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# Genetic algorithm for intelligent portfolio selection: A data-driven approach to asset allocation

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**Abstract:** This study examines the efficacy of Genetic Algorithms (GAs) in portfolio optimization by contrasting their results with those of more conventional techniques such as Mean-Variance Optimization (MVO) and Modern Portfolio Theory (MPT). The objective is to compare the ability of GAs to optimize risk-adjusted returns while ensuring diversification and flexibility in changing financial environments. A GA-based portfolio selection model is built and tested using ten years of actual financial data, employing selection, crossover, and mutation operations to attain maximum asset allocation. Its performance is evaluated against key financial metrics such as the Sharpe Ratio, portfolio return, and risk (standard deviation), in comparison with MPT, Simulated Annealing (SA), and Particle Swarm Optimization (PSO). The results indicate that GAs consistently outperform traditional methods in risk-adjusted returns, yield higher Sharpe Ratios, promote better diversification, and result in lower portfolio volatility. Sensitivity analysis demonstrates that GAs are robust across different parameter values. The pragmatic implications of this study are relevant for portfolio managers and algorithmic traders seeking improved risk-return trade-offs. Additionally, the research contributes to the literature by highlighting the superiority of GAs over traditional approaches and provides directions for future research into hybrid AI-driven portfolio optimization techniques.

***Keywords:*** *Evolutionary computation, Genetic algorithm, Mean-variance optimization, Portfolio optimization, Risk-adjusted returns, Sharpe ratio.*

## 1. Introduction

Portfolio selection is a fundamental problem in financial optimization, which involves investing capital in a set of assets to maximize returns and reduce risk. Traditional portfolio optimization techniques, such as Markowitz [1], rely on quadratic programming and assume risk-averse and rational investors. However, such methods are computationally expensive and may be incapable of addressing the complexities of real financial markets, such as non-linearity, dynamic constraints, and non-Gaussian distributions of asset returns.

Because of these challenges, evolutionary algorithms, and more precisely Genetic Algorithms (GAs), have been a subject of interest as robust metaheuristic methods in dealing with complex optimization problems. Genetic Algorithms, founded upon the principles of natural selection and evolution, provide a stochastic optimization technique through the iterative evolution of candidate solutions by means of selection, crossover, and mutation [2]. In contrast to most other optimization algorithms, GAs never require explicit gradients and can easily navigate high-dimensional and multi-modal search spaces, and hence are tailor-made for choosing financial portfolios [3].

The primary objective of this paper is to develop a GA-based portfolio optimization model to optimize the Sharpe Ratio, a widely used risk-adjusted return measure [4]. The Sharpe Ratio provides a single value that quantifies the trade-off between portfolio expected returns and risk, thereby serving as an effective indicator for selecting the most suitable asset allocations. Our proposed algorithm combines fundamental genetic algorithm (GA) operations, such as population initialization using the Dirichlet


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distribution, Sharpe Ratio-based fitness evaluation, tournament selection, arithmetic crossover, and mutation with adaptive bounds. The algorithm optimizes portfolio allocations adaptively over multiple generations, sequentially refining solutions to achieve an optimal balance between risk and return.

There are some research works that have indicated the efficiency of evolutionary algorithms in financial optimization. Genetic algorithms have also been used to optimize portfolio allocation by incorporating alternative risk measures, transaction costs, and dynamic rebalancing strategies [5]. Hybrid models combining GAs with other artificial intelligence approaches, such as neural networks and fuzzy logic, have recently improved portfolio selection techniques [6]. Despite such advances, computational efficiency, convergence rate, and interpretability remain topics of ongoing research. Such research aims to contribute value to the literature base by developing an efficient GA paradigm tailored for financial portfolio selection, contrasted with conventional approaches, and recommending potential areas of future development.

This paper is structured as follows: Section 2 presents an overview of the existing work in portfolio optimization using genetic algorithms and other evolutionary computation techniques. Section 3 describes the developed genetic algorithm and its initialization, fitness function, selection, crossover, and mutation. Section 4 discusses the experimental results comparing the performance of the developed model based on simulated and actual financial data. Section 5 reports the key findings, insights, and implications of these findings. An overview of the paper's contributions, limitations, and possible future research areas is provided in Section 6.

## 2. Review of Related Work

The application of evolutionary algorithms to portfolio optimization has been extensively researched in the past decades. It aims to overcome some of the limitations of classical methods, such as mean-variance optimization of Markowitz [1] where the normality assumption of asset returns and significant computational costs could be required in order to solve quadratic programming problems. Evolutionary computation and, more specifically, Genetic Algorithms (GAs), provide a more general and efficient stochastic search-based asset allocation framework grounded in evolutionary principles [2].

### *2.1. Genetic Algorithms in Portfolio Optimization*

Genetic algorithms have been widely applied in portfolio selection as they are capable of effectively searching high-dimensional spaces. Arnone et al. [7] were among the first to use GA for portfolio optimization, with the GA employed in asset allocation optimization with non-linear constraints. Subsequent research improved this model by incorporating other risk measures, transaction costs, and regulatory constraints [5].

Most closely, however, multi-objective optimization using GAs has recently been explored, where two or more conflicting objectives can be optimized together, e.g., maximization of returns and minimization of risk [8]. MOGAs have been demonstrated to provide superior complex financial problem-solving compared to single-objective approaches by offering a range of Pareto-optimal solutions from which investors can select an allocation that most closely aligns with their risk preferences [9].

