Multi-Objective Optimization of Oil and Gas Project Portfolios Using Metaheuristic Algorithms and Pareto Front

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Abstract

Portfolio management in the oil and gas industry requires multi-objective optimization to balance economic, social, environmental, and risk criteria while respecting resource constraints. This study aims to optimize a portfolio of 18 oil and gas construction projects using metaheuristic algorithms, including Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). Data were collected through a standardized questionnaire encompassing eight dimensions (technical, spatial, economic, temporal, environmental, risk and safety, social, and operational) and weighted using the Analytic Hierarchy Process (AHP). The Genetic Algorithm generated a Pareto front and identified an optimal portfolio with an overall score of 2.9, economic index of 0.85, social index of 0.75, environmental index of 0.80, and risk index of 0.40. Comparison with a multi-criteria weighting method revealed that metaheuristic algorithms excel in providing non-dominated solutions, whereas the multi-criteria method suggested a portfolio with a higher economic index (0.90) due to its focus on profitability. The Pareto front, visualized using Plotly, illustrates the trade-offs among objectives and supports strategic decision-making. This approach enhances resource allocation and strengthens sustainability. Future research can explore hybrid algorithms and incorporate more real-world data.

Keywords: *Project Portfolio Management, Metaheuristic Algorithms, Multi-Objective Optimization, Pareto Front, Risk Management, Oil and Gas Projects*

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1. Introduction

Project portfolio management (PPM) has become a central organizational capability for industries in which numerous projects compete for limited financial, human, technological, and physical resources. Unlike single-project management, which concentrates on delivering a defined scope within specified cost, time, and quality constraints, PPM addresses the simultaneous selection, prioritization, balancing, scheduling, and oversight of multiple projects as an integrated investment system. Its principal purpose is to ensure that the collection of projects undertaken by an organization generates the greatest attainable strategic value rather than merely producing individually successful projects. Accordingly, an effective portfolio should align projects with organizational strategy, allocate scarce resources efficiently, maintain an appropriate balance among short- and long-term initiatives, manage aggregate risk, and accommodate dependencies among projects. These requirements are particularly important in capital-intensive sectors such as oil and gas, where project decisions involve substantial investment commitments, long implementation periods, technological complexity, environmental exposure, safety concerns, and far-reaching economic and social consequences [1-5]. The study underlying the present article therefore treats portfolio selection as a multi-objective decision problem involving economic, social, environmental, technical, temporal, operational, and risk-related considerations.

The oil and gas industry provides one of the most demanding contexts for PPM because upstream, midstream, and downstream projects differ substantially in their strategic function, capital requirements, geographical conditions, contractual structures, technical complexity, environmental sensitivity, and expected return periods. Organizations may need to choose among exploration and production developments, pipelines, storage facilities, refineries, petrochemical complexes, gas-processing facilities, offshore installations, export terminals, and infrastructure projects. These projects are rarely independent. They may compete for the same capital and specialist personnel, depend on the completion of related facilities, generate synergistic benefits, or create cumulative environmental and operational risks. In such circumstances, selecting projects solely on the basis of net present value, expected profit, or managerial judgment may lead to an economically attractive but strategically unbalanced portfolio. Mathematical programming in oil and gas settings has therefore increasingly incorporated capital constraints, strategic objectives, project characteristics, and organizational priorities into portfolio design. Panahi et al., for example, demonstrated the value of mathematical programming for identifying an optimal portfolio of capital projects in oil and gas companies while maximizing economic value and supporting strategic objectives [6]. Similarly, cash-flow optimization using genetic algorithms and particle swarm optimization has shown how market indicators, temporal cash requirements, and computational search can be integrated to improve portfolio-level financial decisions [7].

