Multi-Objective Investment Portfolio Optimization Using MCDM and MIGP with Financial, Risk, and ESG Constraints

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ABSTRACT

Incorporating Environmental, Social, and Governance (ESG) criteria into investment portfolios is increasingly critical to ensure long-term sustainability and prevent value-destructive capital allocations. Adopting a Malaysian institutional investor perspective, this study develops a structured portfolio optimization framework integrating Multi-Criteria Decision Making (MCDM) and Mixed-Integer Goal Programming (MIGP). Using fiscal year 2022 disclosures from five major oil and gas companies which are PETRONAS, Shell, BP, Chevron, and ExxonMobil, standardized into Malaysian Ringgit (MYR), the Weighted Sum Model (WSM) was applied to rank alternatives across 21 sub-attributes spanning financial, risk, environmental, social, and safety dimensions. Optimal capital allocation was then derived via MIGP under goal-based and ESG constraints implemented in Microsoft Excel and Maple. Results reveal that while international supermajors lead unconstrained WSM rankings due to sheer scale, PETRONAS anchors the optimal MIGP portfolio (86.9% allocation) due to its superior environmental impact and risk profile, paired with Chevron (6.9%) and ExxonMobil (6.2%) to surpass profit targets (MSE = 0.0041). Sensitivity analysis across varying macro-weight mandates confirms allocation stability and demonstrates the necessity of balanced ESG thresholds for feasible capital deployment.

Keywords: Investment Optimization, ESG, Multi-Criteria Decision Making (MCDM), Mixed-Integer Goal Programming (MIGP), Portfolio Allocation, Oil and Gas.

INTRODUCTION

Portfolio optimization focuses on the strategic allocation of assets to maximize expected returns while mitigating associated risks, forming the cornerstone of modern portfolio theory (Markowitz, 1952; Zenios, 2007). Over the past decade, the scope of portfolio construction has evolved beyond purely financial considerations to incorporate Environmental, Social, and Governance (ESG) factors, reflecting a broader global shift toward responsible and sustainable investing (Friede et al., 2015; Khan et al., 2016; Schanzenbach & Sitkoff, 2020). ESG integration aligns investment choices with long-term sustainability benchmarks, evolving regulatory standards, and stakeholder expectations, while preserving financial viability.

Multiple Criteria Decision-Making (MCDM) techniques such as the Analytic Hierarchy Process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and the Weighted Sum Model (WSM) have been widely applied to address the multi-dimensional nature of investment decisions involving profitability, risk exposure, and ESG compliance (Parameshwaran et al., 2015; Sahoo & Goswami, 2023; Triantaphyllou, 2000; Zanakis et al., 1998). While effective, traditional WSM applications are sensitive to assigned criteria weights, which can introduce bias into rankings. Consequently, adaptive weighting and redistribution strategies have been explored to enhance decision robustness and fairness in asset ranking (Pamučar et al., 2017; Torabi & Hassini, 2009; Vafaei et al., 2016).

Mathematical optimization models, particularly Mixed-Integer Linear Programming (MILP) and Goal Programming (GP), complement MCDM by enabling the simultaneous consideration of multiple competing objectives and operational constraints within a quantitative framework (Moreno et al., 2015; Romero, 2001).

By integrating MCDM-derived priority scores directly into a Mixed-Integer Goal Programming model, this study establishes a comprehensive portfolio allocation framework designed to balance profitability, limit risk exposure, and maintain adherence to ESG requirements.

MATERIALS AND METHODS

This study adopts a hybrid decision-making architecture that couples MCDM with Mixed-Integer Goal Programming (MIGP) to evaluate and optimize asset allocations. The workflow comprises data extraction, currency standardization into Malaysian Ringgit (MYR), Min-Max normalization, weighted scoring via WSM, mathematical optimization using MIGP in Maple, Mean Squared Error (MSE) evaluation, and macro-weight sensitivity testing.

