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Balancing Financial Performance and ESG Objectives in Portfolio Optimization: Insights from the S&P 500

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Abstract –*Portfolio optimization is a critical component of informed investment decision-making, balancing risk and return to maximize long-term performance. With increasing focus on sustainability, integrating Environmental, Social, and Governance (ESG) factors into portfolio construction has gained significant importance. This study presents a multi-objective portfolio optimization model that minimizes ESG impact while ensuring financial viability through return and risk constraints. Utilizing the augmented epsilon-constraint method (AECM), the model incorporates ESG considerations without compromising profitability. The analysis is based on a dataset of 20 top market-cap stocks from the S&P 500, evaluated on annual return, risk exposure, and ESG scores. Our findings demonstrate that ESG-conscious portfolios can generate competitive returns while effectively managing risk levels. A sensitivity analysis investigates the trade-off between volatility and profitability, while a correlation heatmap illustrates the relationships between ESG scores and financial metrics. This framework offers a structured methodology for constructing portfolios that are both financially optimal and socially responsible, enabling investors to align their financial goals with sustainable, ethical practices. A theoretical contribution is provided by integrating ESG criteria into a multi-objective optimization framework using the AECM approach. Practically, a replicable method is offered for constructing portfolios that remain both financially viable and socially responsible.*

Keywords*– Portfolio Optimization; ESG Investing; Multi-objective Optimization; Epsilon-constraint; Sustainable Finance.*

I. INTRODUCTION

Financial markets are the backbone of modern economies, facilitating capital allocation and driving economic growth. Investors, whether individuals or institutions, continually seek strategies to maximize returns while efficiently managing risk. Traditional investment decisions have largely been guided by financial metrics such as historical returns, volatility, and correlation among assets. However, with the increasing complexity of global markets, investors are now considering additional factors that go beyond conventional risk-return assessments. The concept of sustainable investing has become a vital approach, highlighting the role of ESG elements in influencing long-term financial outcomes and promoting corporate accountability (Zabavnik & Verbič, 2021; Seiti et al., 2024). Portfolio optimization has been a core area of financial research for many years, with Markowitz's Mean-Variance Model laying the foundation for contemporary portfolio theory. This model introduced the concept of the efficient frontier, where an optimal portfolio is

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one that maximizes expected return for a given level of risk (Markowitz, 1952). Despite its widespread adoption, Markowitz's model is primarily focused on financial risk and return, neglecting broader considerations such as ethical, social, and environmental impacts (Larni-Fooeik et al., 2024a). As sustainability concerns gain traction, investors and financial institutions are increasingly incorporating non-financial criteria into their decision-making processes. ESG-based investing has gained momentum, with studies showing that firms with high ESG scores often exhibit lower risk, enhanced corporate governance, and more stable long-term performance (Pang et al., 2023; Fooeik et al., 2024; Emami et al., 2021).

The consideration of ESG in portfolio optimization presents a new set of challenges. Unlike traditional models, which solely aim to balance risk and return, ESG-focused optimization must consider a third dimension-sustainability impact. While some studies have proposed multi-objective approaches that simultaneously optimize return, risk, and ESG scores, such models often struggle with computational complexity and practical implementation. A more effective approach is to treat ESG as the primary objective function while incorporating risk and return as constraints. This ensures that the portfolio remains financially viable while aligning with sustainable investment principles (Chen et al., 2021; Ghanbari et al., 2024). The stock portfolio optimization problem, while focusing on financial returns and ESG factors, also has implications for logistics and supply chain management. The principles of optimization used in stock portfolio management, such as minimizing risk and maximizing returns, share similarities with supply chain optimization techniques, where resource allocation and risk management are key. Effective portfolio optimization, similar to supply chain planning, requires a strategic approach to balance competing objectives and ensure optimal outcomes (Larni-Fooeik et al, 2024b).

Fig. 1 represents the key terms related to ESG-based portfolio optimization, highlighting the most frequently occurring and relevant concepts in this study. Words such as "portfolio optimization," "ESG," "risk," "return," "sustainability," "Markowitz model," and "epsilon-constraint" stand out, emphasizing the paper's focus on sustainable investment strategies and mathematical optimization techniques. The significance of this WordCloud lies in its ability to quickly convey the core themes of the research. Providing a graphical representation of frequently used terms helps researchers and readers identify key topics at a glance, making it useful for text analysis, academic research, and detecting emerging trends.

Fig. 1. WordCloud representation of key terms in ESG-based portfolio optimization

The main contributions and innovations of this research are summarized as follows:

- An ESG-driven portfolio optimization framework is proposed in which the minimization of ESG impact is formulated as the primary objective, while financial performance is preserved through explicit return and risk constraints.
- A conceptual shift from conventional ESG portfolio models is introduced by moving from simultaneous multi-objective optimization of return, risk, and ESG toward a constraint-based structure that prioritizes sustainability without undermining financial feasibility.
- A mathematical optimization model based on AECM is developed to systematically integrate ESG considerations into the portfolio construction process.
- The study extends the application of AECM to ESG-based portfolio optimization, an area that has received limited attention in the existing literature.
- The proposed framework improves solution efficiency and generates a well-structured set of Pareto-optimal portfolios, facilitating a clearer representation of the trade-offs between sustainability performance and financial objectives.

