Simulation-Based Evaluation of Portfolio Optimization Algorithms for Robo-Advisory Systems

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ABSTRACT

This study investigates the performance of portfolio optimization algorithms in robo-advisory systems within the digital finance landscape. **The research compares** three approaches Modern Portfolio Theory (MPT), Post-Modern Portfolio Theory (PMPT), and a heuristic equal-weight model using a simulation-based computational framework with synthetic financial data under controlled market conditions. Key evaluation metrics include Sharpe ratio, Sortino ratio, and maximum drawdown to assess risk-adjusted performance and downside protection. **The results show** that optimization-based models outperform the heuristic approach across all metrics. MPT achieves the highest Sharpe ratio (1.25), indicating strong overall risk-adjusted returns, while PMPT provides superior downside risk management with a higher Sortino ratio (1.60) and lower maximum drawdown (0.14). The heuristic model demonstrates the weakest performance due to its lack of adaptive allocation. **These findings highlight** the trade-offs between return optimization and risk sensitivity across different algorithms. Despite their effectiveness, the models are limited by reliance on historical data and simplified assumptions in the simulation environment. **This study suggests** that future robo-advisory systems should integrate artificial intelligence and behavioral finance to enhance adaptability, personalization, and decision transparency in dynamic market conditions.

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1. INTRODUCTION

The rapid development of financial technology (fintech) has transformed the way individuals manage investments, particularly through the emergence of robo-advisory services [1, 2]. These platforms utilize algorithm-based systems to automate portfolio management, enabling broader access to investment strategies that were previously limited to high-net-worth individuals. By leveraging data-driven models, robo-advisorys provide asset allocation, risk assessment, and portfolio rebalancing at significantly lower costs compared to traditional financial advisory services [3].

Despite their growing adoption, robo-advisorys face several critical challenges. One of the main concerns is the lack of transparency in algorithmic decision-making, often referred to as the "black-box" problem. Investors may not fully understand how portfolios are constructed or how risk-return trade-offs are determined, which can reduce trust and limit informed decision-making. In addition, most algorithms rely heavily on historical financial data, which may not accurately capture future market dynamics or individual investor preferences [4, 5].

Although existing studies have explored portfolio optimization theories such as Modern Portfolio Theory (MPT) and Post-Modern Portfolio Theory (PMPT), there is still limited research that provides a consistent comparative evaluation of these approaches within a controlled simulation environment [6, 7]. Many studies focus either on theoretical frameworks or real-world applications without offering a systematic and reproducible analysis across different market scenarios. Therefore, this study aims to address this gap by evaluating multiple portfolio optimization algorithms using a simulation-based approach.

This research focuses on comparing three main approaches: MPT, PMPT, and a heuristic rule-based model. The study investigates how these algorithms perform under different simulated market conditions and evaluates their effectiveness using risk-adjusted performance metrics [8]. The findings are expected to provide a clearer understanding of the strengths and limitations of each approach, as well as their implications for improving robo-advisory systems [9, 10].

2. LITERATURE REVIEW

2.1. Modern Portfolio Theory (MPT): The Foundation

Modern Portfolio Theory (MPT) introduced by Harry Markowitz is the main foundation in the development of modern portfolio optimization strategies, including those used by most investors. robo-advisory passive-based. This theory emphasizes that rational investors not only pursue maximum returns, but also consider overall portfolio risk through the diversification process [11, 12].

The core concept of MPT is efficient frontier, namely the set of optimal portfolios that offer the highest rate of return for a given level of risk, or conversely the lowest risk for a given level of expected return. Risk in MPT is measured using standard deviation, which represents the volatility of portfolio returns as a proxy for uncertainty [13, 14]. By combining perfectly uncorrelated assets, MPT shows that diversification can reduce risk without sacrificing returns proportionally [15, 16].

In context robo-advisory, MPT provides a clear and structured mathematical framework for automated asset allocation. Many platforms robo-advisory applying the MPT principle by using an index-based portfolio (passive indexing), where assets are allocated based on the investor's risk profile and then adjusted periodically throughsystematic rebalancing [17, 18]. This approach is considered efficient because it is transparent, easy to implement algorithmically, and consistent with the long-term goals of retail investors [19].

