zero, its standard deviation is the highest. Therefore, its variations or trends are not parallel to BIST100. Henceforth, both standard variation and Beta values should be considered when investigating the Treynor ratio. For instance, KONYA, BUCIM, and CMBTN have reasonable Treynor ratios. But the standard deviation of BUCIM and CMBTN are relatively higher than the standard deviation of KONYA.

Abnormal return values are used in calculating the covariance matrix. Abnormal returns are calculated by subtracting the expected values in Table 3 from the normalized proportional data of each share value in Table 2. A small proportion of these calculated abnormal returns are presented in Table 4. Afterwards, the covariance matrix calculated using Table 4 is given in Table 5. When the covariance matrix is examined, all pairs are positive or too close to zero. This means that there is nearly a correlation between most pairs for those positive values, and the others are almost not correlated. Because there is no negative value in Table 5, there are no negative correlation among pairs. Basically, these companies are in the same country, cement sector, and market; consequently, positive correlation coefficients might be close to each other and greater than zero. These data, in table 5, are prepared for use in Equation 14.

Table 4
Abnormal Returns

Month/Day/Year	AFYON	AKCNS	BSOKE	BTCIM	BUCIM	CIMSA
01/31/2018						
02/28/2018	-0.034	-0.086	-0.072	-0.210	-0.067	-0.080
⋮	⋮	⋮	⋮	⋮	⋮	⋮
11/30/2022	0.292	0.389	0.273	-0.190	0.158	0.154
12/30/2022	0.022	-0.058	0.107	0.030	0.053	0.058
01/31/2023	-0.279	-0.176	-0.036	-0.162	-0.211	-0.224

Month/Day/Year	CMBTN	GOLTS	KONYA	NIBAS	OYAKC
01/31/2018					
02/28/2018	-0.163	-0.119	-0.119	-0.151	-0.034
Month/Day/Year	**CMBTN**	**GOLTS**	**KONYA**	**NIBAS**	**OYAKC**
⋮	⋮	⋮	⋮	⋮	⋮
11/30/2022	0.0711	-0.002	0.3029	0.0525	0.217
12/30/2022	0.053	0.009	0.009	0.037	-0.043
01/31/2023	-0.299	-0.163	-0.163	-0.294	-0.020

Simulation Studies

In this study, a portfolio was created by selecting cement companies with the lowest risk. For this purpose, data between 01/31/2018 and 01/31/2023 were adapted to the MPT problem and optimal weights were determined by the AHA algorithm. In order to obtain the results for this study, a computer with Intel (R) Core (TM) i5-9400 CPU @ 2.90 GHz, 64 bits, and 8 GB RAM was used. The study was conducted using MATLAB 2018a. In the simulation studies, first, AHA was run many times, and its results statistically have been evaluated. Second, Wilxocon tests were performed to specify significant differences among the results.

Table 5
Covariance Matrix

	AFYON	AKCNS	BSOKE	BTCIM	BUCIM	CIMSA	CMBTN	GOLTS	KONYA	NIBAS	OYAKC
AFYON	0.020	0.015	0.014	0.014	0.013	0.013	0.022	0.018	0.018	0.012	0.010
AKCNS	0.015	0.024	0.013	0.013	0.011	0.015	0.016	0.016	0.016	0.004	0.010
BSOKE	0.014	0.013	0.026	0.026	0.010	0.012	0.021	0.016	0.016	0.012	0.004
BTCIM	0.014	0.013	0.026	0.054	0.010	0.015	0.026	0.022	0.022	0.002	0.002
BUCIM	0.013	0.011	0.010	0.010	0.019	0.012	0.022	0.015	0.015	0.006	0.007
CIMSA	0.013	0.015	0.012	0.015	0.012	0.017	0.020	0.016	0.016	0.004	0.008
CMBTN	0.022	0.016	0.021	0.026	0.022	0.020	0.057	0.027	0.027	0.019	0.010
GOLTS	0.018	0.016	0.016	0.022	0.015	0.016	0.027	0.028	0.028	0.007	0.011
KONYA	0.018	0.016	0.016	0.022	0.015	0.016	0.027	0.028	0.028	0.007	0.011
NIBAS	0.012	0.004	0.012	0.002	0.006	0.004	0.019	0.007	0.007	0.169	0.004
OYAKC	0.010	0.010	0.004	0.002	0.007	0.008	0.010	0.011	0.011	0.004	0.016

