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Dynamic portfolio optimization using differential evolution: a Markowitz modern portfolio theory approach

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ABSTRACT

An optimal investment portfolio is one of the main focuses in the financial world to minimize risk while maximizing returns. However, the challenge that arises is how to choose the right asset allocation amidst dynamic market uncertainty. This study aims to optimize portfolios based on Markowitz modern portfolio theory (MPT) by using the differential evolution (DE) algorithm as an optimization technique. The data used includes stocks, bonds, and other financial instruments taken from trusted data sources, such as Bloomberg and Yahoo finance, with an observation period of the last five years. The results show that this approach succeeds in finding optimal portfolios with the right asset weights, higher expected returns, and minimized risks compared to conventional approaches. The implication of this research is that the DE algorithm can be effectively used to address portfolio optimization problems in complex and volatile market environments, offering a more adaptive solution for investors to maximize their returns.

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1. INTRODUCTION

Portfolio management is a crucial aspect of investment strategy, which aims to achieve an optimal balance between risk and return [1], [2]. Recent developments also highlight the use of network theory in portfolio construction to optimize the balance between risk and return. For example, Ioannidis *et al.* [3] proposed a network-based approach to portfolio design, offering a new perspective on asset interconnections and diversification benefits. This aligns with the present study's focus on innovative approaches in portfolio management. Furthermore, unlike genetic algorithms (GA), which have been widely applied in portfolio optimization but are prone to premature convergence [4], the differential evolution (DE) algorithm offers faster convergence and greater robustness in navigating complex search spaces. In this context, modern portfolio theory (MPT), introduced by Harry Markowitz in 1952 [5], has become the cornerstone for many approaches in investment management. MPT offers a systematic framework that allows investors to allocate assets efficiently by considering variance and covariance between different financial instruments [6]–[8]. By using MPT, investors can minimize risk of their portfolio for a given expected rate of return. Although MPT has made significant contributions in financial theory, its implementation in practice often faces complex challenges. The portfolio optimization process, involving many variables and constraints such as asset allocation restrictions and market uncertainty, requires more adaptive and sophisticated methods [9]–[12]. In this regard, DE emerges as a population-based optimization algorithm that offers the potential to address such challenges, with the ability to search for optimal solutions in complex parameter spaces. Recent studies in portfolio optimization have increasingly employed metaheuristic algorithms such as GA, particle swarm optimization (PSO), ant colony optimization (ACO), and DE. GA-based approaches offer flexibility but often suffer from premature convergence, while PSO demonstrates fast convergence but may exhibit instability in highly volatile search spaces. ACO has shown effectiveness in discrete optimization settings, yet its performance in continuous portfolio weight optimization remains limited. In contrast, DE has been widely recognized for its robustness, simplicity, and strong performance in continuous, non-linear optimization problems, making it particularly suitable for portfolio optimization under uncertainty. This research aims to explore the application of DE in portfolio optimization based on MPT theory, in the hope of generating more efficient and effective investment strategies amidst ever-changing market dynamics [11], [13].

Although MPT has become a key pillar in investment strategy, significant challenges are still faced in its real-world application [14], [15]. One of the key issues is the complexity in asset allocation optimization, especially when considering the varying constraints and uncertain nature inherent to financial markets. The use of conventional approaches such as quadratic programming is often limited by the assumption of linearity and may yield inadequate solutions in real scenarios, where interactions between assets and market dynamics tend to be non-linear. Moreover, many previous studies do not fully consider external factors that may affect portfolio performance, such as market volatility and changes in investor sentiment. This raises an urgent need for more flexible and adaptive methods, which can better handle these complexities and uncertainties. Therefore, this research focuses on the application of DE as an alternative optimization method that is able to overcome complex constraints and provide more robust solutions in portfolio management based on MPT principles.

