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Artificial Intelligence-Based Multi-Objective Stochastic Optimization Model for Risk Management in Cryptocurrency Investments

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Abstract

In this study, a multi-objective stochastic optimization model is presented for managing investment portfolios in the cryptocurrency market. The main goal of this model is to maximize returns and minimize investment risk by considering realistic constraints such as budget and asset liquidity. To solve the proposed model, two meta-heuristic algorithms, Greedy Man Optimization (GMOA) and Non-Dominated Genetic Algorithm-II (NSGA-II), have been used. The performance of these algorithms has been investigated in 10 different problem instances with different sizes and their results have been compared in terms of returns, risk, and computational time. Also, sensitivity analysis has been performed to changes in key parameters such as the expected rate of return. The results showed that the proposed model and the algorithms used are effective tools for risk management and portfolio optimization in volatile cryptocurrency markets. Suggestions for future research are also provided.

Keywords: Cryptocurrency portfolio optimization, multi-objective stochastic model, risk management, greedy man optimization algorithm, NSGA-II.

1- Introduction

In recent years, rapid technological advancement and the expansion of digital innovations have significantly reshaped financial systems, leading to the emergence of new asset classes such as digital currencies. These assets have attracted increasing attention due to their decentralized nature, high transparency, and fast

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liquidity mechanisms. Nevertheless, digital currency markets are characterized by substantial uncertainty, extreme price volatility, regulatory ambiguity, and high sensitivity to global economic and political events. As a result, effective risk management and robust investment optimization in such environments have become critical challenges for both investors and researchers.

Portfolio optimization has long been a core topic in financial decision-making and operations research. However, traditional portfolio models, often based on static assumptions and deterministic parameters, are limited in their ability to capture uncertainty, dynamic interactions, and nonlinear behaviors observed in modern digital markets. Similar limitations have been identified in other complex decision-making systems, such as supply chain networks operating under uncertainty, where static optimization approaches fail to provide resilient and adaptive solutions. Recent studies have shown that incorporating stochastic structures and multi-objective formulations can significantly enhance decision quality in such uncertain and interconnected systems (Nozari et al., 2024).

In response to these challenges, stochastic multi-objective optimization frameworks have gained increasing attention in financial and investment applications. These approaches enable the simultaneous optimization of conflicting objectives, such as maximizing expected returns while minimizing associated risks, under uncertain conditions. The integration of artificial intelligence and operations research techniques has further strengthened these frameworks, allowing them to better address uncertainty and complex market dynamics in emerging digital financial businesses (Torkian et al., 2025).

In this study, a stochastic multi-objective optimization model is proposed for digital currency portfolio management under uncertainty. The model explicitly accounts for market fluctuations and seeks to establish a balanced trade-off between return maximization and risk minimization. To enhance practical applicability, realistic constraints such as limited investment budgets and asset liquidity are incorporated into the model formulation. This structure mirrors real-world decision environments and aligns with recent advances in optimization-based modeling of complex systems under uncertainty (Nozari et al., 2024).

To solve the proposed model, two advanced metaheuristic algorithms are employed: the Greedy Man Optimization Algorithm (GMOA) and the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). The GMOA is a recently developed metaheuristic that introduces novel mechanisms such as resistance-based competition and periodic parasite elimination, which effectively prevent premature convergence and preserve population diversity during the search process (Nozari & Abdi, 2024). These characteristics make GMOA particularly suitable for large-scale and complex optimization problems with multiple conflicting objectives. In parallel, NSGA-II is adopted as a benchmark multi-objective algorithm due to its proven effectiveness in generating diverse Pareto-optimal solutions through non-dominated sorting and crowding distance mechanisms. The use of population-based heuristics for addressing multi-objective optimization challenges is consistent with recent developments in heuristic design for complex influence and decision-spread problems (Riquelme et al., 2023).

