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Optimisation Techniques in Investment Risk Management :Scipy, SLSQP and Modern Portfolio Theory

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***Abstract*—Organizations achieve successful investment risk management by achieving optimal risk exposures and return objectives at the same time. The research examines optimization methodologies through its comparison of SciPy's optimization suite to SLSQP while incorporating Modern Portfolio theory. This research analyzes historical financial data to examine both risk-adjusted return metrics along with computational efficiency metrics. The research study provides detailed mathematical definitions about optimization procedures and performs quantitative assessments on data output and suggests future work that integrates machine learning with economic domains. The research demonstrates that these optimization approaches present critical methods to achieve maximum portfolio diversity.**

***Index Terms*—Investment Risk Management, Portfolio Optimization, SciPy, SLSQP, Modern Portfolio Theory**

I. Introduction

Prudent investment management requires a fragile balance between risk and return, as investors endeavour to build portfolios that align with their unique risk inclinations and financial targets. This paper looks at the work of optimization techniques, including SciPy's optimization libraries, Sequential Least Squares Programming, and Modern Portfolio Theory, to address the difficulties of investment risk management.

The review starts by giving an outline of the previously mentioned improvement strategies and their pertinence in the financial domain. This paper sets out to explore the goals of portfolio optimization by conducting a comprehensive survey of theoretical foundations and the practical applications of key optimization techniques.

The literature review highlights the foundational contributions of Markowitz's Modern Portfolio Theory (MPT), emphasizing its pivotal role in promoting portfolio diversification. The assessment examines both operational characteristics of SciPy optimization libraries embedded in Python in addition to their SLSQP algorithm implementation to solve financial optimization problems with nonlinear constraints. Financial optimization problems find solutions through SLSQP algorithm working alongside the SciPy Optimization libraries of Python.The SLSQP algorithm establishes a solution mechanism for solving nonlinear constrained problems. Research into this domain has led to an extensive growth of several optimization procedures functioned together to address the various problems appearing in this context. The optimization of risk-to-return ratios keeps itself as the fundamental organizational challenge.

The main objective of this research unifies different optimization strategies applied for investment risk management. This research evaluation shows multiple optimization approaches that management uses in investment risk handling. A mathematical review evaluates the fundamental equations of these tools and instruments. This analysis evaluates optimization methods by comparing economic performance results gathered from historical financial data.

This research performs a comprehensive examination of optimization methodologies. This paper explores risk management optimization approaches via a study of Python SciPy tools coupled with SLSQP algorithms and basics of Modern Portfolio Theory methods. These methods successfully construct an equilibrium between investment risk and return possibilities.

During 1952 Harry Markowitz developed Modern Portfolio Theory. The pioneering research from 1952 continues to define essential fundamental principles which benefit both theoretical disciplines. The mean-variance optimization approach designed by Markowitz gave birth to fundamental concepts required to build efficient portfolio designs. The efficient portfolios act as tools for investors who seek maximum returns with minimum risk.

Python users access the wide range of optimization algorithms through the SciPy optimization library which serves as a standard Python module. Users can obtain a complete functionality suite from the extensive optimization algorithm collection found in the SciPy optimization library. Users find the SLSQP method inside the SciPy optimization library alongside a large collection of optimization algorithms.

Testing the performance of these optimization techniques required examination of historical financial data obtained from the S&P 500 and NASDAQ indices. The portfolio optimization utilizes SciPy's optimize functions during its process. Integration of constraints including the requirement of non-negative asset amounts takes place within the process.

The included research contains a comparative evaluation of optimization methods. The research examines optimization approaches between SciPy's minimize function, SLSQP and Modern Portfolio Theory. The study aims to provide insights into their relative strengths, weaknesses, and suitability for different investment scenarios.

The findings of this paper emphasize the importance of optimization strategies in investment risk management, delivering a thorough review of the tools and methods utilized in the field. By combining theoretical principles with quantitative analysis of historical financial data, the study highlights the practical relevance of these techniques in achieving an optimal balance between risk and return.

Research in this domain has resulted in multiple studies yet an evaluation gap remains for understanding technique performance across different market circumstances. We conduct this analysis to bridge the existing knowledge gap through direct comparison between SciPy's SLSQP and MPT optimization tools using genuine market data sets.

