Journal of Social Sciences of Mus Alparslan University

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Araştırma Makalesi ● Research Article

A Swarm Intelligence Optimization Algorithm for Cryptocurrency Portfolio Optimization

Kripto Para Birimi Portföy Optimizasyonu için Bir Sürü Zekası Optimizasyon Algoritması

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Abstract: In recent years, cryptocurrency has been widely adopted and seen as an alternative investment tool for investors. However, which cryptocurrency to invest in and how much to invest becomes a problem. Since there is a conflict of multiple criteria, portfolio optimization (PO) is needed to solve the problem. In this study, an Artificial Bee Colony (ABC) algorithm has been developed based on Markowitz's mean-variance model (M-MVM). With this method, the portfolio of cryptocurrencies has been tried to be optimized. Hourly data of 12 cryptocurrencies between 01.09.2020 and 01.04.2021 were used as data. It has been observed that the ABC algorithm achieves good results in the solution of the problem in a reasonable time. In addition, the method was tested with different parameter values and different risk-averse coefficient values (λ). In this study, we proposed a flexible algorithm for the solution of the PO problem. Thus, the algorithm has become easily usable for different data sets and different scenarios. With efficient this algorithm, we have obtained suitable solutions for our problem. The study will be beneficial for the investor as it removes the complexity and uncertainty in portfolio creation.

Keywords: Portfolio Optimization, Artificial Bee Colony, Cryptocurrency

Öz: Son yıllarda kripto para yaygın olarak benimsendi ve yatırımcılar için alternatif bir yatırım aracı olarak görülmeye başlandı. Bununla birlikte hangi kripto paraya yatırım yapılacağı ve ne kadar yapılacağı bir problem haline gelmiştir. Birden çok kriterin çatışma durumu söz konusu olduğundan dolayı problemin çözümü için bir portföy optimizasyonuna ihtiyaç vardır. Bu çalışmada Markowitz'in ortalama varyans modeline dayalı bir Yapay Arı Kolonisi algoritması geliştirilmiştir. Bu yöntem ile kripto paralardan oluşan portföy optimize edilmeye

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Cite as/ Atıf: Yurtsal, A., Karaömer, Y., & Benzer, A. İ. (2022). A swarm ıntelligence optimization algorithm for cryptocurrency portfolio optimization. *Anemon Muş Alparslan Üniversitesi Sosyal Bilimler Dergisi*, *10*(1), 347-363. http://dx.doi.org/10.18506/anemon.975505
Received/Geliş: 28 July/Temmuz 2021
Accepted/Kabul: 08 February/Şubat 2022
Published/Yayın: 30 April/Nisan 2022

e-ISSN: 2149-4622.

çalışılmıştır. Veri olarak 12 kripto paranın 01.09.2020 ile 01.04.2021 tarihleri arasındaki saatlik verileri kullanılmıştır. Yapay Arı Kolonisi algoritmasının problemin çözümünde makul sürede iyi sonuçlar elde ettiği gözlemlenmiştir. Ayrıca yöntem farklı parametre değerleri ve farklı riskten kaçınma katsayı değerleri (λ) ile test edilmiştir. Bu çalışmada, PO probleminin çözümü için esnek bir algoritma önerdik. Böylece algoritma, farklı veri kümeleri ve farklı senaryolar için kolaylıkla kullanılabilir hale gelmiştir. Verimli bu algoritma ile problemimize uygun çözümler elde ettik. Çalışma, portföy oluşturmadaki karmaşıklığı ve belirsizliği ortadan kaldırdığı için yatırımcı için faydalı olacaktır.

Anahtar Kelimeler: Porföy Optimizasyonu, Yapay Arı Kolonisi, Kripto para

1.Introduction

The portfolio can be likened to a flower bouquet made up of many types of flowers. A portfolio may consist of similar assets as well as different assets. Thus, a portfolio is a combination of various assets. The combination may have different risk and return characteristics separate from the components. Therefore, portfolio analysis is an analysis of the risk-return characteristics of the assets in the portfolio and the changes that may occur with other assets due to the interaction between them and the effect of each on the others.

The problem of selecting portfolio assets has always been a challenging task for researchers, investors, and fund managers. There are two basic theories, Traditional Portfolio Theory (TPT) and Modern Portfolio Theory (MPT), which aim to successfully select and manage the portfolio. According to the TPT, the selection and management of a portfolio depend on subjective decisions (ie presentiment, intuition) to be made by the investor. TPT aims to separate the risk into more than one asset. This separation of risk is called lean diversification (simple diversification), which can be defined as "not putting all the eggs in the one basket" or "separating the risk" (Fisher & Jordan, 1987). MPT assumes that maximizing return or minimizing risk will provide optimal returns and that investors' choices and attitudes are only a starting point for investment decisions and strong risk-return analysis is required for the optimization of returns (Avadhani, 2008).

The PO problem is a problem that is widely researched in the fields of economics and finance. Swarm intelligence optimization algorithms are widely used to solve the problem. The ABC method used in the study is also an optimization algorithm based on swarm intelligence. The method was introduced by Dervis Karaboga in 2005. The method is inspired by honey bees' nectar-seeking behaviors in nature. The main purpose of optimization techniques is to maximize the benefit, in other words, to find the most appropriate decision effectively. Therefore, the main purpose of the ABC algorithm is to find the best solution for the target problem with the least cost. In the ABC algorithm, the positions of the food source indicate possible solutions to the problem, and the most appropriate solution is selected according to the nectar amounts of the food sources. The ABC algorithm has received great attention from researchers in different research fields and has been applied to many real-world problems such as financial problems. The ABC algorithm has been developed based on M-MVM. The M-MVM is known as MPT. In his 1952 seminal article, Harry Markowitz stated that the purpose of portfolio selection is to determine the allocation of assets in the portfolio to give the maximum expected return given a certain risk, or the minimum portfolio risk when a given portfolio is given the expected return (Johnson, 2014). The M-MVM is a one-period static portfolio planning model and has recently become the basic decision engine of many portfolio analytics and planning systems in the construction of the risk-return-efficient frontier (Satchell & Scowcroft, 2003).

Cryptocurrency; In its most general definition, it is a digital money type that is based on the internet system and is not connected to a central authority. Cryptocurrencies are based on several ciphers and are traded virtually. The fact that this system is in a development process that will replace the existing money and payment instruments and even replace the traditional monetary theory and practices increases the importance of this system day by day (Alpago, 2018; Eren et al., 2020). Cryptocurrencies are increasingly used in commercial transactions, making various payments, and shopping. In addition to various commercial transactions, the number of cryptocurrency purchases for investment purposes is increasing since cryptocurrencies have just completed their development, their use is increasing and will become more valuable in the future (Katrancı & Kundakcı, 2020).