In the existing literature, a number of studies have explored various approaches in portfolio optimization based on MPT. For example, research by Markowitz [5] demonstrated the importance of asset allocation to minimize risk and maximize return, but did not consider the complexity and dynamics of the market that may affect portfolio performance. Research by Gunjan and Bhattacharyya [16] applied GA for portfolio optimization, but found that the method often gets stuck in local solutions, especially in volatile markets [16]. In this context, Somarin *et al.* [17] recommended the integration of heuristic methods to overcome the limitations of conventional approaches, but has not provided a thorough overview of the application of recent techniques such as DE. Therefore, there is a clear need to develop new methodologies that are not only effective in optimizing asset allocation but are also able to adapt to ever-changing market conditions. This research aims to fill this gap by applying DE as an innovative approach in portfolio optimization, as well as exploring the potential and advantages offered by this algorithm in handling complex constraints and providing more accurate solutions in investment management.

The main objective of this research is to develop an effective portfolio optimization model by applying the DE algorithm based on the MPT introduced by Harry Markowitz. Specifically, this study aims to explore and analyze the ability of DE in reducing portfolio variance while achieving the expected rate of return [18], [19]. By conducting a thorough evaluation of the performance of portfolios optimized using DE, this study seeks to provide new insights in investment risk management [20], [21]. In addition, this research also aims to identify and address challenges in the application of DE, including the complex constraints that often arise in the context of asset allocation [22]–[24]. Through a better understanding of the effectiveness and advantages of DE, it is hoped that this research can make a significant contribution to the practice of portfolio management as well as serve as a reference for future research in this area.

While many previous studies have explored the application of various optimization algorithms in the context of portfolio management, there is still a significant gap in the literature regarding the specific use of DE within the framework of MPT [25]. Existing studies tend to focus on traditional algorithms such as mean variance optimization and other heuristic methods without giving enough attention to DE, even though it shows promising potential in handling the complexity of non-linear optimization problems and fast convergence [26], [27]. Moreover, many previous studies do not consider a broader combination of risk factors, including market uncertainty and dynamic changes in asset behavior. This research aims to fill this gap by providing a comprehensive approach that not only applies DE in portfolio optimization, but also analyzes its performance in the context of the challenges faced by modern investors. As such, this research is expected to broaden the understanding of DE applications in finance and make a significant contribution to the development of more robust portfolio optimization methods. Several recent studies have extended DE into hybrid and multi-objective variants for portfolio optimization. Hybrid DE approaches integrate local search or machine learning components to enhance convergence speed, while multi-objective DE frameworks simultaneously optimize conflicting objectives such as return maximization, risk minimization, and drawdown control. Although these approaches demonstrate promising performance, they often introduce additional algorithmic complexity and parameter dependency. This study deliberately focuses on single-objective DE–MPT formulation to emphasize interpretability and practical applicability.

This research offers a novel contribution to the field of portfolio optimization by applying DE within the framework of MPT in a comprehensive and systematic manner. The main novelty lies in the development of an optimization model that not only integrates DE to minimize portfolio risk but also considers variations in asset returns in the context of dynamic and high-risk markets. In addition, this study conducts an in-depth analysis of the model's sensitivity to the parameters, providing greater insight into how changes in market factors may affect the portfolio optimization outcome. The justification for this research is based on the pressing need for investment strategies that are more adaptive and responsive to volatile market conditions, which is becoming increasingly important in the current era of economic volatility. As such, this research not only contributes to the development of theory and practice in finance, but also provides useful tools for practitioners in making more informed and strategic investment decisions. Unlike existing studies that apply DE merely as a substitute solver for classical mean-variance optimization, this study emphasizes the dynamic adaptation of DE parameters and evaluates portfolio behavior under volatile market conditions. Furthermore, this research explicitly integrates sensitivity analysis and empirical discussion of parameter effects, which are rarely addressed in prior DE-MPT portfolio optimization studies.

2. METHOD

2.1. Research design

This research uses a quantitative approach with an experimental design that utilizes the DE algorithm to optimize investment portfolios. The model built focuses on minimizing portfolio risk measured through variance. It also maintains the expected rate of return in accordance with MPT.