Paper Organization: Section 2 provides a literature review, Section 3 details the methodology, Section 4 explains implementation, Section 5 presents results, Section 6 concludes the findings, and Section 7 explores future research directions.

II. Literature Review

Portfolio optimization has been a subject of broad examination in the field of investment risk management, with specialists and professionals investigating different methods to address the difficulties of adjusting risk and return.

The underpinning of Modern Portfolio Theory, laid out by Harry Markowitz in 1952, has been an original commitment to the field of portfolio optimization. Markowitz's mean-variance improvement structure laid the basis for developing effective portfolios that look to augment returns while limiting risk, making ready for huge headways in investment risk management.

The existing literature features the significance of optimization procedures in addressing the intricacies of investment risk management. Specialists have investigated an extensive variety of optimization models, dynamic methodologies, and computational arrangement calculations pertinent to different financial products and services, including portfolio management and credit risk analysis.

Python's SciPy optimization library has arisen as a conspicuous instrument for financial optimization tasks, giving a thorough set-up of improvement calculations, including the Sequential Least Squares Programming technique. SLSQP, specifically, has acquired consideration for its capacity to deal with nonlinear, constrained optimization issues, making it appropriate for financial optimization applications.[1][2][3][4]

The existing literature expects to expand upon the current examination by directing a near investigation of the improvement methods, SciPy's minimize function, SLSQP, and Modern Portfolio Theory, using historical financial data, to survey their performance on investment risk management. For this examination, the researchers have chosen notable securities exchange files, like the S&P 500 and NASDAQ, as intermediaries for the more extensive market execution, considering an exhaustive evaluation of the improvement methods with regard to genuine financial information.[1][3][5][4]

Various existing research works deliver beneficial insights but they omit complete evaluation of restrictions and practical implementation barriers that diminishes universal adoption. The research expands previous work by assessing both conventional optimization frameworks and heuristic strategies and machine learning methods to address scalability issues and flexibility weaknesses.

Notwithstanding the hypothetical advancements in portfolio improvement, analysts have likewise investigated the functional execution of these methods utilizing computational apparatuses and calculations. Python's SciPy optimization library, a broadly utilized open-source programming, gives an exhaustive set-up of optimization calculations, including the Successive Least Squares Programming strategy[3][6][4]. The Sequential Least Squares Programming (SLSQP) method now stands as an important solution for nonlinear constrained optimization. The method addresses nonlinear constrained optimization problems and functions as a valuable tool in financial optimization applications[3][4].

The analysis of investment risk through optimization techniques continues to drive ongoing research. Researchers assess multiple optimization approaches alongside their effectiveness in diverse investment contexts.

The research uses historical financial data together with stock market indices including S&P 500 and NASDAQ as database sources. The research makes use of optimization methods that utilize SciPy's minimize function, SLSQP algorithm, and Modern Portfolio Theory (MPT).

Statement optimization remains the key objective in contemporary financial research since Markowitz's foundational work[7] His introduction of the efficient frontier and the risk-return trade-off established key frameworks for selecting optimal portfolios through its development framework.

Beasley derives his work from Markowitz's research[2]while developing a comprehensive review of portfolio optimization models alongside solution approaches.

Recent studies have critiqued traditional diversification strategies, such as the naive 1/n portfolio allocation. These risk-management practices produce insufficient chances to achieve optimal returns after risk adjustments therefore requiring improved methodologies.

In the realm of index tracking, innovative methodologies have emerged. A new assessment method for partial index tracking emerges from García[6] through analysis of tracking frontier curvature. The work of Krink[5] adds differential evolution and combinatorial search techniques as enhancements to constrained index-tracking methods.

Lejeune and Samatli-Paç[4] present research on risk-averse enhanced index funds that outline key risk management issues facing index tracking. Li[8] extend this research by applying multi-objective immune algorithms to optimize index tracking while demonstrating the capabilities of contemporary computational approaches.

Portfolios witness increasing importance of machine learning techniques. Perrin and Roncalli[9] present a detailed examination of machine learning applications in their work. These methods demonstrate their capability for enhanced decision-making processes. The research by Yang[10] shows machine learning in equity portfolio management. These findings contribute additional possibilities for resource distribution systems.