Although blockchain technology is a technology that emerged in 1985 long before Bitcoin, it was rediscovered in 2008 with the article about Bitcoin written by Satoshi Nakamoto. In this article, while talking about Bitcoin, which is proposed to solve the problems caused by central authorities in money transfer; The underlying blockchain technology is also mentioned. Satoshi Nakamoto defines blockchain technology as an open source, transparent and distributed consensus system that allows the transactions between parties to be recorded in an unalterable way by encryption, without any authority or financial institution (Yıldırım, 2019).

In recent years, public interest in cryptocurrencies has grown tremendously. In late 2017, the crypto currency market's total capitalization reached above $760 billion, reaching a total of $ 825 billion in early January 2018. The remarkable development of the cryptocurrency market has attracted the attention of investors, regulators, and academics (Schellinger, 2020). Thus, cryptocurrency has been widely adopted and seen as an alternative investment tool for investors. However, which cryptocurrency to invest in and how much to invest becomes a problem. Since there is a conflict of multiple criteria, PO is needed to solve the problem. Studies on mixed cryptocurrency PO are limited in the literature. Brauneis & Mestel (2019) applied M-MVM by using daily data of the 500 cryptocurrencies for the cryptocurrency PO. They found that combining cryptocurrencies enriches the set of 'low'-risk cryptocurrency investment opportunities. Inci & Lagasse (2019) applied the mean-variance optimization technique of Merton (1990) by using daily data of the 3 cryptocurrencies (Bitcoin, Ripple, Litecoin) for the cryptocurrency PO. They found that including all these cryptocurrencies in a portfolio generated the best (most optimal) results. Hrytsiuk et al. (2019) analyzed cryptocurrency PO using the Value-At-Risk (VaR) measure. They stated that cryptocurrencies do not show normal distribution and Bitcoin stands out as the most dominant cryptocurrency in the portfolio with its high return and low-risk profile. Mazanec (2021) applied M-MVM by using daily data of the 32 cryptocurrencies for the cryptocurrency PO. The results indicated that the optimal portfolio consisted of Cardano, Binance Coin, and Bitcoin. Wu & Pandey (2014), Eisl et al. (2015), Brière et al. (2015), Petukhina et al. (2018), Guesmi et al. (2019), Symitsi & Chalvatzis (2019), and Kajtazi & Moro (2019) investigated the portfolio diversification effects of Bitcoin with other financial assets. As a result, since adding Bitcoin to a well-diversified portfolio can improve risk-return characteristics, Bitcoin may have a role in portfolio diversification. Katsiampa et al. (2019), Charles & Darné (2019) stated that the volatility of cryptocurrencies is greater than other financial assets. The volatility of cryptocurrencies is very high due to the lack of a centralized structure and high speculation in the market. Highly volatile, they offer investors an opportunity for high returns. Although cryptocurrencies are still in their infancy, it has been observed in recent years that some knowledgeable individuals have made substantial amounts of money by speculating on cryptocurrencies. Therefore, it is important to develop PO methods that will help cryptocurrency investors control their exposure to risk while maximizing their returns (Mba et al., 2018).

In the literature, it is evident that the application of cryptocurrency PO usually involves the use of M-MVM, Value-At-Risk (VaR), Merton's (1990) mean-variance. In this study, an ABC algorithm has been developed based on M-MVM. With this method, the portfolio of cryptocurrencies has been tried to be optimized. We used high-frequency data for cryptocurrency PO. Cai et al. (2020) stated that there were benefits of using high-frequency data: First, numerous observations could potentially help to a better understanding of the covariance structure of the returns. Second, high-frequency data allow for short-horizon rebalancing and therefore portfolios can quickly adapt to the time volatility of volatilities / co-volatilities.

This study, it is aimed to apply an ABC algorithm by using high-frequency data for cryptocurrency PO. Our study provides several contributions to previous literature. First, previous empirical works mostly used M-MVM, Value-At-Risk (VaR), Merton's (1990) mean-variance, etc. for cryptocurrency PO. Second, it is seen that in previous empirical studies, daily (low-frequency) data was mostly applied for cryptocurrency PO. We apply intraday (high-frequency) data for cryptocurrency PO. Besides, Our study also differs in the context of methodology. The remainder of this work is organized as follows: Section 2 introduces the literature review, section 3 describes the methodology, section 4 explains the application, section 5 describes the experimental results, and section 6 the conclusion.

2. Literature Review

Ge (2014) proposed an ABC algorithm developed for PO and tested its efficiency. For the data of the study, monthly returns of fifty stocks from the Chinese stock market during 2013 were selected. It has been observed that the method achieves good results in solving the problem.

Hsu (2014) proposed an integrated approach using Data Envelopment Analysis, ABC, and Genetic Programming to solve the PO problem. With the proposed approach, the data obtained from the stocks of the Taiwan stock market has been studied for 4 years. The proposed procedure can be regarded as a feasible and effective tool for making successful investment plans.

Tuba & Bacanin (2014) presented the ABC algorithm for cardinality constrained mean-variance PO. ABC algorithm has been hybridized with the Firefly Algorithm. The obtained algorithm has been tested on standard test data used in the literature. At some points, it has been observed that the proposed algorithm gives better results.

Chen (2015) tested the performance of different heuristic methods with a modified ABC method. He identified the PO as the problem, and data were obtained from the Shanghai Stock Exchange. The data of 30 stocks between 2004 and 2005 were used as data.

Yakut & Çankal (2016) used GA and Quadratic Goal Programming methods for PO problems and observed that Goal Programming gives better results. Monthly closing prices of BIST 30 stocks between 2004 and 2013 are used as data in the study.

Suthiwong & Sodanil (2016) have proposed a fast ABC algorithm. They used this method to solve the PO problem. In addition, the performance of the developed method is compared with the state of art algorithms' performance in the PO problem.

Kumar & Mishra (2017), the multi-purpose constant variance-based ABC algorithm was used and tested on the benchmarking problems of PO from the OR library. The good performance of the proposed algorithm has been verified

Kalayci et al. (2017) presented an efficient solution approach based on the ABC algorithm with feasibility application and feasibility tolerance procedures to solve the cardinality constrained PO problem. According to the results obtained from the experiments, the effectiveness of the method was observed.

Strumberger et al. (2018) hybridized the ABC algorithm with elements inspired by Genetic Algorithms (GA). Experimental results on standard comparison datasets from five stock indices and comparative analysis with other algorithms show that the proposed algorithm achieves better results by taking all relevant criteria into account.

Mba et al. (2018) proposed two new approaches derived from the traditional Differential Evolution Method. They then compared these two approaches to optimizing a portfolio of five crypto assets. They have achieved successful results with both methods.