To evaluate the effectiveness of our approach, a case study is conducted using the top 20 largest market-cap stocks from the S&P 500 index, analyzing how the proposed model constructs an optimal portfolio under ESG-driven constraints. This case study highlights the practical application of the proposed model and demonstrates that ESG-conscious portfolios can be optimized to deliver competitive returns while minimizing ESG exposure. What distinguishes the work is the direct focus on ESG minimization as the main optimization goal, while ensuring return and risk constraints, as opposed to treating ESG as a secondary consideration or a mere constraint. By positioning ESG as the primary objective, our model not only addresses a gap in the existing literature but also provides a more innovative, adaptable, and scalable approach to sustainable investing. This advancement bridges the gap between ethical investment goals and optimal financial outcomes, offering a comprehensive solution to the growing demand for responsible and financially sound investment strategies. Compared with prior studies, this paper contributes by: (1) integrating ESG as an explicit objective alongside return and risk within an AECM framework that yields Pareto-consistent efficient sets; (2) enforcing realistic inevitability constraints (budget, bounds, cardinality) in an exact optimization model; (3) providing transparent and reproducible settings (data pipeline, parameterization, solver) with sensitivity checks; and (4) benchmarking against standard baselines (mean-variance and weighted-sum multi-objective) on both out-of-sample performance and ESG attainment.

From a theoretical standpoint, this study contributes to the portfolio optimization and sustainable finance literature by formulating ESG minimization as the primary objective in a multi-objective optimization model, while incorporating risk and return as explicit constraints within the AECM framework that generates Pareto-consistent efficient sets. From a practical perspective, it offers a quantitative and replicable methodology for constructing ESG-conscious portfolios that remain financially viable, providing empirical evidence based on top market-cap S&P 500 stocks that such portfolios can achieve competitive risk–return profiles while enhancing sustainability performance.

The remainder of this paper is organized as follows: Section II reviews the related literature. Section III presents the data and the proposed model based on the AECM with consideration of ESG. Section IV reports the case study and computational results, and Section V concludes the paper and outlines directions for future research.

II. LITERATURE REVIEW

Numerous studies have been conducted in the field of portfolio optimization, exploring various methodologies and approaches. Below, we review the most relevant ones related to our research:

Kaucic et al. (2023) proposed a hybrid Level-Based Learning Swarm Optimizer (LLSO) with a mutation operator to solve large-scale cardinality-constrained portfolio optimization problems. They incorporated a modified Sharpe ratio as the objective function and used a hybrid constraint-handling technique. The model was tested on MSCI World Index data, showing improved solution quality and computational efficiency compared to standard swarm algorithms. Burkhardt & Ulrych. (2023) proposed a joint optimization framework for international portfolio allocation that simultaneously considers asset allocation and currency risk management. Their approach challenges the widely used currency overlay strategy, demonstrating that regularized joint optimization improves out-of-sample Sharpe ratios by 23.3%. By incorporating sparsity and stability techniques, they enhanced the mean-variance model, addressing parameter uncertainty and optimizing international investment decisions. Cui et al. (2024) developed a deep reinforcement learning (DRL) hyper-heuristic approach for multi-period portfolio optimization. Their model improves decision-making by leveraging low-level trading strategies to enhance efficiency. Using data from five global stock indices, they demonstrate superior performance compared to traditional strategies. The results highlight improved portfolio robustness and adaptability to market uncertainties. Puerto et al. (2022) explained a combinatorial optimization method for filtering scenarios in the process of portfolio selection. They developed a mixed-integer quadratic programming (MIQP) model to remove noise from covariance matrices in the Markowitz mean-variance optimization framework. Their approach systematically filters extreme observations that may distort portfolio risk estimation. Empirical results using real financial datasets demonstrate that their method outperforms traditional filtering techniques, improving out-of-sample portfolio performance.

