Portfolio Optimization

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***Abstract*—This study aims to evaluate different algorithmic approaches for making optimal investment decisions in financial markets. By utilizing stock data from ten distinct sectors, portfolios with the best risk-return profiles are constructed using three different optimization algorithms: Genetic Algorithm, Hill Climbing, and Constraint Satisfaction Problem (CSP). The study compares the performance of these algorithms in terms of portfolio diversification, expected return, and risk minimization.**

***Index Terms*—portfolio optimization, financial time series, genetic algorithm, hill climbing, constraint satisfaction problem, volatility, diversification, exploratory data analysis, modern portfolio theory**

I. Presentation And Demo Video Link

https://drive.google.com/drive/folders/18bmV_MzDPnvnD9tSJYBadTcq9neAoj5K?usp=sharing

II. Introduction And Literature Review

In today's dynamic financial markets, making optimal investment decisions is essential for both individual and institutional investors. Portfolio optimization, which focuses on selecting the most suitable combination of financial assets to maximize return while minimizing risk, remains a central problem in finance. With the growing accessibility of financial data and the development of algorithmic methods, computational approaches to portfolio optimization have gained increasing importance.

One of the foundational theories in portfolio optimization is Modern Portfolio Theory (MPT), introduced by Markowitz (1952) [6]. This theory aims to maximize expected return while minimizing portfolio risk, emphasizing the benefits of diversification through the consideration of correlations among assets. According to MPT, investors can construct optimal portfolios based on their individual risk-return preferences.

In recent years, environmental, social, and governance (ESG) factors have gained significant importance in investment decision-making. The study by Hachmi Ben Ameur et al. (2024) demonstrates that green investments can enhance diversification and contribute to risk reduction by using mean conditional value-at-risk optimization methods [7]. Another critical topic is determining the ideal number of stocks for achieving effective diversification. Statman (1987) found that the benefits of diversification diminish beyond a certain number of stocks in a portfolio [8]. Moreover, sector-based diversification has been shown to provide different advantages depending on investors' risk perceptions. According to Yaman and Tunçel (2025), allocating investments across various sectors can help mitigate risk and improve portfolio performance under varying market conditions [9].

Although the field of portfolio optimization encompasses a wide range of studies and conflicting viewpoints, this project will particularly adopt the Constraint Satisfaction Problem (CSP) approach to address sector allocation. Furthermore, for each model implemented, the project will present an analysis of balanced versus unbalanced portfolios based on stock distribution.

This project aims to evaluate and compare different algorithmic techniques for constructing optimal investment portfolios. Stock data from ten distinct sectors—comprising a total of 36 stocks—were collected, and three optimization algorithms were employed: Genetic Algorithm (GA), Hill Climbing (HC), and Constraint Satisfaction Problem (CSP). The historical closing prices (Close) of the selected stocks were retrieved via Yahoo Finance. To prepare the dataset, an extensive data preprocessing and exploratory data analysis (EDA) phase was performed as detailed in Subsection III-C.

Each algorithm takes as input the closing prices of the stocks and a predefined risk-free rate, which is used in the calculation of the Sharpe Ratio—a widely used metric for evaluating portfolio performance. The risk-free rate is derived from U.S. government bonds and is assigned as a default, independent of the portfolio selection process.

The output of each algorithm includes the optimal portfolio weights, selected stocks, expected return, risk level, and Sharpe Ratio. These metrics enable analysis of each portfolio and facilitate direct comparison of the effectiveness of algorithms in achieving the desired risk-return balance.

III. METHODOLOGY

A. Data Collection

A total of 36 stocks representing ten different sectors (see Fig. 1) were selected and their historical closing prices were retrieved from Yahoo Finance. The selected sectors and corresponding tickers are:

- **Technology**: AAPL, MSFT, NVDA, GOOGL
- **Healthcare**: JNJ, PFE, UNH, MRNA
- **Financials**: JPM, BAC, GS, V
- **Consumer Discretionary**: AMZN, TSLA, NKE, MCD
- **Consumer Staples**: PG, KO, WMT, UL
- **Energy**: XOM, CVX, BP, NEE