Akyer et al. (2018) used a PSO algorithm to solve the PO problem in their studies. The method used was applied to BIST30 and BIST100 indices of Borsa Istanbul belonging to Turkey and the results were analyzed. According to the results obtained, it was concluded that a smaller number of portfolios should be invested at high-risk levels and a limited optimal number of portfolios at medium and low-risk levels.

Hüseyinov & Uluçay (2019) investigated a solution to the problem of PO by using PSO and GA methods. Borsa Istanbul and cryptocurrency exchange data were used as data.

Rahmani et al. (2019) studied the problem of PO using ABC, Genetics, and Ant Colony Algorithms (ACA). The data consists of active companies listed on the Tehran Stock Exchange between 2005 and 2015. The findings show that the ABC algorithm works better than the Genetics and ACA in terms of PO.

Kalayci et al. (2020) proposed a powerful hybrid metaheuristic algorithm combining critical components from ACA, ABC, and GA to solve the cardinality-constrained PO problem. The algorithm was applied to seven benchmarking problems. The results confirmed the efficacy of the hybrid method.

3. Methodology

3.1. Markowitz's Mean-Variance Model

The TPT started in the early 1900s and continued until 1952 when American scientist Harry Markowitz proposed the MPT. According to the TPT, investors make portfolio diversification by making a list of all investment assets and selecting non-interrelated securities of different industries or different assets among these investment instruments. Investors also try to reduce the risk of the portfolio by including a large number of assets in a diversified portfolio. This diversification can be seen as logical. However, there are two problems in portfolio diversification. First, how much investors will invest in each asset? Second, how will investors measure the risk and return of each asset?

In the 1950s, many portfolio investors realized that some securities or groups of securities were moving in the same or opposite direction. However, they did not have any idea about how to measure it (Karaşin, 1987). Harry Markowitz, the founder of Modern Portfolio Theory (MPT), introduced in his article titled "Portfolio Selection" in 1952, how to measure the expected return and risk of a portfolio.

Markowitz's portfolio selection process consists of two stages: The first stage starts with observation and experience and ends with beliefs about the future performance of the assets. The second phase starts with the relevant beliefs about the future performance of the portfolio and ends with the selection of the portfolio. Thus, Markowitz explains the relationship between portfolio selection and beliefs according to the mean-variance rule (with 'mean' used interchangeably with the average or expected return, and 'variance' used to denote risk) (Markowitz, 1952).

MPT assumes that investors are rational. Rational investors avoid risk and will minimize their risk and maximize their returns. Rational investors make their decisions based on risk and expected return only. Based on the MPT assumption, a rational investor can build a portfolio of multiple assets that will maximize return for a given level of risk. Similarly, given the desired level of expected return, a rational investor can build a portfolio with the lowest possible risk (Weigand, 2014).

Markowitz (1952) used mathematical calculations for the selection of assets in the portfolio and statistical analysis for risk measurement. He also stated that risk and return are two important factors that investors should consider, and expected return may vary depending on certain assumptions, and risk can be measured by distribution from the average or by statistical calculation tools such as variance and covariance (Avadhani, 2008). In the Markowitz model, the expected return of the portfolio is calculated as follows:

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

The expected return of a portfolio is obtained by multiplying the expected returns of each asset in the portfolio by their weight in the portfolio. Where $E(r_p)$ denotes the expected return of the portfolio; n is the number of individual assets in the portfolio; $E(r_i)$ denotes the expected return of asset i; w_i denotes the weight of the asset i in the portfolio.

The variance and standard deviation of returns are used to measure risk. In the Markowitz model, the risk of the portfolio is calculated as follows:

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{i,j=1}^{n} w_i w_j Cov_{i,j} \quad (2)$$

Where, σ_p^2 denotes the variance of the portfolio; n is the number of individual assets in the portfolio; w_i denotes the weight of the asset i in the portfolio; w_j denotes the weight of the asset j in the portfolio; Cov_{ij} denotes the covariance between the rates of return of assets i and j.

3.2. Artificial Bee Colony

The intelligent behavior of beings living in swarms in nature is called swarms intelligence. A bee colony or an ant colony can be cited as examples of a swarm. The division of labor (Millonas, 1994) and self-organization (Bonabeau et al., 1999) are two important indicators of swarm intelligence. Bees live in colonies in nature. There are specialized bees for the work to be done in the colony. So, there is a division of labor among bees. Bees can self-organize. For this reason, optimization techniques obtained by modeling the intelligent behavior of honey bee swarms hold an important place among the swarm intelligence algorithms. One of these optimization techniques is the algorithm named ABC based on swarm intelligence developed by Karaboga (2005). He developed the algorithm by modeling the foraging behavior of bees.

In the ABC algorithm, the location of a food source refers to a possible solution. In addition, the amount of nectar of a food source indicates the quality of the solution. The purpose of the ABC algorithm is to find the food source with the maximum amount of nectar. There are three types of bees in a real colony. These; The queen, the drone, and the worker bee. Artificial bee species in the artificial colony in the ABC algorithm are as follows; employed bees, onlookers, and scouts.

If a bee goes to a food source that was visited by it to collect nectar, she is named as an employed bee. The employed bees bring the nectar they collect into the hive and then either return to the food source or transfer the information of the food source to the onlooker bees waiting in the hive by a dance show. When the employed bee's food source is depleted, she turns into a scout bee. If the bee has not yet decided which food source to go to and is in the dance area to watch the tail dance of the employed bees, she is named an onlooker bee. As a result of the increase in the nectar amount of a food source, the probability of that food source being selected by the onlooker bee increases. If a bee is looking for a food source randomly, she is named a scout bee. When a scout bee finds a food source, she turns into an employed bee and begins to bring the nectar to the hive.

There are some assumptions in the ABC algorithm. These;

* The nectar of each food source is collected by only one employed bee. Therefore, the number of employed bees is equal to the total number of food sources.

* The number of employed bees is equal to the number of onlooker bees.

* The employed bee, whose food source is depleted, turns into a scout bee.

The locations of the food sources define the possible solutions to the problem. The nectar amount of food sources corresponds to the quality (fitness) of the solutions related to those sources. Therefore, the ABC algorithm tries to find the point (solution) that gives the minimum or maximum of the problem by trying to find the source with the most nectar among the solutions.

The flow diagram of the ABC algorithm is given in Figure 1.

In the initializing stage of the algorithm, the values of the control parameters such as the number of food sources, the maximum number of cycles, and the limit are assigned. The food sources and nectar amounts are randomly generated. The random generation process takes place by generating a random value between the lower and upper limits of each parameter. Then, employed, onlooker bee, and scout bee stages are operated to find better food sources.

Each search cycle of the ABC algorithm consists of three steps.

• Employed bees step: There is an employed bee for each food source. There are as many employed bees as the number of food sources. At this step, the employed bees are sent to the food source and then the nectar amounts of the food sources are calculated. The nectar qualities of food sources are measured by the fitness function value. The employed bee randomly selects a food source that is a neighbor of the food source she visits and evaluates the quality of this new food source. If the quality value of the new food source is higher, it takes the information of the new source into memory and erases the old source from her memory. Otherwise, the employed bee continues to go to its old source.