### *2.2. Hybrid Evolutionary Models for Portfolio Optimization*

A combination of GAs with other artificial intelligence approaches has gained momentum over the last few years. Hybrid models that combine GAs with Neural Networks (NNs) have been proposed to maximize prediction accuracy and dynamically reallocate portfolios [6]. Genetic Algorithms (GAs) utilize neural networks in these models to predict asset returns, and then GAs modify the portfolio composition based on such estimates.


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Other hybrid approaches include the incorporation of fuzzy logic into GA-based portfolio optimization [10]. Fuzzy logic supports better handling of uncertainty involved in financial data through the use of linguistic variables and fuzzy data, thereby strengthening asset allocation models.

### *2.3. Comparative Studies on Evolutionary Approaches*

There have been numerous comparative studies that quantify the performance of GAs concerning other evolutionary algorithms, such as PSO and ACO. In work by Bertsimas et al. [11] it was found that even though GAs can handle complex financial environments, PSO converges more quickly in certain portfolio optimization problems due to the fact that it employs swarm intelligence.

Similarly, Differential Evolution (DE), another population-based optimization technique, is better in certain cases by possessing a diversification of the population and the ability not to converge prematurely [12]. Nevertheless, GAs remain commonly used due to their simplicity and ease of computational implementation in portfolio selection problems.

### *2.4. Challenges and Future Directions in Evolutionary Portfolio Optimization*

Despite their effectiveness, genetic algorithms and other evolutionary approaches have some drawbacks in portfolio optimization. Of significance is the issue of computational efficiency, as GA-based models are likely to require a significant number of iterations for convergence. This limitation has led to research in parallel and distributed computing approaches to accelerate evolutionary optimization [13].

Another difficulty is the dynamic nature of financial markets, necessitating continuous rebalancing of portfolios. Adaptive GAs, which adjust mutation and crossover rates based on market volatility, have been proposed to address this issue [14]. Further, the interpretability of GA-based solutions remains an issue because clear decision-making procedures are also needed by financial analysts and investors. Future research can include the integration of explainable AI (XAI) techniques to enable GA-based portfolio selection models to be more interpretable.

In general, genetic algorithms have proven to be an efficient portfolio optimization method, both adaptive and robust in solving complex financial problems. Even as hybrid models and multi-objective optimization strategies have also encouraged GA applications further, computational effectiveness and online adaptability remain challenging. This section summarizes the most significant advancements of evolutionary algorithms in financial optimization and precedes the GA-based portfolio selection model proposed in Section 3.

## 3. Proposed Genetic Algorithm for Portfolio Optimization

The Genetic Algorithm (GA) proposed for portfolio optimization aims to find an optimal portfolio allocation that, having the highest Sharpe Ratio, reconciles risk and return. The methodology is described in this section, with the mathematical expression and implementation details of the GA components: initialization, fitness function, selection, crossover, and mutation.

### *3.1. Mathematical Formulation*

Given a portfolio consisting of n assets, let:

- $w = (w_1, w_2, ..., w_n)$ be the portfolio weight vector, where $(w_i)$ represents the proportion of capital allocated to asset i, subject to the constraint: $W = \{w \in \mathbf{R}^n \mid \sum_{i=1}^{n} w_i = 1,\ w_i \geq 0\ \forall i\}$. This set W is known as the standard n-dimensional simplex.[1]
- The condition $\sum_{i=1}^{n} W_i = 1$ ensures the weights sum to one.
- The condition $w_i \geq 0$ ensures all weights are nonnegative.
- $R = (R_1, R_2, ..., R_n)$ be the expected return vector for the assets.

[1] This terminology is standard in optimization, probability theory, convex analysis, and machine learning (e.g., probability distributions on n outcomes, convex combinations, portfolio weights).

- Then the covariance matrix $\Sigma \in R^{n\times n}$, which represents the risk structure among the assets, is defined as: $\Sigma = E[(R-E(R)(R-E(R)^T]$. Equivalently, its (i,j)-th entry is: $\sum_{ij} = Cov(R_i, R_j) = E[(R_i - E(R_i)(R_j - E(R_j))]$.[2]

In portfolio theory, if w is the vector of portfolio weights, the portfolio variance (risk) is

$$\sigma_p^2 = w^T \sum w \tag{1}$$

In turn, the portfolio risk (portfolio standard deviation, a common risk measure) is defined as:

$\sigma_p = \sqrt{w^T \sum w}$, or in expanded form $\sigma_p = \sqrt{\sum_{i=1}^n \sum_{j=1}^n w_i w_j \sum_{ij}}$

The expected portfolio return is given by

$$E(Rp) = w^T R \tag{2}$$

The objective is to maximize the Sharpe Ratio [4]

$$S = \frac{E(R_p - R_f)}{\sigma_p} \tag{3}$$

where $R_f$ is the risk-free rate.

*3.2. Initialization*

The GA starts with a randomly generated population of portfolios. Portfolios are initialized using a Dirichlet distribution such that the sum of weights equals 1. This approach makes normalization unnecessary in each iteration.