Benati & Conde (2022) presented a robust ordered weighted averaging (ROWA) model for optimizing portfolios. Their method integrates several Conditional Value at Risk (CVaR) measures to address various risk preferences. The model identifies a compromise portfolio that balances risk aversion and decision-maker preferences. Empirical tests on six financial markets confirm the model’s robustness and efficiency in multi-criteria decision-making. Ranilla-Cortina & Vigo-Aguiar (2024) examined portfolio optimization in markets with delayed insider information. Using anticipating stochastic calculus and white noise theory, they modeled how privileged yet delayed information impacts investment decisions. Their approach is applied to multiple financial models, showing that insider traders consistently achieve higher wealth despite delays. Yeo et al. (2023) described a dynamic strategy for portfolio rebalancing that employs optimized trading indicators and genetic algorithms. They developed two indicators based on the moving average convergence divergence histogram and the relative strength index to improve price forecasting. A neuro-fuzzy system enhances predictions, while genetic algorithms optimize parameters for better performance. Their approach outperforms traditional investment methods in terms of returns and risk management. Al-Majali & Zobaa (2025) presented the Square Shape Slope Index, an innovative multi-criteria decision-making approach for analyzing Pareto fronts in bi-objective optimization. Their approach dynamically adjusts reference points to enhance solution ranking based on geometric properties. Using the Non-Dominated Sorting Genetic Algorithm II, they validated their method across benchmark functions and real-world applications, including portfolio optimization. Results demonstrated the model’s effectiveness in balancing conflicting objectives and improving decision-making flexibility. Ayadi et al. (2023) analyzed portfolio optimization during the Brexit period by constructing two-asset portfolios with stocks from other countries, alongside sixteen commodity types. They used a dynamic conditional correlation GARCH model to estimate variances and covariances, determining optimal asset weights and hedge ratios. Their results suggested that European stocks form optimal portfolios without commodities, while commodities remain essential for hedging American and BRICS equities. Sulas et al. (2025) developed a multi-objective optimization in stocks approach to address systemic risk from overlapping portfolios. They introduced an evolutionary search algorithm to optimize asset allocation while balancing individual and systemic risk. Applying their model to European banks’ sovereign exposures, they find that systemic risk minimization results in highly concentrated portfolios, revealing inefficiencies in observed allocations. Their approach highlights the trade-off between diversification benefits and systemic fragility in financial markets. Prol & Kim (2022) examined the average performance of equity portfolios optimized based on ESG scores in the New York Stock market. Using the Markowitz mean-variance framework, they constructed optimal and efficient portfolios for the years 2018–2019. Their results indicated that high environmental, social, and governance portfolios exhibit lower volatility but also lower returns, leading to reduced Sharpe ratios. These findings suggest that prioritizing sustainability in portfolio construction may come at the cost of financial performance. Behera et al. (2025) addressed the challenge of selecting appropriate stocks for portfolio inclusion, particularly in the context of complex stock forecasting dynamics characterized by nonlinear time series and multiple influencing factors. Ashrafzadeh et al. (2025) improved stock return predictions by applying a clustering approach to selected stocks. They combined clustering methods with prediction models and evaluated their effectiveness using the Diebold-Mariano test. Sa’diyah et al. (2024) proposed a portfolio optimization framework using a mean-variance approach combined with prototype-based stock segmentation. They segmented stocks based on historical return and trading volume data from the Indonesia Stock Exchange, utilizing cross-sectional, histogram, and time-series clustering. Their results showed that portfolio diversification improves when stocks are selected from different cluster combinations, optimizing risk-return trade-offs based on the Sharpe ratio. Som & Kayal. (2022) compared cryptocurrency and gold in portfolio optimization across ten countries using a generalized simulated annealing technique. They assessed the volatility of cryptocurrencies based on value-at-risk (VaR) methods and examined their role alongside gold in risk-adjusted portfolios. Their findings suggest that including Bitcoin enhances portfolio returns but does not fully replace gold, as both assets serve complementary roles in diversification. El Kharrim (2023) presented a multi-period fuzzy model incorporating real constraints. The model integrates a possibilistic mean-semi variance framework with CVaR, transaction costs, and cardinality constraints. A dynamic programming approach is applied to analyze the integer optimization problem. Empirical analysis using Casablanca Stock Exchange data demonstrates the model’s effectiveness in handling uncertainty in investment strategies.

Table I. Literature review in the recent portfolio optimization area

Initial Information		**Year**	**Solution Method**		**Constraints**					**Study Type**			**Model type**
#	**Authors**		**Optimization**	**Simulation**	**Cardinality**	**Boundary**	**Transaction**	**Turnover**	**Others**	**Numerical**	**Case Study**	**Hypothetical**	
1	Silva et al.	2015	✓		✓					✓			LP
2	Chiang & Chen	2016	✓			✓		✓			✓		LP
3	Xidonas et al.	2017	✓		✓		✓			✓			LP
4	Pendharkar & Cusatis	2018	✓				✓			✓			NLP
5	Tian et al.	2019	✓					✓			✓		NLP
6	Fernandez et al.	2019	✓		✓						✓		NLP
7	Zhou & Palomar	2020		✓		✓					✓		LP
8	Takahashi & Takahashi	2021	✓		✓					✓			MLP
9	Som & Kayal	2022	✓				✓			✓			LP
10	Prol & Kim	2022	✓		✓	✓					✓		NLP
11	Puerto et al.	2022	✓						✓		✓		MINLP
12	Kaucic et al.	2023	✓		✓	✓		✓			✓		NLP
13	El Kharrim	2023	✓		✓					✓			MOLP
14	Ayadi et al.	2023	✓		✓						✓		LP
15	Ulrych et al.	2023	✓		✓					✓			NLP
16	Yeo et al.	2023	✓					✓	✓		✓		NLP
17	Cui et al.	2024	✓				✓			✓			LP
18	Benati & Conde	2024	✓						✓			✓	LP

Continue Table I. Literature review in the recent portfolio optimization area

Initial Information		Year	Solution Method		Constraints					Study Type			Model type
#	Authors		Optimization	Simulation	Cardinality	Boundary	Transaction	Turnover	Others	Numerical	Case Study	Hypothetical	
19	Ranilla-Cortina & Vigo-Aguiar	2024	✓					✓			✓		NLP
20	Sa'diyah et al.	2024	✓		✓								NLP
21	Al-Majali & Zobaa	2025								✓			NLP
22	Sulas et al.	2025	✓		✓					✓			NLP
23	Taheripour et al.	2025	✓			✓	✓				✓		LP
24	Wang et al.	2026	✓		✓		✓			✓			NLP
25	Xue et al.	2026	✓		✓					✓	✓		NLP
26	Li et al.	2026	✓			✓	✓			✓			NLP
27	This Article	2026	✓	✓	✓	✓		✓	✓		✓		LP

Linear Programming (LP), Multi-objective Linear Programming (MOLP), Non-Linear Programming (NLP), Mixed-Integer Linear Programming (MILP), Mixed-Integer Non-Linear Programming (MINLP),

Despite extensive research in portfolio optimization, most studies have primarily focused on the traditional mean–variance framework, heuristic optimization techniques, or the incorporation of ESG factors within conventional portfolio constraints. Numerous studies have also examined multi-objective optimization, dynamic asset allocation, and risk management strategies through advanced mathematical models and artificial intelligence-based approaches. However, in much of the existing literature, ESG indicators have generally been treated as secondary considerations or additional constraints within the conventional risk–return framework. Consequently, relatively limited attention has been devoted to optimization models in which ESG performance is explicitly defined as the primary objective while financial feasibility is ensured through risk and return constraints, particularly within the AECM.