• Onlooker bees step: All of the employed bees who gather information about food sources share the nectar information and location information of the food sources with onlooker bees in the dance area. An onlooker bee evaluates the nectar information shared by the employed bees and randomly selects a food source. The ABC algorithm performs the process of selecting the best quality source using a stochastic selection method such as roulette wheel selection. The selection process is related to the nectar quality. If the nectar quality of the new food source is higher, she takes the information of the new source into memory and erases the old source from her memory.

• Scout bee step: With the help of counters, the exploitation number of the food source area is stored. The "limit" value, which is a control parameter, is used to decide whether a food source is exhausted. The limit value is set at the initializing stage. If the current solution is not developed, the counter of the related solution increases by 1. After the employed and onlooker bees steps are completed, the counter values are compared with the limit value. If the counter of the related solution exceeds the value of the limit control variable, the solution will be exhausted. In this case, the employed bee of this food source leaves the source and starts looking for a new food source (solution). As the employed bee starts looking for a new food source, she turns into a scout bee. The scout bee starts searching for the food source (solution) randomly without any guidance. In the ABC algorithm, there is at most one scout bee to search for a new food source in each cycle.

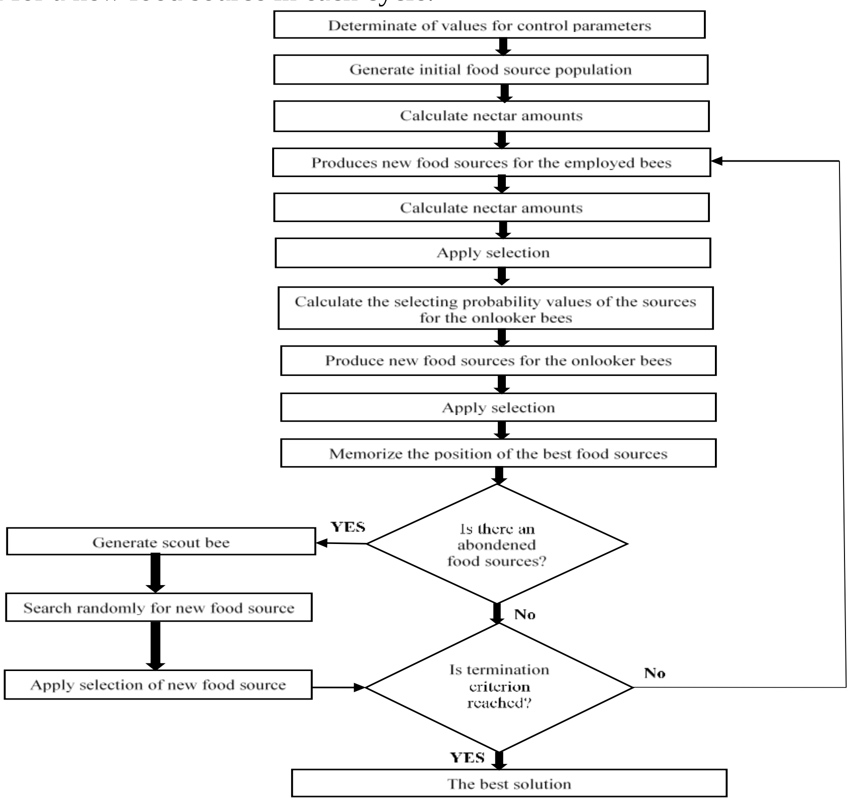

Figure 1. The Flow Diagram of the ABC Algorithm

4. Application

4.1. Research Data

For our analysis, the data consists of the hourly prices of 12 cryptocurrencies versus the US Dollar, from 22:00 on 01th September 2020 to 00:00 on 01th April 2021 inclusive, giving us T=4593 h or data points for each cryptocurrency. The cryptocurrencies data were retrieved from the CryptoDataDownload (2021) website. The availability of data determines the sample's starting date and frequency. The selected cryptocurrencies are shown in Table 1. We calculate logarithmic percentage returns by using the formula: $R_t = \ln(P_t/P_{t-1})$.

Table 1. The Selected Cryptocurrencies

Definition	Abbreviation
Bitcoin	BTC
Ethereum	ETH
Litecon	LTC
Ripple	XRP
Cardano	ADA
Binance Coin	BNB
Dash Coin	DASH
EOS Coin	EOS
NEO Coin	NEO
Tron	TRX
Tezos	XTZ
Zcash	ZEC

4.2. Solution of The Problem

In this section, it is explained step by step how the ABC algorithm is used in the solution of the problem. First of all, how the solutions are coded, the initial population, and how the fitness values of the solutions are calculated were mentioned. Then, the three main steps of the ABC method, employed bee, onlooker bee, and scout bee, are mentioned.

4.2.1. Coding

The first important step of the method is coding the solutions, that is, making the solutions suitable so that the problem can be solved by the method. There are different coding options in the literature. In this study, real number coding was preferred because it is suitable for our problem. An example solution obtained from the application is shown in Figure 2.

0.2455	0.0610	0.1007	0.0179	0.0531	0.1152	0.0997	0.1207	0.0825	0.0045	0.1068	0.1175

Figure 2. A Solution within The Population

4.2.2. Initial Population

After the coding of the solutions is determined, the algorithm first creates the initial population when the application is started to solve the problem. The solutions consist of random numbers generated between 0 and 1 as shown in Figure 2 Afterwards, the scaling process is performed on these solutions so that their totals are equal to 1, Figure 3 shows the scaled version of Figure 2.

0.2182	0.0542	0.0895	0.0159	0.0471	0.1023	0.0886	0.1072	0.0733	0.0039	0.0949	0.1044

Figure 3. Scaled Solution Example

4.2.3. Fitness Function

At this stage, the suitability of each solution for the problem within the population was calculated. This calculation process has been done using Modern Portfolio Theory created by Markowitz. To calculate the fitness value of portfolios, we need the covariance and expected return values of cryptocurrencies. These values are accessed via an excel file. The value of λ is known as the risk aversion coefficient and takes a value between [0,1]. If it is 0, the risk is completely ignored and the suitability value is calculated according to the return. If it is 1, the return is completely ignored and the fitness value is calculated according to the risk. Experiments have been carried out with different values of the λ value.

$$\text{Min}\left[\lambda\sum_{i=1}^{n}\sum_{i,j=1}^{n} w_i w_j Cov_{i,j}-(1-\lambda)\sum_{i=1}^{n} w_i E(r_i)\right] \quad (3)$$

4.2.4. Employed Bee Stage

After the coding of the solutions is determined, the algorithm first creates the initial population when the application is started to solve the problem. The solutions consist of random numbers generated between 0 and 1 as shown in Figure 2 Afterwards, the scaling process is performed on these solutions so that their totals are equal to 1, Figure 3 shows the scaled version of Figure 2. In the ABC method, after obtaining the fitness values of the solutions in the population, the stages of employed bee, onlooker bee, and scout bee are applied to the solutions. In the employed bee stage, a neighboring solution of the solution is determined and its quality is evaluated. If the new solution is of higher quality, the method will forget the old solution and memorize the new solution. At this stage of this study, a change was made from a randomly determined point of the solution. Afterward, since their totals will be a value other than 1, the scaling process was performed again. The application of this stage is shown in Figure 4.

