Iranian Journal of Operations Research
Vol. 14, No. 2, 2023, pp. 149-155
DOI:

Optimization of cryptocurrency investment portfolio under uncertainty internal rate of return based on hybrid algorithm

S. Mohammadpour[1], M. Rahmaty[2*], F. Rahnama Roodposhti[3], R. Ehtesham Rasi[4]

In this article, the modeling and solution of a cryptocurrency capital portfolio optimization problem has been discussed. The presented model, which is based on Markowitz's mean-variance method, aims to maximize the uncertainty internal rate of return (IRR) and minimize the cryptocurrency investment risk. A combined PSO and SCA algorithm was used to optimize this bi-objective model. The results of the investigation of 40 investment portfolios in a probable state showed that with the increase in the IRR, the investment risk increases. So in the optimistic state, there is the highest IRR and in the pessimistic state, there is the lowest investment risk. Investigations of the investment portfolio in the probable state also showed that more than 80% of the investment was made to optimize the objective functions in 5 cryptocurrencies BTC, ETH, USTD, ADA, and XRP. So in the secondary analysis, it was observed that in the case of investing in the top 5 cryptocurrencies, the average IRR increased by 9.92%, and the average investment risk decreased by 0.1%. The results show that the higher the value of the IRR in the investment of 10 known cryptocurrencies, the higher the investment risk. In the most pessimistic case, the annual IRR was equal to 25.72% and the investment risk was equal to 30.47%. In the most optimistic case, the IRR was equal to 195.75% and the investment risk was 70.81%. The model presented in this article can reduce the investment risk against the IRR.

***Keywords**: Cryptocurrency Investment Portfolio Optimization, Uncertainty Internal Rate of Return, Hybrid Algorithm.*

Manuscript was received on 02/16/2024, revised on 04/09/2024 and accepted for publication on 04/16/2024.

1. Introduction

Venture is the contracting of cash or reserves to get extra or certain benefits compared to cash or stores. In expansion to giving benefits (return), venture too contains a hazard that's borne by the financial specialist. The higher the anticipated rate of return of a speculator, the higher the sum of hazards that ought to be covered by the financial specialist [16]. It is conceivable to play down the level of chance at a certain rate of return desires of the speculation portfolio by shaping an appropriate portfolio. In this manner, optimizing the investment portfolio plays a critical part in deciding the procedure for speculators. What financial specialists trust to attain through portfolio optimization is to maximize inside returns and minimize portfolio risk. Since returns shift based on hazard, financial

* Corresponding Author.
[1] PhD industrial management student, Science and Research Branch, Islamic Azad University, Tehran,Iran, Email: author2@email.com.Assistant Professor, Department of Management, Chalous Branch, Islamic Azad University, Chalous, Iran, Email: Rahmaty.maryam61@gmail.com.
[2] Assistant Professor, Department of Management, Chalous Branch, Islamic Azad University, Chalous, Iran, Email: Rahmaty.maryam61@gmail.com.
[3] Professor of all finance and accounting department, science and Research Branch, Islamic Azad University, Tehran, Iran. Email: Roodposhti.rahnama@gmail.Com.
[4] Assistant Professor, Department Of Industrial management, Qazvin Branch, Islamic Azad University, Qazvin, Iran. Email: Ehteshamrasi@qoau.ac.ir

[Downloaded from iors.ir on 2024-05-05]

specialists must adjust the trade-off between chance and return on their venture. Subsequently, there's no ideal portfolio that can fulfill all financial specialists. The ideal portfolio is decided by the investor's chance and returns inclinations [2].