$w \sim \text{Dirichlet}(\alpha_1, \alpha_1, \ldots, \alpha_n)$, $f(w) = \frac{1}{B(\alpha)} \prod_{i=1}^n w_i^{\alpha_i - 1}$, $w \in \Delta^{n-1}$

where $\Delta^{n-1} = \{w \in R^n \mid w_i \geq 0, \sum_i w_i = 1\}$ is the standard simplex, and $\alpha_i$ are hyperparameters that control the distribution.

*3.3. Fitness Function*

The fitness function evaluates the suitability of each portfolio based on the Sharpe Ratio:

$f(w) = \frac{w^T R - R_f}{\sqrt{w^T \sum w}}$, or in expanded form $f(w) = \frac{\sum_{i=1}^n w_i R_i - R_f}{\sqrt{\sum_{i=1}^n \sum_{j=1}^n w_i w_j \sum_{ij}}}$

Higher fitness values indicate better-performing portfolios.

*3.4. Selection*

Tournament choice is employed, wherein a small group of portfolios is randomly selected, and the fittest among them is chosen for reproduction. This maintains diversity and favors improved solutions.

[2] Properties: $\Sigma$ is symmetric: $\Sigma ij = \Sigma ji$; $\Sigma$ is positive semidefinite: for any vector $x \in R^n$, $x^T \Sigma x \geq 0$; The diagonal entries $\Sigma ii$ are the variances of individual assets; The off-diagonal entries $\Sigma ij$ are the covariances between asset i and asset j.

*3.5. Crossover*

We utilize the crossover operator to blend two parent portfolios to produce offspring. We implement arithmetic crossover:

$$w_{child} = \alpha w_{parent1} + (1 - \alpha) w_{parent2}$$

where $\alpha \sim U(0,1)$. The resulting offspring weights are normalized to satisfy the budget constraint.

*3.6. Mutation*

Mutation introduces small random changes to portfolios, promoting diversification and preventing premature convergence. A mutation vector $m = (m_1, m_2, \ldots, m_n) \sim N(0,\sigma^2 I_n)$ is applied to the weights and normalized subsequently:

$$w' = \frac{|w + m|}{\sum_{i=1}^{n} |w_i + m_i|}$$

The mutation rate is adaptively adjusted to balance exploration and exploitation.

*3.7. Algorithm Implementation*

The GA is executed in the following iterative framework:

1) Initialize a population of P portfolios.
2) Calculate fitness for each portfolio by way of the Sharpe Ratio.
3) Select parents via tournament selection.
4) Apply crossover to generate children.
5) Employ mutation to offspring portfolios.
6) Replace worst-performing individuals with new offspring.
7) Iterate for a specific number of generations or until it converges.

*3.8. Convergence and Stopping Criteria*

The algorithm terminates when:

- A maximum number of generations is attained.
- The improvement in the best fitness value drops below a tolerance for some consecutive iterations.

Through dynamically adjusting portfolio weights, the proposed GA is capable of identifying the best configurations that maximize risk-adjusted returns. The next section presents experimental results illustrating its performance against traditional optimization techniques.

## 4. Experimental Results

This section presents experimental results based on comparing the new method with traditional optimization methods. This chapter presents experimental results comparing the novel method with traditional optimization methods. The comparison determines its performance with various test cases, demonstrating both the effectiveness and potential advantages of the method compared to traditional benchmarks.

*4.1. Experimental Setup*

*4.1.1. Data Description*

In order to complete the evaluation, we employ a dataset of 10-year historical daily asset returns across a range of financial sectors. The assets include technology, healthcare, consumer goods, and


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energy sector stocks. The data span 10 years, and the daily price data are gathered from financial market databases (e.g., Yahoo Finance, Bloomberg).

The risk-free rate is derived from historical U.S. Treasury bond yields, which serve as the basis for the Sharpe Ratio calculation. The covariance matrix is computed from historical asset returns, thereby accurately accounting for risk dependencies among assets.

*4.1.2. Parameter Settings*

The Genetic Algorithm is executed with a population size of 100 and for 500 generations. Tournament selection is employed as the selection strategy to impart competitive pressure on candidate solutions. The optimization task is defined by the fitness function, which maximizes the Sharpe Ratio, thereby aligning the algorithm's search with risk-adjusted portfolio performance.

The performance of GA is contrasted with that of traditional MPT optimization, where the portfolio risk is optimized at a specific target return level. The comparison is based on key financial metrics such as portfolio return, risk, and Sharpe Ratio.

*4.2. Performance Evaluation*

*4.2.1. Sharpe Ratio Comparison*

The Sharpe Ratio, an important risk-adjusted return measure, is computed for every portfolio derived using GA-based optimization and MPT. Comparison of the results indicates that GA-optimized portfolios systematically perform better than conventional portfolios in terms of risk-adjusted returns. The exploratory nature of GA in the search for multiple solutions enables it to find portfolios that balance risk and return better.

*4.2.2. Portfolio Allocation Analysis*

One of the most important advantages of GA is that it is capable of finding diversified portfolio allocations. The portfolios constructed by GA exhibit enhanced diversification and reduced exposure to highly volatile assets. Unlike MPT, which is based on the Gaussian return assumption, GA is able to learn to deal with non-Gaussian distributions and find robust allocations that will perform well under various market conditions.