Current practice shows the increasing popularity of heuristic solutions for complex portfolio management tasks. Woodside-Oriakhi[11][12] explore heuristic algorithms explore alternative methods to manage both cardinality constraints and portfolio rebalancing operations. Tiomoko[13] establish a new method that enhances portfolio performance.

Behavioral elements enter the analysis of portfolio strategies. Meade alongside Beasley[14] analyze how behavioral elements influence investment strategies. Research has shown momentum effects as fundamental behavioral factors which affect investment outcomes. Behavioral factors serve as essential players in determining portfolio success rates.

Investigating financial market predictions through Long Short-Term Memory models was the focus of Kumar Harish[15]. The investigation showed that LSTM successfully recognized time-based relationships which delivered enhanced accuracy in forecasting market financial patterns. This research demonstrates that advanced neural networks represent a powerful tool within financial engineering.

Kumar Harish[16] applied machine learning approaches in his 2024 work for forecasting commodity market gold prices. The research implemented predictive models that established new benchmarks in forecasting accuracy which provide concrete benefits to commodity market analysis.

TABLE I
SUMMARY OF LITERATURE REVIEW

Method/Approach	Application	Limitation
Modern Portfolio Theory (MPT) (Markowitz)	The effective frontier streamlines risk versus reward optimization.	This tool has limitations for scalability because it operates under fixed conditions while neglecting human behavior patterns.
SciPy Optimization Library (SLSQP)	The application of nonlinear constrained optimization brings solutions to financial problems.	The system faces difficulties when working with vast datasets while needing specialized adjustments.

III. METHODOLOGY

1. **Sharpe Ratio**
   The Sharpe Ratio measures the excess return per unit of risk for a portfolio. It is defined as:
   $$S(w) = \frac{R_p(w) - R_f}{\sigma_p(w)}$$
   where $R_p(w)$ is the portfolio return, R_f is the risk-free rate, and $\sigma_p(w)$ is the portfolio's standard deviation.

2. **Efficient Frontier**
   Efficient frontier displays portfolios delivering optimal returns for minimal risk. Data from multiple portfolios combines to create the efficient frontier between highest achievable returns and precise risk targets or lowest acceptable risks at set return levels.

Computational Details: The optimization took place within a Python software environment which operated on an Intel i7 processor utilizing 16GB RAM. The runtime patterns from SLSQP showed variability according to problem complexity but maintained an average execution time of 1 minute across medium-sized datasets.

The study analyzed past financial statistics including major stock market indexes of S&P 500 and NASDAQ. A minimize function from SciPy served to execute the optimization workflow. The framework through function delivers both flexibility and efficiency for optimizing processes. The optimization system included restrictions that all asset allocations needed to stay positive.

The study performed optimization analysis using both SciPy-based methods and Modern Portfolio Theory (MPT) to calculate the efficient frontier. The optimal portfolios represent all combinations which maximize eagerly anticipated yield at specific risk levels. The optimization process achieves either the minimum risk when targeting a particular return or maximizes return while maintaining a specified risk threshold. An efficient benchmark exists to help construct optimal solutions.

The researchers used essential performance indicators including risk-adjusted returns and portfolio volatility with diversification benefits to evaluate each optimization strategy's full systemic strength.

The study summarizes various optimization strategies used. The research used Sequential Least Squares Programming (SLSQP) alongside SciPy's minimize function and Modern Portfolio Theory techniques.

SLSQP stands among several optimization strategies built into the SciPy Python optimization library. SLSQP demonstrates outstanding functionality for solving both non-linear optimization problems with constraint limitations. Its capability for handling nonlinear constrained problems gives SLSQP special value in financial applications. Portfolio optimization success relies significantly on this method's capabilities.