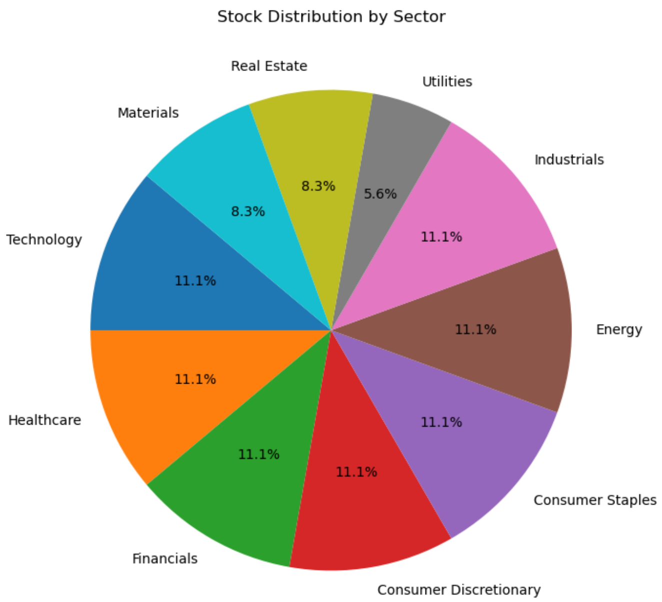

Fig. 1. Percentage distribution of stocks by sector

- **Industrials**: GE, CAT, BA, HON
- **Utilities**: DUK, SO
- **Real Estate**: AMT, SPG, O
- **Materials**: FCX, DOW, LIN

Each stock was chosen to represent its sector, enabling analysis of both within-sector similarities and cross-sector diversification.

B. Data Preprocess

Data preprocess contains handling missing values and calculating return processes for the collected data.

1) Handling Missing Values: In time series analysis, dropping rows with missing values is not generally recommended, as it can distort temporal continuity. Instead, the forward-filling method is preferred, where missing entries are replaced with the most recent available value. However, for the chosen date range and tickers in this project, no missing values were present, so no imputation was necessary. Nonetheless, the possibility of missing values should be considered, especially when working with assets across different markets, different countries where market operating days may vary, or continuous assets such as cryptocurrencies.

2) Return Calculations: Rather than using percentage change, logarithmic returns were employed in this project due to their symmetrical properties. Log returns ensure that equivalent upward and downward movements result in consistent interpretability, which is vital for statistical modeling. They also facilitate normality assumptions in financial modeling.

C. Exploratory Data Analysis (EDA)

In this study, daily closing prices of various stocks traded on the United States (USA) stock markets were used. This data is in the form of time series data collected regularly over a certain period of time. Closing prices reflect the market value of stocks at the end of the day and play a role in calculating return rates and risk analysis. Time series data, arranged in date order, allows examining the past performance of stock prices and predicting future movements. This data set was used to provide a risk-return balance in the portfolio optimization process and to determine the best investment strategies.

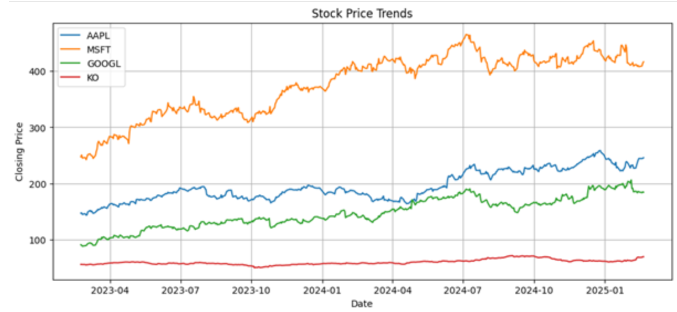

Fig. 2. Stock price trends (Not all 36 stocks are shown for complexity reduction in visualization)

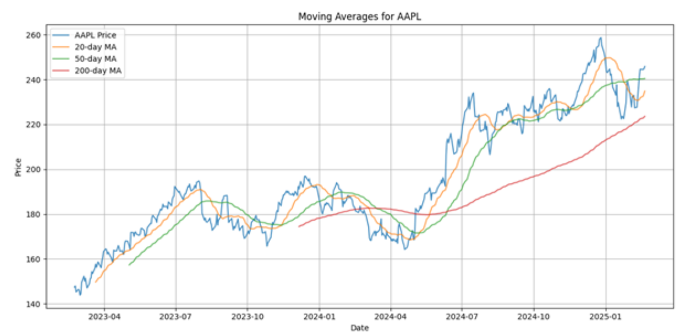

Fig. 3. Moving averages on AAPL stock examined over different time periods

1) Trend Analysis: Initial trend plots were generated to explore the price trajectories of selected stocks. For example, in Fig 2, AAPL, MSFT, and GOOGL—belonging to the Technology sector—demonstrated similar trends, while KO, from Consumer Staples, exhibited a more stable behavior. This contrast emphasized the importance of sectoral diversification in portfolio construction.

2) Rolling Statistics: Moving Average, Rolling Volatility and Rolling Correlation analyses were performed using a moving window to smooth out price fluctuations. With these analyses, trends and volatility became more understandable.

