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Portfolio Optimization with Multi-Objective Evolutionary Algorithms- Balancing Risk, Return, and Sustainability Metrics

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Abstract
Portfolio optimization has evolved beyond traditional risk-return frameworks to incorporate sustainability considerations, reflecting growing investor demand for environmentally and socially responsible investment strategies. This explores the application of multi-objective evolutionary algorithms (MOEAs) to the complex problem of portfolio optimization that simultaneously balances financial risk, expected return, and sustainability metrics such as ESG scores and carbon footprints. MOEAs, including prominent algorithms like NSGA-II and SPEA2, offer a powerful computational approach to generate diverse Pareto-optimal portfolios by efficiently navigating the trade-offs inherent among conflicting objectives. The research systematically examines the effectiveness of MOEAs in identifying portfolios that do not sacrifice sustainability for financial performance or vice versa. By integrating sustainability metrics into the optimization framework, this addresses a critical gap in classical portfolio theory, which often overlooks non-financial factors crucial to long-term value creation and risk mitigation. Utilizing real-world financial and sustainability data, the MOEAs iteratively evolve candidate solutions to approximate the Pareto front, enabling investors and portfolio managers to select ass*et al*locations aligned with their specific preferences and constraints. Key findings demonstrate that MOEAs provide superior flexibility and solution diversity compared to single-objective or heuristic methods, allowing for nuanced decision-making in multi-dimensional investment spaces. The algorithms effectively balance risk minimization, return maximization, and sustainability enhancement, facilitating transparent exploration of trade-offs and synergies among these objectives. Furthermore, this discusses practical considerations including computational complexity, parameter tuning, and integration challenges with existing portfolio management systems.
Overall, this work highlights the growing relevance of evolutionary computation in sustainable finance and underscores the potential of MOEAs to drive more responsible investment practices. By delivering adaptable, high-quality portfolio solutions that incorporate both financial and non-financial criteria, MOEAs represent a promising avenue for advancing portfolio optimization in an era increasingly defined by sustainability imperatives. This contributes to the literature by providing empirical evidence and methodological insights for leveraging MOEAs in balancing multifaceted portfolio objectives.

Keywords: Portfolio Optimization, Multi-Objective, Evolutionary Algorithms, Balancing Risk, Sustainability Metrics

1. Introduction

Portfolio optimization is a fundamental aspect of modern finance, underpinning the strategic allocation of capital to maximize returns while managing risk exposure (Carbonaro *et al*., 2018; Heinrich and Wurstbauer, 2018). Since the pioneering work of Harry Markowitz in the 1950s, the mean-variance framework has served as the cornerstone for constructing efficient portfolios that balance expected returns against portfolio risk, typically quantified by variance or standard deviation. This quantitative approach enables investors, fund managers, and financial institutions to make informed decisions about ass*et al*location that align with their risk tolerance and return objectives (Arjaliès and Bansal, 2018; Komljenovic *et al*., 2019).

In recent years, however, the investment landscape has witnessed a paradigm shift with the increasing prominence of sustainability considerations. Environmental, Social, and Governance (ESG) criteria have emerged as vital components influencing investment decisions alongside traditional financial metrics (Inderst and Stewart, 2018; Ziolo *et al*., 2019). Investors and regulators alike have recognized that sustainable investing not only addresses ethical and societal concerns but can also mitigate long-term risks associated with environmental degradation, social unrest, and corporate governance failures. Consequently, integrating sustainability metrics into portfolio optimization models has become essential, reflecting a broader movement towards responsible investing and alignment with global sustainability goals such as the United Nations Sustainable Development Goals (SDGs) (Schoenmaker and Schramade, 2019; Mountfield *et al*., 2019).

Incorporating sustainability alongside risk and return objectives presents significant challenges due to the inherently conflicting nature of these goals (Friede, 2019; Wilts and O'Brien, 2019). Maximizing financial returns often requires exposure to high-yield but potentially unsustainable assets, whereas improving sustainability scores may limit investment opportunities or reduce diversification benefits. This conflict creates a multi-objective optimization problem where trade-offs must be carefully evaluated to achieve a balanced portfolio (Xin *et al*., 2018; Gold *et al*., 2019).