2.2. Data collection

The data used in this study includes historical prices of a selected set of assets, including stocks, bonds, and other financial instruments. This data is taken from trusted financial data sources, such as Bloomberg and Yahoo finance, with an observation period of the last five years. In the process of data collection, the expected return and covariance between assets are also calculated, which form the basis for calculating the objective function. It should be noted that this study employs a limited dataset consisting of three representative asset classes over a five-year observation period. While this configuration allows for a controlled evaluation of the proposed optimization framework, it may restrict the generalizability of the results to broader and more diverse financial markets. The selection of three representative asset classes (equities, bonds, and mutual funds) was intended to demonstrate the methodological feasibility and interpretability of the proposed DE-MPT framework. These asset classes capture distinct risk return characteristics commonly observed in diversified portfolios. Nevertheless, the proposed optimization framework is scalable and can be readily extended to larger asset universes without structural modification.

2.3. Modeling

The objective function for portfolio optimization is expressed as (1).

$$Minimize\ \sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \tag{1}$$

with constraints as in (2).

$$\sum_{i=1}^{n} w_i = 1\ and\ w_i \geq 0\ \forall_i \tag{2}$$

Where σ_p^2 is the portfolio variance, w_i is the weight of investment in the i-th asset, and σ_{ij} is the covariance between the i-th and j-th assets.

2.4. Differential evolution algorithm

The optimization process using DE consists of several main steps:

i) Population initialization: the initial population is initialized with random weights that are in the range [0, 1], where the total portfolio weight is 1. Weights are normalized to ensure that the portfolio constraints are satisfied.
ii) Fitness evaluation: the objective function value (portfolio variance) is calculated for each individual in the population.
iii) Reproduction: new individuals are generated through differential operations by utilizing randomly selected individuals from the population.
iv) Crossover: performing crossover between the new individual and the old individual to generate a new individual that represents a potential solution.
v) Selection: new individuals are compared with old individuals based on fitness value, where individuals with lower fitness value are retained in the population.

vi) Iteration: the process is repeated until a convergence criterion is reached, such as a maximum number of iterations or no significant change in the solution.

2.5. Analysis of results

After the optimization process, an analysis of the results is performed by assessing the optimal portfolio found, including the weight of each asset and the expected return. An objective function value convergence graph is also presented to show the efficiency of the algorithm in achieving the optimal solution. Classical quadratic programming approaches assume convexity and linear constraints, which may limit flexibility in dynamic markets. GA and PSO-based portfolio optimization methods have shown competitive performance; however, they often exhibit sensitivity to parameter settings and premature convergence. DE offers a favorable trade-off between robustness, convergence stability, and implementation simplicity, motivating its selection in this study.

3. RESULTS AND DISCUSSION

MPT proposed by Harry Markowitz in 1952 is an approach to optimizing investment portfolios by considering risk and return. The objective of MPT is to maximize portfolio return for a given level of risk or minimize risk for a given level of expected return. In this context, the use of DE algorithm can be implemented to optimize the combination of assets that provide the optimal portfolio.

3.1. Markowitz modern portfolio theory model

In MPT, a portfolio consisting of several assets is designed to minimize risk (variance) and maximize returns. Two important components in MPT are:

i) Portfolio return *(Rp)*: is the weighted sum of returns of individual assets in portfolio, as defined in (3).

$$R_p = \sum_{i=1}^{n} w_i R_i \tag{3}$$

Where *Rp* is portfolio return, w_i is the proportion (weight) of the i-th asset in portfolio, R_i is expected return of the i-th asset, *n* is number of assets in the portfolio

ii) Portfolio risk (variance) (σ_p^2): portfolio risk is measured through the variance of portfolio returns, which depends on the correlation between assets as defined in (4). Where: σ_p^2 is portfolio variance, $w_i w_j$ is i-th and j-th asset weights, σ_{ij} is covariance of returns between i-th and j-th assets.