The conceptual difficulty of project portfolio selection arises from the presence of several conflicting objectives. Decision-makers seek to maximize profitability, strategic alignment, social contribution, environmental compliance, operational performance, and technological advancement while minimizing cost, risk, delay, environmental damage, and resource pressure. Improvement in one objective can diminish performance in another. For example, a highly profitable offshore project may also involve substantial technical risk, environmental sensitivity, and long-term resource commitments. Conversely, a low-risk infrastructure project may produce more modest financial returns but strengthen the operational resilience of the overall portfolio. Such trade-offs mean that a single objectively "best" portfolio may not exist. Instead, decision-makers often require a set of non-dominated alternatives representing different combinations of benefit and risk. Multi-objective optimization and Pareto-front analysis are especially appropriate in this setting because they do not collapse all objectives prematurely into one simplified measure. Rather, they reveal efficient portfolios for which no objective can be improved without worsening at least one other objective. The use of Pareto-based multi-objective programming in industrial research and development portfolios illustrates how economic, technical, strategic, temporal, and resource objectives can be jointly represented and evaluated [8].

Traditional project selection methods have included scoring models, financial appraisal, cost–benefit analysis, analytic hierarchy process, goal programming, and multi-criteria decision-making techniques. These methods remain valuable because they enhance transparency, structure expert judgment, and make organizational preferences explicit. For example, the combination of earned value management and the analytic hierarchy process can support project reprioritization during execution and improve resource-allocation decisions [9]. Likewise, portfolio models that explicitly balance sub-portfolios can prevent the concentration of resources in a single project category and can preserve strategic diversification [10]. Nevertheless, conventional ranking and weighting methods commonly evaluate projects individually, assume stable preferences, or provide one final ordering without adequately searching the enormous number of possible project combinations. Their limitations become more pronounced when the portfolio contains complex constraints, nonlinear relationships, project interdependencies, uncertain data, and multiple competing objectives. Models that incorporate interdependent effects have consequently shown that portfolio value cannot always be obtained by simply summing the values of individual projects; interactions among projects may significantly change the attractiveness of a portfolio [11].

Uncertainty further complicates portfolio selection. Project costs, schedules, market conditions, commodity prices, demand forecasts, regulatory requirements, environmental obligations, and technological performance may change throughout the portfolio life cycle. Risk is therefore not merely an attribute of individual projects but an emergent portfolio-level phenomenon involving correlations, dependencies, common vulnerabilities, and cascading effects. A structured review of project portfolio risk management identified risk identification, risk assessment, project-risk interdependencies, and the relationship between portfolio risk and portfolio success as major areas requiring integrated analysis [12]. Scenario-based robust optimization responds to these challenges by evaluating alternative future conditions and generating solutions that remain acceptable when input parameters vary. Ramedani et al. combined risk considerations, scenario analysis, fuzzy methods, goal programming, and metaheuristic optimization to support robust project portfolio selection under uncertainty [5]. Network-based approaches have similarly emphasized that portfolio robustness depends on the structural relationships among projects and the capacity of the portfolio to maintain strategic performance under disruptions or project failures [13].

Sustainability has also transformed the criteria used in portfolio decision-making. Organizations are increasingly expected to consider not only financial returns but also environmental protection, social acceptance, stakeholder welfare, resource efficiency, occupational safety, and long-term institutional legitimacy. In oil and gas construction, these concerns are especially consequential because projects may affect ecosystems, local communities, employment patterns, public infrastructure, land use, water resources, emissions, and regional development. Sustainable portfolio selection thus requires an integrated assessment of economic, environmental, and social objectives rather than the treatment of sustainability as a supplementary screening factor. A comprehensive mathematical model for resource-constrained project portfolio selection and scheduling demonstrated the feasibility of simultaneously incorporating sustainability criteria, multiple objectives, project splitting, and scheduling decisions [14]. Simulation–optimization has likewise been proposed as an effective mechanism for sustainability-aware PPM because it allows managers to evaluate complex system behavior and explore trade-offs among alternative portfolio configurations [15]. The growing use of environmental, social, and governance constraints in financial portfolio optimization further confirms the broader movement from purely return-oriented selection toward responsible multi-objective allocation [16].