Third, optimal portfolios are determined that is variances and weights of portfolios by using AHA results. Fourth, the performance results of the portfolio, such as CAPM-Er, Sharpe ratio, and Treynor ratio, were calculated to be able to compare. All results were expressed in tables or graphs to ensure clear and intelligibility.

In the experiments, AHA was separately run 30 times for different swarm sizes and numbers of iterations. The minimum, maximum, average, and standard deviation results of each run were calculated. The results are presented in tables and graphs. The optimal portfolio weights in the MPT problem were determined by independently running the AHA swarm numbers 30, 50, and 100 and the iterations 100 and 500 independently times. The findings of 30 independent experiments are presented in Table 6. In addition, the maximum, minimum, and expected values of the results obtained when run 30 times are plotted in Figure 2. The minimum values are given in the graphics titles. Numerical results can be better examined in Table 6 because the numerical values cannot be seen and printed in these graphics. When the minimum values of the objective function given in Table 6 were examined, the minimum value of the objective function decreased as the swarm size and number of iterations increased. When their maximum values are checked, it is seen that the maximum value decreased as the swarm size

Table 6

Statistical Evaluation of The Results Obtained By The Optimization

Number of iterations (N_{max})	**100**	**100**	**100**
Swarm size (n)	30	50	100
Minimum	0.103241317	0.1030515	0.1029558
Maximum	0.1043611	0.1040476	0.1036067
Expected Value	0.1036291	0.1033945	0.1032650
Standard deviation	3.3872e-04	2.2329e-04	1.6692e-04
Number of iterations	500	500	500
Swarm size	30	50	100
Minimum	0.1028794	0.102879426	0.10287942
Maximum	0.1028822	0.102879513	0.10287946
Expected Value	0.1028796	0.102879444	0.10287942
Standard deviation	5.1684e-07	2.1794e-08	7.0664e-09