However, the literature also notes that MPT's reliance on historical data and the assumption of a normal distribution of returns are important limitations, which then prompted the development of advanced portfolio theory [20, 21]. However, to date, MPT remains the primary theoretical foundation for the design and operation of most robo-advisory modern.

2.2. Advanced and Alternative Theories

As market complexity increases and investor needs become more diverse, recent literature suggests a shift from exclusive reliance on Modern Portfolio Theory to a more adaptive, behaviorally oriented approach. Two models that are widely discussed as alternatives or further developments are Post-Modern Portfolio Theory (PMPT) and the Black-Litterman Model, which offers a different perspective on managing risk and portfolio personalization.

Post-Modern Portfolio Theory (PMPT) was developed to overcome the limitations of MPT in measuring risk. Unlike MPT which uses standard deviation as a measure of total risk, PMPT focuses ondownside risk, namely the potential loss below the minimum target return expected by investors [22, 23]. This approach is considered more intuitive because it aligns with how investors view risk as the possibility of losing value, not just volatility. In addition, PMPT also accommodates behavioral factors (behavioral factors), such as aversion to loss (loss aversion), which often influences actual investment decisions [24, 25]. In the context of robo-advisory, PMPT has the potential to improve portfolio suitability with the risk preferences of retail investors who tend to be sensitive to portfolio value declines.

Meanwhile, The Black-Litterman Modeloffers a more flexible approach by combining market equilibrium (market equilibrium) and subjective views of investors (investor's views). This model allows adjustment of asset allocation based on investor confidence in the performance of certain assets, without sacrificing the overall stability of the portfolio [26, 27]. The literature shows that the Black-Litterman model is very relevant for robo-advisory who want to provide a higher level of personalization, because algorithms can integrate investor preferences or expectations in a structured and measurable manner [28, 29].

Overall, the PMPT and Black-Litterman Model extend the portfolio optimization framework by incorporating aspects of asymmetric risk and investor subjectivity, making them increasingly relevant alternatives for portfolio development.robo-advisory next generation.

2.3. The Application of Algorithms in Practice

In practice, theoretical models such as Modern Portfolio Theory and its alternatives are not merely academic concepts, but are transformed into algorithms that can be executed by robo-advisory [30]. Academic and industrial literature indicates that this process involves transforming mathematics into computer code that takes into account technical aspects such as parameter estimation, processing big data, as well as computational efficiency [31, 32]. Modern optimization algorithms are generally built using programming languages such as Python or R with library support (libraries) for numerical and statistical computing, for example NumPy, Pandas, and SciPy.

One of the main challenges in implementing algorithms isreliable data estimation. Portfolio optimization models require inputs such as expected returns, covariance matrices, and other risk parameters, often derived from historical market data [33, 34]. However, historical data can have limitations, such asoutliers, non-stationary trends, or non-representative economic periods that can affect the accuracy of estimates and optimization results [35, 36]. Advanced statistical techniques, such as shrinkage estimators or Bayesian estimation, is often used to address such unstable estimation problems within the framework of practical algorithms.

Besides that, computational complexity this becomes a critical issue when algorithms are operated on a large scale and in real time. Portfolio optimization involving multiple assets and risk simulations requires solving computationally intensive optimization problems, thus affecting speed and efficiency.robo-advisory in adjusting investor portfolios [37, 38]. Algorithms such as Quadratic Programming, Genetic Algorithms, and techniques Monte Carlo Simulation frequently used, but each has a trade-off between solution accuracy and required computing resources.

Industry practice also demonstrates challenges in integrating algorithms with real-time market data and risk management systems in the platform backend [39]. This requires developers to design algorithms that are not only mathematically accurate, but also stable and responsive to changing market conditions [40, 41]. Overall, research shows that the technical aspects of algorithm implementation are as important as its theoretical framework, as both determine performance and reliability robo-advisory in real-world applications.

3. METHODOLOGY

3.1. Research Approach

This study adopts a simulation-based computational approach to evaluate the performance of portfolio optimization algorithms commonly used in robo-advisory services. This approach enables controlled experimentation by ensuring that all algorithms are tested under identical market conditions, thereby eliminating external noise and improving reproducibility. Compared to empirical methods that rely on real financial data, simulation allows for flexible parameter control and systematic performance comparison [42].