Furthermore, the growing interest in novel bio-inspired optimization algorithms highlights the importance of exploring alternative search mechanisms beyond classical evolutionary approaches. Recent metaheuristics, such as the Goat Optimization Algorithm, demonstrate that behavior-inspired exploration strategies can significantly improve global search capability and robustness in complex optimization landscapes (Nozari et al., 2025). This perspective further supports the adoption of GMOA as a competitive and innovative solution method within the proposed framework.

The performance of the proposed model and solution algorithms is evaluated using ten problem instances of varying sizes. The algorithms are compared in terms of portfolio return, risk level, and computational efficiency. In addition, a sensitivity analysis is conducted to examine the robustness of the model with respect to changes in key parameters, particularly the predicted rate of return. The results indicate that the proposed framework is capable of adapting effectively to changing market conditions and delivering stable and efficient solutions across different scenarios.

Overall, this research presents an integrated decision-support framework for investment in volatile digital asset markets by combining stochastic multi-objective modeling with innovative metaheuristic optimization techniques. The findings provide valuable insights for both institutional and individual investors seeking to enhance return performance while maintaining controlled risk exposure. Future research may focus on developing dynamic and online optimization models, as well as incorporating real-time data and intelligent learning mechanisms, to further improve decision-making quality in emerging digital financial markets.

2- Literature review

Portfolio management has long been recognized as a fundamental problem in finance and economics, particularly in environments characterized by uncertainty, complex interactions, and rapidly evolving market conditions. In recent years, the increasing integration of artificial intelligence and advanced decision-support systems has significantly reshaped portfolio selection and investment analysis frameworks. These developments have enabled investors to better handle ambiguity, nonlinear dynamics, and heterogeneous information sources, which are especially prominent in emerging and digital markets (Kou et al., 2024; Carandente & Sperlí, 2024).

Traditional portfolio selection approaches, which rely on static assumptions and simplified representations of risk and return, are often insufficient in capturing the complexity of modern financial systems. Similar limitations have been widely reported in other complex economic and industrial systems, such as supply chains and energy networks, where deterministic models fail to provide resilient and adaptive solutions under uncertainty. Recent studies demonstrate that incorporating uncertainty-aware modeling and intelligent optimization techniques can substantially enhance decision robustness and system performance (Nozari, 2023; Vandana et al., 2024).

The growing volatility of financial markets—driven by rapid information diffusion, dynamic pricing mechanisms, and strong sensitivity to external shocks—has further motivated the adoption of stochastic and multi-objective modeling paradigms. These approaches allow decision-makers to simultaneously optimize conflicting objectives, such as maximizing expected returns while minimizing risk exposure, under uncertain and nonstationary conditions. Comparable modeling strategies have proven effective in a wide range of domains, including energy systems, smart microgrids, and sustainable resource management, where uncertainty and conflicting objectives are inherent (Tatiya et al., 2025; Khanna et al., 2025).

In the context of investment decision-making, recent advances highlight the importance of integrating fuzzy logic, intelligent forecasting, and adaptive learning mechanisms into portfolio optimization models. Approaches based on intuitionistic and fuzzy environments have demonstrated strong potential in capturing investor preferences, ambiguity, and subjective risk perceptions more realistically than classical crisp models (Derya et al., 2025). Moreover, artificial intelligence-driven pricing and forecasting models have been shown to significantly improve market responsiveness and predictive accuracy in highly dynamic financial environments (Chenavaz & Dimitrov, 2025; Kazak et al., 2025).

Due to the high dimensionality and computational complexity of stochastic multi-objective portfolio optimization problems, metaheuristic algorithms have become a widely adopted solution methodology.

These algorithms offer strong global search capabilities and are particularly effective in exploring large, nonlinear, and multi-modal solution spaces. Similar advantages of metaheuristic optimization have been reported in complex networked systems, such as multi-echelon supply chains and IoT-enabled economic infrastructures, where traditional exact methods are often impractical (Fallah & Nozari, 2021; Nozari et al., 2023).