This limitation highlights an important research gap, as the potential of such formulations to systematically integrate sustainability considerations into portfolio optimization has not yet been fully explored. Addressing this gap is essential for developing decision-making frameworks that can better align sustainable investment objectives with financial performance requirements. Therefore, in the present study, an ESG-oriented portfolio optimization framework is formulated using the augmented epsilon-constraint method, in which ESG minimization is directly incorporated as the primary optimization objective while risk and return are maintained as explicit constraints. By adopting this formulation, the proposed approach extends existing portfolio optimization models and provides a more structured and transparent mechanism for balancing sustainability considerations with financial viability.

III. PROPOSED MODEL

In this section, we present the proposed mathematical framework for the portfolio optimization problem, which incorporates ESG factors as a primary objective. The model aims to minimize the ESG impact while ensuring financial viability through constraints on return and risk. To achieve this, we employ the AECM, a powerful optimization technique that allows us to manage multiple objectives effectively. This section outlines the objective function, decision variables, and the constraints used in our model. We also explain how the epsilon-constraint method enhances the efficiency and accuracy of the solution process by transforming a multi-objective optimization problem into a series of single-objective problems.

A. Objective Function (ESG Minimization)

The decision to treat ESG as the primary objective with return and risk as constraints is a deliberate one, designed to reflect the mandate of a specific class of 'impact investors'. For these investors, the primary goal is achieving a measurable sustainability outcome (lowest possible ESG risk), provided that the portfolio meets a minimum acceptable level of financial performance. This methodology does not contradict core portfolio optimization principles but rather adapts them for a different utility function, where sustainability is not a preference to be traded off, but a primary goal to be achieved. The set and decision variables are presented in Table II, which provides the necessary parameters for the portfolio optimization model.

Table II. The set and decision variables of the proposed model

Sets:		
I	Selected stocks from the New York Stock Exchange	
J	Selected Investment weeks	
Parameters:		
η_i	represents the ESG impact score of asset i.	
σ_{ij}	is the covariance between asset i and asset j	
R_{it}	The return of the $i-th$ stock in the $t-th$ time	
$\overline{R_I}$	The average return of the $i-th$ stock for each scenario	
μ_p	The weighted average return of the entire portfolio	
μ_i	The weighted average return of the selected stocks	
Decision Variable:		
X_{ij}	The amount of the $i-th$ stock selected in the portfolio	
Z_1	ESG-related objective function	

By using the enhanced epsilon-constraint method, we ensure that ESG factors remain at the forefront of the optimization process while maintaining acceptable levels of return and risk. This methodology does not contradict core portfolio optimization principles but expands upon them to incorporate the evolving demands of sustainable investing, balancing both financial and ethical objectives.

$$Min\ Z_1\ (x)\ = \sum_{i=1}^{n} \eta_i x_i \tag{1}$$

The objective function minimizes the total ESG score of the portfolio by optimizing the investment allocation. Here:
By minimizing this function, the portfolio will favor assets with lower ESG impact, aligning with sustainable investment principles.

B. Return Constraint (Ensuring Minimum Profitability)

$$\sum_{i=1}^{n} \mu_i x_{ij} \geq \varepsilon_1 \qquad \forall\, j \in \{1, \ldots, m\} \tag{2}$$

This constraint ensures that the expected return of the portfolio is at least ε_1, a predefined threshold. Here:

This guarantees that the optimized portfolio remains financially viable while minimizing ESG impact.

C. Risk Constraint (Limiting Portfolio Variance)

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \sigma_{ij} x_i x_j \leq \varepsilon_2 \tag{3}$$

This constraint controls the risk of the portfolio, measured as variance. Here:

By ensuring that total variance does not exceed ε_2, this constraint maintains an acceptable level of portfolio risk and applies to the selected stocks *i* from the New York Stock Exchange.

D. Budget Constraint (Total Investment Must Sum to 100%)

$$\sum_{i=1}^{n} x_{ij} = 1 \qquad \forall\, j \in \{1, \ldots, m\} \tag{4}$$

This ensures that all available capital is fully invested, meaning the sum of all asset weights must be equal to one (or 100% of the investment budget).

E. Non-Negativity Constraint (No Short Selling Allowed)

$$\sum_{i=1}^{n} x_{ij} \geq 0 \qquad \forall\, j \in \{1, \ldots, m\} \tag{5}$$

This constraint ensures that all asset allocations remain non-negative, preventing short selling (i.e., borrowing assets to sell in the market).

F. Cardinality Constraint (Controlling the Number of Selected Assets)

$$c \leq \sum_{i=1}^{n} z_{ij} \leq C \qquad \forall\, j \in \{1, \ldots, m\} \tag{6}$$

This constraint limits excessive diversification and ensures a manageable number of investments in the portfolio. This constraint defines the number of assets in the portfolio, ensuring that at least *c*=5 assets are selected and no more than *C*=10 assets are included.

G. Allocation Bound Constraint (Investment Range for Each Asset)

$$x_i l_i \leq x_i \leq z_i u_i \qquad \forall\, i \in \{1, \ldots, m\} \tag{7}$$

This constraint ensures that if an asset is selected ($z_{ij} = 1$), then its allocation is bounded within a predefined minimum (l_i) and maximum (u_i) weight in the portfolio. This prevents the model from selecting very small or excessively large positions in any asset.