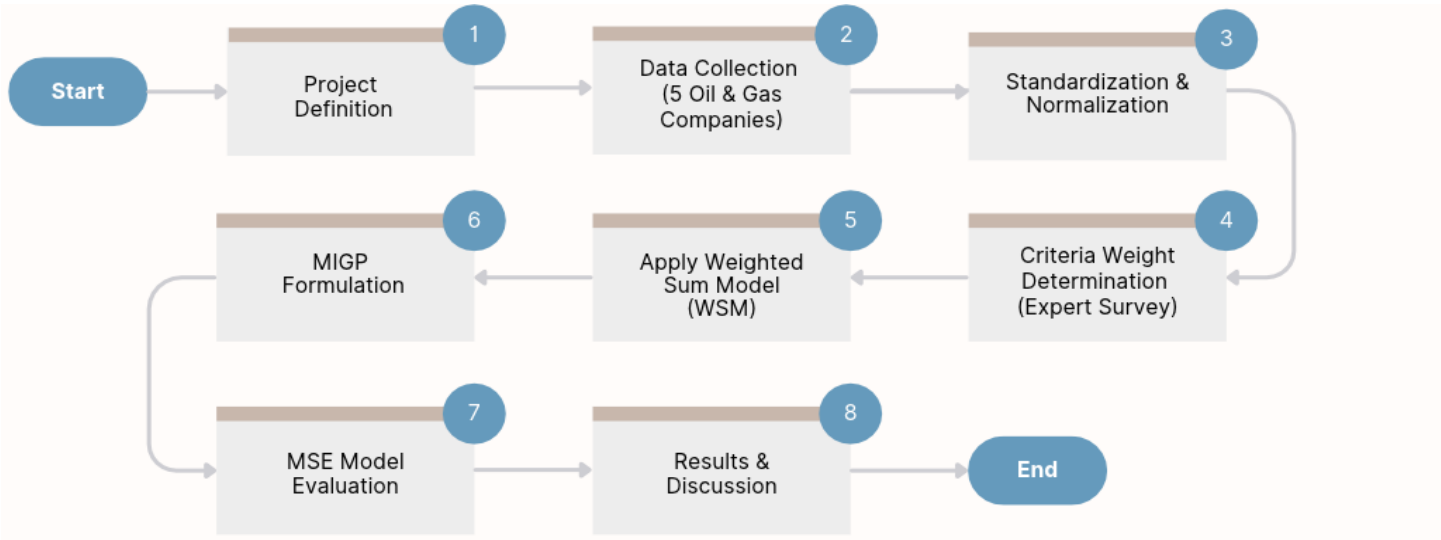


Figure 1: Systematic research methodology and procedural workflow of the hybrid MCDM–MIGP portfolio model.

A. Data Collection

The empirical analysis was conducted using data extracted from the fiscal year 2022 audited annual reports and sustainability disclosures of five major oil and gas corporations: Petroliam Nasional Berhad (PETRONAS), Shell plc, BP plc, Chevron Corporation, and Exxon Mobil Corporation. These firms were selected to benchmark Malaysia's national oil corporation (PETRONAS) against leading global energy peers. In alignment with high-hazard energy sector imperatives, the evaluation taxonomy spans five primary dimensions: financial, risk, environmental, social, and occupational safety, subdivided into 21 quantifiable indicators (Table 1).

Table 1. Measurable Evaluation Indicators Across Primary Dimensions

Key Evaluation Dimension	Sub-Attribute Indicator	Variable Code
Financial	Total Assets	C1
	Total Equity	C2
	Total Liabilities	C3
	Revenue	C4
	Profit / (Loss) for the Year	C5
	Total Comprehensive Income / (Loss)	C6

Risk	Credit Risk	C7
	Liquidity Risk	C8
	Interest Rate Risk	C9
	Foreign Exchange Risk	C10
Environmental	Energy Consumed	C11
	Freshwater Withdrawal	C12
	Wastewater Discharge	C13
	Hazardous Waste Generation	C14
	Nitrogen Oxides (NOx) Emissions	C15
	Sulphur Oxides (SOx) Emissions	C16
Social	Women in Senior Leadership	C17
	Representation of Diverse Nationalities in Senior Leadership	C18
	Idea Generation Platforms for Young Talents	C19
Safety	Fatalities	C20
	Total Recordable Cases (TRC)	C21

B. Standardization and Normalization

To ensure dimensional uniformity across diverse accounting currencies and reporting conventions, monetary indicators in USD were converted into Malaysian Ringgit (MYR). Min-Max normalization was subsequently performed on the empirical dataset across all sub-attributes, bounding all normalized scores within [0, 1]:

$$\text{Normalized Score}_{ij} = \frac{\text{Score}_{ij} - \text{Min}_j}{\text{Max}_j - \text{Min}_j}$$

C. Criteria Weight Determination

Criteria weighting was determined via structured expert surveys administered to domain specialists. Experts assigned relative importance ratings to each metric within the primary clusters. A composite index—the Total Average Score—was calculated by averaging expert ratings.