Nowadays, one of the sorts of speculations is contributing to advanced cash. Computerized money is a monetary standard that is put away and exchanged electronically in financial exercises, and their base is zero and one [14]. Advanced cash alludes to any esteem made on an advanced stage. This concept is restricted to physical middle people such as bank notes or coins. Advanced money has the same characteristics as physical monetary forms, but exchanges and capital exchanges in computerized monetary standards can be done immediately and without borders between individuals [6]. Virtual monetary standards and cryptocurrencies are both illustrations of advanced monetary forms, but not all computerized money may be virtual money or cryptocurrency. Advanced cash, like physical cash, is utilized to purchase merchandise and administrations, but it can also be restricted to utilize in certain settings. In later a long time, different computerized monetary standards such as Bitcoin, Swell, Ethereum, etc. have delighted in a one-of-a-kind notoriety and acknowledgment among financial specialists. So numerous of these financial specialists look to extricate and change over their capital into advanced cash [17]. However, due to the vagueness of some rules and regulations, this type of investment carries a very high risk for them. Creating a suitable investment portfolio of cryptocurrencies that can simultaneously increase profits (IRR), risk Reduction investment has become a very important issue today. In this article, to optimize these objective functions, a mathematical model based on Markowitz mean-variance under uncertainty conditions is presented, in which the optimization of 10 valid cryptocurrencies in 2023 has been done with a new combined PSO and SCA algorithm.

The structure of the article is as follows, in the second part, the background of the research related to the optimization of the investment portfolio is discussed. In the third part, the investment portfolio optimization model is presented under uncertainty conditions, and the combined meta-heuristic algorithm of PSO and SCA is introduced. In the fourth part, the analysis and presentation of the results of the implementation of the approach on 10 valid cryptocurrencies have been discussed. In the fifth part, the conclusions and suggestions of the research are discussed.

2. Literature Review

Hrytsiuk et al. [8], in a study aimed at assessing the risks of major digital currencies and diversifying investment risk using a portfolio model, analyzed the daily returns of the most common cryptocurrencies. For this purpose, they used the Cauchy distribution function the VaR technique, and the modified Markowitz model. Fallah et al. [5] used discriminant analysis and data coverage analysis to separate efficient units from inefficient units on oil companies admitted to the Iranian Stock Exchange. Ma et al., [10], in research, investigated portfolio optimization and the impact of the diversification factor. The results showed that diversification in most cases increases returns and reduces portfolio volatility and higher returns than traditional portfolios for the same level of risk. Aliahmadi et al. [1] studied the optimization of the portfolio of digital currencies by considering risk. It was found that the profitability of digital currency is not subject to normal distribution due to heavy profitability. The results of the calculations showed that the high profitability and low risk of Bitcoin determine its dominance in the portfolio of digital currencies.

Kurosaki and Kim [9] studied portfolio optimization of four major digital currencies. For this purpose, they used the time series model and optimized the portfolio in terms of Foster-Hart risk. The results showed that Foster-Hart optimization gives a more profitable portfolio with a good balance of risk and return. Čuljak et al. [4], investigated the performance and benefits of portfolio optimization of digital currency classification. In this regard, they used different optimization models. The results indicated the effectiveness of the presented models. Souza [13], investigated the optimization of the portfolio of digital currencies by genetic algorithms considering the two approaches of limited trading and open trading. The results indicated the better performance of the limited trading approach and the success of the genetic algorithm in both approaches.

[Downloaded from iors.ir on 2024-05-05]

Nguyen et al. [11] proposed an effective algorithm based on neural networks for using digital currencies in investment. The results showed that the proposed algorithm can generate neural networks that can earn profit in different market situations. Gaskin et al. [7] investigated the effectiveness of time series models to determine the financial benefits of building portfolios based on estimated distributions. They created and compared different forecasting models for digital currencies. Platanakis and Sutcliffe [12] compared the performance of seven heuristic algorithms in forming a set of six popular cryptocurrencies. The results showed little difference in the performance of these seven strategies. Cui et al. [3] presented an investment portfolio optimization model for cryptocurrencies in which, using a deep learning machine, data training was performed in different periods and a meta-heuristic method was presented to solve it.

According to the research background, it can be said that various methods have been used to optimize the investment portfolio. This article, taking into account the uncertainty in the IRR of cryptocurrencies and the combined use of PSO and SCA algorithms, has tried to achieve a new approach to cryptocurrency investment portfolio optimization.