- **Moving Average (MA)**: Smoothed price series using sliding windows to detect trends. In Fig. 3, illustrates the moving averages for AAPL across different time windows to produce and observe smoother trend lines.
- **Rolling Volatility**: Computed standard deviation within a moving window to capture short-term fluctuations. See Fig. 4.
- **Rolling Correlation**: Measured how closely stocks moved together over time. In Fig. 5, AAPL and MSFT

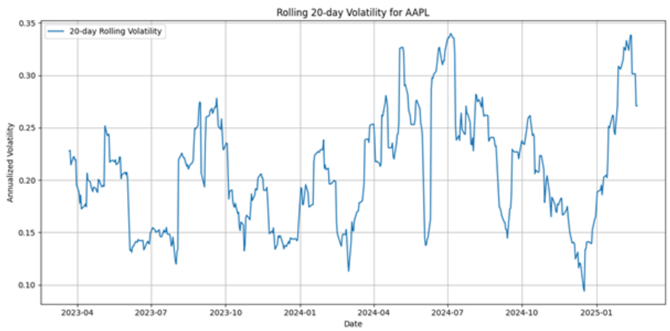

Fig. 4. Moving volatility values of APPLE calculated with 20-day time period

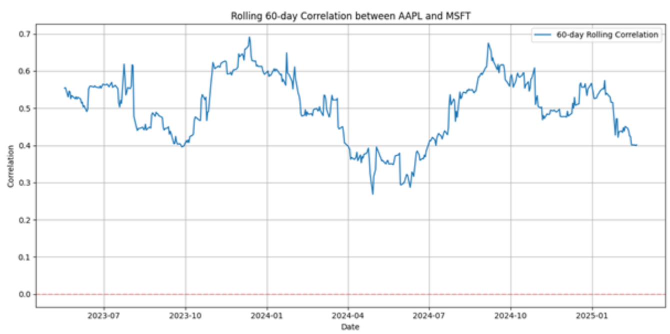

Fig. 5. Correlation relationship between two stocks from the same sector (Technology)

show strong positive correlation as both belong to the Technology sector, while in Fig. 6, AAPL and XOM demonstrate much weaker correlation, reflecting their sectoral differences.

These rolling analyses highlighted the evolving relationships and risks between different stocks, especially within or across sectors.

3) Return Distributions: To gain further insights into the behavior of returns Kernel Density Estimation and Boxplots were used. As a general conclusion, while stocks within the same sector generally show similar return distributions, cross-sector comparisons reveal more variability.

Kernel Density Estimation (KDE) was used to analyze the distribution of returns of different stocks. The reason

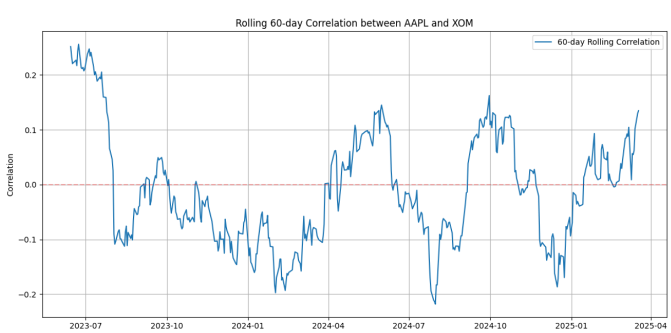

Fig. 6. Correlation relationship between two stocks from different sectors

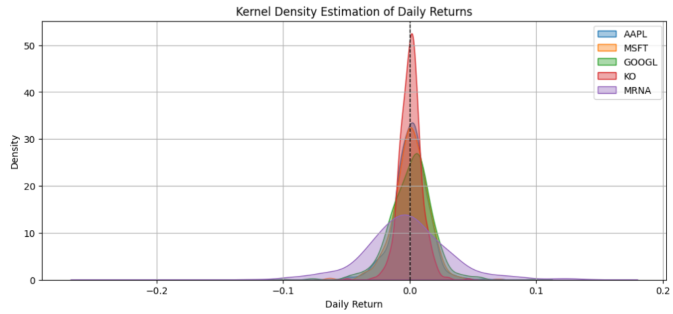

Fig. 7. Kernel Density Estimation of Daily Returns for Selected Stocks

for using KDE instead of histogram is that it provides a visually more interpretable and less complex output. In the return distributions, it was observed that the selected stocks offered different returns. This diversity provides an important advantage for portfolio diversification and offers different risk profiles.