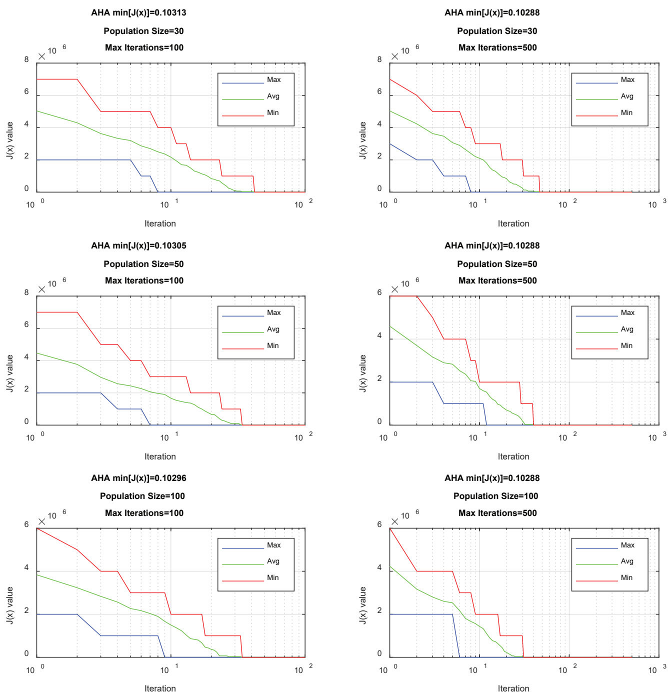

Figure 2. The convergence results of the AHA

and number of iterations increased. Similarly, when the expected values and standard deviation of the AHA results are examined, the expected values and standard deviation decrease as the number of iterations and swarm sizes increase. This means that the AHA has found close results around the global minimum; thus, the results are close to each other when the expected values and standard deviation decrease. Wilxocon tests were performed to determine whether the AHA algorithm produced significant differences in the results. The significance values of the test results are given in Table 7. When the results were examined, it was observed that there was a significant difference between them since the values written in bold were less than 0.05. However, it was observed there is no significant difference in the results when the swarm sizes and number of iterations increased. This is because the AHA produced results that were close to the global optimum. In other words, there were significant differences between the results obtained by the AHA algorithm when the number of iterations and the swarm size increased.

Table 7

Wilxocon Test Results

	N_{max} = 100 n = 30	N_{max} = 100 n = 50	N_{max} = 100 n = 100	N_{max} = 30 n = 500	N_{max} = 50 n = 500	N_{max} = 100 n = 500
N_{max} = 100 n = 30	1.0000	**2.2531e-02**	**2.4626e-03**	**1.5805e-06**	**3.3918e-06**	**3.3918e-06**
N_{max} = 100 n = 50	**2.2531e-02**	1.0000	**3.6150e-01**	**1.5805e-06**	**3.3918e-06**	**3.3918e-06**
N_{max} = 100 n = 100	**2.4626e-03**	**3.6150e-01**	1.0000	**1.5805e-06**	**3.3918e-06**	**3.3918e-06**
N_{max} = 30 n = 500	**1.5805e-06**	**1.5805e-06**	**1.5805e-06**	1.0000	**3.4415e-04**	**9.8596e-05**
N_{max} = 30 n = 500	**3.3918e-06**	**3.3918e-06**	**3.3918e-06**	**3.4415e-04**	1.0000	7.0892E-01
N_{max} = 100 n = 500	**3.3918e-06**	**3.3918e-06**	**3.3918e-06**	**9.8596e-05**	7.0892E-01	1.0000

The optimal weights according to the minimum values obtained as a result of the analysis are given in Table 7. Eight different portfolios were constructed, including the BIST 100 and XTAST portfolios.

Total normalized proportional returns, variances, standard deviations, risk coefficients, Beta, CAMP-Er, Sharpe ratio, and Treynor ratio for each portfolio are given in Table 9. Moreover, these results were tried to be depicted in Figure 3-6. When total normalized proportional returns of portfolios are examined in Table 9, optimized portfolios that are Portfolio 1- Portfolio 6 produced close and reasonable results. If variances are investigated among the optimized portfolios, Portfolio 5 and Portfolio 6 produced minimum values. When the risk of the portfolios is observed among the optimized portfolios in Table 9, Portfolio 6 produced the minimum risk value. Standard deviations and returns are depicted are depicted in Figures 3 and 4a for each stock and portfolio. Furthermore, Figure 4b

Table 8

Percentage Weights of Portfolio Shares

	Portfolio 1	**Portfolio 2**	**Portfolio 3**	**Portfolio 4**
Number of iterations	100	100	100	500
Swarm size	30	50	100	30
Objective Values-Variances	0.01063615	0.010619613	0.010599914	0.010584182
AFYON	0.13	0.07	0.03	0.00

	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4
AKCNS	0.24	0.32	0.07	0.00
BSOKE	12.71	14.66	14.63	14.78
BTCIM	3.41	2.59	4.54	3.90
BUCIM	21.68	23.24	23.36	22.49
CIMSA	12.20	9.53	8.57	9.70
CMBTN	0.06	0.06	0.03	0.00
GOLTS	0.08	0.19	0.08	0.00
KONYA	0.42	0.09	0.07	0.00
NIBAS	3.47	3.20	3.11	3.18
OYAKC	45.60	46.05	45.51	45.94
BIST 100	0	0	0	0
XTAST	0	0	0	0
	Portfolio 5	**Portfolio 6**	**Portfolio 7-BIST 100**	**Portfolio 8-XTAST**
Number of iterations	500	500	--	--
Swarm size	50	100	--	--
Objective Values-Variances	0.010584176	0.010584176	0.00792938	0.01084827
AFYON	0.00	0.00	0	0
AKCNS	0.00	0.00	0	0
BSOKE	14.80	14.80	0	0
BTCIM	3.91	3.91	0	0
BUCIM	22.52	22.53	0	0
CIMSA	9.64	9.63	0	0
CMBTN	0.00	0.00	0	0
GOLTS	0.00	0.00	0	0
KONYA	0.00	0.00	0	0
NIBAS	3.17	3.17	0	0
OYAKC	45.95	45.95	0	0
BIST 100	0	0	100	0
XTAST	0	0	0	100