D. Weighted Sum Model (WSM)

The WSM algorithm was executed in Microsoft Excel to establish multi-attribute benchmark rankings. For each firm, normalized indicator scores were multiplied by their corresponding sub-attribute weights, and category aggregate scores were combined with their overarching macro-weights:

$$\text{Weighted Score}_i = \sum_{j=1}^{m} \left(W_j \times \text{Normalized Score}_{ij} \right),$$

E. Mixed-Integer Goal Programming (MIGP)

The capital allocation problem was formulated using Mixed-Integer Goal Programming (MIGP). The model targets two primary goals simultaneously: minimizing profit shortfalls below a defined return target and minimizing risk excesses beyond a predefined risk ceiling, under strict capital budget limits and ESG performance constraints. Let x_i denote the capital proportion assigned to company i. The deviation variables d_1m and d_1p represent under-achievement and over-achievement of the profit target, respectively; d_2m and d_2p

denote under-achievement and over-achievement of the risk ceiling. The objective function penalizes only unfavorable deviations:

$$Minimize\ Z = d_1 m + d_2 p$$

$$0.7999X_p + 0.6999X_s + 0.4033X_{bp} + 0.4459X_c + 0.9792X_{ex} + d_1 m - d_1 p = 0.7$$

$$0.3198X_p + 0.6628X_s + 0.7970X_{bp} + 0.4312X_c + 0.3056X_{ex} + d_2 m - d_2 p = 0.3$$

Subject to:

Capital Budget Conservation: $X_p + X_s + X_{bp} + X_c + X_{ex} = 1.0$

Environmental Ceiling: $0.0510X_p + 0.6604X_s + 0.1389X_{bp} + 0.2926X_c + 0.6766X_{ex} \leq 0.1064$

Social Floor: $0.2905X_p + 0.2693X_s + 0.6900X_{bp} + 0.3500X_c + X_{ex} \geq 0.0670$

Safety & Health Floor: $0.1X_p + 0.7X_s + 0.2994X_{bp} + 0.5051X_c + 0.2938X_{ex} \geq 0.1400$

Mixed-integer Linking & Non-negative Bounds: $0 \leq x_i \leq 1\ for\ \{p, s, bp, c, ex\}$

$d_1 m, d_1 p, d_2 m, d_2 p \geq 0$

F. Mean Squared Error (MSE) Evaluation

To measure how accurately the model met its profit and risk targets, the Mean Squared Error (MSE) was computed using the final system deviation variables:

$$MSE = \frac{(d_1 p)^2 + (d_2 p)^2}{2}$$

RESULTS AND DISCUSSION

A. MCDM Ranking Analysis

The WSM produced clear standalone performance hierarchies as summarized in Table 2.

Table 2. Composite WSM Evaluation Scores and Company Rankings

Company Alternative	WSM Composite Performance Score	Standalone Rank
ExxonMobil	0.67313	**1**
Shell	0.65559	**2**
Chevron	0.40844	**3**
BP	0.3835	**4**
PETRONAS	0.165	**5**

B. Optimal MIGP Allocation

Solving the MIGP formulation in Maple yielded the optimal capital allocation proportions and goal deviation variables presented in Table 3.

Table 3. Optimal MIGP Decision and Goal Deviation Outputs

Variable Parameter	Optimal Value	Operational & Managerial Interpretation

Xp (PETRONAS)	0.869	86.9% of capital allocated to PETRONAS
Xs (Shell)	0	0.0% capital allocation (excluded from portfolio)
Xbp (BP)	0	0.0% capital allocation (excluded from portfolio)
Xc (Chevron)	0.069	6.9% of capital allocated to Chevron
Xex (ExxonMobil)	0.062	6.2% of capital allocated to ExxonMobil
d_1m	0	Zero shortfall in achieving target profitability
d_1p	0.0866	Target profit overachieved by approximately 8.66%
d_2m	0	No slack below risk ceiling
d_2p	0.0266	Risk target marginally exceeded by 2.66%

