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Financial Portfolio Optimization using Simulation and Evolutionary Artificial Intelligence

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ABSTRACT
Modern Portfolio Theory (MPT), also known as the mean–variance approach, focuses on constructing portfolios that minimize risk for a desired return or maximize return for a defined risk level. This paper integrates simulation and artificial intelligence techniques to enhance portfolio optimization, providing improved decision-making by effectively balancing risk and return. Monte Carlo simulation served as the primary simulation method. The results showed that combining MPT with advanced optimization techniques, including Monte Carlo simulation and NSGA-II that produces robust and efficient portfolios. All methods delivered consistent outcomes, with NSGA-II achieving a high Sharpe ratio of 2.113 and exhibiting early, stable convergence. Pareto-front analysis emphasized the dominance of large-cap technology stocks, particularly Apple and Amazon, with Microsoft contributing stability and Tesla appearing mainly in higher-risk allocations. The convergence of these techniques underscores the portfolio's robustness and reflects a market environment favoring major tech leaders, illustrating the value of blending simulation and AI to balance risk and return in financial strategy.

General Terms
Modern Portfolio Theory, Monte Carlo simulation, Artificial Intelligence.

Keywords
Modern Portfolio Theory, Monte Carlo simulation, Artificial Intelligence, NSGA-II.

1. INTRODUCTION
Harry Markowitz, who received the Nobel Prize in Economics, introduced Modern Portfolio Theory (MPT). MPT, also known as the mean–variance approach, optimizes portfolios by minimizing risk for a chosen expected return or maximizing return for a given level of risk. It underscores the fundamental trade-off between return (mean) and risk (variance) [1].

Traditional financial portfolio optimization depends on mathematical frameworks like MPT to balance risk and return [2], [3]. However, these models often fall short when confronted with real-world complexities such as market volatility, nonlinear behavior, dynamic constraints, and computational limitations [4]. Moreover, classical methods may not adjust effectively to evolving market conditions, resulting in less-than-optimal investment decisions.

This paper integrates simulation and artificial intelligence techniques to enhance portfolio optimization, providing improved decision-making by effectively balancing risk and return. Monte Carlo simulation served as the primary simulation method. Combining MPT with advanced optimization techniques, including Monte Carlo simulation and NSGA-II [5] are assumed to produce robust and efficient portfolios.

The paper is organized into four sections. Section 1 introduces the project's objectives. Section 2 reviews relevant literature, theories, and prior research. Section 3 focuses on the proposed system, providing analysis and design and case study results. Section 4 concludes the paper by summarizing key findings and offering recommendations for future work.

2. REVIEW OF LITERATURE
A portfolio p is defined as:

$$p(t) = \sum_{i=1}^{n} w_i^t \quad s_i \tag{1}$$

where s denotes securities, and w denotes weights. Market dynamics influence investment decisions, requiring skilled analysts to consider opportunities, goals, and objectives before allocating or reallocating stocks [6].

Table 1 shows classical approaches for portfolio optimization

Table 1. Classical approaches for portfolio optimization

Model	Advantages	Limitations
Mean-Variance [7]	Effective for small risk levels, simple return distributions, and frequent rebalancing.	Performs poorly with high-risk settings; relies on the assumption of normally distributed returns.
Variance with Skewness [8]	Useful when return distributions deviate from normality.	Optimization often converges only to a local optimum.
Value-at-Risk (VaR) [9]	Intuitive risk measure and scalable to large asset sets.	Can be misleading, ignores worst-case losses, and becomes challenging with very large portfolios.
Conditional Value-at-Risk (CVaR) [10]	Captures tail-risk by focusing on extreme losses; suitable for volatile markets.	Does not provide the absolute maximum possible loss.
Mean-Absolute Deviation (MAD) [11]	Faster than mean-variance due to linear programming; suitable for	Ignores the covariance structure and penalizes deviations in both directions.

Model	Advantages	Limitations
	multivariate normal returns.	
Minimax [12]	Efficient with non-normal returns, fast via linear programming, and supports complex constraints.	Highly sensitive to outliers and unreliable with incomplete historical data.
Lower Partial Moment (LPM) [13]	Matches investor risk preferences by focusing on downside risk only.	Computationally demanding and sensitive to extreme values.