depicts the standard deviations and returns of only the optimized portfolios. In Figure 3, most of the stock has higher standard deviations, implying high risk. In addition, an efficient frontier line is drawn in Figures 4a and 4b in dashed blue to obtain the optimal portfolio. Subsequently, Capital Allocation Line (CAL) is drawn in dashed magenta in Figures 4a and 4b. The CAL curve is a straight line that connects the risk-free rate of return (R_f=0.88%) to the point at which the efficient frontier intersects the y-axis (maximum return). It is assumed that this intersected point reveals the optimal portfolio shown in Figures 4a and 4b because the slope of CAL is the highest, which means that an investor can achieve the highest return per additional unit of risk. Moreover, the total normalized proportional of each portfolio to be obtained by an investor who made an investment of 1000 TL in 1.31.2018 in return for the cash to be obtained on 1.31.2023 is given in Table 9. Under this condition, Porfolio 1 returns 5414.373907 TL, but its risk is slightly higher than those of other optimized portfolios. In order to calculate the systematic risk of the portfolios, Equation 17 is used to calculate the beta values given in Table 9. These values are employed to Equation 15 to obtain the expected market return (CAPM-Er). As shown in Table 9, CAPM-Er values of the portfolios are less than the total normalized proportional returns of the portfolio. In Figure 5a, the total normalized proportional returns and Beta values are plotted. The optimized portfolios produced higher returns than Portfolios 7-BIST 100 and 8-XTAST. Figure 5b plots the CAPM-Er and beta values. The optimized portfolios produced lower returns than Portfolios 7-BIST 100 and 8-XTAST. This implies that the market undervalued the same optimized portfolio. The reason is systematic risks or the beta of portfolios is lower level than market. That difference has caused their expected return values to decrease. To illustrate the percentage of return of optimized portfolios with respect to CAPM is calculated as to total normalized proportional returns. The results are shown in Figure 6. Consequently, CAPM results for optimized portfolios are negative compared to total normalized proportional returns. On the other hand, performances of the portfolios with respect to Sharpe ratio and Treynor ratio are measured. The results are given in Table 9 and depicted in Figure 7. When the optimized portfolios are examined in terms of Sharpe and Treynor ratios, the results are observed to be very close. However, in terms of Sharpe ratio, the result for Portfolio 1 is 0.316773, which is better than the other portfolios. That means Portfolio 1, unit return per risk is highest for portfolio 1. Regarding the Treynor ratio, the result for Portfolio 6 is 0.094180534, which is better than the other portfolios. That means Portfolio 6, unit return to systematic risk is highest for portfolio 6.