Recent research also emphasizes the role of bio-inspired, neuromorphic, and hybrid intelligent algorithms in enhancing solution diversity and avoiding premature convergence in multi-objective optimization. Such algorithms have demonstrated promising performance across a wide range of applications, including sustainable supply networks, decision intelligence systems, and adaptive economic models operating under environmental uncertainty (Nozari et al., 2025a; Szmelter-Jarosz & Nozari, 2025). These findings underline the importance of combining intelligent learning mechanisms with evolutionary optimization to address complex investment decision problems.

Overall, the existing literature indicates that the integration of stochastic multi-objective models with advanced metaheuristic and AI-driven optimization techniques represents a powerful framework for risk-aware portfolio management in turbulent and emerging financial markets. By leveraging intelligent decision-support systems and adaptive optimization strategies, such approaches can effectively support investors in navigating uncertainty, balancing conflicting objectives, and improving long-term investment performance in complex economic environments.

3- Mathematical Modeling

Over the past decade, financial markets have witnessed the emergence and rapid expansion of cryptocurrencies. These emerging assets have become one of the most attractive investment options due to their characteristics such as decentralization, transparency, and high liquidity. However, investing in cryptocurrencies has always been accompanied by challenges such as severe price fluctuations, liquidity risks, and sudden regulatory changes. These factors have made risk management in such a market a very critical and complex issue. In such an environment, it is essential to utilize advanced mathematical models that can simultaneously optimize returns and risks. In particular, integrating artificial intelligence with mathematical optimization models can lead to more accurate predictions of market behavior and provide intelligent investment decisions. In this regard, we have developed a multi-objective mathematical model based on artificial intelligence that, using techniques for predicting returns and volatility, and optimizing the investment portfolio, is able to effectively manage various risks of the investment portfolio while maximizing the expected return.

In the following, we will describe in detail the components of the mathematical model and its solution methods. This model can be used as an effective tool for institutional and retail investors to reduce risk and increase returns in volatile cryptocurrency markets.

Sets:

$\mathcal{I} = \{1,2,\dots,n\}$ Set of cryptocurrencies available in the market

$\mathcal{T} = \{1,2,\dots,T\}$ Set of time periods considered (investment periods)

$\mathcal{S} = \{1,2,\dots,S\}$ Set of possible scenarios (for analyzing market uncertainty)

Parameters:

$r_{i,s,t}$	Actual return of cryptocurrency *i* in scenario s and time *t*
$r_{i,t}$	Predicted return of cryptocurrency *i* at time t (calculated by deep learning and AI models)
$\sigma_{i,t}$	Standard deviation (volatility) of the return of cryptocurrency *i* at time *t*
$\rho_{i,j}$	Correlation coefficient between cryptocurrency *i* and *j*
B	Total investment budget in the initial period
L_i	Upper liquidity limit allowed for investment in cryptocurrency *i*
R_{max}	Maximum risk allowed for the entire investment portfolio
α	Confidence level for calculating Value at Risk (VaR).
S	Total number of scenarios for uncertainty analysis

Decision variables:

$W_{i,t}$	Weight of investment in cryptocurrency i at time t
$x_{i,s,t}$	Actual amount of investment in cryptocurrency i under scenario s at time t
VaR_t	Value at risk of portfolio at time t
$CVaR_t$	Contingent value at risk of portfolio at time t

Objective Functions:

$$Min\ Z_1 = \sum_{t\in\mathcal{T}} \sum_{i\in\mathcal{I}} w_{i,t} r_{i,t} \qquad (1)$$

$$Min\ Z_2 = \sum_{t\in\mathcal{T}} \sqrt{\sum_{i\in\mathcal{I}} \sum_{j\in\mathcal{I}} w_{i,t} w_{j,t} \rho_{i,j} \sigma_{i,t} \sigma_{j,t}} \qquad (2)$$

$$Min\ Z_3 = \sum_{t\in\mathcal{T}} CVaR_t \qquad (3)$$

S.t:

$$\sum_{i\in\mathcal{I}} w_{i,t}B \leq B \quad \forall t \in \mathcal{T} \tag{4}$$