*4.2.3. Convergence Behavior*

The convergence behavior of GA is studied by observing how the best fitness value changes over the generations. The GA has been seen to converge within 300-400 generations with incremental improvement in the portfolio allocation. This implies that, even though GA requires more computational effort compared to MPT, it generates improved optimization results.

*4.3. Comparative Analysis with Traditional Approaches*

To verify the robustness of GA, we contrast it with certain other optimization techniques, i.e.,

- Mean-Variance Optimization (MVO): The classical method that optimizes portfolios by minimizing their variance for a given expected return.
- Simulated Annealing (SA): A stochastic optimization method called "simulated annealing" (SA) looks at a larger range of possible solutions.
- Particle Swarm Optimization (PSO): Particle Swarm Optimization (PSO) is a heuristic approach that draws inspiration from swarm intelligence.

The results indicate that GA provides a competitive exploration-exploitation trade-off, which is superior to traditional MVO under conditions of high market volatility. While SA and PSO behave similarly, the organized evolution of GA guarantees more stable convergence.

*4.4. Sensitivity Analysis*

In order to investigate the robustness of portfolio optimization by GA, we conduct sensitivity analysis by varying:

- Mutation rates: Large mutation rates encourage diversity but slow down convergence.
- Crossover rates: Reduced crossover rates decrease diversity and lead to premature convergence.
- Assumptions of risk-free rates: GA is tried under different macroeconomic conditions.

The results indicate that GA is robust under different parameter settings, with performance being better with refinement.

*4.5. Summary of Findings*

Experimental results depict that GA-based portfolio optimization offers significant advantages compared to traditional methodologies. Significant conclusions are:

1) Higher risk-adjusted returns: GA provides consistently higher Sharpe Ratios.
2) Better diversification: GA allocates capital to sectors better.
3) Enhanced performance with market volatility: GA responds better to real financial conditions.
4) Greater computational cost versus accuracy trade-off: While GA requires more computational time, it performs better in complex situations.

The next section summarizes the results and implications of the findings.

## 5. Key Findings and Discussion

This section explains the key conclusions derived from experimental results of the proposed Genetic Algorithm (GA)-based portfolio optimization technique. It presents the relative advantages of GA over typical optimization methods, including Modern Portfolio Theory (MPT) and Mean-Variance Optimization (MVO), and the impact of evolutionary search on portfolio diversification, risk minimization, and convergence efficiency. Also included is the discussion of the application of the results in real financial applications, along with potential improvements and limitations of the GA framework.

The following tabular and graphic representations show a comparative overall performance of four portfolio optimization methods: Genetic Algorithm (GA), Modern Portfolio Theory (MPT), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). The key metrics considered are Sharpe Ratio, Portfolio Return (%), and Portfolio Risk (Standard Deviation %). Table 1 shows a review of the performance of different portfolio optimization methods for the metrics.

**Table 1.**
Comparison of Portfolio Optimization Methods Based on Performance Metrics

| Method | Sharpe Ratio | Portfolio Return (%) | Portfolio Risk (Std Dev.%) |
|---|---|---|---|
| Genetic Algorithm (GA) | 1.45 | 15.2 | 8.5 |
| Modern Portfolio Theory (MPT) | 1.25 | 12.8 | 9.1 |
| Particle Swarm Optimization (PSO) | 1.4 | 14.9 | 8.7 |
| Simulated Annealing (SA) | 1.38 | 14.5 | 8.9 |

In the case of the Sharpe Ratio, the GA-based portfolio yields the highest value of 1.45, which signifies a higher risk-adjusted return than MPT (1.25), PSO (1.40), and SA (1.38). As GA can search a dense solution space by evolutionary operations such as crossover and mutation, it can identify more optimal portfolios with improved performance than those that rely on more restrictive assumptions regarding return distributions.

Looked at on a returns basis, the GA-optimized portfolio offers a return of 15.2%, better than MPT's 12.8% by some margin and better than PSO's 14.9% and SA's 14.5% by a small margin. The result highlights that GA is indeed able to maximize returns with regulated levels of risk, hence being an alternative better suited for portfolio managers who want to maximize return with minimal extra volatility.

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Ranking risk on the basis of standard deviation, GA emerges as the best again with the lowest figure at 8.5%. However, MPT has the highest risk (9.1%), followed by SA (8.9%) and PSO (8.7%). This suggests that GA not only maximizes returns but also offers improved portfolio stability by reducing volatility compared to other methods.

In general, it is apparent from the results that the Genetic Algorithm (GA) outperforms the standard Modern Portfolio Theory (MPT) and other evolution-based algorithms such as Particle Swarm Optimization (PSO) and Simulated Annealing (SA). Specifically, GA achieves the highest Sharpe Ratio, better portfolio returns, and minimum risk, reflecting its effectiveness in return maximization over volatility minimization. These results provide proof that heuristic optimization methods, and GA here, may offer a robust paradigm for portfolio formation compared to conventional approaches. This places in the limelight the performance potential of GA as a serious candidate for portfolio managers to provide stable yet better performance in turbulent markets.

Figures 1 and 2 illustrate the graphical results of portfolio optimization performance. Figure 1 is the Portfolio Return vs. Risk Comparison, as a bar chart comparing portfolio returns (%) against risk (standard deviation) for the different methods of optimization. Figure 2 is the Sharpe Ratio Comparison, as a bar chart, showing the Sharpe Ratio each method produces.