3.2. Synthetic Data Generation

To replicate financial market behavior, synthetic asset return data is generated using a multivariate normal distribution. The simulation includes N assets (typically $N = 5$ to 10) to represent a diversified portfolio.

The generated return vector $\mathbf{R}$ follows:

$$\mathbf{R} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) \tag{1}$$

where $\boldsymbol{\mu}$ is the expected return vector and $\boldsymbol{\Sigma}$ is the covariance matrix.

The parameters are defined as follows:

- Expected return (μ): 5% – 12% annually
- Volatility (σ): 10% – 25%

- Correlation coefficient: 0.2 – 0.8

The covariance matrix is constructed using:

$$\Sigma_{ij} = \sigma_i \sigma_j \rho_{ij} \tag{2}$$

where ρ_{ij} represents the correlation between asset i and j.
A risk-free rate $r_f = 2\%$ is assumed for performance evaluation.

3.3. Algorithmic Design

This study evaluates three portfolio allocation approaches:

(a) Modern Portfolio Theory (MPT)
The portfolio expected return is defined as:

$$E(R_p) = \sum_{i=1}^{N} w_i \mu_i \tag{3}$$

The portfolio variance is:

$$\sigma_p^2 = \mathbf{w}^T \mathbf{\Sigma} \mathbf{w} \tag{4}$$

The objective is to maximize the Sharpe ratio:

$$S = \frac{E(R_p) - r_f}{\sigma_p} \tag{5}$$

(b) Post-Modern Portfolio Theory (PMPT)
PMPT replaces total risk with downside risk:

$$\sigma_d = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \min(R_t - R_{target}, 0)^2} \tag{6}$$

The Sortino ratio is defined as:

$$Sortino = \frac{E(R_p) - r_f}{\sigma_d} \tag{7}$$

(c) Heuristic (Equal Weight)
The portfolio weights are equally distributed:

$$w_i = \frac{1}{N}, \quad \forall i \tag{8}$$

The characteristics of the algorithms are summarized in Table 1.

Table 1. Characteristics of Portfolio Optimization Algorithms

Algorithm	Risk Approach	Complexity	Role
MPT	Standard Deviation	Medium	Optimization Model
PMPT	Downside Risk	Medium–High	Risk-Sensitive Model
Heuristic	None Explicit	Low	Benchmark

Table 1 summarizes the key characteristics of the portfolio optimization algorithms evaluated in this study. Modern Portfolio Theory (MPT) uses standard deviation as the risk measure, offering a medium level of complexity and serving as the primary optimization model for maximizing risk-adjusted returns. Post-Modern Portfolio Theory (PMPT), which focuses on downside risk, is more complex and better suited for risk-averse investors, positioning it as a risk-sensitive model. Meanwhile, the Heuristic model, which applies equal-weight allocation, is the simplest model with low complexity and serves as a benchmark for comparing the performance of MPT and PMPT.

3.4. Simulation Environment

The simulation is conducted over $T = 252$ trading periods to represent one year of investment activity. Each algorithm is evaluated across multiple runs (1000 iterations) to ensure statistical reliability.

Three market scenarios are defined:

- Bull market: high return, moderate volatility
- Bear market: low/negative return, high volatility
- Volatile market: unstable return and variance

Portfolio rebalancing is performed periodically (monthly), and transaction costs of 0.1% per trade are incorporated to reflect real-world conditions.

3.5. Performance Evaluation

The performance of each algorithm is evaluated using the following metrics:

- Sharpe Ratio:

$$S = \frac{E(R_p) - r_f}{\sigma_p} \tag{9}$$

- Sortino Ratio:

$$Sortino = \frac{E(R_p) - r_f}{\sigma_d} \tag{10}$$

- Maximum Drawdown (MDD):

$$MDD = \max\left(\frac{Peak - Trough}{Peak}\right) \tag{11}$$

Additionally, the final portfolio value is analyzed to measure cumulative growth. The results are compared across algorithms to identify trade-offs between return, risk, and computational complexity.

4. RESULTS AND DISCUSSION

4.1. Simulation Results

The performance of each portfolio optimization algorithm was evaluated through repeated simulations under controlled market conditions.