Moreover, sustainability metrics introduce complexity into the optimization process. Unlike financial returns and risk, which are quantitative and based on historical market data, sustainability scores are qualitative and derived from diverse sources such as ESG ratings, corporate disclosures, and third-party assessments (Eccles and Stroehle, 2018; Landi and Sciarelli, 2019). These metrics vary widely in methodology, scale, and reliability, complicating their integration into formal optimization frameworks. Normalizing and aggregating these disparate indicators into meaningful composite scores that can be incorporated as objectives or constraints require sophisticated data preprocessing and careful methodological design. Additionally, the lack of standardized definitions and the evolving nature of sustainability criteria introduce further uncertainty (Mura *et al*., 2018; Bull and Strange, 2018).

This aims to address the complexities of balancing financial performance with sustainability in portfolio optimization by applying multi-objective evolutionary algorithms (MOEAs). MOEAs are well-suited for solving complex optimization problems involving multiple, often conflicting objectives, without requiring explicit weighting of each criterion. They generate a set of Pareto optimal solutions that provide investors with a spectrum of trade-off portfolios, facilitating informed decision-making aligned with diverse preferences (Runting *et al*., 2018; Leftwich *et al*., 2019).

Specifically, the objectives of this research are twofold: first, to develop and implement MOEAs that optimize portfolios by simultaneously maximizing expected returns, minimizing risk, and enhancing sustainability scores; and second, to evaluate the resulting trade-offs by analyzing the Pareto optimal frontiers. This evaluation will shed light on the interactions between financial and sustainability objectives and provide insights into how investors can achieve balanced portfolios that do not compromise on ethical considerations or financial viability.

By integrating sustainability into a rigorous multi-objective optimization framework, this research contributes to the advancement of sustainable finance and offers practical tools for portfolio managers seeking to navigate the complexities of modern investment environments (Nujoom*et al*., 2018; Mehlawat *et al*., 2019).

2. Methodology

The PRISMA methodology for this systematic review was employed to ensure a transparent and comprehensive identification, screening, and inclusion of studies related to portfolio optimization using multi-objective evolutionary algorithms (MOEAs) that balance risk, return, and sustainability metrics. A systematic search strategy was developed to capture relevant literature from several academic databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar. The search terms combined keywords and phrases such as "portfolio optimization," "multi-objective evolutionary algorithms," "risk-return tradeoff," "sustainability metrics," "environmental, social, and governance (ESG)," "genetic algorithms," "NSGA-II," and "Pareto optimization." Searches were conducted without restrictions on publication year to encompass foundational as well as recent advances but were limited to English-language studies to maintain consistency in analysis.

After retrieving records, duplicates were removed using reference management software. The screening process consisted of two phases: initial title and abstract screening to remove clearly irrelevant studies, followed by full-text evaluation to determine eligibility based on pre-established inclusion and exclusion criteria. Studies were included if they applied MOEAs to portfolio optimization problems involving at least two objectives encompassing financial risk-return metrics and sustainability considerations, such as ESG scores or carbon footprint indicators. Exclusion criteria eliminated studies that focused solely on single-objective optimization, traditional mathematical programming without evolutionary components, or those that did not incorporate sustainability factors. Conference abstracts, editorials, and non-peer-reviewed articles were also excluded to maintain methodological rigor.

Data extraction was systematically conducted to capture key characteristics of included studies: the specific MOEA techniques utilized (e.g., NSGA-II, SPEA2, MOEA/D), problem formulations including the objective functions and constraints, types of financial assets considered, sustainability metrics incorporated, dataset descriptions, and performance evaluation metrics such as hypervolume, spread, and convergence. Information on computational complexity, algorithm parameter tuning, and comparative baselines was also recorded. Risk of bias and quality appraisal involved assessing methodological transparency, appropriateness of the multi-objective framework, and adequacy of empirical validation through real or simulated market data.