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{ij} \tag{4}$$

iii) Optimization objective: basically, the optimization objective of MPT is to maximize the Sharpe ratio, which is defined as the ratio of excess return to risk (standard deviation) as defined in (5). Where R_f is risk-free return.

$$\text{Maximize} = \frac{R_p - R_f}{\sigma_p} \tag{5}$$

3.2. Differential evolution algorithm

DE is a population-based optimization algorithm that works by iteratively modifying candidate solutions. It is well suited for optimizing difficult multivariable functions, including functions that cannot be analytically dissected such as in portfolio optimization. Steps of DE algorithm:

i) Initialization: create an initial population consisting of candidate solutions (random portfolios) that represent the asset weights (w_i) in the portfolio. Each member of the population $w_i^{(g)}$ is a weight vector that satisfies the condition $\sum_{i=1}^{n} w_i = 1$. The initialization equation is given as (6).

$$w_i^{(g)} = \left[w_1^{(g)}, w_2^{(g)}, \cdots, w_n^{(g)}\right] \tag{6}$$

ii) Mutation: at each generation, create a new solution by modifying the weights of the existing solution. A mutation vector $v_i^{(g+1)}$generated using random differences between other individuals in the population: The mutation equation is expressed as (7).

$$v_i^{(g+1)} = w_{r1}^{(g)} + F\ x\ \left(w_{r2}^{(g)} - w_{r3}^{(g)}\right) \tag{7}$$

Where $w_{r1}^{(g)}, w_{r2}^{(g)}, w_{r3}^{(g)}$ is a random solution that differs from the current population, F is the mutation scale factor (usually between 0.5 to 1).

iii) Recombination (crossover): combines the original solution with the mutation vector to create a new candidate solution. The crossover equation is given as (8).

$$u_i^{(g+1)} = \begin{cases} v_i^{(g+1)} & , if\ rand_i \leq C_r \\ w_i^{(g)} & , others \end{cases} \tag{8}$$

Where C_r is the crossover probability.

iv) Selection: evaluate the objective function (e.g., Sharpe ratio) of the new solution and compare it with original solution. Select the best solution for next generation. The selection equation is expressed as (9).

$$w_i^{(g+1)} = \begin{cases} u_i^{(g+1)} & , if\ f\left(u_i^{(g+1)}\right) > f\left(w_i^{(g)}\right) \\ w_i^{(g)} & , others \end{cases} \tag{9}$$

v) Repetition: repeat the mutation, crossover, and selection process until a stopping criterion is reached (e.g., maximum number of iterations or convergence of solutions).

3.3. Optimization with differential evolution for Markowitz portfolio

DE plays an important role in optimizing portfolios within the framework of MPT by adjusting the allocation weights of assets to achieve an optimal balance between return and risk. In this approach, DE iteratively modifies the proportion of stocks, bonds, and other financial instruments in the portfolio using historical return and volatility data as evaluation parameters. The algorithm evaluates candidate portfolios based on objectives such as maximizing the Sharpe ratio or minimizing portfolio variance, enabling investors to identify asset combinations that provide better risk-adjusted returns.

3.4. Objective function

The objective function optimized by DE can be the Sharpe ratio, which maximizes the return relative to the risk of the portfolio. The Sharpe ratio objective function is defined as (10).

$$\text{Objective: maximize} \frac{R_p - R_f}{\sigma_p} \tag{10}$$

Or it could be minimizing the portfolio variance for a given target return as expressed in (11).

$$\text{Objective: minimize } \sigma_p^2\ with\ R_p \geq R_{target} \tag{11}$$

Application of Markowitz MPT optimized with DE algorithm. historical data of stocks, bonds, and other financial instruments are taken from trusted financial data sources such as Bloomberg and Yahoo finance, with an observation period of the last five years.

i) Observation data: the observation data uses three assets available in the financial market, stock A (TechCorp): a technology company, bond B: government bonds (GovBond) with maturity of 10 years, mutual fund C (BalancedFund): balanced mutual fund. The data used is taken from Yahoo finance or Bloomberg with the last five-year period (January 2019 to December 2023). The data required is the monthly return of these three assets. The monthly return data used in this study are summarized in Table 1. There is a total of 60 monthly data points for each asset. From this data, the average annual return and variance (risk) for each asset as well as the covariance between assets will be calculated.