IV. Implementation

A. Data Extraction And Preprocessing

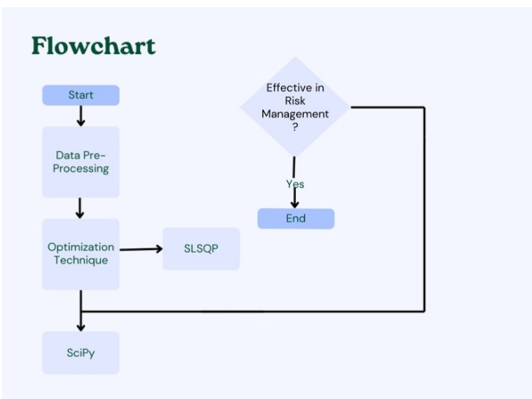

Fig. 1. Data Extraction and Preprocessing

Fig. 1. shows a clear representation of optimization-based risk management procedure steps. A risk management system starts with data pre-processing followed by an optimization technique application. Within the SciPy framework the SLSQP method functions as the chosen optimization procedure. The process evaluates the risk management effectiveness before concluding its execution or returning to further enhancement. The process uses cycles to establish optimal risk management results. Suppose we have a set of financial assets A1,A2,. . . ,An , where the returns over time are represented by the matrix R of dimensions m×n (with m as the number of time periods and n as the number of assets).

1. **Data Extraction**
   We extract historical data of assets over time and calculate their returns. For an asset Ai , its return at time t, denoted by rt,i, is calculated as:

$$r_{t,i} = \frac{P_{t,i}P_t - P_{t-1,i}}{P_{t-1,i}}$$

   where Pt,i is the price of asset Ai at time t.

2. **Preprocessing** Mean Return: For each asset Ai, the mean return over the observed time period is:

$$\mu_i = \sum_{t=1}^{m} r_{t,i}$$

   Thus, the vector of mean returns for all assets is:

$$\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \vdots \\ \vdots \\ \mu_n \end{bmatrix}$$

   Covariance Matrix: describes the variance and covariance Σ between We calculate the covariance matrix, which asset returns. For assets Ai and Aj, the covariance is defined as:

$$\sum_{i,j} = \frac{1}{m-1} \sum_{t=1}^{m} (r_{t,i} - \mu_i)(r_{t,j} - \mu_j)$$

   The covariance matrix Σ for all assets is an n×n symmetric matrix:

$$\Sigma = \begin{bmatrix} \sum_{1,1} & \sum_{1,2} & \cdots & \sum_{1,n} \\ \sum_{2,1} & \sum_{2,2} & \cdots & \sum_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ \sum_{n,1} & \sum_{n,2} & \cdots & \sum_{n,n} \end{bmatrix}$$

B. Portfolio Optimization

We aim to determine the optimal portfolio weights w=(w1,w2,. . . ,wn)τ such that the portfolio's expected return is maximized within a specified risk range.

1. **Portfolio Return**
   The expected return of the portfolio is given by:

$$R_p(w) = w^{\tau}\mu = \sum_{i=1}^{n} w_i \mu_i$$

2. **Portfolio Risk (Variance)**
   The portfolio's risk is measured by the variance (or standard deviation) of its return. The variance of the portfolio, which measures the overall risk, can be calculated using the following formula:

$$\sigma_p^2(w) = w^{\tau}\Sigma w$$

   The risk, or standard deviation, of the portfolio is calculated as the square root of the portfolio variance:

$$\sigma_p(w) = \sqrt{w^{\tau}\Sigma w}$$

3. **Objective Function**
   The optimization goal in portfolio management is to maximize the portfolio's return while minimizing its risk. This is commonly achieved by maximizing the Sharpe Ratio, which is defined as:

$$S(w) = \frac{R_p(w) - R_f}{\sigma_p(w)}$$

Where Rf is the risk-free rate of return.

4. **Risk Constraint**
We impose a constraint that the portfolio risk σp(w) must lie within a specified range [σmin,σmax]. Therefore, the constraint can be written as:

$$\sigma_{\text{min}} \leq \sigma_p(w) \leq \sigma_{\text{max}}$$

Or equivalently:

$$\sigma^2_{\text{min}} \leq w^\tau \Sigma w \leq \sigma^2_{\text{max}}$$

5. **Constraints on Weights**
Additionally, the weights must sum to 1 (i.e., a fully invested portfolio):

$$\sum_{i=1}^{n} w_i = 1$$

And, in most cases, the weights are constrained between 0 and 1 to ensure no short-selling:

$$0 \leq w_i \leq 1, \quad \forall i$$

C. SLSQP Optimization Method

The optimization problem requires solution by Sequential Least Squares Programming (SLSQP) method. The method shows exceptional effectiveness for dealing with constraints in optimized non-linear systems.