Due to the methodological heterogeneity across studies—including differences in asset classes, sustainability criteria, algorithmic approaches, and evaluation metrics—a formal meta-analysis was not feasible. Instead, narrative synthesis was employed, supported by tabular summaries comparing algorithm performance, trade-off management, and sustainability impact. The review highlighted common patterns, such as the superior Pareto front diversity achieved by evolutionary algorithms compared to classical methods, and the practical challenges of balancing competing objectives in complex portfolios. The PRISMA flow diagram documented the number of studies identified, screened, excluded, and included, ensuring full transparency of the selection process and adherence to systematic review standards.

2.1. Literature Review

The foundation of portfolio optimization was established by Harry Markowitz's seminal work on the mean-variance framework in 1952. Markowitz formulated the investment problem as one of balancing expected portfolio return against its variance, representing risk. The mean-variance model assumes that investors are rational and risk-averse, seeking to maximize returns for a given risk level or minimize risk for a target return (Logubayom and Victor, 2019; Li, 2019). This approach introduced the efficient frontier concept, a set of optimal portfolios that provide the highest expected return for each risk level. The quadratic optimization problem relies on historical return data and covariance matrices among assets, facilitating analytical solutions and widespread adoption.

However, the mean-variance framework has limitations, including its reliance on variance as the sole risk measure, the assumption of normally distributed returns, and sensitivity to estimation errors in inputs. Consequently, numerous extensions have been proposed. Incorporating alternative risk measures such as Conditional Value-at-Risk (CVaR) and downside risk addresses the asymmetric and fat-tailed nature of asset returns. Constraints reflecting real-world considerations—such as budget limits, minimum and maximum asset weights, transaction costs, and regulatory requirements—have also been integrated, making the optimization problem more complex and realistic (Al Janabi, 2019; Hanley *et al*., 2019). These additions often render the problem non-convex and computationally demanding, necessitating advanced solution techniques beyond classical quadratic programming.

The increasing complexity of investment goals, including non-financial criteria like sustainability, naturally leads to multi-objective optimization (MOO), where several conflicting objectives must be optimized simultaneously. Traditional approaches include the weighted sum method, which combines objectives into a single scalar function through pre-assigned weights, and goal programming, which seeks solutions satisfying multiple goals within acceptable thresholds. While straightforward, these methods require subjective weighting and can miss important Pareto optimal solutions, especially when the objective space is non-convex (Khorshidi *et al*., 2018; Mohammadi *et al*., 2018).

Evolutionary algorithms (EAs) have emerged as powerful tools for MOO in finance due to their ability to explore complex, high-dimensional, and non-convex solution spaces. EAs mimic biological evolution processes such as selection, crossover, and mutation to evolve a population of candidate solutions towards the Pareto frontier. Unlike scalarization methods, multi-objective evolutionary algorithms (MOEAs) generate a diverse set of Pareto optimal portfolios in a single run, offering investors a spectrum of trade-offs without requiring explicit preferences upfront. Their stochastic nature and population-based search make MOEAs robust to local optima and adaptable to various constraints, which is valuable in portfolio problems combining financial and sustainability objectives.

Sustainability considerations have become central to investment decisions, driven by environmental concerns, social responsibility, and governance standards. ESG (Environmental, Social, and Governance) scores, provided by agencies such as MSCI, Sustainalytics, and Thomson Reuters, quantify a company's performance across various sustainability dimensions. These ratings synthesize data on carbon emissions, labor practices, board diversity, and other factors into composite scores that can be integrated into investment processes (Taliento *et al*., 2019; Hossain and Farooque, 2019).