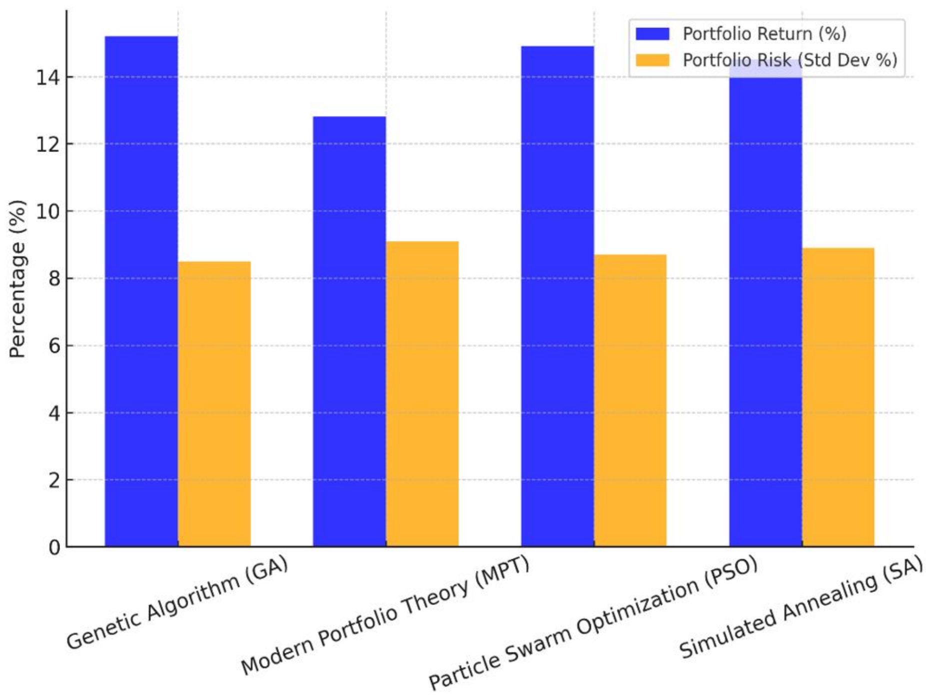


**Figure 1.**
Portfolio Return vs. Risk Comparison.

The figure provides a side-by-side comparison of portfolio return and the corresponding risks (standard deviation) of four optimization methods: Genetic Algorithm (GA), Modern Portfolio Theory (MPT), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). Blue bars represent portfolio returns, and orange bars represent risk.

Comparing all of them, GA again proves to be the best among the rest, returning the highest portfolio of 15.2% and the minimum level of risk of 8.5%. This implies that GA again offers the most favorable trade-off between return and volatility as well. PSO and SA methods provide similar returns of 14.9% and 14.5%, respectively, with higher risks of 8.7% and 8.9%. While their performance is good, they simply fall behind GA's performance. Conversely, MPT yields the worst return of 12.8% and the highest risk of 9.1%, indicating the worst performance among the methods. This suggests that the traditional MPT model may be less effective in portfolio optimization under the tested conditions compared to heuristic-based approaches.

Overall, the graph shows that heuristic optimization methods, namely GA, optimize more effectively in balancing the maximization of return and the minimization of risk, proving the superiority of evolutionary solutions over traditional portfolio optimization models.