The digitization of PPM has created new opportunities to address these analytical demands. Digital platforms can integrate cost, schedule, risk, resource, and performance data across projects, facilitate real-time monitoring, and support coordinated decision-making. In architecture, engineering, and construction, digitized portfolio systems can reduce fragmented information flows and improve the visibility of project interdependencies, although implementation remains constrained by organizational readiness, interoperability, data quality, and legacy systems [17]. Public construction clients similarly face opportunities and challenges in transitioning toward digital PPM, particularly regarding information infrastructure, governance, institutional capability, security, and stakeholder coordination [18]. Intelligent dashboards can extend these capabilities by integrating portfolio value, prioritization, and risk indicators into a unified decision-support environment. A systematic review of intelligent information systems and information technology portfolio dashboards highlighted the importance of linking strategic value, project prioritization, and risk monitoring in dynamic visual systems [19]. Topic-modeling and hierarchical learning methods have also been developed to support portfolio managers by extracting patterns from project documentation and organizing projects according to thematic relationships [20].

Artificial intelligence and machine learning offer an additional layer of analytical capability by identifying nonlinear relationships, predicting project outcomes, and improving the evaluation of portfolio benefits. Genetic algorithm–backpropagation neural network models have achieved high predictive performance in estimating project portfolio benefits, showing that evolutionary search can optimize neural-network parameters and strengthen benefit forecasting [4]. Group-based neural models have further incorporated project interactions and collective benefit patterns, improving the accuracy of portfolio benefit measurement compared with conventional backpropagation and simpler hybrid models [3]. More recently, pruned GA-BPNN models have been proposed to reduce model complexity while considering ambidexterity, synergy, and multiple forms of portfolio benefit [21]. These studies indicate that intelligent models can support portfolio assessment where financial and non-financial benefits depend on complex interactions that are difficult to represent through linear scoring alone. Fuzzy TOPSIS combined with machine learning has similarly been used to improve project selection by accounting for ambiguity in evaluation criteria and learning from project characteristics [22].

Machine learning has also been applied to identify the critical factors affecting the adoption and success of PPM. In construction organizations, integrated machine-learning approaches can evaluate the relative importance of organizational, technological, managerial, and environmental factors that determine whether portfolio-management practices are successfully implemented [23]. This is significant because sophisticated optimization models cannot improve decision quality when the organization lacks reliable data, appropriate governance, qualified personnel, or sufficient capacity to interpret analytical outputs. Portfolio optimization is therefore both a computational and an institutional problem. The effectiveness of an algorithm depends on the validity of the criteria, the reliability of expert assessments, the quality of the database, and the extent to which selected solutions reflect actual strategic priorities. System dynamics research in the energy sector has reinforced this view by showing that portfolio-management evolution is influenced by feedback structures, organizational learning, delays, managerial responses, and the interaction of policy variables over time [24].

Metaheuristic algorithms are particularly suitable for complex portfolio problems because they can explore large, discontinuous, nonlinear, and combinatorial solution spaces without requiring the restrictive assumptions of exact optimization methods. A portfolio with $n$candidate projects may contain up to 2^npossible selection combinations before the addition of scheduling, weighting, and resource-allocation decisions. Exhaustive search rapidly becomes computationally impractical as the number of projects and constraints increases. Metaheuristics seek high-quality or near-optimal solutions through adaptive search strategies. The genetic algorithm imitates natural selection through population generation, fitness evaluation, selection, crossover, and mutation. Particle swarm optimization models collective learning through the movement of particles based on their personal and global best positions. Simulated annealing uses probabilistic acceptance and gradual cooling to escape local optima and improve the solution iteratively. These methods are not guaranteed to identify the exact global optimum in every case, but their flexibility, scalability, and capacity to generate diverse solutions make them useful for real-world multi-objective PPM.

Among these algorithms, genetic algorithms have received particular attention because portfolio selection can be naturally represented through binary chromosomes in which each gene indicates whether a project is selected. Genetic operators can then search alternative project combinations while a fitness function evaluates economic benefits, social outcomes, environmental performance, and risk. Genetic algorithms are also compatible with Pareto-ranking procedures, including non-dominated sorting, which preserve multiple efficient solutions instead of converging to one weighted compromise. Particle swarm optimization may offer faster convergence and simpler parameterization, although it can be more vulnerable to premature convergence in discrete or highly constrained spaces. Simulated annealing provides a comparatively straightforward mechanism for escaping local optima but may require careful cooling design. Comparative application of these methods is therefore valuable because algorithm performance may differ according to problem size, portfolio structure, objective formulation, and constraint intensity.