Table 9
Portfolio Results

	Portfolio 1	**Portfolio 2**	**Portfolio 3**	**Portfolio 4**
Total normalized proportional returns of Portfolio	0.0414697	0.041073894	0.041359475	0.041271351
Portfolio Variance	0.01063615	0.010619613	0.010599914	0.010584182
Risk of Portfolio	0.103131744	0.103051507	0.102955888	0.102879456
Coefficient of variation	2.486918	2.50893	2.489294	2.492757
Portfolio Return (TL)	5414.373907	5337.935954	5371.872573	5362.172354
Beta of Portfolio	0.3515066	0.350473671	0.3451784	0.3471826
CAPM-Er	0.020283615	0.02011115010	0.02003882748	0.02007348806
Sharpe Ratio	0.316773	0.313182164	0.316246872	0.31562522
Treynor Ratio	0.09294	0.0920865	0.09424	0.093528
	Portfolio 5	**Portfolio 6**	**Portfolio 7 BIST 100**	**Portfolio 8 XTAST**
Total normalized proportional returns of Portfolio	0.041265095	0.041265188	0.02783477	0.0332309
Portfolio Variance	0.010584176	0.010584176	0.00792938	0.01084827
Risk of Portfolio	0.102879426	0.102879424	0.08904706	0.10415503
Coefficient of variation	2.493134	2.493129	3.19913038	3.1342825
Portfolio Return (TL)	5361.143112	5361.120165	3163.46660	4249.8906
Beta of Portfolio	0.3471302	0.347122944	1.00	0.714986953
CAPM-Er	0.020069614	0.020069411	0.027834770	0.026267774
Sharpe Ratio	0.315564503	0.315565413	0.213760791	0.234562843
Treynor Ratio	0.093524259	0.094180534	0.01903477	0.034169714