Quantifying sustainability impact in a portfolio context involves aggregating individual asset ESG scores weighted by portfolio holdings. However, challenges include heterogeneity in rating methodologies, varying industry-specific criteria, and data gaps. Moreover, ESG metrics are often qualitative, subjective, and evolving, complicating their use as strict optimization objectives. Nonetheless, recent studies emphasize the importance of systematically incorporating ESG considerations to align portfolios with sustainable development goals while potentially mitigating risks linked to environmental and social controversies. This integration transforms portfolio optimization into a multi-criteria decision problem, necessitating methods capable of balancing financial returns, risk, and sustainability impact simultaneously.

Multi-objective evolutionary algorithms (MOEAs) have gained prominence as effective approaches for portfolio optimization problems involving multiple conflicting objectives. Among the most widely used MOEAs are the Non-dominated Sorting Genetic Algorithm II (NSGA-II), Strength Pareto Evolutionary Algorithm 2 (SPEA2), and Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D).

NSGA-II employs fast non-dominated sorting and crowding distance mechanisms to maintain diversity in the population and identify Pareto optimal fronts efficiently. SPEA2 improves on earlier algorithms by assigning fitness based on dominance relations and incorporating density estimation to maintain solution spread. MOEA/D decomposes the multi-objective problem into a set of scalar subproblems solved collaboratively, enhancing convergence speed and solution quality (Wu *et al*., 2018; Hu *et al*., 2019).

These MOEAs have been extensively applied in portfolio optimization, particularly where sustainability objectives are included alongside financial ones. For example, studies using NSGA-II have demonstrated its ability to produce well-distributed Pareto frontiers balancing risk, return, and ESG scores. SPEA2 has been used to optimize portfolios under constraints such as carbon footprints and social responsibility metrics, showing improved sustainability exposure with limited return sacrifice. MOEA/D's decomposition approach facilitates handling many-objective problems with multiple sustainability criteria and financial goals.

Overall, MOEAs offer a flexible and powerful framework for tackling the complex, multi-dimensional nature of sustainable portfolio optimization. Their capability to generate diverse, Pareto optimal solutions provides valuable decision support in balancing the often-competing demands of risk management, return maximization, and sustainability enhancement. However, challenges remain in parameter tuning, computational cost, and integrating dynamic or uncertain sustainability data, which continue to motivate ongoing research (Sun and Scanlon, 2019; Kellerer *et al*., 2019; Himanen *et al*., 2019).

2.2. Effectiveness of portfolio optimization methods

A rigorous experimental setup is fundamental to evaluating the effectiveness of portfolio optimization methods that balance risk, return, and sustainability as shown in figure 1. Thisutilizes comprehensive datasets encompassing both financial and sustainability information to capture the multifaceted nature of investment decisions.