Table 2 shows intelligent approaches for portfolio optimization.

Table 2. Intelligent approaches for portfolio optimization

Methods	Advantages	Limitations
Integer and Categorical Particle Swarm Optimization (ICPSO) [14]	Capable of solving discrete optimization problems involving both integer and categorical variables.	Assumes variable independence and is prone to bias sensitivity.
Support Vector Machine (SVM) [15]	Easy to implement, performs well in high-dimensional spaces, and is computationally efficient.	Performs poorly with very large datasets and noisy data; requires a clearly separable margin.
Bayesian-Based Approach [16]	Utilizes prior knowledge for informed decision-making and supports conditional inference.	Selecting appropriate priors is challenging, and outputs may be difficult to interpret.
Long Short-Term Memory (LSTM) [17]	Learns long-term dependencies effectively.	Difficult to implement and can suffer from gradient-related problems.
Recurrent Reinforcement Learning (RRL) [18]	Optimizes performance criteria, discovers investment strategies, avoids Bellman's curse of dimensionality, and works in discrete action spaces.	Not suitable for immediate estimation tasks; initial allocations may cause losses.
Stacked Deep	Handles	Limited neural-model

Methods	Advantages	Limitations
Dynamic Recurrent Reinforcement Learning (SDDRRL) [19]	continuous action spaces in multidimensional environments, does not require time-series forecasting, and adapts to updated market information.	analysis, computationally expensive, and depends on current market data.
Multi-Objective Evolutionary Algorithms (MOEAs) [20]	Solve complex multi-objective problems and handle non-linear, non-differentiable, non-continuous, and non-convex spaces.	Suffer from reproducibility issues and require challenging parameter tuning.
Non-Dominated Sorting Genetic Algorithm II (NSGA-II) [21]	Provides fast non-dominated sorting, efficient crowding distance estimation, and uses a simple comparison mechanism.	Limited reproducibility, difficult parameter tuning, and requires careful parameter selection.
Multi-Objective Particle Swarm Optimization (MOPSO) [22]	Effective for multi-objective optimization with lower computational cost than evolutionary methods.	Challenging to set initial design parameters, prone to premature convergence, and unsuitable for discrete problems.
GARCH [23]	Useful for estimating return volatility in large datasets.	Highly sensitive to data frequency and performs best with very large time series.
Quantum-Inspired Tabu Search (QTS) [24]	Outperforms many heuristic methods, prevents premature convergence, and offers flexibility and stability.	Efficiency decreases as the number of items increases.

3. PROPOSED SYSTEM

3.1 Analysis and design

Fig. 1 shows the use-case of the proposed system, followed by sequence diagram in Fig. 2, and class diagram in Fig. 3.

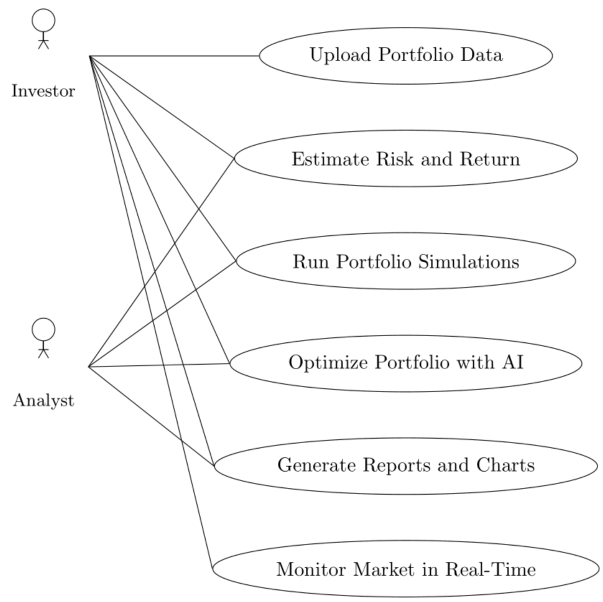

Fig 1: Use Case

The use case diagram illustrates the interactions between two primary actors (Investor and Analyst) and the system's core functionalities. Both actors are able to upload portfolio data, estimate risk and return, run portfolio simulations, and optimize portfolios using AI-based methods. The Analyst, however, has access to additional advanced capabilities, including generating reports and charts and monitoring the market in real time. The diagram highlights how the system supports both general portfolio analysis tasks shared by all users and specialized analytical functions tailored to professional analysts.