In Fig. 7, the daily return distributions of selected stocks are visualized using Kernel Density Estimation. Stocks from the Technology sector (AAPL, MSFT, GOOGL) exhibit relatively similar, sharp-peaked distributions centered around zero, indicating moderate volatility and frequent small fluctuations. In contrast, MRNA, a Healthcare stock, displays a wider and flatter distribution, suggesting higher volatility and greater deviation from the mean. KO, from the Consumer Staples sector, shows a narrow and steep peak, implying more stable and less volatile returns. This analysis highlights how sectoral characteristics are reflected in return behavior and underscores the importance of diversification in portfolio construction.

Figure 8 allows for a comparison of spread, median, and outliers. The stocks are the same as in Fig. 7 and it is possible to see that Figure 7 and Figure 8 support each other. MRNA displays the widest interquartile range and the largest number of extreme values, confirming its high volatility as already suggested by its flatter KDE curve. In contrast, KO has the narrowest box and fewer outliers, reinforcing its role as a stable stock with lower risk. The Technology stocks (AAPL, MSFT, GOOGL) exhibit moderate variability, with symmetrical distributions and relatively few extreme returns. This visualization supports the prior KDE analysis and highlights the different risk profiles that each stock brings to a portfolio.

4) Correlation and Diversification: A correlation heatmap was generated to identify relationships between stock returns. Stocks from the same sector were lined up one after the other to make observation easier. It confirmed high correlations among stocks from the same sector (e.g., AAPL and MSFT) and lower correlations between stocks from different sectors (e.g., AAPL and MRNA). These patterns supported the importance of diversification as a risk mitigation strategy.

5) Autocorrelation Analysis: Autocorrelation functions (ACF) were applied to both closing prices and log returns. Results showed that while closing prices had significant positive autocorrelation at short lags, log returns were largely

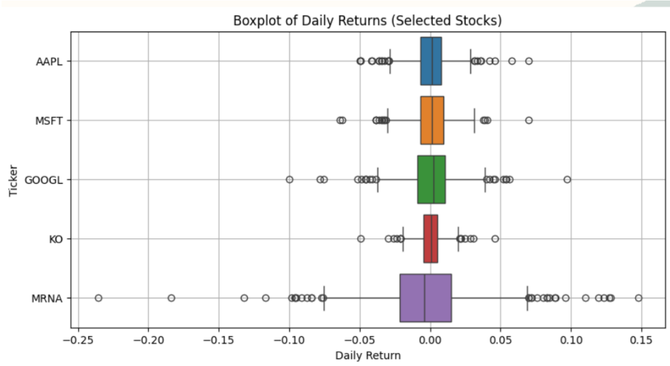

Fig. 8. Boxplot of Daily Returns for Selected Stocks

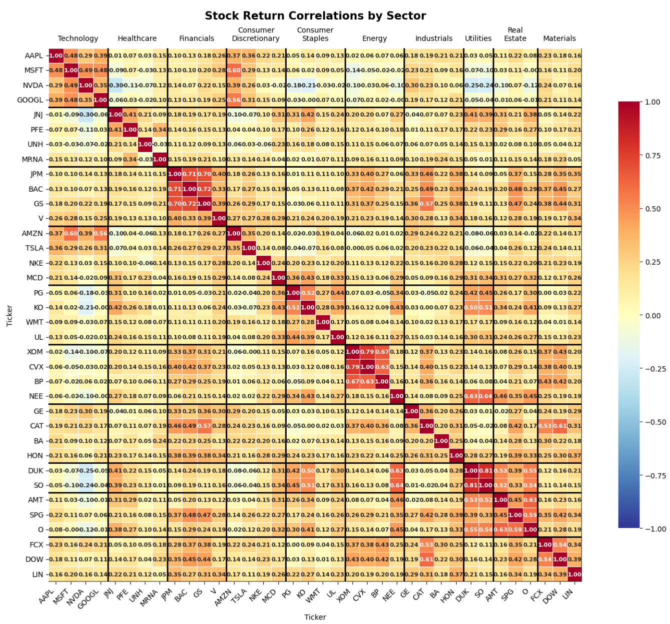

Fig. 9. Correlation heatmap of stocks

uncorrelated, validating the common assumption that returns behave like a white noise process. (See. Fig 10)

The EDA (Exploratory Data Analysis) process provides insights into why certain portfolio metrics, such as return or risk, are performing the way they are and can guide improvements. However, as discussed in III-C5 , future

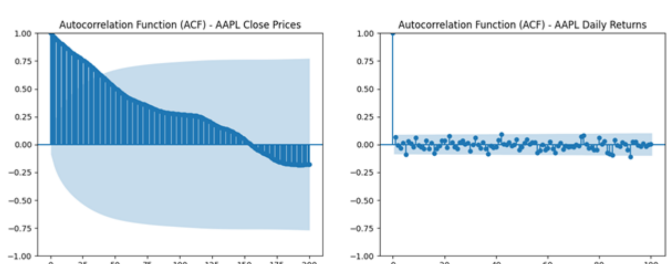

Fig. 10. Autocorrelation Function (ACF) results for AAPL closing prices and daily logarithmic returns

returns are inherently unpredictable in real-world financial markets. While risk-reducing strategies such as diversification are implemented during portfolio construction, the uncertainty of market dynamics means that results may not always be in line with expectations.