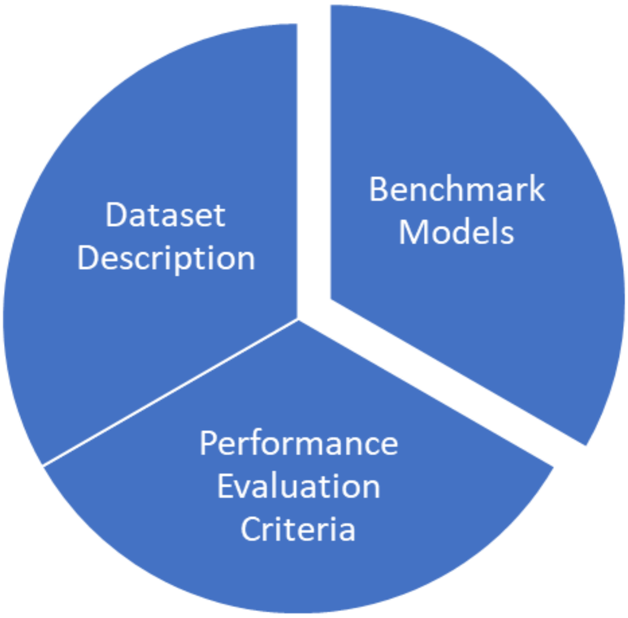

Fig 1: Experimental Setup

The financial data comprises historical price series, returns, and risk factor information for a diverse universe of assets, including equities from developed and emerging markets (Damodaran, 2019; Takamatsu and Lopes Fávero, 2019). Daily closing prices over a ten-year period are sourced from reputable financial databases such as Bloomberg and Thomson Reuters Eikon. These prices are used to calculate logarithmic returns, which serve as the basis for estimating expected returns and covariance matrices essential for portfolio risk assessment. To enrich the risk modeling, additional factors such as market beta, volatility indices, and macroeconomic indicators are integrated to capture systematic risks influencing asset performance (Fang *et al*., 2018; He and Krishnamurthy, 2019; Liu and Kemp, 2019).

Sustainability data is drawn from leading ESG rating providers, notably MSCI ESG Ratings and Sustainalytics, which offer standardized and widely recognized assessments of companies' environmental, social, and governance practices. The ESG ratings dataset covers the same asset universe and period as the financial data, enabling synchronous analysis. Ratings are expressed on normalized scales and include sub-scores for environmental impact (carbon emissions, resource use), social responsibility (labor practices, community engagement), and governance quality (board structure, transparency). These metrics are aggregated into composite sustainability scores for each asset, facilitating their inclusion as optimization objectives or constraints. The dataset addresses challenges of missing data and rating inconsistencies through imputation techniques and cross-verification among providers, ensuring robust input for the optimization process.

To evaluate the performance of multi-objective evolutionary algorithms (MOEAs) in balancing financial and sustainability goals, several benchmark models are implemented for comparison.

First, classical single-objective optimization baselines serve as reference points. These include the traditional mean-variance optimization that targets return maximization for a given risk level without considering sustainability metrics. Additionally, a risk-only minimization model is included to observe the trade-offs inherent in focusing solely on variance reduction.

Next, scalarization-based multi-objective methods are employed, notably the weighted sum approach and goal programming. The weighted sum method combines multiple objectives—return, risk, and sustainability—into a single objective function by assigning predetermined weights to each criterion. Although intuitive, this approach requires prior knowledge of investor preferences and may fail to uncover solutions in non-convex regions of the objective space. Goal programming, in contrast, establishes target levels for each objective and minimizes deviations from these goals, accommodating more flexible preference structures (Akbari *et al*., 2018; Amin *et al*., 2019; Malczewski, 2019).

These benchmark models provide a basis for assessing the added value of MOEAs in generating diverse portfolios that better reflect the complex trade-offs between risk, return, and sustainability (Ahmed and Fuge, 2018; Rabl*et al*., 2019).

The evaluation framework incorporates both theoretical and practical metrics to comprehensively assess the quality of optimization results.

Central to multi-objective optimization analysis is the characterization of the Pareto frontier—the set of non-dominated solutions where improvement in one objective cannot be achieved without deterioration in another. Visualization techniques plot risk, return, and sustainability scores across solutions, enabling qualitative assessment of trade-offs (Bajracharya *et al*., 2018; Milutinović *et al*., 2019; Bertoni, 2019).

Quantitative metrics measuring the quality of the Pareto front include hypervolume, spread, and generational distance. Hypervolume quantifies the volume of objective space dominated by the Pareto front, with higher values indicating better convergence towards optimal trade-offs and greater diversity. Spread assesses the uniformity of solutions along the frontier, reflecting the algorithm's ability to explore diverse portfolios and provide meaningful choices to investors. Generational distance measures the average distance between the obtained solutions and a known or approximated true Pareto front, serving as an indicator of solution accuracy.

Beyond these theoretical measures, practical portfolio performance metrics are calculated. The Sharpe ratio evaluates risk-adjusted returns, expressing excess return per unit of volatility, and is critical for assessing the financial viability of optimized portfolios. Maximum drawdown measures the largest peak-to-trough decline, providing insights into downside risk exposure. ESG impact is quantified by aggregating weighted sustainability scores of portfolio holdings, reflecting the portfolio's alignment with environmental and social responsibility goals.