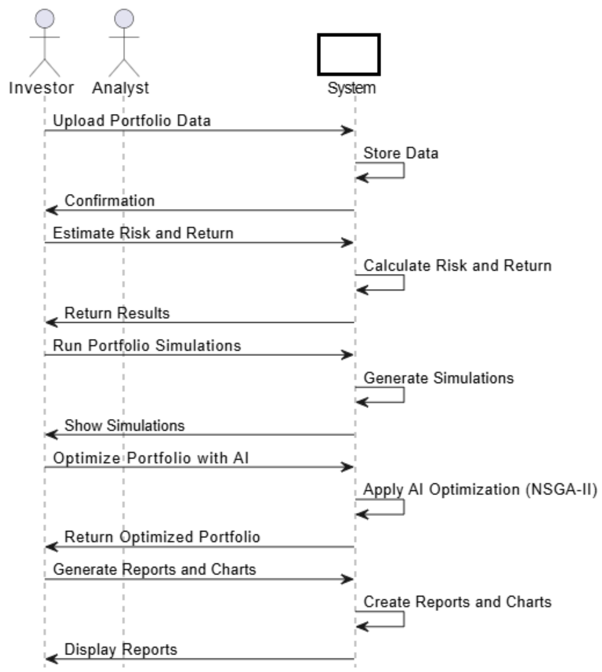

Fig 2: Sequence Diagram

The Portfolio class manages a collection of Stock objects and their associated weights, providing methods to calculate both portfolio return and risk. Each Stock object stores its name and historical prices, along with a method to compute daily returns.

The NSGA2Optimizer class handles the optimization of portfolios through evolutionary operations such as selection, mutation, and crossover. It maintains a population of portfolios and iteratively refines them to identify an optimal set based on the trade-off between risk and return. In terms of relationships, a Portfolio is composed of multiple Stock objects, while the NSGA2Optimizer operates on a population of portfolios to determine the most efficient configurations.

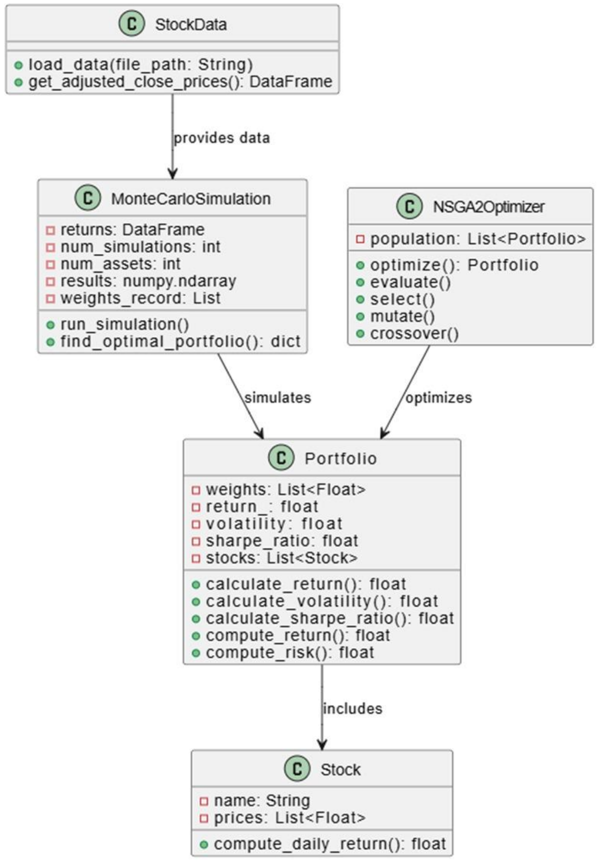

Fig 3: UML Class diagram

3.2 Case study

The assets to try them are Tesla [25], Microsoft [26], Apple [27], Amazon [28] and Alphabet (formerly Google) [29]. Fig. 4 shows all the stocks' open price, while Fig. 5 shows the scatter matrix among the selected assets. The diagonal elements show histograms of individual stock opening prices, while the off-diagonal elements show scatterplots comparing different stock pairs.