D. Portfolio Optimization Algorithms

1) Genetic Algorithm: The Genetic Algorithm (GA) is a population-based search method inspired by the principles of natural selection. In its general form, GA involves the creation of an initial population, ranking individuals based on a predefined fitness function, generating new individuals from the fittest members, and iteratively continuing this process until a defined stopping criterion is met.

In the literature, GA has been widely applied to portfolio optimization tasks, often in more advanced forms that integrate real-world constraints [1], [2], [3]. For instance, the study "Applications of Genetic Algorithm to Portfolio Optimization with Practical Transaction Constraints" [1] focuses on incorporating transaction costs, while "Selection of Optimal Investment Portfolios with Cardinality Constraints" [3] addresses limitations on the number of assets in a portfolio.

In this project, the implementation of GA deviates from traditional approaches, particularly in the selection and reproduction mechanisms. The principle of "survival of the fittest" is strictly applied—individuals not meeting the fitness threshold are directly removed from the population and have no influence on future generations. While mutation is retained as in classic implementations, its behavior is adjusted to align with this stricter selection framework.

Workflow of the Genetic Algorithm implemented in this study is as follows:

- **Initialization**: A random population of portfolio weights is generated.
- **Evaluation**: The Sharpe Ratio is calculated for each portfolio and used as the fitness function.
- **Selection**: The top 50% of portfolios based on Sharpe Ratio are retained. This strict filtering ensures that only the most efficient portfolios survive.
- **Crossover**: New portfolios are generated by combining weights from selected portfolios using arithmetic crossover. The alpha parameter determines the contribution of each parent.
- **Mutation**: Random changes are introduced to the new portfolios with a mutation probability of 0.1. This helps avoid premature convergence to local optima.
- **Iteration**: The evaluation, selection, crossover, and mutation steps are repeated until a maximum generation limit or a convergence threshold is reached.

Unlike traditional GA implementations where the entire population may influence the next generation, this project restricts reproduction to the top 50% of individuals. This is intended to improve the likelihood of achieving higher risk-adjusted returns in future generations.

Limitations of the Genetic Algorithm are stated below under the current conditions of the study.

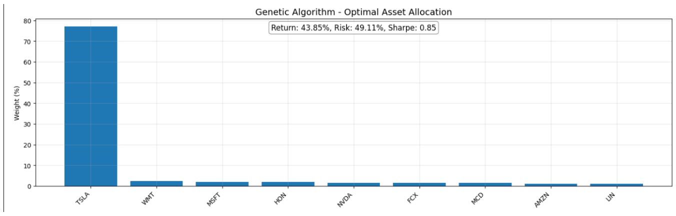

Fig. 11. Optimal asset allocation after performing Genetic Algorithm

- **Computational Limitations**: The GA implementation in this project required significant computational time for convergence. Due to hardware limitations, constraints were placed on population size and the number of generations, potentially preventing the algorithm from reaching a global optimum. The Sharpe Ratio showed incremental improvements even near the stopping point, suggesting better results might be possible with extended runs.
- **Design Trade-offs**: If the imposed limitations are not critically restrictive, the unconventional design choices—particularly in selection and reproduction—may have reduced the algorithm's efficiency compared to standard implementations. The results obtained using the Hill Climbing method suggest that the issue is not with the stock pool itself.
- **Lack of Real-World Constraints**: Another major limitation is the algorithm's inability to account for real-world constraints. As illustrated in the results, the portfolio is heavily concentrated in a single asset, violating the principle of diversification and increasing overall portfolio risk. This motivates the integration of constraint-based optimization, which is addressed in the later stages of this project using the Constraint Satisfaction Problem (CSP) framework.

The asset allocation of the Genetic Algorithm's output optimal portfolio (Fig. 11) reveals a severe concentration issue, with over 75% of the total weight allocated to a single stock—TSLA from the Consumer Discretionary sector. While the remaining assets, such as WMT (Consumer Staples), MSFT and NVDA (Technology), and others from sectors like Industrials, Materials, and Healthcare, are present, their individual contributions are minimal and collectively do not provide meaningful diversification. Sector-wise, the portfolio is overwhelmingly dominated by Consumer Discretionary, leading to increased exposure to asset-specific and sector-specific risk. This imbalance is reflected in the portfolio's high annual risk (49.11%) and a relatively low Sharpe Ratio of 0.85, despite having a comparable expected return (43.85%) to other methods. The lack of constraint enforcement in the Genetic Algorithm clearly impacts its effectiveness in producing a practically viable portfolio.