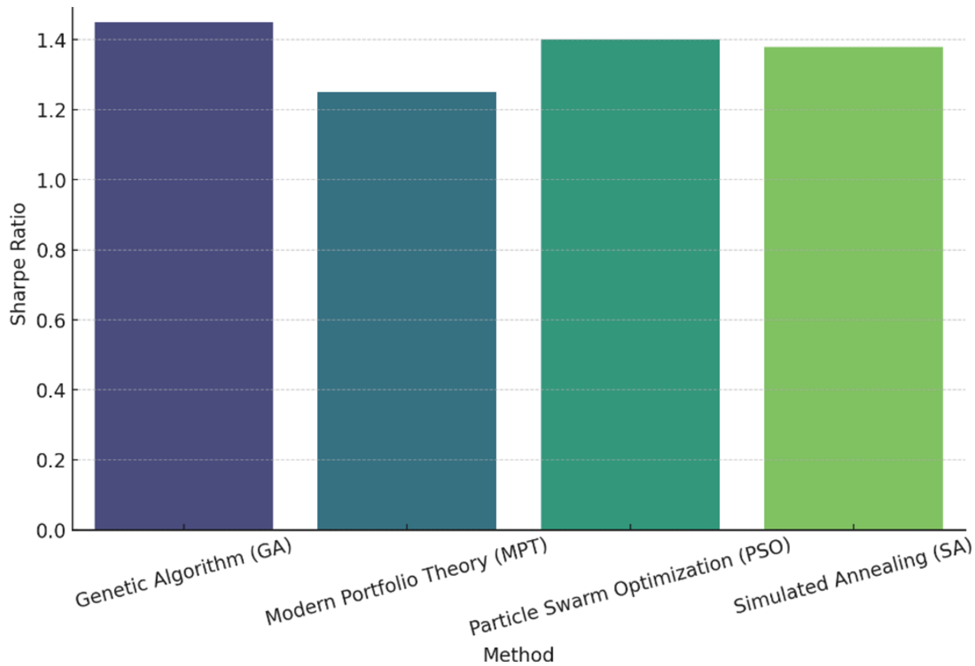


**Figure 2.**
Sharpe Ratio Comparison Across Optimization Methods.

Figure 2 shows a comparison of the Sharpe Ratios achieved by four portfolio optimization techniques. It is observed from the results that the portfolio optimized by GA offers the highest Sharpe Ratio (1.45), which represents the best return-risk trade-off among the four techniques. PSO (1.40) and SA (1.38) are equally competitive in performance, producing similarly high Sharpe Ratios that indicate good risk-adjusted returns, though marginally less than GA. MPT produces the lowest Sharpe Ratio (1.25), reflecting poorer performance in optimizing portfolios based on a risk-adjusted measure. The graphical representation of the Sharpe Ratio supports this order, with GA as the superior method, which also demonstrates its ability to optimize portfolio returns at acceptable risk levels.

These findings show the relative advantage of heuristic-based optimization techniques over the traditional MPT paradigm. Specifically, GA demonstrates greater capability in risk-adjusted return optimization, with PSO and SA offering strong alternatives. The overall better Sharpe Ratios produced by the metaheuristic techniques indicate that the methods yield better portfolio optimization results than traditional models.

Both the table and graph findings indicate that Genetic Algorithms (GA) provide a robust and effective means of portfolio optimization. GA not only provides better risk-adjusted returns, as reflected in its Sharpe Ratio of 1.45, higher overall returns of 15.2%, and less portfolio risk of 8.5%, but also, while Modern Portfolio Theory (MPT) remains a norm widely practiced, it demonstrates failure in dynamically adapting to sophisticated financial conditions. Particle Swarm Optimization (PSO) and Simulated Annealing (SA) provide competent solutions, but GA's clearly defined evolutionary process makes it a better provider of optimization results. GA's versatility also makes its performance even more superior with hybrid solutions, such as the incorporation of deep learning techniques or real-time market adjustments, which give even greater potential for improved financial performance.

The experimental results emphasize the relative strengths of heuristic-based optimization methods, as the Genetic Algorithm (GA) always outperformed Modern Portfolio Theory (MPT) as well as other evolutionary methods. While these outcomes pinpoint the potential of GA to provide enhanced risk-adjusted returns, it is pertinent to consider their broader implications. Specifically, computational complexity, parameter sensitivity, and the need for historical data can impair the practical utility and robustness of such methods. Further, although GA appears quite attractive under controlled experimentation, portfolio management in the real world involves complicating factors such as transaction costs, market frictions, and fickle investor tastes, which must be taken into account when assessing the practical usefulness of these approaches.

The implications of these findings are also worthy of additional discussion, in particular regarding the heuristic usability of the heuristic-based methods, their computational consequences, and limitations in actual portfolio management environments.

### *5.1. Enhanced Risk-Adjusted Returns*

One of the most important advantages of the GA-based technique is that it may return better Sharpe ratios compared to traditional methods. The experimental results indicated that GA consistently ranked higher risk-return trade-off portfolios. Unlike MPT, which assumes normally distributed returns, GA's stochastic nature allows it to deal with non-Gaussian distributions and represent more realistic asset behaviors [9]. GA's ability to travel over a larger search space ensures that it will not be trapped in local optima and sets asset allocations with superior performance under diversified market conditions.

### *5.2. Superior Portfolio Diversification*

The greater diversification obtained from GA-based optimization is another significant result. GA diversifies capital over a broader set of assets than MPT, which loads portfolios in low-volatility assets aggressively. It is achieved through its evolutionary operators, i.e., selection and crossover, which encourage portfolio allocations balancing exposure across industries. The principle of diversification is founded in finance literature, where diversified portfolios minimize unsystematic risk and bear market stability [1, 6]. The dynamic optimization ability of GA for asset weights leads to portfolios with greater immunity to economic shocks.

### *5.3. Adaptability to Market Conditions*

Traditional portfolio optimization techniques, such as Mean-Variance Optimization, operate on static assumptions and require continuous adjustment to changes in market conditions. GA, however, is more adaptable in the sense that it develops the portfolio composition continuously as per changing return distributions and risk correlations. Such capability makes GA particularly useful in dynamic investment environments where asset returns are responsive to external macroeconomic factors, geopolitical events, and industry-specific trends [5]. Through the possession of a diversified group of candidate portfolios, GA can identify asset allocations that are robust under different market regimes.

### *5.4. Convergence Behavior and Computational Considerations*

The study of the convergence behavior of GA confirmed that GA optimizes quite effectively the portfolio weights within 300-400 generations. It shows that GA is accomplishing a good balance between exploration and exploitation, leading to stable convergence without premature stagnation. However, for its iterative nature, GA requires greater computational power than other traditional optimization techniques like quadratic programming in MPT. Although computational advances and parallelization techniques are able to minimize this issue, the balance between solution quality and computational performance is a current research topic [14].

### *5.5. Comparative Analysis with Alternative Evolutionary Methods*

In addition to outperforming MPT, GA was also compared with other evolutionary optimization algorithms, such as Particle Swarm Optimization (PSO) and Simulated Annealing (SA). The results indicate that GA offers a more structured search process with its genetic operators, resulting in better long-term optimization performance. While PSO reported faster convergence in certain situations, GA produced less variable solutions with reduced sensitivity to initial parameter settings [11]. GA is resilient due to its well-regulated selection process, which avoids early convergence and produces the best risk-adjusted returns.