Although PETRONAS ranked fifth in the standalone Weighted Sum Model (WSM) evaluation (composite score: 0.05653), it secured 86.9% of the optimal portfolio in the MIGP optimization. This apparent paradox occurs because WSM evaluates firms via an unconstrained linear aggregation where international supermajors (ExxonMobil and Shell) dominate due to massive asset and revenue scale, whereas MIGP enforces strict, non-compensatory environmental and risk boundaries. As shown in Table 4, PETRONAS exhibits the lowest environmental impact burden among all five peers (0.05099) and a low-risk exposure score (0.31975). Conversely, ExxonMobil (0.67656) and Shell (0.66038) carry high environmental impact scores that violate the portfolio's strict environmental ceiling. Consequently, the MIGP solver anchors the portfolio in PETRONAS (86.9%) to satisfy the environmental cap while blending small allocations of Chevron (6.9%) and ExxonMobil (6.2%) to satisfy the social ($0.3386 \geq 0.0670$) and safety ($0.1400 \geq 0.1400$) floors and exceed the 0.70 profit goal (0.7866).

Table 4. Disaggregated Key Attribute Scores and Optimal MIGP Capital Allocation

Company	Financial (0.333)	Risk (0.133)	Env. (≤0.1064)	Social (≥0.067)	Safety (≥0.140)	WSM Score	MIGP Weight
ExxonMobil	0.97922	0.30562	0.67656	1	0.2938	0.67313	0.0620 (6.2%)
Shell	0.69993	0.66276	0.66038	0.26929	0.7	0.65559	0.0000 (0.0%)
Chevron	0.44595	0.43115	0.29256	0.35	0.50514	0.40844	0.0690 (6.9%)
BP	0.40331	0.79698	0.13891	0.69	0.29938	0.3835	0.0000 (0.0%)
PETRONAS	0.7999	0.31975	0.05099	0.29053	0.1	0.05653	0.8690 (86.9%)

C. Sensitivity Analysis Across Macro-Weight Scenarios

To evaluate the robustness of the optimal portfolio against shifting investor priorities, a sensitivity analysis was conducted by varying the macro-weights assigned to Financial, Risk, and combined ESG–Safety dimensions across four strategic mandates as shown in Table 5.

Table 5. Sensitivity Analysis of Optimal MIGP Portfolio Allocations Across Macro-Weight Scenarios

Macro-Weight Scenario	PETRONAS	Shell	BP	Chevron	ExxonMobil	Obj. (Z)	MSE
Survey Base (33.3% Fin–13.3% Risk–53.4% ESG)	0.869	0	0	0.069	0.062	0.0266	0.0041
Financial-Dominant (50% Fin–30% Risk–20% ESG)	—	—	—	—	—	Infeasible	—
Balanced Mandate (40% Fin–30% Risk–30% ESG)	0.986	0	0	0	0.014	0.0196	0.0054
ESG-Prioritized (30% Fin–30% Risk–40% ESG)	0.9541	0	0	0	0.0459	0.0191	0.006

The optimal portfolio exhibits strong structural stability across feasible mandates. Under both the Balanced (40–30–30) and ESG-Prioritized (30–30–40) scenarios, PETRONAS remains the dominant core holding (95.41% to 98.60%), paired with a minor ExxonMobil allocation (1.40% to 4.59%) to satisfy social and profit goals while keeping total deviation Z below 0.0200 and MSE below 0.0061. Conversely, shifting to an aggressive Financial-Dominant (50–30–20) weighting scales the environmental ceiling down to 0.0399, rendering the optimization infeasible because even the cleanest peer (PETRONAS, 0.0510) exceeds that threshold. This confirms that hybrid MCDM–MIGP models require balanced ESG weightings to maintain feasible capital solutions in carbon-intensive sectors. The low MSE of 0.0041 demonstrates exceptional objective convergence, validating the ability of the hybrid MCDM–MIGP approach to resolve trade-offs between aggressive returns and ESG stewardship.

CONCLUSION

This study presents a hybrid MCDM–MIGP framework for multi-objective portfolio optimization across five major oil and gas enterprises from a Malaysian institutional investor perspective. By coupling the Weighted Sum Model for multi-dimensional screening with Mixed-Integer Goal Programming for constrained asset allocation, the methodology proves that standalone multi-criteria rankings must be reconciled with mathematical portfolio optimization to account for risk hedging and binding environmental boundaries. Specifically, resolving the PETRONAS allocation paradox demonstrates how a lower-ranked WSM firm can serve as an indispensable portfolio anchor when strict ecological ceilings are enforced. The framework offers a practical, quantitatively validated tool for institutional funds and corporate treasuries operating in environmentally sensitive sectors.

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