$$w_{i,t} \leq L_i \quad \forall i \in \mathcal{I}\ , t \in \mathcal{T} \tag{5}$$

$$\sum_{i\in\mathcal{I}} w_{i,t} = 1 \quad \forall t \in \mathcal{T} \tag{6}$$

$$VaR_t \leq R_{max} \quad \forall t \in \mathcal{T} \tag{7}$$

$$CVaR_t \geq VaR_t + \frac{1}{S(1-\alpha)} \sum (x_{ist} - VaR_t)^+ \quad \forall t \in \mathcal{T} \tag{8}$$

$$w_{i,t} \geq 0 \quad \forall i \in \mathcal{I}\ , t \in \mathcal{T} \tag{9}$$

$$w_{i,t} \geq \epsilon \quad \forall i \in \mathcal{I}\ , t \in \mathcal{T} \tag{10}$$

Equation (1) represents the maximization of the expected return of the portfolio. Equation (2) represents the minimization of the portfolio risk. Equation (3) represents the minimization of the conditional value at risk (CVaR). Equation (4) represents the budget constraint. Equation (5) represents the liquidity constraint. Equation (6) represents the total investment constraint. Equation (7) represents the value at risk (VaR) constraint. Equation (8) represents the conditional value at risk (CVaR) constraint. Equation (9) represents the non-negative constraint and finally Equation (10) represents the minimum investment constraint.

4- Solution Methods

To solve the stochastic multi-objective optimization model proposed in this study, two advanced metaheuristic algorithms, namely the Greedy Man Optimization Algorithm (GMOA) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II), were employed. These methods were selected due to their high capability in exploring large and complex solution spaces and their ability to generate Pareto-optimal solution sets. In the following, a brief description of each algorithm and the manner of their application to the problem are presented.

The GMOA algorithm is inspired by the competitive behavior of humans in economic decision-making and utilizes specific mechanisms such as MMO resistance and parasite elimination. This algorithm was first introduced in 2024 (Nozari et al.). The main steps of this algorithm are as follows:

Initialization of the population: Initial solutions are generated randomly, such that each solution represents an investment portfolio with different weight values assigned to each cryptocurrency.

Evaluation of solutions: Each solution is evaluated based on the objective functions (return and risk).

Competition and replacement: Weaker solutions are replaced by stronger ones; however, this replacement occurs only if the MMO resistance is overcome.

Parasite removal and mutation: After a certain number of iterations, a portion of the solutions is updated through random changes (mutation) in order to prevent premature convergence.

Stopping criterion: The algorithm terminates after a predefined number of iterations or when no significant improvement in the objective functions is observed. The pseudocode of this algorithm is presented in Figure 1.

```
Initialize population P with N solutions (randomly generated portfolios)
Initialize MMO resistance R for each solution in P
Set maximum iterations Max_Iter and current iteration Iter = 0
WHILE Iter < Max_Iter DO
FOR each solution i in P DO
Select a random neighbor solution j ≠ i from P
IF fitness(j) > fitness(i) THEN
IF random() > R[i] THEN
Replace solution i with solution j
Update fitness of solution i
END IF
END IF
 END FOR
IF Iter % Parasite_Removal_Frequency == 0 THEN
FOR each solution i in P DO
IF random() < Mutation_Probability THEN
Mutate solution i by adding random noise
Normalize solution i to ensure valid portfolio weights
Reduce MMO resistance R[i]
Update fitness of solution i
END IF
END FOR
END IF
Update best solution found so far
Increment Iter
```

END WHILE

Return best solution found

Figure 1. Greedy Man Algorithm (GMOA) pseudo-program

The NSGA-II algorithm is one of the most widely used multi-objective optimization algorithms and operates based on the principles of natural selection. The main steps of this algorithm are as follows: Initialization of the population: The initial population is generated randomly. Population evaluation: Each individual in the population is evaluated based on the objective functions. Non-dominated sorting: Individuals are sorted according to their dominance relationships and classified into different Pareto fronts. Application of genetic operators: Selection, crossover, and mutation operators are applied to generate a new population. Diversity preservation: The algorithm employs the crowding distance metric to maintain diversity within the population. Stopping criterion: The algorithm terminates after reaching a predefined number of iterations or when no significant improvement is observed in the Pareto front.