2) Hill Climbing: Hill Climbing is a local search-based heuristic optimization method frequently employed in portfolio optimization problems. As observed in the literature [4], [5], heuristic methods such as Threshold Accepting and Hill Climbing have proven to be viable alternatives to traditional models like Markowitz. For example, in [4], a heuristic approach applied to the Milan Stock Market achieved results within a 4.1% error margin compared to the Markowitz model.

Hill Climbing begins with an initial solution and iteratively explores its neighborhood in search of improvements. In this project, each solution represents a portfolio weight vector, and neighboring solutions are generated by applying small changes to the weights. These changes aim to produce portfolios with higher Sharpe Ratios.

Workflow of the Hill Climbing implemented in this study is as follows:

- **Initialization**: The algorithm starts with a randomly generated portfolio weight vector.
- **Evaluation**: The Sharpe Ratio of the current portfolio is calculated to evaluate fitness.
- **Neighbor Generation**: Neighboring portfolios are created by slightly modifying the current weights. The adjustment step size is adaptive and decreases over iterations, allowing for fine-tuning in later stages.
- **Selection**: If a neighbor with a higher Sharpe Ratio is found, it replaces the current portfolio as the new solution.
- **Iteration**: The process continues until no improvement is observed or a predefined stopping criterion is met.

The adaptive step size mechanism, similar to simulated annealing, enables broader exploration in the early stages and more precise refinements in the later iterations. The performance of the algorithm, in terms of Sharpe Ratio improvements, has shown to be noticeably superior compared to the Genetic Algorithm in this implementation. Although the Genetic Algorithm also exhibits a gradual improvement trend, the Hill Climbing method was able to achieve significantly higher Sharpe Ratios within fewer iterations.

Limitations of the Hill Climbing are stated below.

- The resulting portfolio weights and observed level of diversification suggest that Hill Climbing, in this case, outperformed the Genetic Algorithm in optimizing risk-adjusted returns.
- However, a major limitation of Hill Climbing is its sensitivity to initial conditions. Since it is a greedy algorithm, starting from different initial portfolios may lead to different local optima, and the method does not guarantee consistent results across multiple runs.
- Additionally, the algorithm may become trapped in local maxima and lacks mechanisms to escape them. Moreover, similar to GA, Hill Climbing does not inherently consider real-world investment constraints such as maximum asset weights, which can result in excessive allocation to a single stock. This can compromise diversification and expose the portfolio to higher volatility.
- Especially under volatile market conditions, the portfolio's performance may become overly dependent on a few assets. Therefore, despite its relatively better performance in this project, the results should not be interpreted as universally stable or robust.

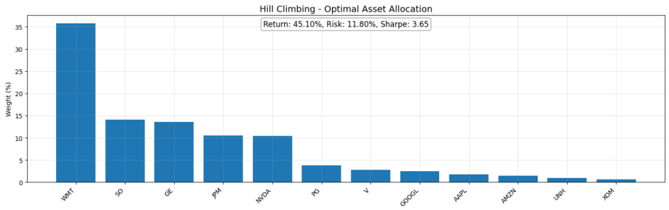

Fig. 12. Optimal asset allocation after performing Hill Climbing

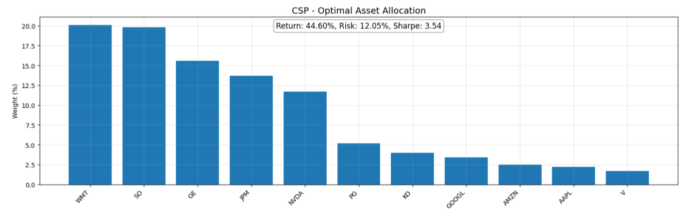

Fig. 13. Optimal asset allocation after performing CSP approach

- To address these shortcomings, the next phase of this project proposes the use of the Constraint Satisfaction Problem (CSP) framework. The primary constraint to be integrated involves placing upper thresholds on individual asset weights to ensure better diversification and risk control.

The asset allocation of the Hill Climbing optimal portfolio (Fig. 12) displays a more balanced distribution compared to the Genetic Algorithm, though some concentration remains. The largest allocation is given to WMT (Consumer Staples), accounting for over 35% of the portfolio, followed by SO (Utilities), GE (Industrials), JPM (Financials), and NVDA (Technology), each with moderate weights. While diversification is better than in the Genetic Algorithm output, the portfolio still demonstrates partial concentration risk, particularly in its overweight position in WMT.