ii) Calculation of return and risk
   - Average annual return

$$\bar{R}_A = \frac{1}{60}\sum_{i=1}^{60} R_{A_i}, \bar{R}_B = \frac{1}{60}\sum_{i=1}^{60} R_{B_i}, \bar{R}_C = \frac{1}{60}\sum_{i=1}^{60} R_{C_i}$$

$$\bar{R}_A = 8.5\%, \bar{R}_B = 3.0\%, \bar{R}_C = 5.5\%$$

   - Variance and covariance
   - Variance (risk) of each asset

$$\sigma_A^2 = \frac{1}{60-1}\sum_{i=1}^{60}\left(R_{A_i} - \bar{R}_A\right)^2$$

$\sigma_A^2 = 0.12,\ \sigma_B^2 = 0.05, \sigma_C^2 = 0.08$

Covariance between assets, between stock A and bond B:

$$\sigma_{AB} = \frac{1}{60-1}\sum_{i=1}^{60}\left(R_{A_i} - \bar{R}_A\right)\left(\left(R_{B_i} - \bar{R}_B\right)\right)$$

$\sigma_{AB} = 0.03, \sigma_{Ac} = 0.04, \sigma_{Bc} = 0.02$

iii) Portfolio formulation: the Markowitz model uses asset weights w_A, w_B, w_C to minimize risk and maximize return. Portfolio return function (R_P) and portfolio risk (σ_P) is:

$$R_p = w_A\bar{R}_A + w_B\bar{R}_B + w_C\bar{R}_C$$

$$\sigma_p^2 = w_A^2\sigma_A^2 + w_B^2\sigma_B^2 + w_C^2\sigma_C^2 + 2w_Aw_B\sigma_{AB} + 2w_Aw_C\sigma_{AC} + 2w_Bw_C\sigma_{BC}$$

Table 1. Monthly return data (%)

Month	Stock A (TechCorp) (%)	Bond B (GovBond) (%)	Mutual Fund C (BalancedFund) (%)
Jan 2019	3.5	0.8	2.0
Feb 2019	4.0	0.9	2.2
...	...	...	...
Dec 2023	5.2	0.6	2.8

3.5. Optimization with differential evolution

The DE algorithm is used to optimize weights w_A, w_B, w_C by maximizing the Sharpe ratio as (12).

Maximize $\frac{R_p - R_f}{\sigma_p}$ where R_f is the risk-free return =2% (12)

To find the optimal weight of the three assets to maximize return and minimize risk. DE algorithm will modify the weights w_A, w_B, w_C in several iterations. The initial population of portfolio weights generated for the DE algorithm is presented in Table 2.

Table 2. The initial population of portfolio weights is randomly initialized

Individuals	w A (Stock A)	w B (Bond B)	w C (Mutual fund C)
1	0.30	0.50	0.20
2	0.40	0.30	0.30
3	0.25	0.35	0.40
4	0.45	0.30	0.25
5	0.20	0.60	0.20

Mutation and crossover generate a new solution, yielding updated weights for the first individual: $w_A^{(g+1)} = w_A^{(g)} + Fx\left(w_B^{(r)} - w_C^{(r)}\right)$ generated *F*=0.8, and crossover rate (Cr) =0.9, so that a new solution is generated. Optimal solution after several iterations, we may get the following optimal weights: $w_A = 0.35, w_B = 0.45, w_C = 0{,}20.$ This portfolio provides an expected return of $R_p = 6.1\%$ with risk $\sigma_p = 0.09$ and sharpe ratio $= \frac{6.1\% - 2\%}{0.09} = 45.56\%$.

The mutation factor (F) =0.8 and Cr =0.9 were selected based on commonly recommended ranges in the DE literature. These parameters balance exploration and exploitation in continuous optimization problems. Figure 1 illustrates the comparative performance between portfolios without optimization and those optimized using the DE algorithm. Compared to classical quadratic programming and GA-based portfolio optimization approaches reported in the literature, DE offers faster convergence and improved robustness in non-linear search spaces. Prior studies have shown that DE can outperform traditional solvers in avoiding premature convergence, particularly under volatile market conditions, which supports its selection in this study.