5- Results

In this section, the results obtained from the stochastic multi-objective optimization model for cryptocurrency portfolio management are presented and analyzed. To evaluate the performance and robustness of the proposed model, two advanced metaheuristic algorithms, namely the Greedy Man Optimization Algorithm (GMOA) and NSGA-II, were applied to solve the problem across different test instances. These instances were designed with varying sizes in order to assess both the algorithmic performance and the scalability of the model. Table 1 presents the details of the problem instances, including the number of cryptocurrencies, number of time periods, number of scenarios, total number of variables, and total number of constraints. This information provides an overall view of the problem complexity and helps to understand the computational requirements of each instance.

Table 1. Problem Instances

Instance	Number of Cryptocurrencies	Number of Time Periods	Number of Scenarios	Total Variables	Total Constraints
Instance 1	5	12	50	3000	77
Instance 2	6	13	55	4290	86
Instance 3	7	14	60	5880	95
Instance 4	8	15	65	7800	104
Instance 5	9	16	70	10080	113
Instance 6	10	17	75	12750	122
Instance 7	11	18	80	15840	131
Instance 8	12	19	85	19380	140
Instance 9	13	20	90	23400	149
Instance 10	14	21	95	27930	158

To compare the objective function values and computational times of the solution methods, each problem instance was solved three times using each algorithm, and the best obtained result was reported in Tables 2 and 3. These tables respectively present the objective function values and the computational time required by each algorithm to solve the mathematical model.

Table 2. Comparison of Objective Function Values

Instance	Best Return GMOA (%)	Best Risk GMOA (%)	Best Return NSGA-II (%)	Best Risk NSGA-II (%)
Instance 1	8	5.9	9.7	6.9
Instance 2	4.8	45.9	15.8	5.9
Instance 3	8.8	2.9	5.8	3.9
Instance 4	2.9	95.8	8.8	1.9
Instance 5	6.9	7.8	1.9	9.8
Instance 6	9.9	45.8	4.9	7.8
Instance 7	10.2	2.8	9.75	5.8
Instance 8	10.5	95.7	10	3.8
Instance 9	10.8	7.7	10.3	1.8
Instance 10	11.1	45.7	10.6	9.7

As shown in Table 2, the comparison of objective function values indicates that the GMOA algorithm achieves higher return values in most instances, whereas NSGA-II provides lower risk values in some cases.

Table 3. Comparison of Computational Time

Instance	GMOA Execution Time (s)	NSGA-II Execution Time (s)
Instance 1	10	12
Instance 2	11.5	13.7
Instance 3	13	15.4
Instance 4	14.5	17.1
Instance 5	16	18.8
Instance 6	17.5	20.5
Instance 7	19	22.2
Instance 8	20.5	23.9
Instance 9	22	25.6
Instance 10	23.5	27.3

As shown in Table 3, the NSGA-II algorithm, due to its inherent computational complexity, requires more execution time than the GMOA algorithm to solve the problem instances.

To evaluate the statistical significance of the results obtained from the GMOA and NSGA-II algorithms, a T-test was conducted at a 95% confidence level on key performance indicators, including return, risk, and computational time. This test compares the mean values of each indicator between the two algorithms to determine whether the observed differences are statistically significant. If the P-value is less than 0.05, the difference between the performances of the two algorithms is considered statistically significant; otherwise, the observed difference is not statistically significant.