From a sectoral perspective, the portfolio spans a variety of sectors including Consumer Staples, Utilities, Industrials, Financials, Technology, and Healthcare. This broad sector exposure contributes to risk reduction and improved portfolio robustness. The portfolio achieves a high expected return of 45.10% and a relatively low risk of 11.80%, resulting in a strong Sharpe Ratio of 3.65— the highest among the three optimization methods. Despite the absence of explicit constraints, Hill Climbing managed to generate a well-performing and reasonably diversified portfolio, although some real-world restrictions (e.g., maximum stock/sector exposure) were not enforced.

3) Constraint Satisfaction Problem (CSP) Approach: To address the limitations observed in previous methods—particularly the lack of diversification and disregard for real-world constraints—a Constraint Satisfaction Problem (CSP)-based approach was implemented for portfolio optimization. Unlike Genetic Algorithm and Hill Climbing, which operate primarily as heuristic optimizers, this method formulates the problem as a constrained optimization task solved using the Sequential Least Squares Programming (SLSQP) algorithm provided by the SciPy library.

The objective of the CSP formulation is to maximize the portfolio's Sharpe Ratio while enforcing practical constraints on asset and sector-level allocations. The core of the method minimizes the negative Sharpe Ratio, defined as the excess return over the risk-free rate divided by the portfolio's standard deviation.

To reflect realistic investment policies, two key constraints are applied:

- The weight of any single stock is limited to a maximum of 20%.
- The cumulative weight of any sector is restricted to a maximum of 30%.

Additionally, a standard constraint ensures that the sum of all portfolio weights equals one. Sector-based constraints are dynamically defined by grouping stocks under their respective sectors and enforcing the sector-level upper bounds accordingly. Stock weights are further constrained through individual bounds, and initial portfolio weights are evenly distributed across all assets.

Although the optimal portfolio obtained through Hill Climbing achieved a higher Sharpe Ratio of 3.74, the CSP-based method produced a competitive result with a Sharpe Ratio of 3.53. Despite falling slightly short in numerical performance, the CSP approach offers an advantage by incorporating real-world constraints, leading to a more balanced and diversified portfolio with reduced overall risk. This demonstrates that the method not only achieves strong risk-adjusted returns but does so within practical investment boundaries.

The asset allocation of the CSP's output optimal portfolio (Fig. 13) demonstrates a well-diversified structure, with no single asset exceeding the 20% weight limit. The highest allocations are given to WMT (Consumer Staples) and SO (Utilities), each capped at approximately 20%, followed by GE (Industrials) and JPM (Financials). The portfolio includes stocks from various sectors such as Technology (NVDA, AAPL, GOOGL), Financials (JPM, V), Consumer Staples (WMT, KO, PG), and Utilities (SO), ensuring a balanced sector exposure. This distribution reflects the enforcement of sector-level constraints and results in a strong risk-adjusted performance with a return of 44.60%, risk of 12.05%, and Sharpe Ratio of 3.54.

IV. Performance Comparison

The experimental results reveal that the Genetic Algorithm consistently underperforms compared to the other methods in terms of Sharpe Ratio. Despite showing improvements across iterations, the algorithm was unable to surpass a Sharpe Ratio of 1. In many trials, it even yielded negative Sharpe Ratios, indicating suboptimal portfolio configurations. This underperformance is further reflected in the portfolio's structure, where over 75% of the total allocation was concentrated in a single asset (TSLA), significantly violating diversification principles. Hill Climbing, while producing a notably higher Sharpe Ratio of 3.74, still resulted in a concentrated portfolio with more than 35% allocated to WMT. In contrast, the CSP approach, with a Sharpe Ratio of 3.53, maintained both strong performance and adherence to practical constraints, such as capping individual stock and sector weights. The comparative analysis underscores that, while heuristic methods may offer potential, constraint-based optimization provides a more reliable and risk-aware strategy for real-world portfolio construction.

V. Conclusion

The comparative analysis of the three portfolio optimization methods—CSP, Genetic Algorithm, and Hill Climbing—demonstrates clear trade-offs between performance and constraint satisfaction. As shown in Table I, Hill Climbing achieved the highest Sharpe Ratio (3.65) and the highest expected return (45.10%) with a relatively low risk level (11.80%), making it the best-performing method in terms of pure numerical output. The CSP approach closely followed with a Sharpe Ratio of 3.54 and the lowest portfolio risk (12.05%), while also ensuring real-world applicability through strict stock- and sector-level constraints. On the other hand, the Genetic Algorithm, despite being a popular heuristic technique, underperformed significantly with a Sharpe Ratio of only 0.85 and a high volatility of 49.11%. These results highlight that while heuristic methods may offer flexible search capabilities, constraint-based optimization provides more stable and risk-aware portfolio configurations. Overall, the CSP method stands out as a strong candidate for practical portfolio design, balancing return, risk, and regulatory constraints effectively.