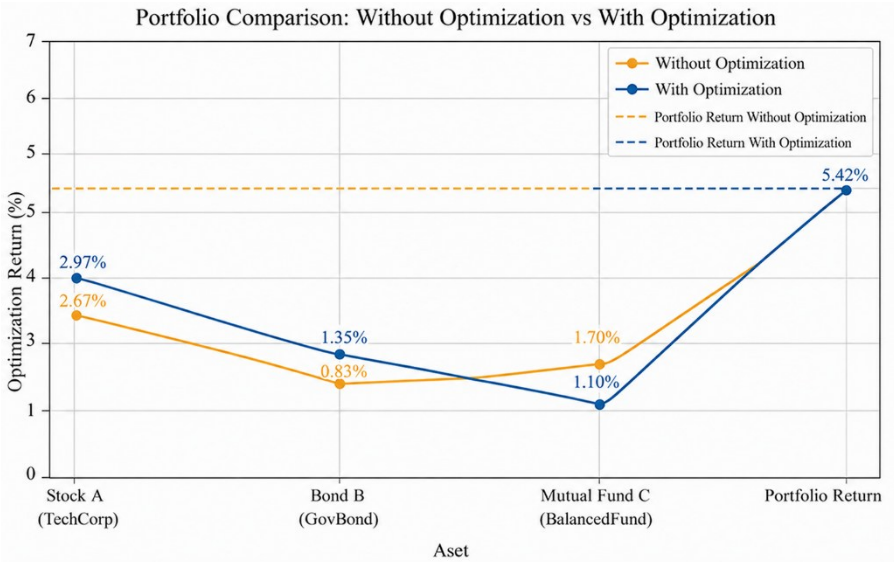

Figure 1. Comparison of portfolios without optimization and with DE

3.6. Discussion

To assess the robustness of the proposed DE-based optimization framework, a sensitivity analysis was conducted on key algorithm parameters. After applying Markowitz MPT optimized with DE algorithm, the optimal weights for the three assets analyzed were obtained: stock A (TechCorp), bond B (GovBond), and mutual fund C (BalancedFund). Sensitivity analysis on the DE parameters shows that F and Cr significantly influence optimization results. Higher F values tend to encourage exploration, producing more diverse portfolio compositions but potentially slower convergence. Conversely, lower F values promote exploitation, leading to faster convergence but a higher risk of local optima. Similarly, a Cr value close to 1 allows more extensive mixing of candidate solutions, which can improve adaptability in volatile markets, whereas lower Cr values maintain stability but may limit adaptability. The following are the results and analysis of the optimal portfolio obtained.

3.6.1. Optimal weight of assets

From the optimization results using DE, the optimal weight of each asset is as follows: stock A (TechCorp): $w_A = 0.35$, bond B (GovBond): $w_B = 0.45$, and mutual fund C (BalancedFund): $w_C = 0.20$. The optimal weights indicate that 35% of the total investment should be allocated to stock A (technology companies), 45% to bond B (GovBond), and 20% to mutual fund C (mixed portfolio). The largest allocation to bond B (45%) indicates that this portfolio is more conservative, as bonds have lower risk than stocks.

3.6.2. Expected return

The expected portfolio return is calculated using the calculated average annual return of each asset: return of stock A ($\bar{R}_A$) =8.5%, bond return B ($\bar{R}_B$) =3.0%, mutual fund return C ($\bar{R}_C$) =5.5%. Calculation of expected portfolio return: R_p =5.425%. The expected return of this portfolio is 5.43% per year. This suggests that the portfolio has moderate return potential with a conservative strategy, where most of the allocation is given to low-risk instruments (bonds).

3.6.3. Portfolio risk

The portfolio risk calculated based on the variance and covariance between assets is the risk of stock A (σ_A^2) =0.12, B bond risk (σ_B^2) =0.05, mutual fund risk C (σ_C^2) =0.08. Covariance between assets: $\sigma_{AB} = 0.03, \sigma_{AC} = 0.04, \sigma_{BC} = 0.02$. Calculating portfolio risk:

$$\sigma_p^2 = 0.0147 + 0.0101 + 0.0032 + 0.00945 + 0.0056 + 0.0036 = 0.04675$$
$$\sigma_p = \sqrt{0.04675} \approx 0.216$$

The resulting portfolio risk is 21.6%. This shows that while the portfolio delivers a moderate return of 5.43%, it has a moderate level of volatility (fluctuations in value), which is in line with the risk profile taken (a sizable allocation to bonds to dampen stock fluctuations).