3. Problem definition

There are different models of investment portfolio optimization in the literature. In this article, according to the type of investment, Markowitz's average variance method is used. In this model, there are N different types of cryptocurrencies, each of which has an uncertain IRR and associated investment risk. $\tilde{\mu}_i$ Is the uncertainty IRR of each currency and σ_{ij} is the covariance or investment risk between two currencies$i, j \in N$. According to the amount of investment, X_i is a percentage of investment of cryptocurrency$i \in N$, which requires$\sum_{i=1}^{N} X_i = 1$. The maximization of the uncertainty IRR from cryptocurrency investment and the minimization of investment risk are presented in equations (1) and (2). Also, the IRR of each share is considered as an uncertainty fuzzy parameter$\tilde{\mu}_i \sim \left(\mu_i^o, \mu_i^m, \mu_i^p\right)$.

$$Max \sum_{i=1}^{N} \frac{\left(\mu_i^o + 2\mu_i^m + \mu_i^p\right)}{4} X_i \tag{1}$$

$$Min \sum_{i=1}^{N} \sum_{j=1}^{N} \sigma_{ij} X_i X_j \tag{2}$$

The non-linearity of the investment risk minimization objective function has led to the use of meta-heuristic solution methods with continuous local search. Hence, a hybrid method of PSO and SCA is introduced, which improves the search of the problem solution space for better cryptocurrency portfolio investment. Figure (1) shows the code network of the proposed algorithm. In this pseudo-code, the solution space search is a combination of sine and cosine equations and particle velocity and motion.

Start
Initialize search set (Initial Solution X_i^t)
While ($t < Max\ it$)
  Evaluate each solution according to its functions (Eqs 1 & 2)
  Update the best solution in each iteration ($P_i^t = X_i^t$)
  Update the best solution so far ($G_i = P_i^t$)
  Update the position based on $X_i^{t+1} = X_i^t + a - t\frac{a}{Max\ it}.sin([0,2\pi]).|3P_i^t - X_i^t|$
  Update the position based on $X_i^{t+1} = X_i^t + a - t\frac{a}{Max\ it}.cos([0,2\pi]).|2P_i^t - X_i^t|$
  Update the position and velocity based on $\begin{cases} V_i^{t+1} = wV_i^t + c_1 a - t\frac{a}{Max\ it}(P_i^t - X_i^t) + c_2[0,2\pi](G_i - X_i^t) \\ X_i^{t+1} = X_i^t + V_i^{t+1} \end{cases}$

[Downloaded from iors.ir on 2024-05-05]

Return best solution
End

Figure 1. Pseudocode of the proposed algorithm

In Figure (1), a ،w ،c_1 ،c_2 and Max it are the primary parameters of the proposed algorithm, which is obtained in Figure (2) using Taguchi method, the Means of SN Ratio diagram. In this diagram, the best-combined levels of the primary parameters are specified.

Level	*Max it*	c_1	c_2	w	a
1	*24.0*	*26.0*	*25.6*	*27.5*	*27.9*
2	*27.4*	*29.3*	*28.3*	*25.9*	*27.1*
3	*28.1*	*23.8*	*25.7*	*26.1*	*24.1*
δ	*4.16*	*5.51*	*2.63*	*1.54*	*3.89*
Rank	*2*	*1*	*4*	*5*	*3*

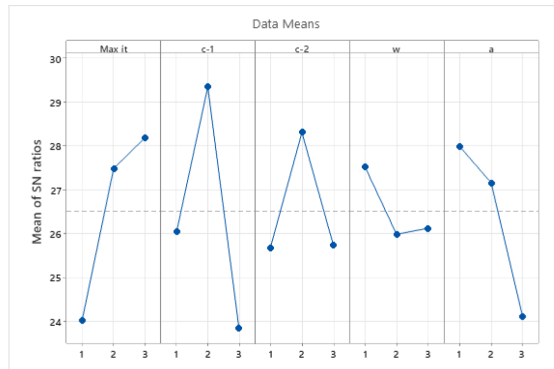

Figure 2. Parameter setting of the proposed algorithm

According to figure (2) and determining the optimal levels of the parameters of the proposed algorithm, $Max\ it = 200$ ،$c_1 = 1.5$ ،$c_2 = 1.5$ ،$w = 0.8$ and $a = 3$ have been determined.

4. Analysis of results

After introducing the solution method, in order to optimize the cryptocurrency investment portfolio, 10 currencies BTC, ETH, USDT, BNB, SOL, XRP, ADA, DOGE, BCH and UNI have been considered in 2023, and the goal of investing in these currencies It is in such a way that the uncertain IRR increases and the investment risk decreases. Based on the results obtained from the proposed algorithm, the Pareto front of the problem is shown in figure (3).