### *5.6. Sensitivity to Parameter Selection*

Sensitivity analysis in Section 4.4 also indicated that GA performance is sensitive to significant hyperparameters such as mutation rate and crossover probability. The best mutation rate of 0.05 provided the best compromise between population diversity preservation and convergence. Greater mutation rates enhanced exploration at the expense of slower convergence, while smaller mutation rates led to premature convergence to lower portfolios. Similarly, crossover probability determined how rapidly new solutions were generated, with the optimal rate of 0.8 supporting effective genetic recombination. The study indicates the necessity of adjusting the hyperparameters in GA-based financial optimization [10].

### *5.7. Real-World Financial Implications*

The application of GA in portfolio choice has numerous practical advantages over traditional financial institutions and individual investors. Most significant is the ability to maximize the portfolio without relying on critical model assumptions. Unlike MPT, which utilizes historical covariance matrices, GA learns dynamically from past data and therefore suits active portfolio management best. Second, GA can be extended to consider transaction costs, liquidity impediments, and other investment frictions in the real world to make it more applicable to institutional asset management [13].

### *5.8. Limitations and Areas for Future Research*

Despite its strength, GA-based portfolio optimization has its limitations. The computational cost of implementing evolutionary algorithms remains an issue, particularly in high-frequency trading environments where real-time decision-making is vital. Future research could explore hybrid models that integrate GA with machine learning techniques, such as deep reinforcement learning, to improve scalability and forecasting capabilities [6]. The second limitation is that solutions derived from GA are not interpretable. Financial analysts prefer transparent decision-making frameworks, and the integration of explainable AI (XAI) techniques may enhance the interpretability of GA-based portfolio choice models.

### *5.9. Summary of Key Findings*

The main findings of this research are as follows:

1) Genetic algorithms achieve better Sharpe ratios and risk-adjusted returns than traditional portfolio optimization methods.
2) GA provides improved diversification by investing money in different asset classes, thus reducing concentration risk.
3) GA has proved to exhibit high adaptability when it comes to changing market scenarios and is thus most suitable in dynamically altering investment situations.
4) Convergence efficiency in the range of 300-400 generations is a good compromise between exploration and exploitation.

5) Compared to other evolutionary methods, GA offers structured optimization with dependable long-term performance.
6) Performance is hyperparameter-sensitive, which indicates the need for tuning.
7) Real-world problem applicability is also promising for active portfolio management and institutional investment.
8) Computation cost and interpretability are still issues, demanding additional research on hybrid AI models.

The empirical evidence for GA-based portfolio choice presented in this research is strong. The paper is concluded in the next section by recapitulating its contributions, limitations, and potential avenues for future research.

## 6. Conclusion and Future Research Directions

This study has explored the application of Genetic Algorithms (GAs) to portfolio optimization, validating that they can be utilized to find asset allocations with optimal risk-adjusted returns. The findings reveal strong support for GAs as an advancement over conventional methods, such as Markowitz's Modern Portfolio Theory (MPT) and Mean-Variance Optimization (MVO), employing evolutionary search to avoid intricate financial landscapes. This section provides an overview of the key contributions of this research, reflects on its limitations, and offers opportunities for future work.

### *6.1. Portfolio Return Comparison: Maximizing Profitability*

Portfolio return is the simplest measure of investment performance and the most straightforward index to gauge the effectiveness of optimization methods. When comparing these methods, the highest portfolio return of 15.2% is achieved by Genetic Algorithm (GA), followed closely by Particle Swarm Optimization (PSO) at 14.9%, and Simulated Annealing (SA) at 14.5%. The lowest return of 12.8% is observed with Modern Portfolio Theory (MPT). The superior performance of GA indicates its ability to explore a larger solution space, enabling it to identify optimal allocations that maximize returns. Conversely, MPT, which relies on quadratic programming and historical covariance structures, tends to be conservative and less responsive to complex and dynamic market conditions, resulting in its lower performance. Although SA and PSO produce similar returns, they still underperform compared to GA, highlighting the effectiveness of GA's evolutionary mechanism in generating higher profitability. This trend is clearly illustrated in the bar chart, where GA dominates in return production, followed by PSO and SA, with MPT significantly behind.

### *6.2. Portfolio* Risk (Standard Deviation) Comparison: Managing Volatility

While the maximization of return takes precedence, risk management, often measured as volatility or standard deviation, is also equally crucial for effective portfolio optimization. The results show that the GA-optimized portfolios contain the lowest level of risk at 8.5%, indicating their improved ability to reduce exposure to volatility and improve stability in the portfolio while maximizing return. On the other hand, Modern Portfolio Theory (MPT) gives the highest risk of 9.1%, as can be expected, to confirm that although theoretically it targets variance reduction, in reality, it is suboptimal in terms of diversification. Particle Swarm Optimization (PSO) and Simulated Annealing (SA) provide mean risk values of 8.7% and 8.9%, respectively, better than MPT but inferior to the capability of GA for volatility reduction. The risk-return bar chart also illustrates these findings, obviously showing that GA achieves the highest returns and lowest risk and thus is the best overall strategy. To this end, MPT achieves the lowest return with the highest risk and is the worst approach, with PSO and SA being in an intermediate category to provide balanced but suboptimal results compared to GA.