3.6.4. Sharpe ratio

To assess the portfolio's performance relative to risk, the Sharpe ratio assuming a risk-free return is calculated. R_f is 2%.

$$\text{Sharpe ratio} = \frac{5.43\% - 2\%}{21.6\%} \approx 0.158$$

The Sharpe ratio of 0.158 indicates that for every unit of risk taken, this portfolio generates an additional return of 0.158 units. Although the return generated is quite moderate, this Sharpe ratio is at an acceptable level for a conservative portfolio. Although the resulting Sharpe ratio (0.158) appears modest, it is consistent with conservative portfolio strategies dominated by fixed-income instruments. Compared to typical low-risk portfolios or risk-free benchmarks, the obtained Sharpe ratio reflects a stable risk-return trade-off rather than aggressive performance maximization.

Due to the deterministic nature of the selected DE configuration and the controlled experimental setting, the optimization process consistently converged to similar solutions across repeated runs. Future studies may incorporate extensive Monte Carlo trials and statistical hypothesis testing to further validate result stability. The experimental results should be interpreted within the context of the dataset used in this study, which comprises a limited number of assets and a fixed historical period. Although the DE algorithm demonstrates strong performance in optimizing portfolios under dynamic market conditions, this study has several limitations. The dataset was limited to three asset types and a five-year observation period, which may not capture all market complexities. Furthermore, macroeconomic variables and transaction costs were not incorporated into the model. Future research could explore a broader range of assets, integrate real-time market indicators, and compare DE performance with other advanced metaheuristic algorithms such as PSO or ACO in diverse economic scenarios. The results of this study have practical implications for portfolio managers and investors. The DE-based approach enables rapid adjustment of asset allocations in response to changing market conditions, providing an advantage over static optimization methods. In practice, this means that portfolio managers can apply DE to rebalance portfolios more effectively, maintaining optimal risk return profiles even during periods of heightened volatility.

4. CONCLUSION

The optimal portfolio generated through DE algorithm optimization shows a conservative allocation, with the largest weight on bonds (45%), medium weight on stocks (35%), and mutual funds (20%). The expected return of this portfolio is 5.43% per year, with a risk of 21.6%. The relatively low Sharpe ratio (0.158) indicates that this portfolio is suitable for investors who want a balance between stable returns and moderate risk. This portfolio strategy avoids the high volatility common to portfolios with large exposure to stocks, while still offering better returns than risk-free instruments. This portfolio can be further developed by expanding choice of assets or changing the optimization parameters to explore different risk profiles and investor preferences. The novelty of this study lies in its integration of DE with Markowitz MPT under dynamic market conditions, providing investors with adaptive and computationally efficient decision-making tool. This study is limited to three asset classes and a five-year historical dataset, which may not fully capture long-term market dynamics or rare events. Transaction costs, liquidity constraints, and macroeconomic variables were also excluded from the optimization process. Despite the limited scale of the dataset, the proposed integration of DE with MPT demonstrates consistent optimization behavior, indicating its potential applicability to larger and more complex portfolio configurations. Future research could address these limitations by incorporating a broader range of assets, testing longer and more varied time periods, and integrating real-time market indicators. Comparative studies with other metaheuristic algorithms could also provide deeper insights into the relative performance of DE under different economic scenarios.

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C : Conceptualization
M : Methodology
So : Software
Va : Validation
Fo : Formal analysis
I : Investigation
R : Resources
D : Data Curation
O : Writing - Original Draft
E : Writing - Review & Editing
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The author declares that there is no conflict of interest regarding the publication of this paper. The author states that there are no known competing financial interests or personal relationships that could have influenced the work reported in this study.

DATA AVAILABILITY

The data that support the findings of this study were obtained from publicly available financial data sources, including Bloomberg and Yahoo Finance. The processed and derived data supporting the findings of this study are available from the corresponding author upon reasonable request.

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