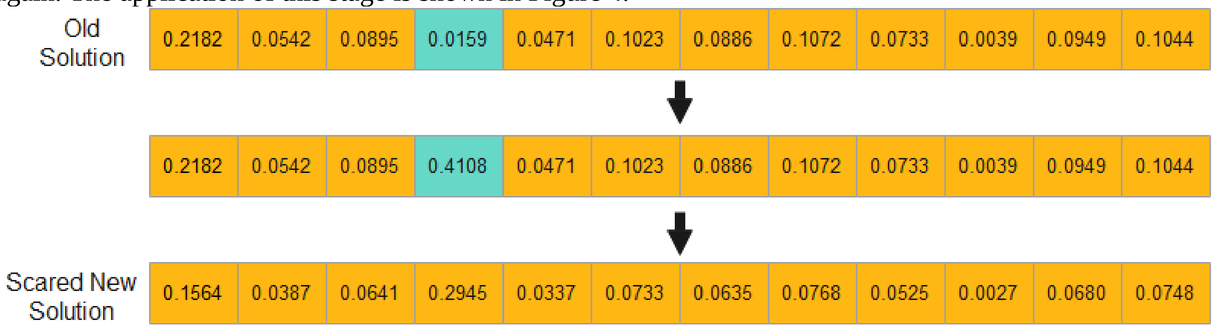

Figure 4. Employed Bee Stage Example

4.2.5. Onlooker Bee Stage

Solutions are selected from the population with a method determined at the onlooker bee stage. This selection process is made according to the fitness value. Higher-quality solutions are more likely to be chosen. Neighboring solutions of the selected solutions are determined as in the employed bee stage. If these solutions are of higher quality, they are kept in memory, otherwise, the old solution is continued. Methods such as the Roulette Wheel are used for the selection process. In this study, the fitness values of the solutions within the population were averaged and everyone above average was selected. The application of this stage is shown in Figure 5.

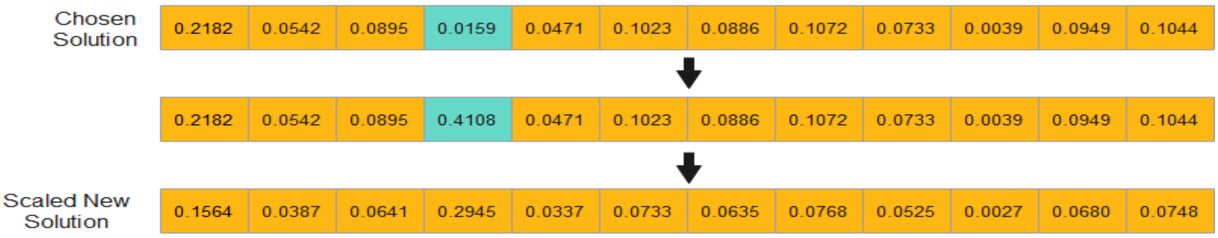

Figure 5. Onlooker Bee Stage Example

4.2.6. Scout Bee Stage

In the ABC method, a limit value is determined before the algorithm starts. In the initial population, each solution has a failure value and is assigned a value of 0. The failure value of solutions that do not experience improvement in employed bee or onlooker stages is increased by 1. In the scout bee phase, if the failure value of the solution reaches the limit value, this solution is deleted and a new solution is produced instead. The way of applying this stage in this study is shown in Figure 6.

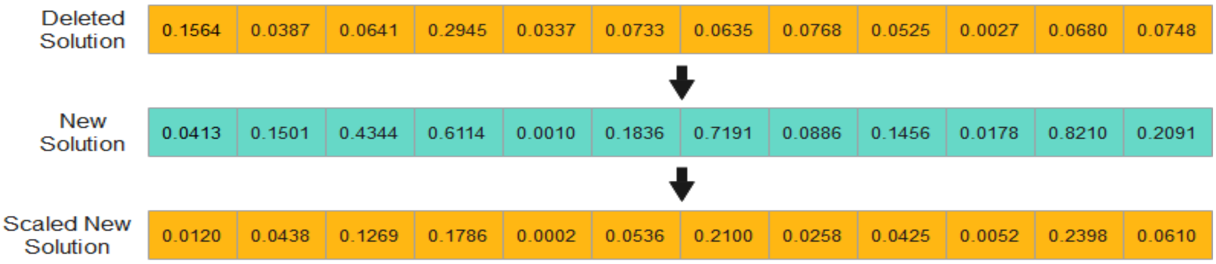

Figure 6. Scout Bee Stage Example

5. Experimental Results

In the implementation stage of this study, the Matlab R2016a version was used. The data has been extracted from the excel file. In this section, the experimental results obtained with different parameter values are shared.

For the ABC method, the limit value is an important parameter that can affect the result. In Table 2, Table 3, Table 4, and Table 5, the results of the experiments performed with different limits were shared by keeping other parameters constant. In addition, the convergence curve graphs of the experiment were shared in Figure 7, Figure 8, Figure 9, and Figure 10. According to these results, it shows that the limit value is between the number of iterations / 2 and the number of iterations will increase the possibility of obtaining better results. However, the experiments related to the number of the different initial populations and the number of iterations were seen in these tables and it was seen how the fitness values changed.