Fig. 6 depicts the Efficient Frontier from Modern Portfolio Theory (MPT), showing Annualized Return versus Annualized Volatility. Monte Carlo portfolios (blue/purple points) illustrate random asset combinations, with color intensity indicating the Sharpe Ratio. The orange line represents the Efficient Frontier, highlighting portfolios that maximize return for a given risk or minimize risk for a given return. Red points show the NSGA-II Pareto Front, closely matching the theoretical frontier, validating the effectiveness of the genetic algorithm. The large circled point marks the Best Sharpe (2.11) Tangency Portfolio, offering the highest risk-adjusted return.

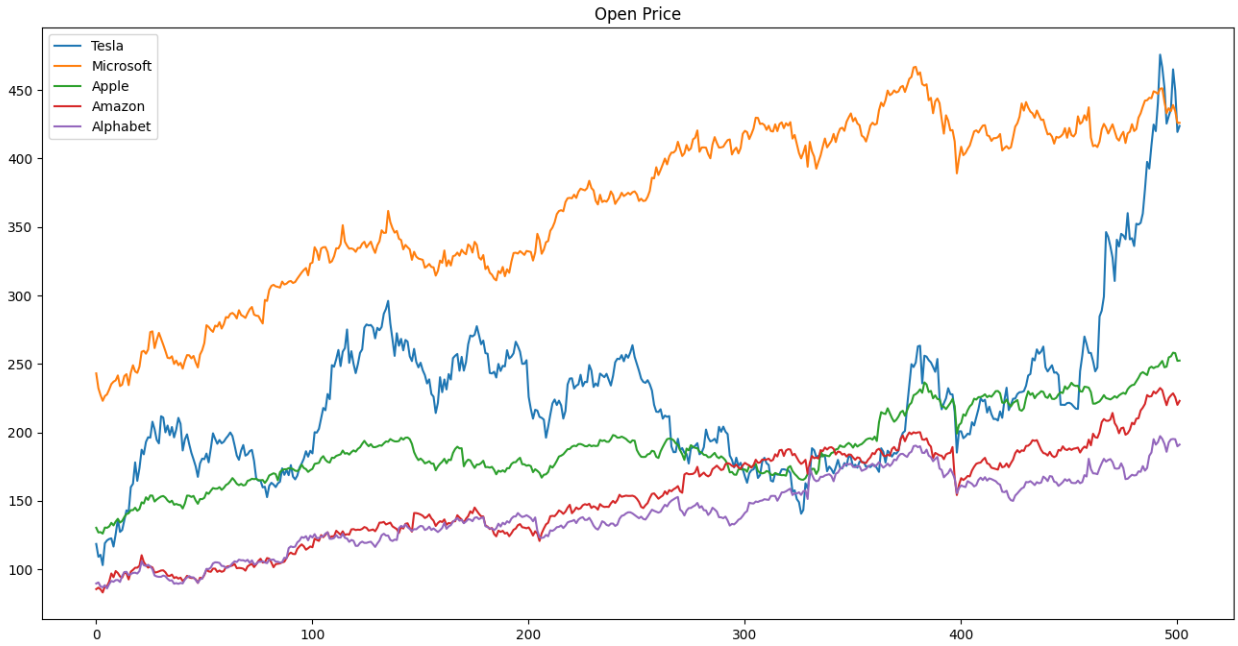

Fig 4: All the stocks' Open price