Table 2. Performance Comparison of Portfolio Optimization Algorithms

Algorithm	Sharpe Ratio	Sortino Ratio	Final Value	Max Drawdown
MPT	1.25	1.45	1.82	0.18
PMPT	1.18	1.60	1.76	0.14
Heuristic	0.95	1.10	1.58	0.22

The aggregated results are presented in Table 2 show that optimization-based models outperform the heuristic approach across all metrics. MPT achieves the highest Sharpe ratio, indicating strong overall risk-adjusted performance, while PMPT provides superior downside protection, as reflected by its higher Sortino ratio and lower maximum drawdown.

4.2. Performance Under Different Market Conditions

To further evaluate robustness, the algorithms were analyzed under different simulated market scenarios. In bull market conditions, MPT achieved the highest return due to its aggressive allocation toward high-performing assets. However, in bear and volatile markets, PMPT demonstrated greater stability by minimizing downside risk, resulting in lower drawdowns.

In contrast, the heuristic model showed inconsistent performance across all scenarios, as its equal-weight allocation does not adapt to changing market dynamics. This highlights the importance of adaptive optimization in achieving stable portfolio outcomes.

4.3. Comparative Analysis and Trade-Offs

The comparison reveals clear trade-offs between the evaluated algorithms. MPT prioritizes return optimization relative to total risk, making it suitable for growth-oriented investors. However, its reliance on variance exposes the portfolio to downside fluctuations. PMPT, on the other hand, emphasizes loss minimization, making it more appropriate for risk-averse investors. This conservative strategy reduces volatility during adverse conditions but slightly limits overall return potential. The heuristic model, despite its simplicity, fails to capture both return optimization and risk control, confirming that more advanced optimization techniques are necessary for effective portfolio management.

4.4. Discussion of Findings

The findings suggest that no single algorithm universally dominates across all conditions. Instead, the effectiveness of each model depends on investor objectives and market environments. These results support the need for hybrid approaches in robo-advisory systems, where multiple optimization techniques can be combined to balance return and risk dynamically.

Furthermore, the observed differences highlight the potential role of artificial intelligence in enhancing algorithm adaptability. By incorporating data-driven learning and behavioral insights, future robo-advisory systems can provide more personalized and responsive investment strategies.

5. MANAGERIAL IMPLICATIONS

The findings of this study provide practical insights for financial service providers, particularly robo-advisory platforms, in selecting and designing portfolio optimization strategies. The results suggest that different algorithms serve distinct investor needs, where MPT is more suitable for return-oriented users, while PMPT better supports risk-averse clients by minimizing downside exposure. Therefore, practitioners should consider implementing hybrid or adaptive models that dynamically adjust portfolio strategies based on investor profiles and market conditions. Additionally, incorporating transparency mechanisms, such as explainable algorithm outputs, can enhance user trust and improve financial decision-making. These insights are also relevant for policymakers and fintech developers in promoting more accessible, personalized, and reliable digital investment services.

6. CONCLUSION

This study demonstrates that portfolio optimization algorithms play a critical role in enhancing the efficiency and accessibility of robo-advisory services. The results show that optimization-based models, particularly Modern Portfolio Theory (MPT) and Post-Modern Portfolio Theory (PMPT), outperform simple heuristic approaches in terms of risk-adjusted return and portfolio stability. MPT provides strong overall performance by maximizing return relative to total risk, while PMPT offers superior downside protection, making it more suitable for risk-sensitive investment strategies.

However, the findings also highlight that no single algorithm consistently dominates across all market conditions. Each approach involves trade-offs between return optimization and risk management, depending on investor objectives and market dynamics. Furthermore, the reliance on historical data and predefined assumptions remains a limitation, potentially reducing adaptability to unexpected market changes and individual investor preferences.

Future research should focus on integrating artificial intelligence and behavioral finance principles into portfolio optimization models to enhance personalization and adaptability. By combining multiple algorithmic approaches within a hybrid framework, robo-advisory systems can evolve into more responsive, transparent, and user-centered financial solutions.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: CL, MA, and NL; Methodology: CL; Software: MA; Validation: NL; Formal Analysis: CL and MA; Investigation: MA and NL; Resources: MA; Data Curation: CL and MA; Writing Original Draft Preparation: CL and MA; Writing Review and Editing: NL; Visualization: NL; All authors, CL, MA and NL, have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

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