Table 2. Test Results with 0 λValue, 5 Initial Population and Different Limit Values

Initial Population	Iteration	Limit Value	λValue	Fitness Value (Best Cost)
5	50	5	0	-40.5948
5	50	10	0	-40.9293
5	50	25	0	-41.2905
5	50	35	0	-41.3789
5	50	50	0	-41.3331

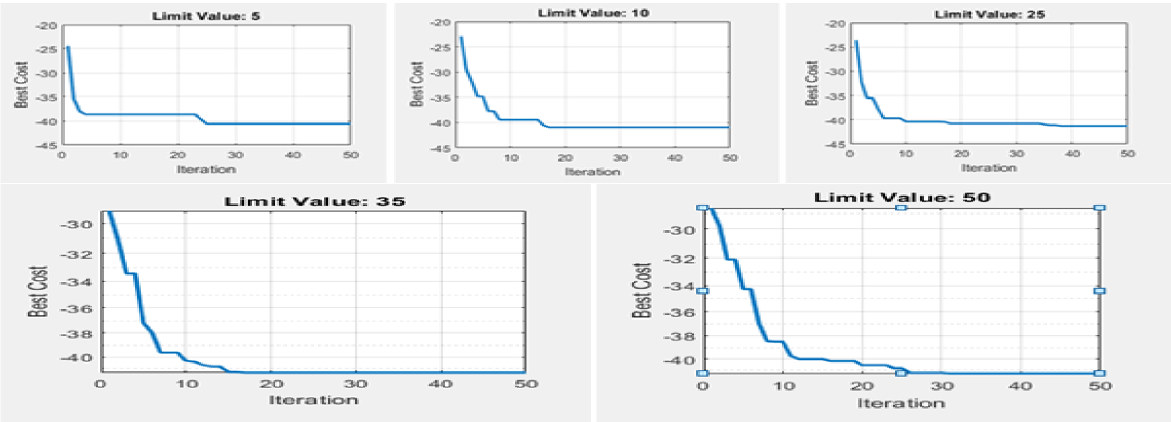

Figure 7. Convergence Curves of 0 λValue, 5 Initial Population and Different Limit Values

Table 3. Test Results with 0 λValue, 10 Initial Population and Different Limit Values

Initial Population	Iteration	Limit Value	λValue	Fitness Value (Best Cost)
10	50	5	0	-38.8416
10	50	10	0	-40.9700
10	50	25	0	-41.3371
10	50	35	0	-41.3362
10	50	50	0	-41.4670

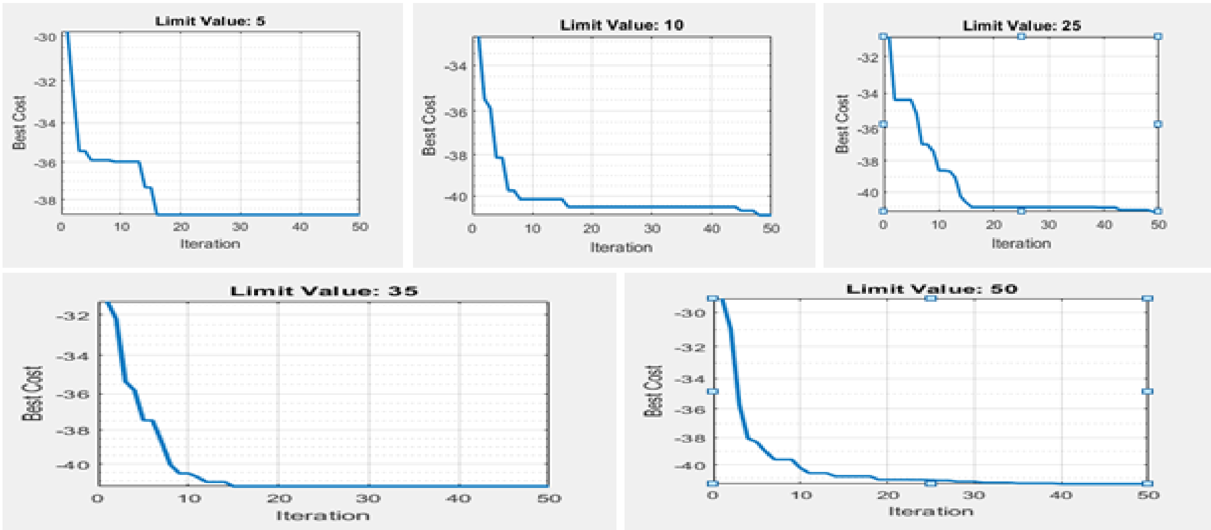

Figure 8. Convergence Curves of 0 λValue, 10 Initial Population, and Different Limit Values

Table 4. Test Results with 1 λ value, 100 Iteration and Different Limit Values

Initial Population	Iteration	Limit Value	λValue	Fitness Value (Best Cost)
5	100	5	1	2.3212
5	100	10	1	2.1375
5	100	25	1	0.6527
5	100	50	1	0.1826
5	100	75	1	0.0711
5	100	100	1	0.1084

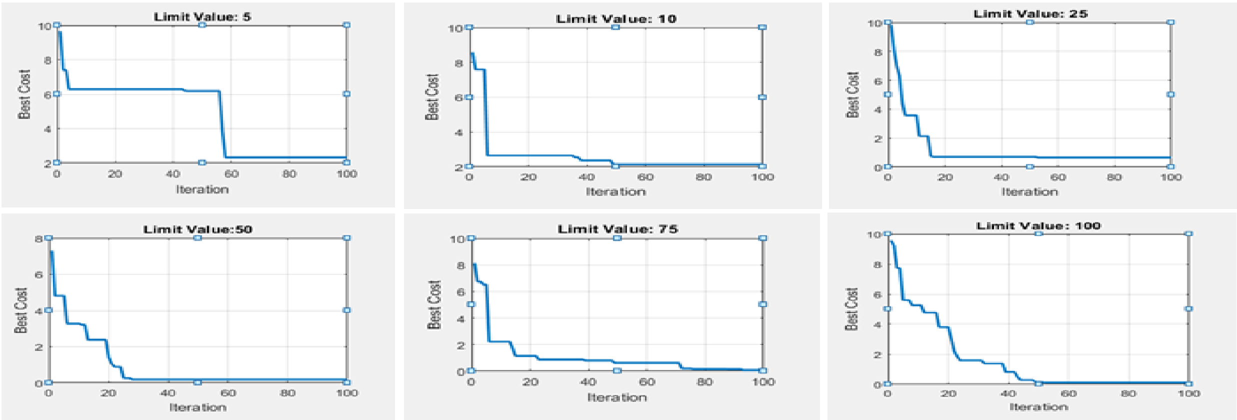

Figure 9. Convergence Curves of 1 λ Value, 100 Iteration and Different Limit Values

Table 5. Test Results with 1 λ Value, 200 Iteration and Different Limit Values

Initial Population	Iteration	Limit Value	λValue	Fitness Value (Best Cost)
5	200	5	1	1.8448
5	200	25	1	0.5187
5	200	50	1	0.2040
5	200	100	1	0.0694
5	200	150	1	0.0119
5	200	200	1	0.0031