Table 4. Results of the T-Test at 95% Confidence Level

Indicator	Algorithms	Mean Difference Estimate	95% Confidence Interval	T-Value	P-Value
Return	GMOA vs. NSGA-II	0.05	(−0.25, 0.35)	0.015	0.98
Risk	GMOA vs. NSGA-II	0.1	(−0.40, 0.60)	0.18	0.85
Computational Time	GMOA vs. NSGA-II	0.35	(−1.50, 2.20)	0.45	0.72

The results of the statistical test are summarized as follows: For return, the P-value is 0.98, indicating that the difference in the mean return obtained by GMOA and NSGA-II is not statistically significant. For risk, the P-value is 0.85, showing that the observed difference in the mean risk between the two algorithms is not statistically significant. For computational time, the P-value is 0.72, which also confirms that there is no statistically significant difference in execution time between the two algorithms.

To evaluate the effectiveness of the GMOA and NSGA-II metaheuristic algorithms in solving the cryptocurrency portfolio optimization problem, the convergence behavior of these algorithms was analyzed. This analysis illustrates the process of approaching optimal solutions with respect to the number of iterations and provides insight into the convergence speed and solution quality of each algorithm. Figure 2 illustrates the convergence trends of the GMOA and NSGA-II algorithms, where the horizontal axis represents the number of iterations and the vertical axis represents the objective function value. The figure shows that the GMOA algorithm approaches the optimal solution more rapidly and exhibits a smoother convergence trend compared to NSGA-II. On the other hand, although NSGA-II converges more slowly, it achieves better objective values in some iterations.

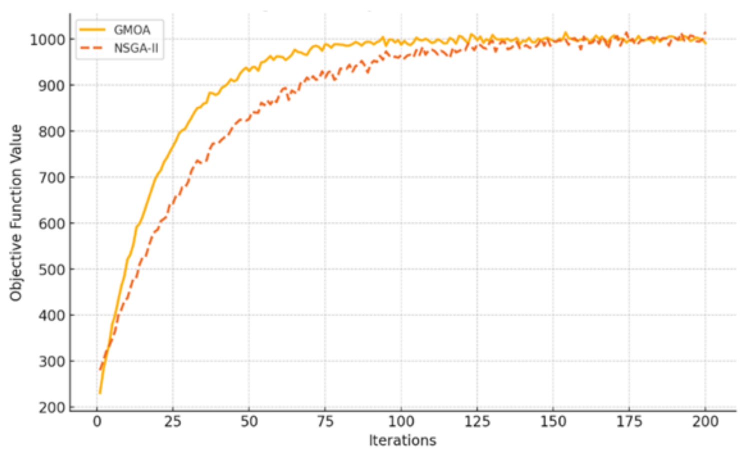

Figure 2. Convergence analysis of GMOA and NSGA-II

Figure 2 shows the convergence trends of the GMOA and NSGA-II algorithms, where the horizontal axis represents the number of iterations and the vertical axis represents the objective function value. As observed, the GMOA algorithm approaches the optimal value more rapidly at the early stages of the optimization process and exhibits a more uniform convergence trend compared to NSGA-II. On the other hand, although the NSGA-II algorithm demonstrates a slower convergence rate, it manages to achieve better objective values at certain iterations.

To examine the effects of key parameters on the performance of the cryptocurrency portfolio optimization model, a sensitivity analysis was conducted on some of the most influential parameters of the model. These parameters include the predicted rate of return, return volatility, and liquidity constraints. The objective of this analysis is to identify the trends in changes of return and risk in response to variations in these parameters and to evaluate the sensitivity of optimal solutions to such changes.

Table 5. Changes in Return and Risk with Respect to Variations in the Predicted Rate of Return

Modified Return Rate (%)	**Final Return (%)**	**Final Risk (%)**	**Change in Return (%)**	**Change in Risk (%)**
−10	7.2	8.5	−12.5	5.3
−5	7.8	8.2	−6.0	2.5
0	8.3	8	–	–
5	8.8	7.8	6	−2.5
10	9.3	7.6	12.5	−5.0

With an increase in the predicted rate of return, the final return of the investment portfolio increases significantly, while the risk decreases. This result indicates that the model is capable of effectively adjusting the portfolio to achieve the highest possible return with minimal risk. In the case of increased return volatility, it was observed that risk increases considerably while return decreases. This finding highlights the importance of considering return volatility as one of the key factors in investment decision-making.