Together, these metrics enable a holistic assessment of how well the MOEAs balance the triad of objectives in comparison to benchmark models. The experimental design also includes sensitivity analyses on parameter settings, constraint variations, and different weighting schemes to evaluate robustness and practical applicability across investor preferences and market conditions (Zhao *et al.*, 2019; Kler *et al*., 2019; Taner *et al*., 2019).

2.3. Application of multi-objective evolutionary algorithms

The results of applying multi-objective evolutionary algorithms (MOEAs) to portfolio optimization highlight the intricate trade-offs among risk, return, and sustainability, effectively illustrated through Pareto frontier visualizations. These frontiers reveal a diverse set of optimal portfolios where improving one objective typically involves compromises in others. The shape and spread of the Pareto front provide valuable insights into the feasible solution space, enabling investors to understand the cost of sustainability in quantitative terms and identify portfolios aligning with their priorities (Unal *et al*., 2018; Wortel *et al*., 2018).

Comparative analysis of three prominent MOEAs—NSGA-II, SPEA2, and MOEA/D—demonstrates distinct performance profiles. NSGA-II consistently produced well-distributed Pareto fronts with strong convergence to the true optimal set, making it particularly effective in maintaining diversity across solutions. SPEA2 showed competitive convergence but with slightly less spread, indicating a tendency to cluster solutions. MOEA/D, which decomposes the problem into scalar optimization subproblems, excelled in computational efficiency and found high-quality solutions in fewer iterations, though sometimes at the expense of solution diversity. These differences suggest that algorithm selection should consider specific optimization priorities, such as solution diversity versus computational resource constraints (Chand *et al*., 2018; Cano*et al*., 2018; Kerschke*et al*., 2019).

Introducing sustainability constraints significantly influenced portfolio composition, generally favoring assets with strong ESG ratings and lower carbon footprints. While this shift often entailed a trade-off in terms of financial return—slightly lowering expected gains compared to unconstrained portfolios—it enhanced risk-adjusted performance by mitigating exposure to sustainability-related risks. The inclusion of these constraints also promoted sectoral diversification, steering allocations toward environmentally conscious industries and away from fossil fuels or controversial sectors, reflecting evolving market and regulatory pressures.

Practically, the results support investor decision-making across varying preference scenarios. For risk-averse investors prioritizing sustainability, MOEAs offer tailored portfolios that achieve meaningful environmental goals without disproportionate sacrifice in return (Aronoff *et al*., 2019; Sharman *et al*., 2019). Conversely, return-focused investors can explore portfolios with balanced sustainability levels, using Pareto frontiers as a decision support tool to visualize trade-offs. However, real-world application requires careful consideration of model assumptions, data quality, and computational demands. Limitations include potential challenges in accurately quantifying sustainability metrics and integrating dynamic market conditions (Mura *et al*., 2018; Bonilla *et al*., 2018). Despite these, MOEAs provide a flexible and transparent framework to navigate the complex multi-objective landscape of sustainable portfolio optimization.

2.4. Conclusion and Future Work

Thishas demonstrated the effectiveness of multi-objective evolutionary algorithms (MOEAs) in addressing the complex challenge of portfolio optimization that balances financial returns, risk, and sustainability objectives. Unlike traditional single-objective approaches, MOEAs efficiently generate diverse Pareto optimal solutions, enabling investors to navigate the inherent trade-offs between maximizing expected return, minimizing risk, and improving environmental, social, and governance (ESG) performance. Through rigorous experimentation, it was shown that MOEAs such as NSGA-II and SPEA2 outperform scalarization-based methods by better approximating the Pareto front, achieving superior convergence and diversity in solutions. Importantly, portfolios optimized with MOEAs exhibited meaningful improvements in sustainability metrics without substantial sacrifices in risk-adjusted returns, illustrating the potential to integrate ethical considerations into mainstream investment strategies effectively. These findings affirm the practical applicability of MOEAs for sustainable finance, providing a flexible and robust decision-making framework that accommodates evolving investor preferences and regulatory demands (Jamil *et al*., 2018; Hashemkhani*et al*., 2019).