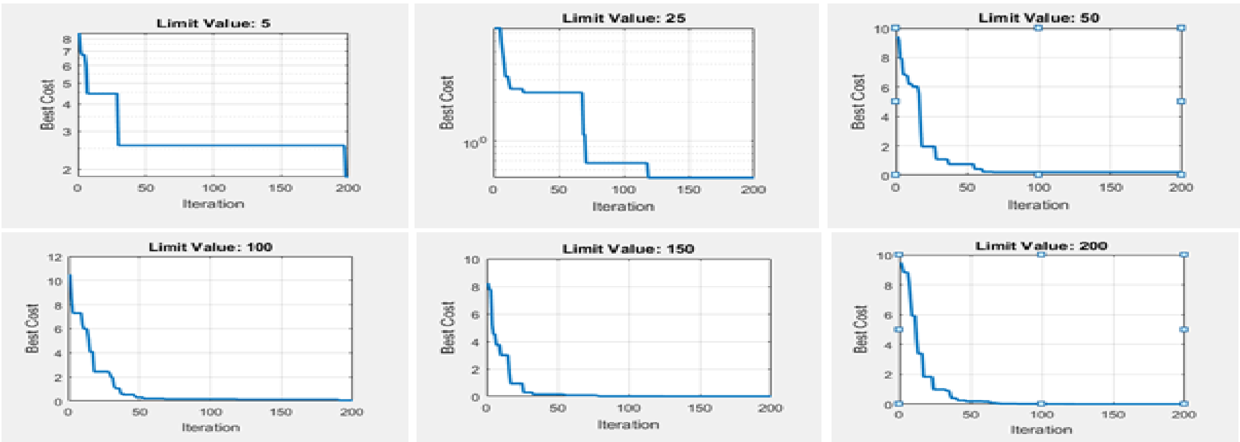

Figure 10. Convergence Curves of 1 λ Value, 200 Iteration, and Different Limit Values

In Table 6, experiments were made with different iteration numbers by keeping the starting population constant. According to these experiments, it has been observed that the increase in the number of iterations has a positive effect on the fitness value. The convergence curves of these experiments are shared in Figure 11. According to these convergence curves, it has been observed that a rapid convergence generally takes place until the number of iterations reaches 20.

Table 6. Test Results with 1 λValue, 5 Initial Population and Different Iteration Values

Initial Population	Iteration	Limit Value	λValue	Fitness Value (Best Cost)
5	30	15	1	1.8448
5	50	25	1	0.5187
5	100	50	1	0.2040
5	150	75	1	0.0694
5	200	100	1	0.0119
5	300	150	1	0.0031

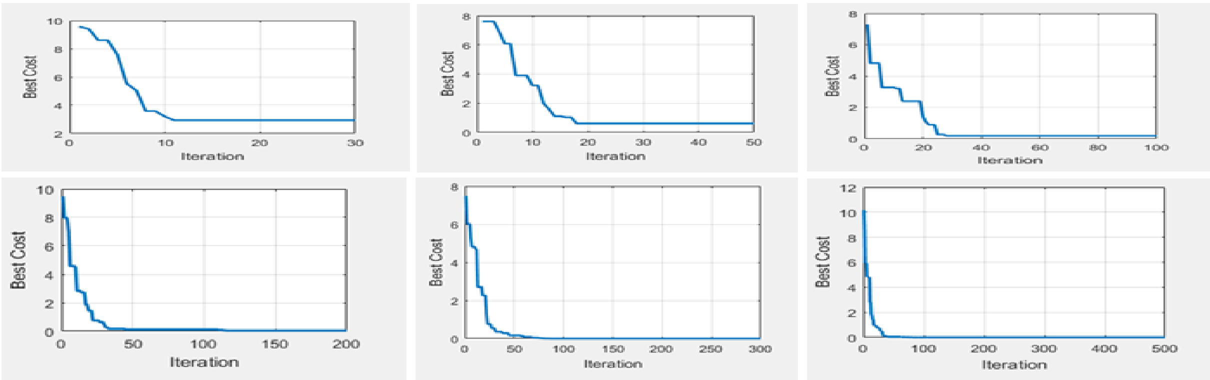

Figure 11. Convergence Curves of 1 λ Value, 5 Initial Population and Different Iteration Values

In Table 7, experiments were made with different initial population numbers by keeping the iteration numbers constant. According to these experiments, the effect of the increase in the initial population number on the fitness value was not always good.

In Figure 12, the convergence curves of these experiments are shared. According to these convergence curves, the change in the number of the initial population generally did not positively affect the first fitness values of the solutions. Previously, we said that it λ is 0, we only take the return, and if it is 1, it solves the problem by taking risks only. [0,1] The calculation is made according to formula 3 and the calculation is made according to the value of λ which one will get more between risk and return. The experimental results related to this are shared in Table 8 and the convergence curves of these experiments are shared in Figure 13. In addition, the cryptocurrency obtained from these experiments is shared in Table 9.

Table 7. Test Results with 1 λValue, 50 Iteration and Different Initial Population Values

Initial Population	Iteration	Limit Value	λValue	Fitness Value (Best Cost)
5	50	25	1	0.6093
10	50	25	1	1.1687
30	50	25	1	0.6845
50	50	25	1	0.4644
75	50	25	1	0.1351
100	50	25	1	0.3669

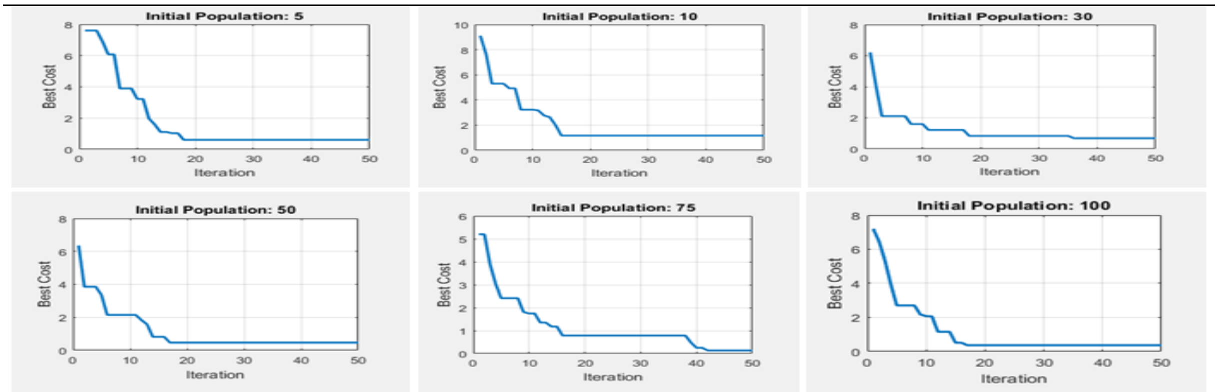

Figure 12. Convergence Curves of 1 λ Value, 50 Iteration, and Different Initial Population Values

Previously, we said that it λ is 0, we only take the return, and if it is 1, it solves the problem by taking risks only. [0,1] The calculation is made according to formula 3 and the calculation is made according to the value of λ which one will get more between risk and return. The experimental results related to this are shared in Table 8 and the convergence curves of these experiments are shared in Figure 13. In addition, the cryptocurrency obtained from these experiments is shared in Table 9.