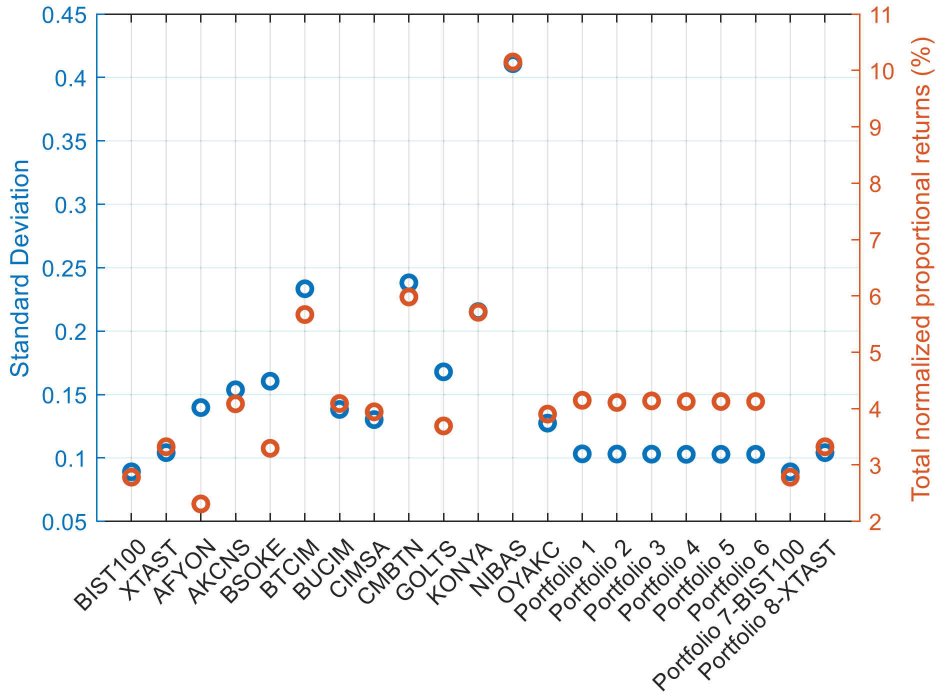

Figure 3. Standard deviations and total normalized proportional returns

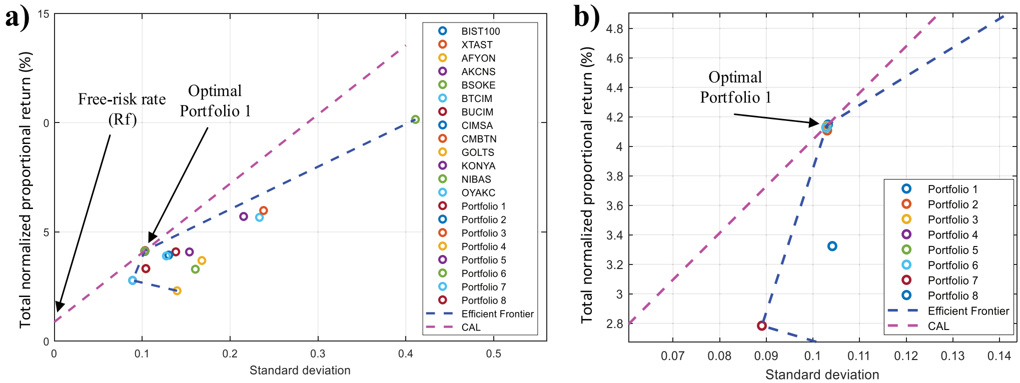

Figure 4. Efficient Frontier Line and CAL-optimal Portfolios

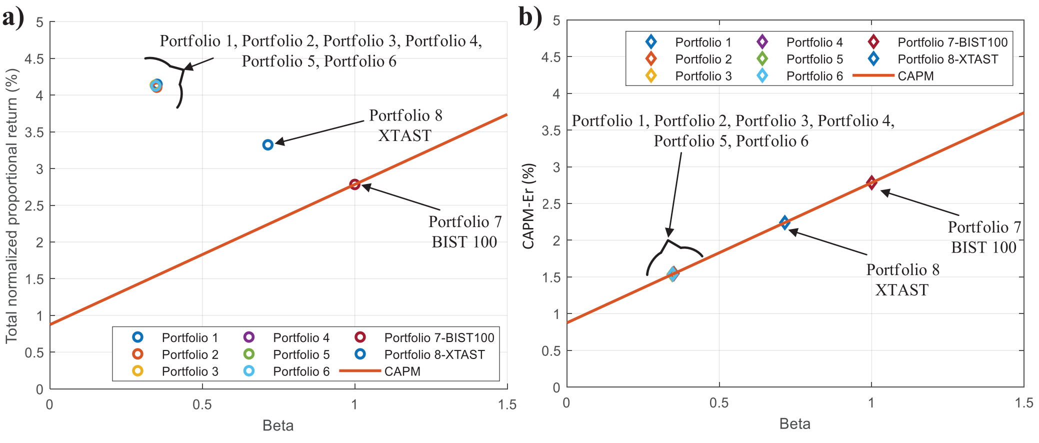

Figure 5. a) Total normalized proportional return versus beta. ***b)*** CAPM expected return versus beta