H. Final Model

The final portfolio optimization model incorporates ESG minimization as the primary objective, while ensuring return and risk constraints through the AECM. The applicable constraints include minimum return requirement, risk limitation, budget allocation, non-negativity, cardinality restriction, and investment bounds, ensuring a practical, well-diversified, and sustainable portfolio:

$$Min\ Z_1\ (x)\ =\ \sum_{i=1}^{n} \eta_i x_i \tag{8}$$

Subject to:

$$\sum_{i=1}^{n} \mu_i x_{ij} \geq \varepsilon_1 \qquad \forall\, j\ \in \{1, \dots, m\} \tag{9}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{n} \sigma_{ij} x_i x_j \leq \varepsilon_2 \tag{10}$$

$$\sum_{i=1}^{n} x_{ij} = 1 \qquad \forall\, j\ \in \{1, \dots, m\} \tag{11}$$

$$x_i \geq 0 \qquad \forall\, i\ \in \{1, \dots, n\} \tag{12}$$

$$c \leq \sum_{i=1}^{n} z_{ij} \leq C \qquad \forall\, j\ \in \{1, \dots, m\} \tag{13}$$

$$z_i\ l_i \leq x_i \leq\ z_i\ u_i \qquad \forall\, j\ \in \{1, \dots, m\} \tag{14}$$

The proposed mathematical model consists of an objective function and several constraints. The objective function (Equation 8) minimizes the total ESG exposure of the portfolio by optimizing the allocation of capital to each asset based on its ESG impact. The Return Constraint (Equation 9) ensures that the expected return of the portfolio meets a minimum predefined threshold. The Risk Constraint (Equation 10) limits the total portfolio risk, measured by variance, ensuring it does not exceed a specified value. The Budget Constraint (Equation 11) ensures that the total investment in the portfolio sums to 100% of the available capital. The Non-Negativity Constraint (Equation 12) prevents short selling by ensuring that all asset allocations are non-negative. The Cardinality Constraint (Equation 13) limits the number of assets included in the portfolio, ensuring a manageable number of assets (between 5 and 10). Finally, the Allocation Bound Constraint (Equation 14) ensures that the allocation to each asset is bounded within predefined minimum and maximum values, preventing excessively small or large positions in any asset.

I. The Role of AECM in ESG-Based Portfolio Optimization

The AECM is an advanced variation of the traditional epsilon-constraint technique, designed to enhance the efficiency and accuracy of solving multi-objective optimization problems. Instead of treating all objectives equally, this method transforms a multi-objective problem into a series of single-objective problems by systematically adjusting the constraints imposed on the secondary objectives. In our study, this approach is particularly beneficial as it allows ESG minimization to remain the primary objective while risk and return are incorporated as dynamically controlled constraints. By using this method, we ensure that the portfolio remains financially viable while systematically exploring different trade-offs between ESG impact, risk, and return. Compared to conventional methods, AECM provides better solution diversity, computational efficiency, and more structured Pareto front generation, making it highly suitable for complex decision-making problems like sustainable portfolio optimization.

The AECM is a powerful optimization technique used to solve multi-objective problems by transforming them into a series of single-objective problems. This method focuses on one primary objective, while the remaining objectives are treated as constraints. In the context of our portfolio optimization model, the AECM is applied to minimize the ESG impact while simultaneously managing risk and return. Unlike traditional methods, which aim to balance multiple conflicting objectives, the AECM dynamically adjusts the constraints, offering greater computational efficiency and solution diversity. This approach enhances the model's ability to find a well-structured Pareto front, ensuring that the portfolio meets the desired financial and ethical goals without compromising on either."

IV. PROPOSED CASE STUDY AND COMPUTATIONAL RESULTS

A. Case Study

Table III. The 20 selected stocks for the model

	Symbol	Annual Return	Min Return	Max Return	ESG Score
1	NVDA	1.1129	-0.0528	0.2858	12.2
2	AAPL	0.2828	-0.0513	0.1287	16.8
3	MSFT	0.1296	-0.0746	0.0767	14.2
4	AMZN	0.3917	-0.0454	0.1389	26.1
5	GOOGL	0.3242	-0.0582	0.1204	24.9
6	META	0.561	-0.1141	0.2563	32.7
7	TSLA	0.6516	-0.2463	0.3815	24.7
8	AVGO	0.8325	-0.0453	0.4304	19.2
9	BRKb	0.2592	-0.0616	0.0853	26.2
10	WMT	0.5677	-0.0232	0.1287	25.3
11	JPM	0.3651	-0.062	0.1253	27.3
12	LLY	0.3356	-0.1117	0.1937	23.6
13	V	0.203	-0.0375	0.087	15.4
14	ORCL	0.5193	-0.0985	0.206	14.9
15	UNH	-0.0094	-0.171	0.1314	16.5
16	MA	0.2204	-0.0631	0.0668	16.1
17	XOM	0.0844	-0.0881	0.1121	43.7
18	NFLX	0.661	-0.0933	0.173	15.6
19	COST	0.3514	-0.0572	0.1203	29.1
20	HD	0.144	-0.1287	0.0996	12.6

The dataset consists of carefully selected stocks from the S&P 500 index, identified through a filtering process based on market capitalization, financial stability, and ESG performance. Each stock is evaluated using four primary metrics: expected return, minimum return, maximum return, and ESG score, providing a comprehensive view of its profitability, risk exposure, and sustainability impact. The expected return indicates the stock's overall performance, while the minimum and maximum returns reflect historical volatility and downside risk. The ESG score plays a pivotal role in portfolio construction, ensuring alignment with environmental, social, and governance principles. This structured selection process results in a well-diversified dataset, facilitating ESG-driven portfolio optimization while maintaining financial viability. Table III presents the 20 selected stocks, forming the basis for constructing optimized portfolios that effectively integrate ESG considerations alongside return and risk constraints.