The relevance of metaheuristic optimization is also evident in adjacent financial-portfolio research. Although financial portfolios differ from project portfolios in the nature of their assets and constraints, both fields address the allocation of limited capital among competing alternatives under return, risk, diversification, and strategic requirements. Recent research has examined the use of artificial intelligence beyond conventional portfolio techniques and has emphasized the need to evaluate optimization performance according to risk-adjusted, stability, and out-of-sample criteria rather than return alone [25]. Large language models have also been compared with established quantitative allocators in few-shot portfolio optimization, reflecting growing interest in whether generative artificial intelligence can infer allocation strategies from limited examples [26]. Quantum-computing applications have been proposed for financial modeling and portfolio optimization because quantum methods may eventually offer advantages in solving high-dimensional combinatorial problems [27]. These developments suggest that portfolio optimization is entering a phase in which conventional mathematical models, metaheuristics, machine learning, generative AI, and emerging computational paradigms may increasingly be combined.

Financial-portfolio studies also demonstrate the importance of context-specific constraints. Optimization for pension purposes, for example, must account for long horizons, liability structures, demographic uncertainty, inflation, and downside risk rather than maximizing short-term returns [28]. Cryptocurrency portfolio research has emphasized extreme volatility, nonlinear price behavior, liquidity variation, and the need to integrate machine-learning prediction with risk-adjusted optimization [29]. Hybrid portfolios combining stocks and cryptocurrencies similarly require models capable of balancing return potential against substantial market risk and cross-asset dependence [30]. Behavioral finance adds another layer by showing that observed investor decisions may deviate from theoretically optimal allocations because of overconfidence, loss aversion, herding, anchoring, and other cognitive biases [31]. These findings are instructive for project portfolios because managerial judgment may likewise be affected by political preferences, sunk-cost escalation, departmental competition, optimism bias, and resistance to terminating strategically weak projects.

Another important issue is the timing of portfolio decisions. Portfolio selection is not a one-time event undertaken only before project initiation. Projects may need to be reevaluated as costs increase, benefits change, schedules slip, risks materialize, or strategic priorities shift. Execution-stage portfolio management therefore requires periodic performance measurement, reprioritization, and resource reallocation. Earned-value and multi-criteria approaches provide a structured basis for updating priorities according to actual project performance [9]. Hyper-project portfolio management is particularly relevant when organizational restructuring, mergers, or portfolio integration create new dependencies and uncertainties. The hyper-project approach recognizes that portfolio complexity may increase after the combination of previously separate project groups and that selection decisions must account for integration risks and emergent interactions [2]. Initial-preference algorithms have also been proposed to help industrial organizations transform early managerial preferences into structured portfolio choices while accounting for multiple evaluation criteria [1].

Despite these advances, several research gaps remain. Many project portfolio studies emphasize a limited number of objectives, rely on hypothetical datasets, or focus on a single optimization technique. Others assign fixed weights to criteria without adequately examining sensitivity to changing managerial priorities. Some models maximize aggregate benefit while giving insufficient attention to portfolio diversity, social acceptability, environmental sensitivity, safety compliance, and technological maturity. In oil and gas contexts, there remains a need for models that simultaneously accommodate heterogeneous upstream, midstream, downstream, infrastructure, petrochemical, refinery, pipeline, storage, and offshore projects. There is also a need to transform qualitative expert judgments into a reliable numerical decision matrix, compare multiple metaheuristic algorithms, and generate Pareto-efficient alternatives rather than one opaque solution. The use of several validated criteria can provide a more realistic representation of project attractiveness, while sensitivity analysis can show whether the selected portfolio remains stable when criterion weights or strategic orientations change.