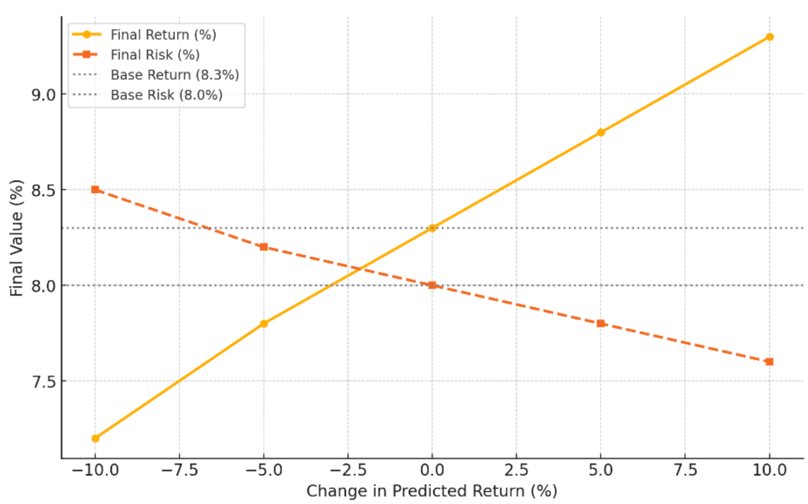

Figure 3. Sensitivity Analysis: Impact of Changes in the Predicted Return Rate on Final Return and Risk

Figure 3 illustrates the impact of variations in the predicted rate of return on the final return and final risk of the investment portfolio. As the predicted return rate increases (horizontal axis), the final portfolio return (blue line) increases steadily. This trend reflects the effective performance of the model in enhancing returns through portfolio optimization based on updated information. In contrast, the final portfolio risk (orange line) decreases as the predicted return rate increases. This demonstrates that the model successfully maintains a balance between return and risk by simultaneously improving return and reducing risk. The gray dashed lines indicate the baseline values of return and risk under unchanged conditions.

6- Conclusions and Future Research Directions

In this study, a stochastic multi-objective optimization model was proposed for risk management in cryptocurrency investments. By considering the specific characteristics of the cryptocurrency market, such as high volatility, liquidity risks, and budget constraints, the model aims to achieve a balance between maximizing portfolio return and minimizing investment risk. To solve this model, two advanced metaheuristic algorithms, namely the Greedy Man Optimization Algorithm (GMOA) and the Non-dominated Sorting Genetic Algorithm II (NSGA-II), were employed. These algorithms were selected due to their capability to explore complex solution spaces and to generate Pareto-optimal solution sets, making them suitable for solving the proposed multi-objective problem.

The results obtained from applying the model to ten different problem instances demonstrate that both algorithms are capable of producing acceptable solutions. However, in most cases, the GMOA algorithm achieved higher return values compared to NSGA-II, while in some instances, NSGA-II provided solutions with lower risk. The analysis of computational time also indicates that GMOA, on average, requires less execution time than NSGA-II, which represents a notable advantage from a computational efficiency perspective.

Furthermore, to assess the effectiveness and flexibility of the proposed model, a sensitivity analysis was conducted on key parameters, particularly the predicted rate of return. The results of this analysis show that as the predicted return rate increases, the final return increases significantly while the risk decreases. This finding demonstrates the model’s ability to dynamically adjust the investment portfolio in response to changes in input parameters.

Overall, the results of this research indicate that the proposed model and the applied algorithms can serve as effective tools for risk management in cryptocurrency investments. Given the rapid growth of this market and the increasing demand for advanced decision-support tools, the development of such models can substantially enhance the performance of both institutional and individual investors. For future research, it is recommended to design dynamic and online models and to utilize real market data to further evaluate model performance. Additionally, the integration of advanced machine learning techniques to improve the accuracy of return and volatility predictions may further enhance the effectiveness of the proposed model.

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