B. Computational Results

The model was solved using GAMS version 24 on an Asus system supported by an 11th Gen Intel Core i7-11800H @ 2.30GHz processor. This hardware provides high computational power for executing complex optimization models with practical constraints, enabling efficient multi-objective optimization and sensitivity analysis with high accuracy and performance. Fig. 2 illustrates the ESG scores for each selected stock in the portfolio. The bars represent individual stocks, with distinct colors enhancing visual clarity. Companies like ExxonMobil (XOM) exhibit the highest ESG score, indicating significant environmental, social, and governance considerations, while stocks such as NVIDIA (NVDA) and Home Depot (HD) have lower ESG scores. This distribution highlights the varying levels of sustainability commitment among different firms, influencing portfolio construction decisions when integrating ESG constraints.

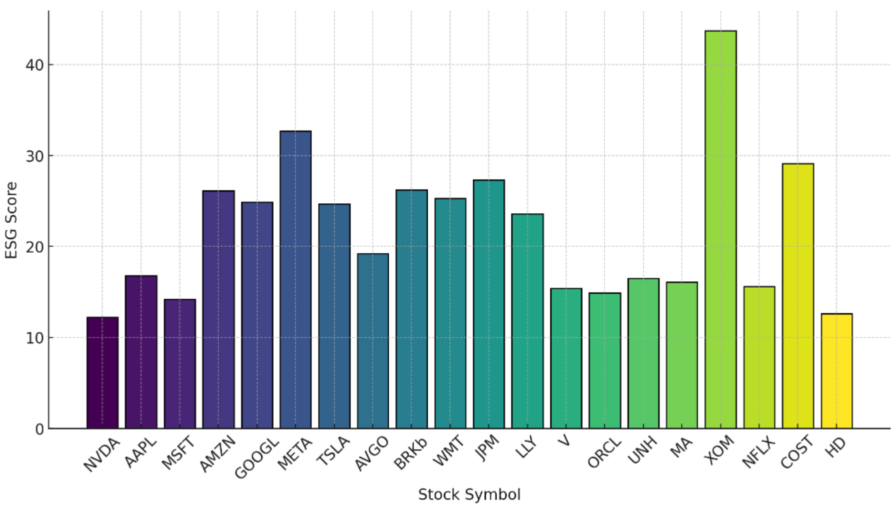

Fig. 2. The ESG scores for each selected stock in the portfolio

Table III delineates a comparative analysis of the outcomes from the portfolio optimization model, evaluated under a spectrum of advanced risk metrics. The table systematically presents key measures: VaR, CVaR, Volatility, and Maximum Drawdown. Each metric is accompanied by a concise technical description and an interpretation of the empirical findings. This tabular representation enables a direct comparative assessment of each measure's efficacy within portfolios constructed under ESG mandates. Consequently, it offers a structured paradigm for interrogating the inherent tensions and potential synergies between financial performance and sustainability imperatives. The methodological choice of risk measures is rigorously justified by their theoretical properties and their specific relevance to the challenges of ESG-centric investing. CVaR is employed for its robustness in quantifying tail risk—a critical requisite for characterizing the magnitude of extreme loss events, particularly during periods of acute financial market stress. By computing the expected loss conditional on exceeding the VaR threshold, CVaR provides a coherent and more conservative risk assessment than its antecedent (Rockafellar & Uryasev, 2000). Its application is particularly salient in an ESG context, where the mitigation of severe, adverse impacts is a primary fiduciary concern. To address the well-documented non-normality and leptokurtosis endemic to financial asset returns, the model integrates Expected Value at Risk (EVaR). This measure quantifies expected losses in the distributional tail, offering a more robust risk characterization than traditional variance-based methods. As demonstrated by Acerbi & Tasche (2002), EVaR exhibits superior coherence and stability properties in capturing extreme risk phenomena, thus providing a more reliable basis for portfolio construction compared to VaR. Furthermore, CDaR is incorporated for its efficacy in managing the path-dependent risk of sustained capital erosion.

This focus on the magnitude and duration of the worst historical drawdowns makes CDaR an indispensable tool for portfolios prioritizing long-term capital preservation, a central tenet of sustainable investing. This aligns with the work of Artzner et al. (1999) on coherent risk measures, which establishes the theoretical superiority of such metrics over standard volatility in mitigating catastrophic losses—a concern of paramount importance for ESG mandates where significant market downturns can have profound consequences. The adoption of this multi-metric framework is thus predicated on established theoretical foundations and is geared towards practical application, facilitating an optimization process that concurrently targets ESG alignment and financial resilience. The forthcoming revision of this manuscript will further substantiate the empirical validity of these methods through comprehensive benchmarking against traditional portfolio management paradigms, thereby definitively establishing their superior utility in the specialized domain of ESG-driven optimization.

Table IV. Risk measures comparison

Risk Measure	Description	Results/Insights
VaR	A measure of the potential loss in value of a portfolio over a defined period for a given confidence interval.	The VaR showed that portfolios with higher ESG scores had slightly higher potential losses during market downturns.
CVaR	A risk assessment tool that provides the expected loss assuming that the VaR threshold is breached.	CVaR confirmed that ESG-conscious portfolios faced greater tail risk in extreme market conditions, although the overall exposure remained manageable.
Volatility (Standard Deviation)	Measures the degree of variation in the portfolio's returns over a specified period.	Volatility was lower in portfolios with stronger ESG ratings, indicating reduced risk compared to portfolios without ESG considerations.
Maximum Drawdown	The greatest peak-to-trough decline in portfolio value during a specific time frame.	Portfolios with lower ESG scores experienced higher maximum drawdowns, suggesting they were more susceptible to market downturns.