TABLE I
Portfolio Metrics Summary

Algorithm	Expected Return (%)	Risk (%)	Sharpe Ratio
CSP	44.60	12.05	3.54
Genetic Algorithm	43.85	49.11	0.85
Hill Climbing	45.10	11.80	3.65

Figures 14, 15 and 16 allow for the examination and overall comparison of annual return, volatility, and Sharpe Ratio across all three algorithms.

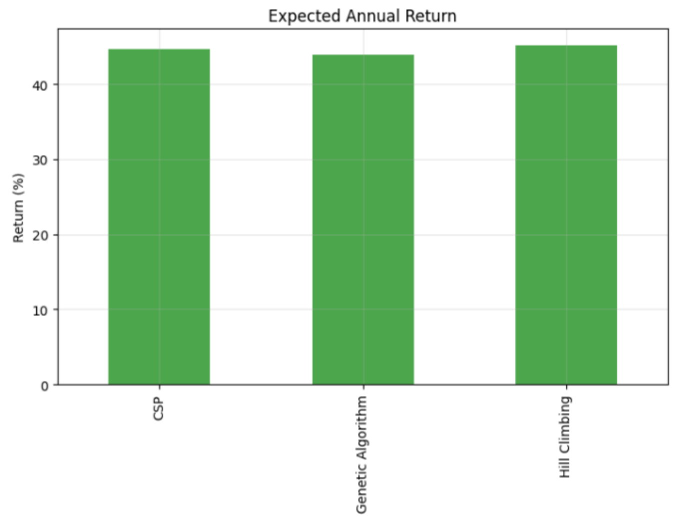

Fig. 14. Expected annual return for the optimal portfolio output of each algorithm

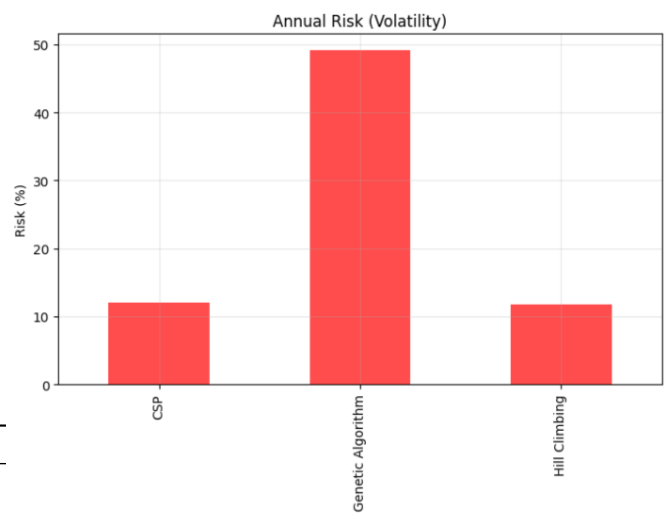

Fig. 15. Volatility for the optimal portfolio output of each algorithm

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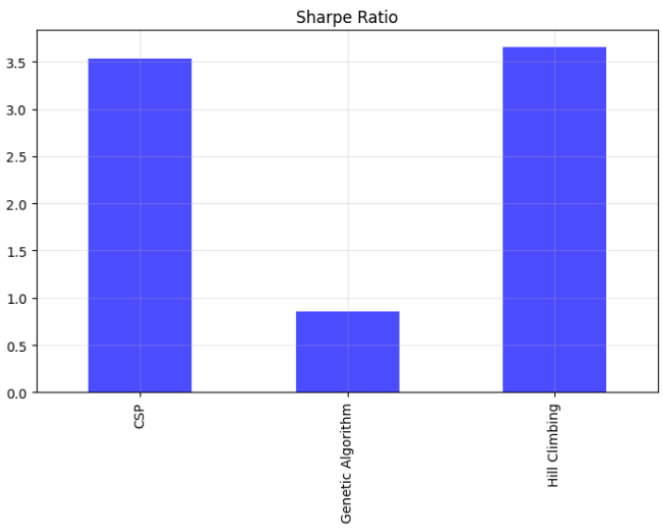

Fig. 16. Sharpe Ratio for the optimal portfolio output of each algorithm