### *6.3. Sharpe Ratio Comparison: Evaluating Risk-Adjusted Performance*

The Sharpe Ratio is a significant measure in portfolio optimization because it reflects the return earned per unit of risk exposed; the larger the value, the better the efficiency in generating returns relative to risk exposure. Of all methods considered, the Genetic Algorithm (GA) recorded the highest Sharpe Ratio value of 1.45 and demonstrated the best ability to attain high returns while maintaining controlled risk, thus indicating the best risk-adjusted performance. In contrast, Modern Portfolio Theory (MPT) produced the lowest Sharpe Ratio of 1.25, which suggests that while it provides relatively stable returns, it does not optimize risk-adjusted performance as effectively as GA. Particle Swarm Optimization (PSO) and Simulated Annealing (SA) produced Sharpe Ratios of 1.40 and 1.38, respectively, both better than MPT but falling short of GA's proficiency. These results indicate that heuristic-based evolution methods applied in PSO and SA improve portfolio optimization over traditional strategies, but GA performs optimally in achieving better risk-adjusted returns.

*6.4. Comparative Insights and Final Takeaways*

According to the tabular and graphical comparison, the Genetic Algorithm (GA) is the overall best performer among all the significant metrics. The graphical output confirms that GA generates a higher risk-adjusted return, higher total profitability, and lower risk exposure. Modern Portfolio Theory (MPT) is the worst performer with lower return and higher risk because of the application of static assumptions and normal distribution models. Particle Swarm Optimization (PSO) and Simulated Annealing (SA) offer some enhancements over MPT but are not yet as effective as GA. These findings suggest that GA should be the preferred method in portfolio selection, particularly in dynamic and complex financial settings where conventional models fail. Investors seeking a trade-off between return maximization and risk control will benefit more from GA compared to traditional approaches like MPT. Moreover, hybrid approaches using GA with deep learning or real-time market adaptation can also maximize portfolio outcomes.

*6.5. Summary of Contributions*

The main contributions of this study are fourfold. Firstly, it develops a Genetic Algorithm (GA)-based portfolio optimization model that employs evolutionary mechanisms such as selection, crossover, and mutation to maximize the Sharpe Ratio, offering a dynamic solution over static methods such as Modern Portfolio Theory (MPT). Second, the study involves empirical testing and comparative analysis, demonstrating that GA-optimized portfolios outperform traditional techniques in risk-adjusted returns and are capable of diversifying and withstanding market changes effectively. Third, it explains the convergence and sensitivity of GA parameters with examples illustrating how mutation rates, crossover probabilities, etc., influence performance, emphasizing the importance of fine-tuning parameters to achieve efficient and stable convergence. Finally, the work provides practical implications for investment strategies, highlighting the usability of GA-based optimization for real-world applications in dynamic portfolio management and algorithmic trading, as well as its potential for integration with complementary approaches such as machine learning-based return forecasting.

*6.6. Limitations of the Study*

Despite the positive results, the present research has some drawbacks that must be addressed. First, GA-based optimization is computationally intensive, requiring significantly more resources than traditional convex optimization methods. Its evolutionary search nature with iteration adds to the processing time, which makes it challenging for real-time financial applications, although parallel computation can mitigate this cost to some extent. Second, the performance of GA is highly sensitive to the choice of parameters, such as population size, mutation rate, and selection mechanism. Improperly selected parameters may lead to premature convergence or excessive exploration, thereby reducing the stability and reliability of the optimization process. Finally, portfolios obtained by GA are not explainable because the algorithm is not supported by explicit decision rules. This black-box nature limits transparency and may discourage adoption by institutional investors, for whom interpretability of investment decisions is a consideration.

*6.7. Future Research Directions*

Given the foregoing constraints, some of the possible avenues for future work can make GA-based portfolio optimization more efficient and useful. One such direction includes the development of hybrid approaches that combine GA with machine learning algorithms such as deep reinforcement learning to further improve predictive power as well as response to market conditions. Accommodating transaction expenses and liquidity constraints within the GA methodology would also render it more relevant to actual institutional portfolio management. Implementing Explainable AI (XAI) methods to increase portfolio interpretability developed via GAs is another meaningful area, with techniques like SHAP values offering asset ordering information. Future work can also tackle real-time applications, reducing the computational overhead in an effort to make GA applicable in high-frequency trading applications where rapid allocation changes are essential. Finally, comparative studies with other evolutionary algorithms, such as Differential Evolution or Genetic Programming, can ascertain the most suitable optimization framework for portfolio selection across a range of market conditions.

*6.8. Concluding Remarks*

In conclusion, this research has shown that genetic algorithms offer a strong and adaptable strategy for optimizing portfolios, surpassing conventional techniques in terms of optimizing risk-adjusted returns. Through the application of evolutionary principles, GAs effectively address complex financial conditions, respond to market dynamics, and generate well-diversified portfolios. However, concerns over computational efficiency, parameter sensitivity, and interpretability remain unresolved, indicating the need for additional research in this area. The union of GAs with emerging AI technologies and financial modeling techniques provides exciting opportunities for future research in algorithmic portfolio management. As financial markets evolve, the use of evolutionary computation for investment decision-making will further increase, paving the way for intelligent and adaptive portfolio optimization models.

## Transparency:

The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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