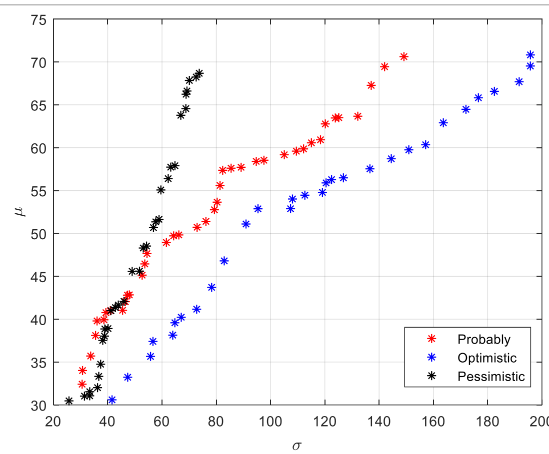

Figure 3. The Pareto front obtained from the optimization of the cryptocurrency investment portfolio

Figure (3) shows that the higher the value of the IRR in the investment of 10 known cryptocurrencies, the higher the investment risk. This figure also shows that in the optimistic state, the IRR increases to 195%, while the investment risk in the optimistic state is also much higher than

[Downloaded from iors.ir on 2024-05-05]

in the probable and pessimistic state. In the most pessimistic case, the annual IRR was equal to 25.72% and the investment risk was equal to 30.47%. In the most optimistic case, the IRR was equal to 195.75% and the investment risk was 70.81%. In short, the average internal return and investment risk in the cryptocurrency portfolio can be shown in Table (1).

Table 1. Average internal return and risk of the cryptocurrency investment portfolio in different modes

State	Average		Best		Worst	
	μT	$Risk$	μT	$Risk$	μT	$Risk$
Optimistic	116.71 %	52.64 %	195.75 %	70.61 %	41.58 %	30.59 %
Probably	78.86 %	51.82 %	149.14 %	70.81 %	30.56 %	32.41 %
Pessimistic	51.07 %	47.82 %	73.72 %	68.67 %	25.72 %	30.47 %

In this analysis, 40 types of investment portfolios have been obtained for the considered cryptocurrencies, and the first investment portfolio is discussed further. In figure (4), the share of investment by each of the cryptocurrencies is shown separately.