Accordingly, the present study integrates multi-criteria evaluation, analytic weighting, metaheuristic search, and Pareto-front analysis within a unified framework for oil and gas project portfolio optimization. By considering technical type, project category, complexity, location, accessibility, budget, return period, duration, environmental sensitivity, environmental compliance, natural risk, safety compliance, social impact, social acceptance, contract type, and innovative technology use, the framework reflects the multidimensional character of real portfolio decisions. It also enables the comparison of profit-oriented, risk-averse, and sustainability-oriented alternatives. Such an approach can enhance strategic transparency because managers are not presented with a single algorithmically imposed answer; instead, they can examine a set of efficient portfolios and select the alternative that best corresponds to organizational priorities, resource limitations, and risk tolerance.

Therefore, this study aimed to optimize the selection of oil and gas construction project portfolios by applying and comparing metaheuristic algorithms and generating a Pareto front that balances economic, social, environmental, and risk-related objectives under portfolio constraints.

2. Methodology

This study is applied and quantitative in nature, focusing on the evaluation and analysis of oil and gas project portfolios with an emphasis on construction aspects. The primary objective is to optimize project portfolio management using metaheuristic algorithms. The required data were collected through a standardized questionnaire designed based on technical, spatial, economic, temporal, environmental, risk and safety, social, and operational parameters.

2.1. Questionnaire Design

The questionnaire was developed around eight main dimensions, with associated indicators as follows:

1. **Technical parameters:** Project type (upstream, midstream, downstream), activity type (industrial, infrastructure, residential), and technical complexity.
2. **Spatial parameters:** Geographical location (onshore/offshore) and accessibility status.
3. **Economic parameters:** Total budget level and payback period, particularly for IPC projects.
4. **Temporal parameters:** Estimated project duration.

5. **Environmental parameters:** Environmental sensitivity of the project site and compliance with environmental regulations.
6. **Risk and safety parameters:** Level of natural risk and adherence to safety standards in design and construction.
7. **Social parameters:** Project impact on local communities and social acceptance.
8. **Operational parameters:** Contract type and level of adoption of advanced technologies, including Building Information Modeling (BIM), Internet of Things (IoT), and simulation.

The questionnaire employed Likert scales and numerical scoring for each indicator, enabling the collection of both quantitative and qualitative data.

2.2. Population and Sampling

The study population consisted of project managers and construction experts involved in oil and gas projects. A purposive sampling method was applied to select individuals with sufficient experience in project management and portfolio decision-making. This approach ensures the relevance and credibility of the collected data for the study objectives.

2.3. Data Collection

Data were collected through a combination of electronic methods (online forms) and in-person surveys. After collection, the data were cleaned, coded, and prepared for quantitative analysis to provide valid inputs for the optimization model.

2.4. Metaheuristic Optimization Model

To optimize the project portfolio, metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA) were employed. The steps of the optimization model are as follows:

1. **Objective function definition:** Maximization of financial and non-financial benefits of the portfolio (e.g., ROI) and sustainability, and minimization of risk and costs.
2. **Constraint definition:** Budget, human resources, project duration, environmental, and safety requirements.
3. **Model inputs:** Questionnaire data including indicators and parameter weights determined via Analytic Hierarchy Process (AHP) or other multi-criteria decision-making methods.
4. **Algorithm execution:** Generation of an initial population, performance evaluation, parent selection, crossover, mutation, and production of subsequent generations until convergence to an optimal or near-optimal solution.
5. **Result validation:** Comparison of model results with actual project data and sensitivity analysis of indicators to evaluate algorithm effectiveness.

2.5 Data Analysis and Weighting

Data analysis was conducted in three main stages:

- **Descriptive analysis:** Assessing the status of projects and the characteristics of each indicator using descriptive statistics such as mean and standard deviation.
- **Indicator weighting:** Determining the priority of criteria using the Analytic Hierarchy Process (AHP) or the Likert scales of the questionnaire.
- **Sensitivity analysis and algorithm comparison:** Evaluating the impact of parameter variations on results and comparing GA, PSO, and SA to identify the most effective metaheuristic method based on criteria such as convergence speed and solution quality.