Table 8. Test Results with 5 Initial Population,100 Iteration and Different λValues

Initial Population	Iteration	Limit Value	λValue	Fitness Value (Best Cost)
5	100	50	0	-41.4146
5	100	50	0.2	-32.4677
5	100	50	0.4	-24.5646
5	100	50	0.5	-20.4424
5	100	50	0.6	-16.2584
5	100	50	0.8	-7.3613
5	100	50	1	0.1826

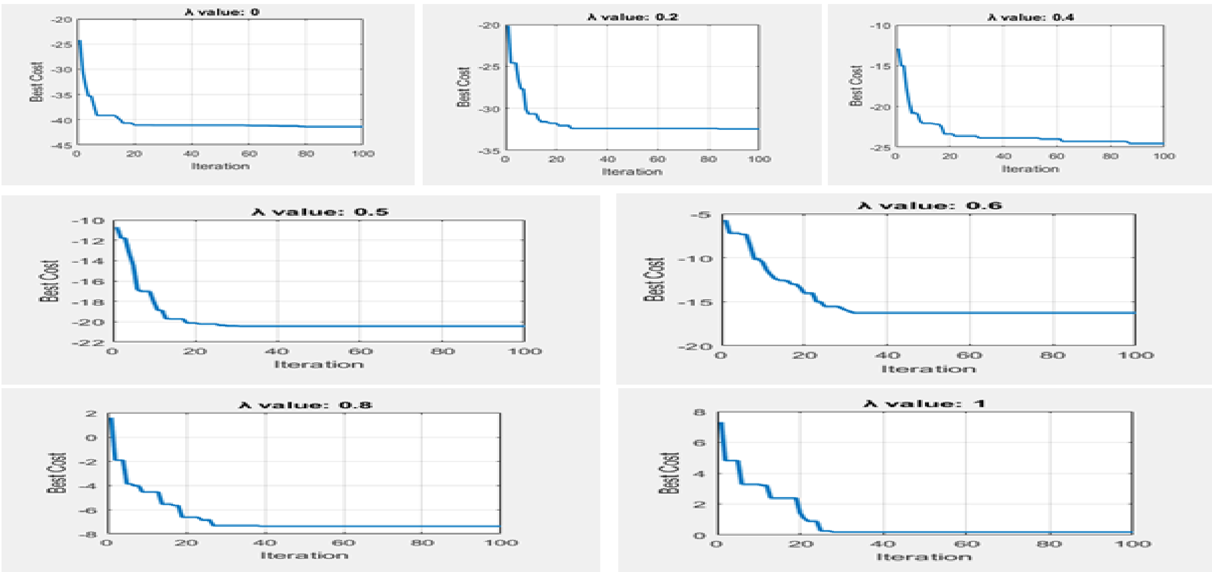

Figure 13. Convergence Curves of 5 Initial Population, 100 iteration and different λ Values

In Table 9, the results obtained about how much investment should be made in cryptocurrencies with different λ values are shared. The algorithm has been created in such a way that it cannot assign a zero value to any cryptocurrency. According to the results of these experiments, it was concluded that mostly BTC, ETC, and ADA cryptocurrencies need to be invested and very small investments should be made in other cryptocurrencies.

Table 9. Cryptocurrency Rates Obtained According to the Results in Table 8

λ	BTC	ETH	LTC	XRP	ADA	BNB	DAS	ZEC	EOS	NEO	TRX	XTZ
0	0.8253	3.2856e-05	4.6652e-05	5.6664e-05	0.1724	6.0359e-04	4.3763e-04	8.4543e-05	4.6260e-04	7.0634e-05	7.5204e-05	4.1011e-04
0.2	0.0092	0.0548	1.5615e-04	1.0794e-05	0.9347	1.6650e-04	5.6468e-05	1.3579e-04	1.1837e-04	1.7444e-04	1.9154e-04	2.0695e-04
0.4	0.9574	0.0048	2.3224e-04	2.2175e-04	0.0362	2.0085e-04	1.1348e-04	2.7235e-04	2.3937e-04	2.8036e-04	9.9075e-05	2.8072e-05
0.5	0.0107	6.6567e-04	2.1235e-04	4.2969e-04	0.9864	1.4351e-04	1.2091e-04	4.6753e-04	1.3570e-04	2.6013e-04	2.1426e-04	2.6542e-04
0.6	0.0130	0.0025	0.0017	7.1974e-05	0.9824	7.5186e-05	6.0999e-05	5.0618e-05	7.2457e-05	3.2460e-05	3.8476e-04	2.6427e-04
0.8	0.0040	0.9911	2.9480e-04	2.1875e-04	4.1077e-04	7.8015e-04	6.6038e-05	0.0010	3.2066e-04	1.3765e-04	6.4959e-04	0.0010
1	0.9902	0.0014	6.8135e-04	6.6954e-04	0.0013	4.1451e-04	0.0014	0.0011	0.0016	3.0869e-04	3.5970e-04	5.2066e-04

6. Conclusion

In this study, we proposed a flexible algorithm for the solution of the PO problem. Thus, the algorithm has become easily usable for different data sets and different scenarios. With efficient this algorithm, we have obtained suitable solutions for our problem. The study will be beneficial for the investor as it removes the complexity and uncertainty in portfolio creation. In this way, the investor responds better to financial risk protection. Furthermore, the study on cryptocurrency PO in the literature is limited, this study may encourage further research. In our future studies, it is planned to increase the performance of the algorithm and to compare it with different algorithms.

The process of selecting and managing portfolio assets is considered a difficult task. The fulfilling of this task requires a strong risk-return analysis, in other words PO. In recent years, the cryptocurrencies have gained an important place in the portfolios of investors. However, due to the high volatility of cryptocurrencies, managing cryptocurrency portfolios is complex and requires more effective PO techniques. The swarm intelligent optimization algorithms offer significant opportunities for more effective portfolio optimization.

In this study, the artificial bee algorithm, which is one of the swarm intelligence algorithms, was used for portfolio optimization. The risk aversion coefficient values (λ) used for the fitness function in the algorithm were calculated according to the mean-variance model of Markowitz. The portfolio consists of 12 different cryptocurrencies. The developed algorithm was analyzed with different parameter values. The algorithm we proposed in the study had a very flexible structure. Thus, we were able to obtain suitable solutions for our problem. The study will be beneficial for the investor as it removes the complexity and uncertainty in portfolio creation. In this way, the investor responds better to financial risk protection. Furthermore, the study on cryptocurrency PO in the literature is limited, this study may encourage further research. In our future studies, it is planned to increase the performance of the algorithm and to compare it with different algorithms.

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Disclosure Statements

1. Contribution rate statement of researchers: First author %35, Second author %35, Third author %30.

2. No potential conflict of interest was reported by the authors.