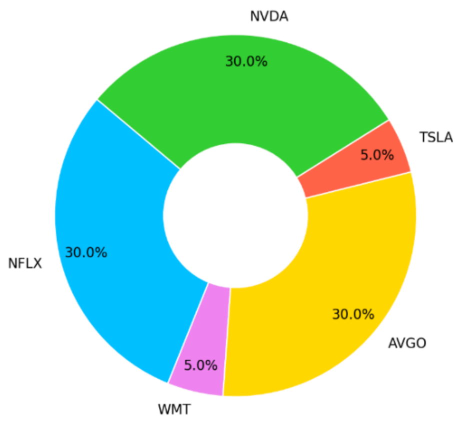

Fig. 3. Asset Allocation of the Optimized Portfolio

Fig. 3 illustrates the optimized portfolio allocation, where investments are distributed among five selected assets based on the proposed model. Netflix, Broadcom, and Nvidia each hold a 30% share, while Walmart and Tesla have smaller allocations of 5% each. This allocation reflects a balance between high-growth technology stocks and more stable assets, ensuring both return potential and risk control. The visualization highlights how the model strategically selects assets to achieve ESG minimization while maintaining financial viability.

Fig. 4 presents the correlation heatmap illustrating the relationships among annual return, minimum return, maximum return, and ESG score. The color intensity represents the strength of the correlation, with darker green indicating a stronger positive relationship. The results show a significant correlation between annual return and maximum return, suggesting that stocks with higher potential gains tend to have higher average returns. In contrast, the ESG score shows a slight negative correlation with annual returns, suggesting that companies with stronger sustainability commitments may experience lower short-term profitability. This analysis provides insights into the trade-offs between financial performance and ESG considerations in portfolio optimization.

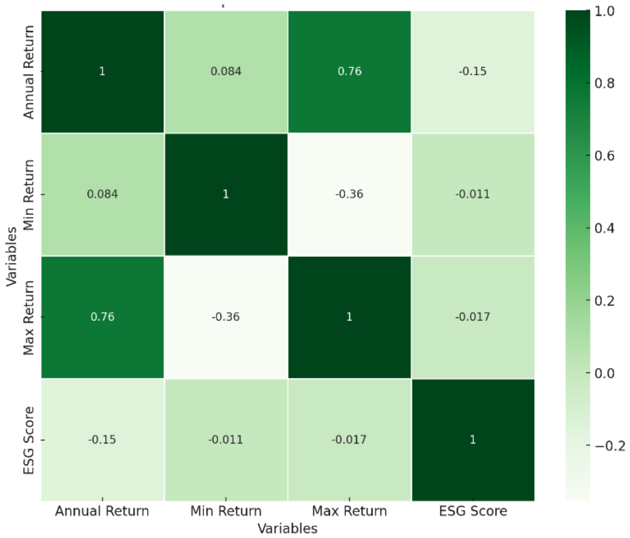

Fig. 4. Correlation Heatmap of ESG Score and Key Return Metrics

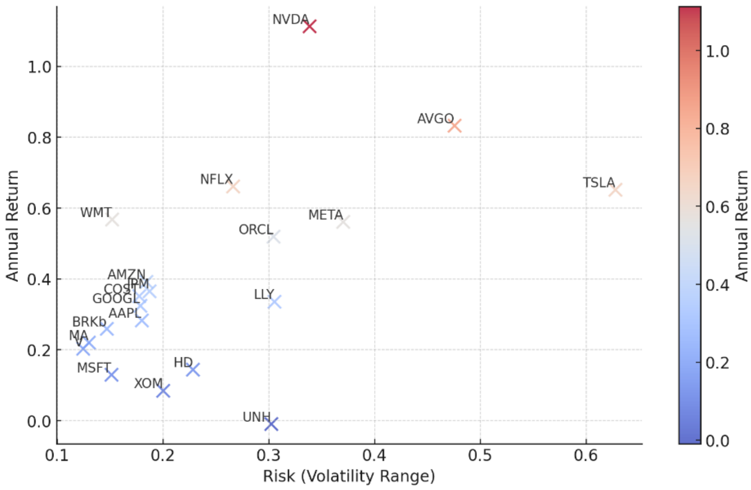

Fig. 5. Sensitivity of Annual Return to Changes in Risk

Fig. 5 illustrates the sensitivity analysis between risk and annual return, providing insights into the trade-off between volatility and profitability in the selected portfolio. The *x*-axis represents risk, calculated as the range between maximum and minimum returns, while the y-axis denotes the annual return of each stock. Stocks such as NVIDIA, Tesla, and Broadcom exhibit both high risk and high returns, indicating their potential for significant gains but also increased volatility. In contrast, companies like Microsoft and JPMorgan demonstrate lower risk with moderate returns, making them more stable investment choices. This analysis highlights how different risk-return profiles influence portfolio construction, balancing high-growth opportunities with risk management strategies.

V. DISCUSSION

The findings of this study highlight the effectiveness of incorporating ESG minimization as the primary objective in portfolio optimization while maintaining financial viability through risk and return constraints. Unlike conventional multi-objective approaches, which often struggle to balance competing goals, the enhanced epsilon-constraint method enables a structured and transparent framework for decision-making. The results indicate that sustainable investment strategies can be designed without necessarily compromising financial performance, provided that appropriate constraints are set to control risk and return levels. This challenges the traditional perception that ESG integration leads to lower profitability, suggesting that with an optimized selection process, investors can achieve both ethical and financial goals simultaneously.