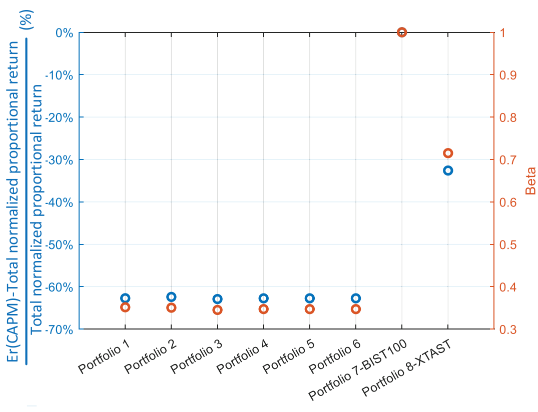

Figure 6. Percentage of return results relative to CAPM

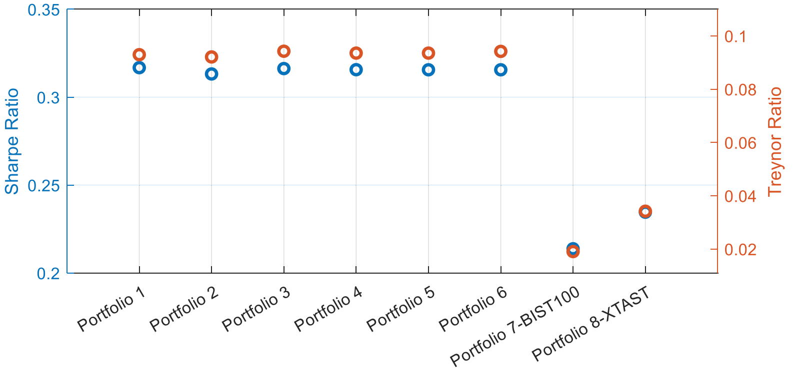

Figure 7. Sharpe and Treynor ratios of portfolios

The performance values such as Total normalized proportional return, CAPM, Sharpe ratio, and Traynor ratio, for the optimal portfolios obtained according to the minimum variance criterion for MDP with the AHA algorithm is calculated and are given in Table 9. In addition, Table 10 provides a brief demonstration of the best portfolio for the performance method. As shown in Table 10, Portfolio 1 produced the best result for the total normalized proportional return criterion. Moreover, Portfolio 1 has shown the best performance according to the CAPM, Sharpe ratio, and Traynor ratio criteria in Table 10. Apart from that, in Figure 4, Portfolio 1 also exhibited the optimal portfolio on the CAL and efficient frontier line. On the other hand, in Table 10, the best result for the minimum variance criterion was obtained by Portfolio 6. This portfolio exhibits the lowest variance, and the lowest risk compared to other portfolios. According to the CAPM analysis, the portfolio expected to produce the best return is Portfolio 7-BIST 100. The reason for this is that, as mentioned earlier, expected returns are low due to the low beta coefficients of the other portfolios.

Table 10
Comparison pf Returns And Risks For Optimal Portfolios

Performance Method	***Optimal Portfolio***	***Return***	***Variance***	***CAPM***	***Sharpe***	***Traynor***
Total normalized proportional return	*Portfolio 1*	*0.0414697*	*0.01063615*	*0.020283615*	*0.316773*	*0.09294*
Min Variance MDP	*Portfolio 6*	*0.041265188*	*0.010584176*	*0.020069411*	*0.315565413*	*0.094180534*
CAPM	Portfolio 7-BIST 100	*0.02783477*	*0.00792938*	*0.027834770*	*0.213760791*	*0.01903477*
Sharpe Ratio	*Portfolio 1*	*0.0414697*	*0.01063615*	*0.020283615*	*0.316773*	*0.09294*
Traynor Ratio	*Portfolio 1*	*0.0414697*	*0.01063615*	*0.020283615*	*0.316773*	*0.09294*
	Portfolio 3	*0.041359475*	*0.010599914*	*0.02003882748*	*0.316246872*	*0.09424*

Conclusion

This study aims to create an optimal portfolio with minimum risk in the cement sector following the Kahramanmaraş Earthquake in Turkey. The originality of this study lies in the application of the AHA within the MPT, using 11 cement sector stocks for the past 5 years. The AHA was run independently 30 times with varying iteration numbers and swarm sizes to test its performance, and the results were statistically evaluated based on minimum, maximum, average, and standard deviation values. Additionally, the Wilcoxon test was used to assess the significance of differences in results.

Several portfolios were created according to each iteration number and AHA swarm size. The performance of these portfolios was then evaluated using total normalized returns, CAPM analysis, Sharpe Ratio, and Treynor Ratio. The results indicate that, due to systematic risk, the expected return of the CAPM underestimated the optimized portfolios, except for

Portfolio 7-BIST 100, which was not optimized in this study. Notably, Portfolio 1 demonstrated the best performance in terms of total normalized returns, Sharpe Ratio, and Treynor Ratio, and was identified as the intersection point of the efficient frontier line and the Capital Market Line (CAL). However, Portfolio 6 exhibited the best performance in terms of the minimum risk criteria among the optimized portfolios using AHA.

Optimization algorithms provide speed, flexibility, and convenience to investors for determining a portfolio's performance. Thus, future studies will explore portfolio optimization using recently developed algorithms like AHA to further enhance optimization performance for other industrial sectors. In addition to minimizing risk, these studies consider other performance criteria, such as Sharpe Ratio, Treynor Ratio, Fama criteria, M^2, and T^2, to a broader range of investor preferences.

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