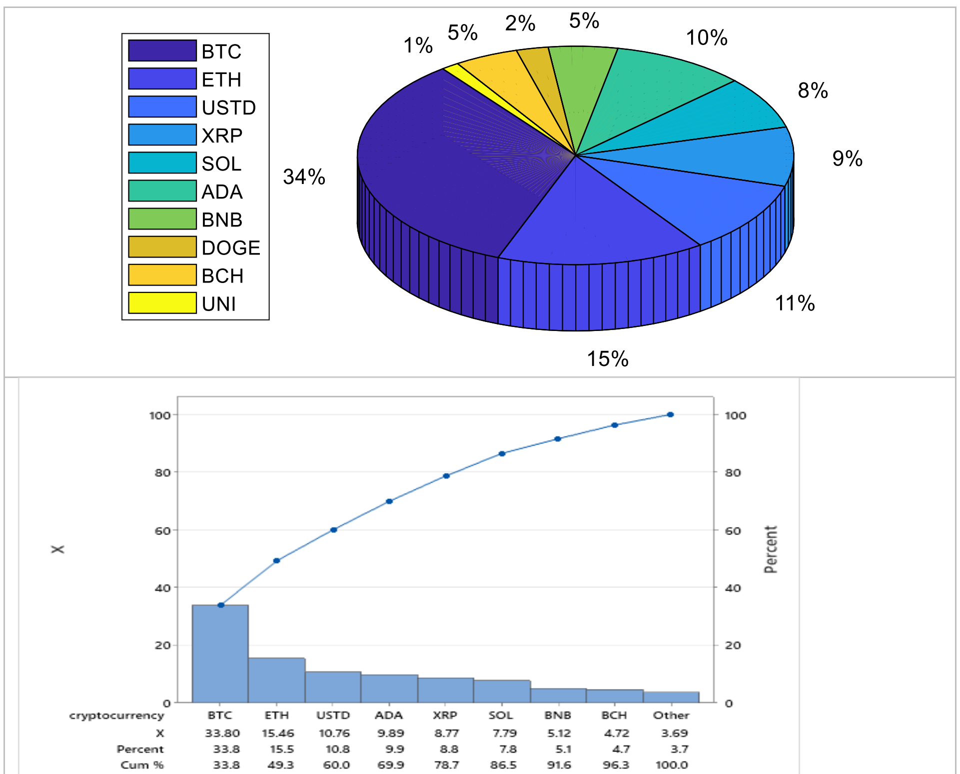

Figure 4. The share of each cryptocurrency in the first investment portfolio

Figure (4) shows that the largest share of investment in the selected portfolio is related to BTC with 34% of the total value of the portfolio. Also, the UNI currency has less than 1% of the investment value in this portfolio. Based on the Pareto chart presented in Figure (5), it can be concluded that more than 80% of investments were on 5 cryptocurrencies BTC, ETH, USTD, ADA and XRP. The average IRR as well as the investment risk is obtained by considering the 5 specified currencies in table (2).

[Downloaded from iors.ir on 2024-05-05]

Table 2. Value of stock portfolio return and investment risk in different scenarios

State	10 cryptocurrency		Best 5 cryptocurrency	
	μT	$Risk$	μT	$Risk$
Optimistic	116.71 %	52.64 %	120.39 %	48.15 %
Probably	78.86 %	51.82 %	86.69 %	47.25 %
Pessimistic	51.07 %	47.82 %	54.25 %	43.48 %

The results of Table (2) show that investing in 5 cryptocurrencies BTC, ETH, USTD, ADA and XRP has led to an increase in the IRR and a decrease in investment risk. So that in the probable case, the average IRR has increased by 9.92% and the average investment risk has decreased by 0.1%.

5. Conclusion

In this article, a cryptocurrency investment portfolio optimization model was presented based on Markowitz mean-variance. In this model, the goal was to maximize the uncertainty IRR from cryptocurrency investment and reduce investment risk. To optimize this stock portfolio, a combined algorithm of PSO and SCA was considered, in which the operators of the two algorithms are combined to achieve the best investment. Considering 10 cryptocurrencies BTC, ETH, USDT, BNB, SOL, XRP, ADA, DOGE, BCH, and UNI in 2023, the Pareto front was analyzed in three states, optimistic, probable and pessimistic, and it was found that with increasing Investment risk, IRR increases in all three cases. On the other hand, 40 types of investment portfolios in probable mode, 30 types of investment portfolios in optimistic mode, and 33 types of investment portfolios in pessimistic mode were determined. The average IRR in the optimistic mode was higher than other modes and the investment risk in the pessimistic mode was lower than other modes. The results show that the higher the value of the IRR in the investment of 10 known cryptocurrencies, the higher the investment risk. In the most pessimistic case, the annual IRR was equal to 25.72% and the investment risk was equal to 30.47%. In the most optimistic case, the IRR was equal to 195.75% and the investment risk was 70.81%

By examining the first investment portfolio in a probable state, it was observed that its IRR was equal to 30.56% and the investment risk was equal to 32.41%. So the largest share of investment in the selected portfolio was related to BTC with 34% of the total value of the portfolio. By examining the Pareto chart, it was also observed that 5 cryptocurrencies BTC, ETH, USTD, ADA, and XRP had the largest share of investment in this basket. If the investment is made only on these 5 cryptocurrencies, the average IRR will increase by 9.92% and the average investment risk will decrease by 0.1%.

The model presented in this article can help digital currency investors in reducing investment risk and increasing the IRR. So that it can simultaneously present the most optimistic, most probable and pessimistic scenarios for the investor to create the best investment portfolio. In this way, the investment risk is reduced against the profit earned from the stock portfolio. Also, investors can see the priority of the obtained digital currencies and determine the combination of the best portfolio.

The importance of achieving a suitable investment portfolio in the next periods will lead to the use of a learning machine in predicting the price of cryptocurrency and the IRR in future research. Also, the development of exact and meta-heuristic solution methods can lead to achieving better results than the method proposed in this article. One of the limitations of the research is not paying attention to the maximum investment in a particular share. In this model, regardless of the type of share, the amount of investment is considered unlimited, and it is necessary to limit the investment in some shares based on the market conditions. To solve this issue, it is suggested to consider the investment limit for each share.