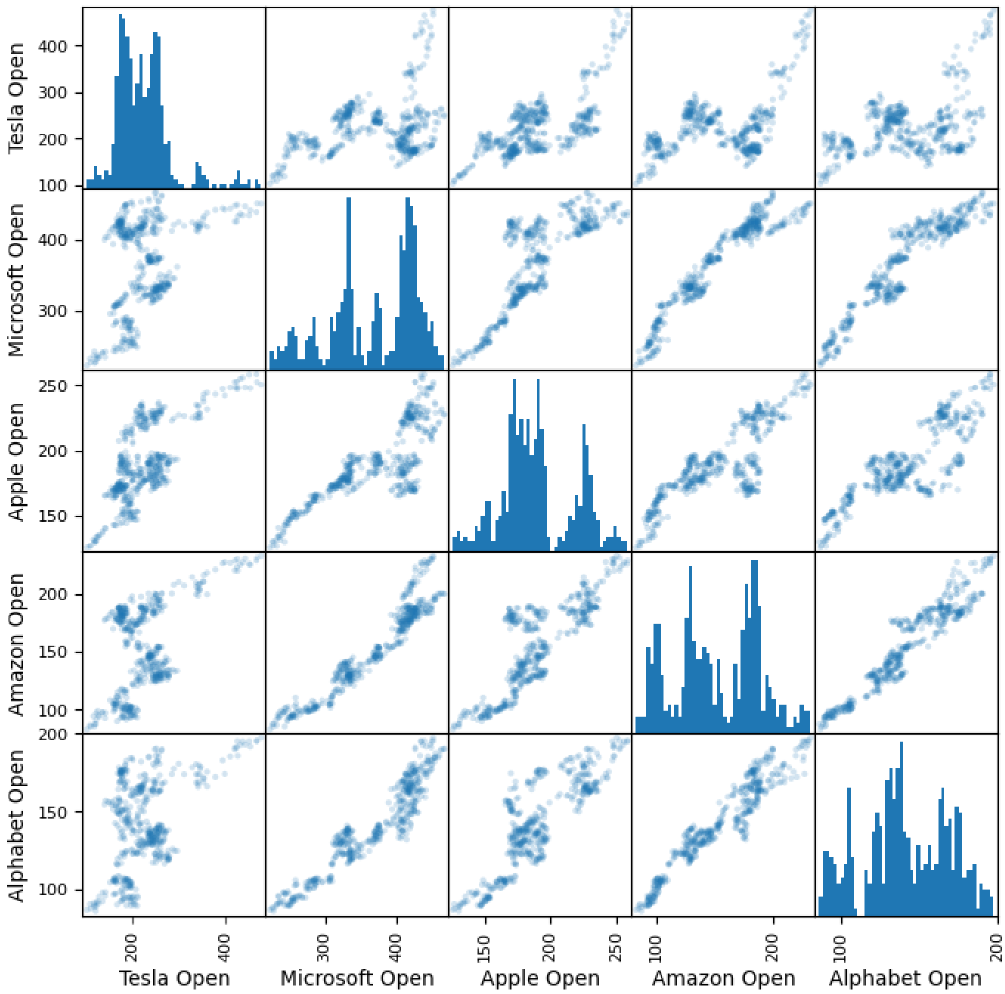

Fig 5: Scatter matrix among the selected assets

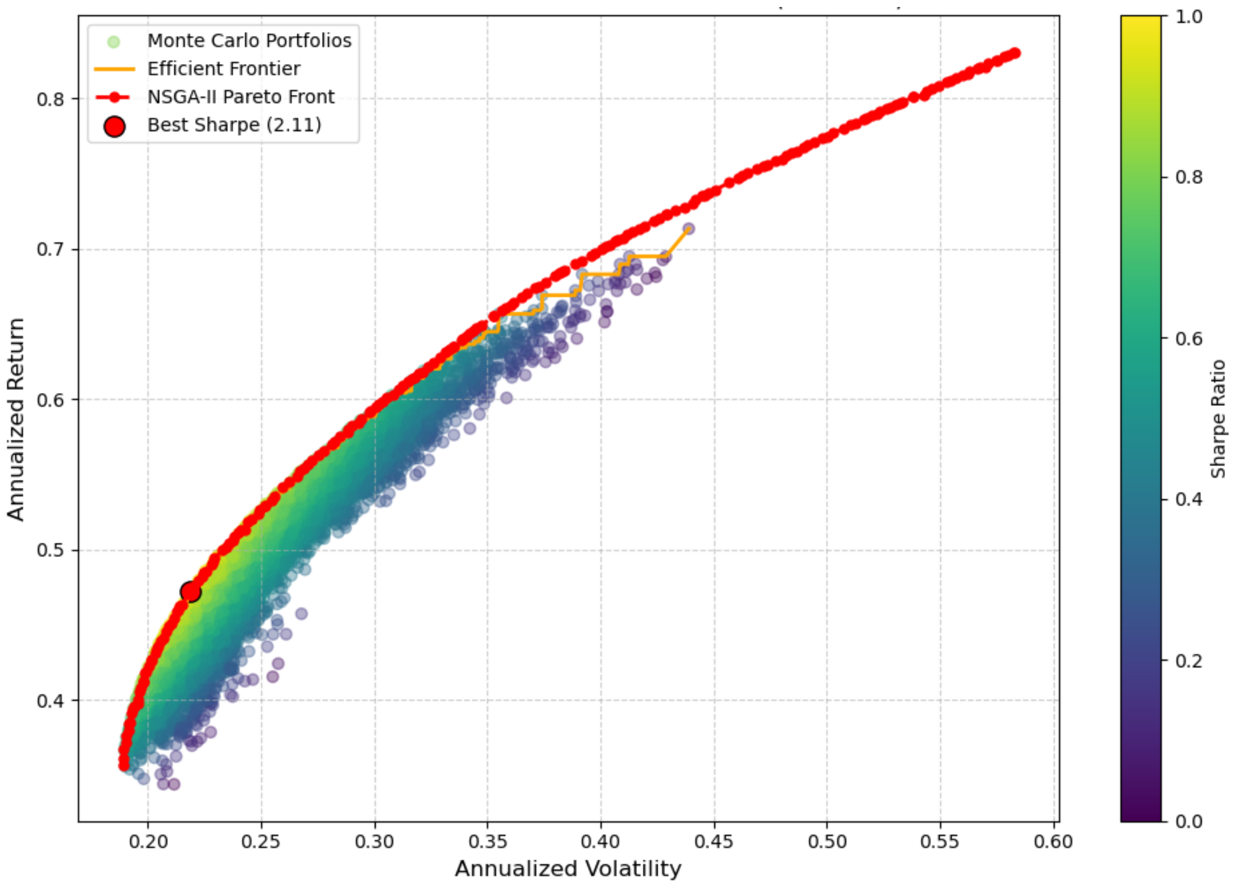

Fig 6: Efficient Frontier

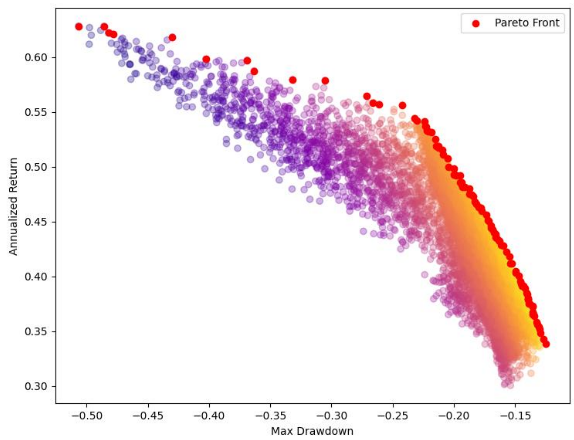

Fig 7: Return Vs. Max Drawdown

Fig. 7 shows Return Vs. Max Drawdown. Fig. 8 shows Sortino Ratio. Fig. 9 depicts CvaR vs. Volatility. Fig. 10 shows Calmar Ratio. The integration of the Sortino Ratio, Maximum Drawdown, Calmar Ratio, and CVaR into portfolio evaluation reveals that while aggressive, high-return strategies can yield annual gains exceeding 60%, they expose investors to significant "tail risk," characterized by a Maximum Drawdown of over 50% and a Conditional Value at Risk (CVaR) indicating expected losses of 6.71% on the worst days. In contrast, evaluating the portfolio through the lens of the Calmar and Sortino Ratios identifies a more efficient middle ground where portfolios achieve robust annualized returns (approx. 34–40%) while maintaining a much lower "pain threshold," with drawdowns limited to roughly 12–15%. By specifically penalizing downside deviation rather than total volatility and measuring the return relative to the steepest historical price drops, these metrics demonstrate that the most optimized tech-heavy portfolios provide superior risk-adjusted stability compared to more volatile, high-beta allocations that suffer from diminished recovery potential and greater exposure to catastrophic shortfalls.