1. **Optimization Problem**
Maximize the Sharpe Ratio:

$$\text{Max } S(w) = \frac{w^\tau - R_f}{\sqrt{w^\tau \Sigma w}}$$

Subject to:

$$\sum_{i=1}^{n} w_i = 1$$

$$\sigma^2_{\text{min}} \leq w^\tau \Sigma w \leq \sigma^2_{\text{max}}$$

$$0 \leq w_i \leq 1, \quad \forall i$$

2. **SLSQP Algorithm**
The Sequential Least Squares Programming (SLSQP) method resolves optimization issues through successive iterations which fine-tune portfolio weight distribution throughout multiple constraints evaluation.

V. RESULTS AND ANALYSIS

Practical Implications: Analysis reveals that SLSQP handles nonlinear constraints to make significant contributions for improving portfolio management systems. Applying SLSQP to big-scale data problems meets performance obstacles. Large-scale data applications become accessible to recursive genetic algorithms because of their flexible operations at the cost of substantial computational demands.

After solving the optimization problem using SLSQP, the following key outputs are obtained:

1) Optimal Weights w*: Asset weights achieve maximum return within defined risk limits make up the optimal set.
2) Expected Portfolio Return Rp (w*): The expected return of the optimal portfolio.
3) Portfolio Risk σp(w*): The value of standard deviation for the best portfolio configuration.

Results for portfolio analysis can be graphically displayed on Efficient Frontier visualizations. The design utilizes σp portfolio risk as the x-coordinate and shows Rp portfolio return on the y-axis.

TABLE II
COMPARISON OF OPTIMIZATION TECHNIQUES

Metric	SLSQP	Genetic Algorithms	MPT
Convergence Speed	High	Moderate	High
Scalability	Moderate	Low	High
Practicality	High	Moderate	High

VI. CONCLUSION

Multiple research methods were extensively applied during a comprehensive study. The SLSQP approach together with optimize function and Modern Portfolio Theory serve as optimization methods to enhance functionality. The researchers examined system performance by analyzing historical financial data stored in exchange records. The optimization techniques demonstrate their ability to manage risk-return relationships effectively. This work delivers essential information which benefits stock market investment advisors together with decision-makers.

The analysis presents limitations due to the use of historical data but maintains mathematical programming theory and SLSQP methods and the methodological SLSQP scalability constraints. Using custom portfolio optimization methods for diversity management systems implementation faces significant financial implementation hurdles.

The results of this study underscore the importance of optimization in financial management, as effectively implementing these processes can lead to significant improvements in portfolio performance and risk-adjusted returns. Furthermore, the researchers have pointed out the potential for future advancements, such as the integration of optimization methods with AI and data analysis, which could pave the way for new opportunities in portfolio optimization and risk management.

Overall, this study contributes to the growing body of literature on advancements in finance by providing a detailed and multi-faceted analysis of the tools and strategies that can be employed to enhance investment decision-making and risk management practices. **Limitations:**

1) Lack of Real-Time Integration: Real-time artificial intelligence and data analytics systems do not optimally integrate with existing optimization methods which reduces their capability to accommodate fast-changing market environments.
2) Economic Scenario Testing Gaps: Evaluation of these optimization methods across multiple economic conditions

and asset classes remains limited which restricts their broad applicability.

3) Computational Challenges: Current optimization methods suffer from scalability issues alongside computational efficiency problems that become critically problematic when applied to large-scale portfolios containing complex constraints.

VII. Future Scope

Investigatory procedures research has identified different optimization methods, such as the optimize function in SciPy, the SLSQP approach, and Modern Portfolio Theory. Analysts used historical financial data including records to examine these methods exhibition in changing risk while maintaining return levels.

These research findings will help understand venture experts and specialists' dynamic flows to generate new insights about the effectiveness of optimization techniques in financial services.

Research in this field needs examination of how these enhancement methods integrate with artificial intelligence systems and data analytical methods to create new portfolio optimization and risk management paths.

Tests of performance must evaluate these optimization methods under different economic situations and investment classes. Further analysis of asset classes combined with evaluation methodologies will give additional insights about their performance. The findings of this research have significant implications for investors and managers responsible for handling investment portfolios. The comparative analysis of the optimization techniques offers valuable insights into their strengths, weaknesses, and suitability for different investment contexts, empowering professionals to make informed choices in their risk management strategies.

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