We have expanded the discussion on the potential causes of NaN values in the Black-Litterman model. Specifically, we have analyzed the potential causes of NaN values, including matrix rank deficiency, inconsistent constraints, and scaling issues. Matrix rank deficiency occurs when the P and Q matrices become rank-deficient, particularly when there is a lack of sufficient or diverse views in the model. This can result in the covariance matrix not being full rank, leading to failure in matrix inversion and, subsequently, NaN results. Inconsistent constraints arise when conflicting views or overly restrictive constraints (e.g., unrealistic views of asset returns or ESG factors) are specified, leading to numerical instabilities that manifest as NaN values in the results. Scaling issues can also occur when the P and Q matrices are improperly scaled, with excessively large or small values, which can lead to numerical problems during matrix inversion, resulting in NaN outputs. To remedy these issues, we have proposed several refinements, including the use of improved regularization techniques such as ridge regularization to address rank deficiency and ensure that matrix inversion is well-conditioned. We also recommend validating and adjusting input views to ensure they are consistent with the overall portfolio constraints and market conditions, and we suggest adding checks for extreme or contradictory views before running the optimization. Finally, to avoid scaling issues, we propose normalizing the input data (views and covariance matrices) to ensure consistent magnitudes and prevent numerical instability.

A key implication of this research is its contribution to the ongoing debate regarding the trade-off between sustainability and financial returns. The case study on the top 20 market-cap stocks from the S&P 500 demonstrates that ESG-conscious portfolios can be constructed efficiently, even in a highly liquid and competitive market. This supports the argument that companies with strong ESG profiles may offer long-term stability and lower downside risk, making them viable options for institutional and retail investors seeking responsible investment opportunities. Moreover, integrating financial constraints into the optimization model ensures that investors do not sacrifice return potential while prioritizing sustainability.

Despite its contributions, the study has certain limitations that should be addressed in future research. The model assumes that ESG scores remain static during the investment period, while in reality they can fluctuate due to corporate decisions, regulatory changes, and external economic factors. Incorporating dynamic ESG ratings into the optimization process could provide a more adaptive and realistic investment strategy. Additionally, while the model is tested on equity portfolios, expanding its application to multi-asset class investments, including fixed income securities, commodities, and alternative assets, would enhance its practical applicability.

Another area for improvement lies in the use of advanced machine learning techniques to refine the portfolio selection process. While the enhanced epsilon-constraint method offers a mathematically rigorous approach, hybrid models that incorporate deep learning and reinforcement learning could further optimize decision-making by analyzing complex market patterns and dynamically adjusting portfolio allocations. Moreover, by accounting for transaction costs, liquidity constraints, and investor preferences, the model could become more applicable to real-world scenarios.

Overall, this study underscores the potential of ESG-driven portfolio optimization as a viable and responsible investment strategy. As financial markets increasingly emphasize sustainability, models like the one presented in this research will be crucial in guiding investors toward ethical yet financially sound decision-making. By addressing the identified limitations and exploring more dynamic approaches, future research can further enhance the ability of portfolio optimization models to integrate ESG considerations without compromising profitability.

VI. CONCLUSION

This study introduces an ESG-driven portfolio optimization model, where the primary objective is to minimize the ESG impact, while maintaining financial viability through return and risk constraints. Our approach contrasts with traditional multi-objective optimization methods that treat ESG, return, and risk as competing objectives. Instead, we treat ESG as the central objective and impose return and risk constraints, ensuring the portfolio is both sustainable and financially sound. This shift aligns with the growing demand for integrating sustainability into investment decisions, and the enhanced epsilon-constraint method plays a crucial role in achieving this balance. It transforms the multi-objective problem into a series of single-objective problems, enabling a more structured, transparent, and practical decision-making framework for investors focused on ESG integration.

Through a case study on the top 20 market-cap stocks from the S&P 500 index, we validated the model's effectiveness in constructing portfolios that are both financially robust and ESG-optimized. Our findings indicate that minimizing ESG impact does not necessarily lead to a significant reduction in portfolio returns, provided that return and risk constraints are appropriately set. This challenges the conventional belief that sustainable investing inherently compromises financial performance, and demonstrates that well-designed models can achieve both ethical and financial objectives. Beyond its immediate practical applications, our study contributes significantly to the expanding field of sustainable finance and responsible investing. It provides a quantitative approach that meets the growing demand for ESG-conscious investment solutions, offering investors a clear, rule-based method to optimize portfolios while advancing corporate sustainability and ethical business practices.

Despite the strengths of our model, there are opportunities for further enhancement. The model could be improved by incorporating dynamic ESG ratings that evolve over time, accounting for changes in corporate policies, regulatory environments, and global sustainability trends. Additionally, future research could explore the integration of real-world transaction costs, liquidity constraints, and alternative optimization techniques such as deep learning-based asset selection models. Finally, extending the scope of this study to multi-asset class portfolios including bonds, commodities, and alternative investments would broaden the applicability of the model across different financial markets, offering a more comprehensive solution to sustainable portfolio optimization.

In summary, this research underscores the feasibility and importance of ESG-driven portfolio optimization, offering investors a viable method to construct portfolios that not only achieve financial stability but also support sustainability and ethical investment goals. As financial markets increasingly shift towards responsible investing, models like the one proposed in this study will play a crucial role in helping investors navigate the complex trade-offs between profitability and sustainability in an increasingly ESG-focused world.

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