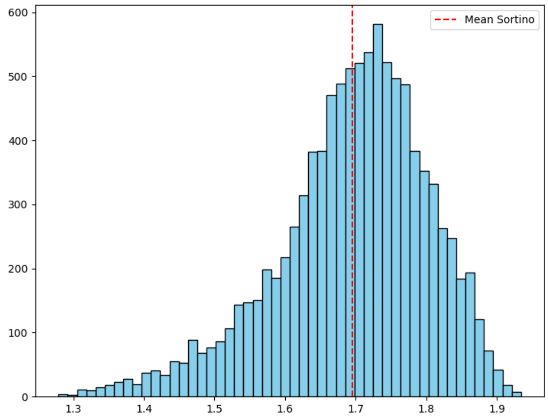

Fig 8: Sortino Ratio

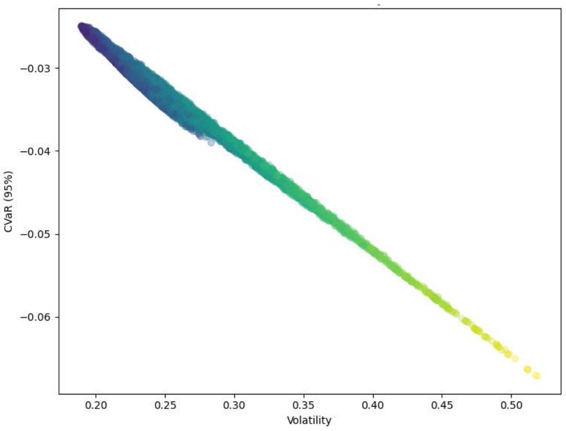

Fig 9: CvaR vs. Volatility

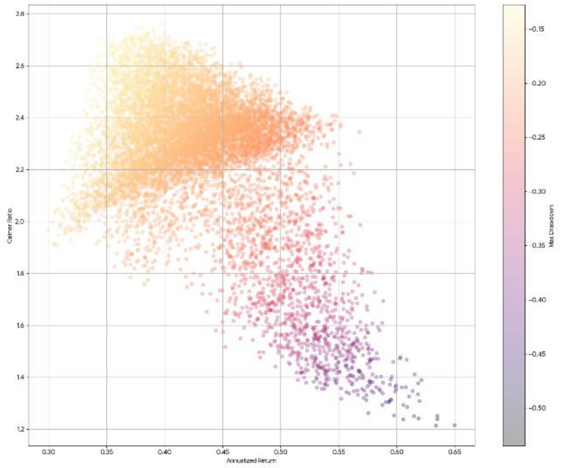

Fig 10: Calmar Ratio

4. CONCLUSION AND FUTURE WORK

This paper demonstrated the effectiveness of integrating Modern Portfolio Theory with advanced optimization techniques, including Monte Carlo simulation and NSGA-II, to construct robust and efficient financial portfolios. The results showed strong consistency across all methods, with NSGA-II achieving a best Sharpe ratio of approximately 2.113, reflecting early convergence and high stability. Pareto-front analysis highlighted a consistent dominance of large-cap technology stocks, particularly Apple and Amazon, across optimized portfolios, while Microsoft often acted as a stabilizing asset and Tesla appeared primarily in higher-risk allocations. The convergence of different optimization approaches toward the same efficient region underscores the robustness of the portfolio structure and reflects a market environment favoring major technology leaders. The combination of simulation and AI techniques proved highly effective in balancing risk and return, enhancing decision-making in complex financial landscapes.

Several avenues exist to extend and refine this research. Expanding the portfolio universe beyond a small set of technology stocks to include multiple sectors, international equities, bonds, commodities, and alternative assets would allow for deeper diversification analysis. Incorporating dynamic or regime-switching models could capture shifting market conditions and assess the stability of optimization results under varying volatility environments. Future work may also integrate advanced machine learning models, such as reinforcement learning, deep neural networks, or transformer-based predictors, to improve forecasts of returns, volatility, or covariance structures. Introducing realistic constraints, such as transaction costs, liquidity limits, or carbon-risk metrics, would enhance practical applicability, while real-time optimization or deployment as an interactive decision-support tool could further increase the system's value for investors and financial analysts.

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