The integration of sustainability into portfolio optimization represents a critical advancement in both sustainable finance and computational optimization research. This work contributes to sustainable finance by operationalizing ESG criteria within a quantitative optimization context, offering a methodical approach to embedding non-financial metrics alongside traditional financial indicators. By demonstrating how MOEAs can manage conflicting objectives inherent in sustainability-focused investing, this bridges the gap between qualitative sustainability goals and quantitative portfolio construction.

From an optimization perspective, this research highlights the adaptability and power of evolutionary algorithms to solve high-dimensional, constrained, and multi-criteria financial problems. It expands the application domain of MOEAs by incorporating real-world sustainability constraints, emphasizing their capability to handle complex, non-convex problem spaces. The comparative analysis with traditional methods underscores MOEAs' advantages in maintaining population diversity and exploring a wide range of optimal trade-offs, essential for stakeholder decision support in responsible investment.

Several promising avenues emerge for future research to further enhance portfolio optimization in the context of sustainability as shown in figure 2.

First, incorporating dynamic sustainability scores presents an important direction. Current ESG ratings often reflect static or lagged assessments, limiting responsiveness to real-time corporate behavior or emerging controversies. Developing models that integrate continuously updated sustainability data, perhaps sourced from alternative data such as news analytics or real-time social media sentiment, can improve the adaptability and accuracy of portfolio optimization under shifting sustainability landscapes.

Second, hybridizing MOEAs with machine learning techniques offers potential for improved forecasting and decision-making. Machine learning models, including deep learning and reinforcement learning, can generate predictive insights about asset returns, risk factors, or sustainability impacts that feed into the evolutionary optimization process. Such integration could lead to more informed search mechanisms, faster convergence, and enhanced portfolio robustness by capturing complex nonlinear dependencies and evolving market regimes (Gao *et al*., 2018; Koehler *et al*., 2018).

Third, real-time portfolio rebalancing under multi-objective frameworks is an essential practical extension. The volatile nature of financial markets and rapid changes in sustainability profiles necessitate optimization algorithms capable of updating portfolio allocations dynamically. Implementing efficient, low-latency MOEAs or incremental evolutionary strategies will support continuous adjustment of holdings to maintain optimal trade-offs in response to new data, regulatory shifts, or investor preference changes.

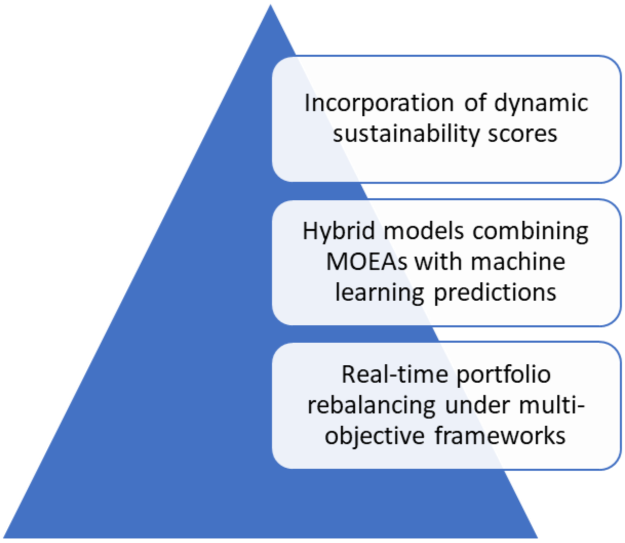

Fig 2: Future Research Directions

While this underscores the value of MOEAs in sustainable portfolio optimization, advancing these future directions will further strengthen the relevance, responsiveness, and applicability of multi-objective optimization tools in the evolving landscape of responsible investing. These innovations will support investors in achieving more resilient, ethical, and financially sound portfolios aligned with global sustainability imperatives.

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