[Downloaded from iors.ir on 2024-05-05]

References:

[1] Aliahmadi, A., Ghahremani-Nahr, J., & Nozari, H. (2023). Pricing decisions in the closed-loop supply chain network, taking into account the queuing system in production centers. *Expert Systems with applications*, *212*, 118741.

[2] Chen, W., Zhang, H., Mehlawat, M. K., & Jia, L. (2021). Mean–variance portfolio optimization using machine learning-based stock price prediction. *Applied Soft Computing*, *100*, *106943*.

[3] Cui, T., Du, N., Yang, X., & Ding, S. (2024). Multi-period portfolio optimization using a deep reinforcement learning hyper-heuristic approach. *Technological Forecasting and Social Change*, *198*, 122944..

[4] Čuljak, M., Tomić, B., & Žiković, S. (2022). Benefits of sectoral cryptocurrency portfolio optimization. *Research in international business and finance*, *60*, 101615.

[5] Fallah, M., Hosseinzadeh Lotfi, F., & Hosseinzadeh, M. M. (2020). Discriminant analysis and data envelopment analysis with specific data and Its application for companies in the Iranian stock exchange. *Iranian Journal of Operations Research*, *11*(1), 144-156.

[6] Ganesan, A., & Harika, B. V. S. (2021). Overview of Risk Estimation Methods for Cryptocurrency. *United International Journal for Research & Technology*, *2*(08), 133-137.

[7] Gaskin, S., Kalim, R., Wallace, K. J., Islip, D., Kwon, R. H., & Liew, J. K. S. (2023). Portfolio Optimization Techniques for Cryptocurrencies. *The Journal of Investing*.

[8] Hrytsiuk, P., Babych, T., & Bachyshyna, L. (2019, September). Cryptocurrency portfolio optimization using Value-at-Risk measure. In *6th International Conference on Strategies, Models and Technologies of Economic Systems Management (SMTESM 2019)* (pp. 385-389). Atlantis Press.

[9] Kurosaki, T., & Kim, Y. S. (2022). Cryptocurrency portfolio optimization with multivariate normal tempered stable processes and Foster-Hart risk. *Finance Research Letters*, *45*, 102143.

[10] Ma, Y., Ahmad, F., Liu, M., & Wang, Z. (2020). Portfolio optimization in the era of digital financialization using cryptocurrencies. *Technological forecasting and social change*, *161*, 120265.

[11] Nguyen, Q. M., Tran, D. T., Kanniainen, J., Iosifidis, A., & Gabbouj, M. (2023, December). Cryptocurrency Portfolio Optimization by Neural Networks. In *2023 IEEE Symposium Series on Computational Intelligence (SSCI)* (pp. 25-32). IEEE.

[12] Platanakis, E., & Sutcliffe, C. (2023). Cryptocurrency portfolios using heuristics. In *Essays on Financial Analytics: Applications and Methods* (pp. 117-128). Cham: Springer International Publishing.

[13] Sousa, M. R. P. D. (2023). Cryptocurrency portfolio optimization using genetic algorithms (Doctoral dissertation).

[14] Tomić, B., Žiković, S., & Jovanović, L. (2022). Crypto portfolio optimization through lens of tail risk and variance measures. *Zbornik radova Ekonomskog fakulteta u Rijeci: časopis za ekonomsku teoriju i praksu*, *40*(2), 297-312.

[15] Tripathi, R. P., & Mishra, S. M. (2013). Optimal ordering policy with stock-dependent demand rate under permissible delay in payments.

[16] Vasiani, V. D., Handari, B. D., & Hertono, G. F. (2020). Stock portfolio optimization using priority index and genetic algorithm. In *Journal of physics: conference series* (Vol. 1442, No. 1, p. 012031). IOP Publishing.

[17] Zuniga, E. W. V., Ranieri, C. M., Zhao, L., Ueyama, J., Zhu, Y. T., & Ji, D. (2023). Maximizing portfolio profitability during a cryptocurrency downtrend: A Bitcoin Blockchain transaction-based approach. *Procedia Computer Science*, *222*, 539-548.

[Downloaded from iors.ir on 2024-05-05]

[Downloaded from iors.ir on 2024-05-05]