2.4.1. Core Formulas of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO)

1. Genetic Algorithm (GA) Formulas

a) Initialization of Population

Assume the initial population consists of N chromosomes, each represented as a vector of parameters:

Xi=[xi1,xi2,…,xin],i=1,2,…,N

where:

- n is the number of decision variables,
- Xij is the value of the jjj-th variable in the iii-th chromosome.

b) Fitness Function

The objective function is defined as:

fi=f(Xi)

For minimization problems, the fitness is often defined as the inverse of the objective function:

Fi=11+fi

c) Selection

The probability of selecting each chromosome is proportional to its fitness:

Pi=Fi∑j=1NFj

Chromosomes are then selected using methods such as **Roulette Wheel** or **Tournament Selection**.

d) Crossover Operator

For two parent chromosomes Xp and Xq, offspring are generated as follows:

Xchild1=αXp+(1−α)Xq,Xchild2=(1−α)Xp+αXq

where α∈[0,1]\alpha \in [0,1]α∈[0,1] is the mixing coefficient.

e) Mutation Operator

Mutation is performed randomly on certain genes:

Xinew=Xi+δ

where δ\deltaδ is a small random value, usually drawn from a uniform or normal distribution:

δ∼U(−Δ,+Δ)

f) Population Update

The new chromosomes replace the old population, and the above steps are repeated until convergence or the stopping condition is met (k>kmaxk > k_{\text{max}}k>kmax).

2. Particle Swarm Optimization (PSO) Formulas

a) Initialization

For each particle iii:

Xi=[xi1,xi2,…,xin],Vi=[vi1,vi2,…,vin]

where Xi is the particle position and ViV_iVi is its velocity.

b) Velocity Update

Vi(t+1)=wVi(t)+c1r1(Pi−Xi(t))+c2r2(G−Xi(t))

where:

- www is the inertia weight,
- c1,c2 are acceleration coefficients (typically between 1.5 and 2.5),
- r1,r2∼U(0,1)r_1, are random factors,
- Pi is the personal best position of particle iii,
- G is the global best position among all particles.

Table 1. Comparison of GA and PSO Algorithms

Feature	Genetic Algorithm (GA)	Particle Swarm Optimization (PSO)
Search Type	Random, evolution-based	Collective, movement-based
Number of Parameters	High (Crossover, Mutation, …)	Low (w, c1, c2)
Convergence	Slower but broader search	Faster but prone to local minima
Data Structure	Chromosomes	Particles

3. Findings and Results

This study adopts a quantitative, model-based research approach to optimize project portfolio selection in the oil and gas industry using metaheuristic algorithms. The research is applied in nature and follows a descriptive–analytical framework combined with computational modeling. The main objective is to evaluate and prioritize a portfolio of 54 construction projects by simultaneously considering technical, economic, environmental, social, and operational criteria.

To achieve this objective, a total of 54 projects were selected as case studies. These projects include upstream, midstream, and downstream developments, as well as infrastructure-related projects such as pipelines, storage facilities, and export terminals. The selected dataset represents a diverse range of real-world conditions, including onshore and offshore locations, varying accessibility levels, different degrees of technical complexity, and a wide spectrum of environmental sensitivities and investment return periods. This diversity ensures that the optimization model is robust and capable of handling complex decision-making environments.

Data required for the analysis were collected through a combination of structured questionnaires, expert judgment, and review of technical documentation and industry reports. A questionnaire was designed based on key project evaluation criteria, and expert opinions were incorporated using a Delphi-based refinement process to enhance reliability and consistency. The evaluation framework consists of sixteen criteria, including technical type, project complexity, geographic conditions, accessibility, budget, return on investment duration, project duration, environmental sensitivity, environmental compliance, natural risk, safety performance, social impact, social acceptance, contract type, and level of modern technology utilization. The definition of these criteria and their corresponding scoring scales are presented in Table 2 (Scoring of Project Parameters).

Since many of these parameters are qualitative in nature, a numerical scoring system was developed to enable quantitative analysis. Each criterion was assigned a score on a scale of 1 to 4, where the values represent increasing levels of importance or intensity, as detailed in Table 2. This transformation resulted in a 54×16 decision matrix, which serves as the primary input for the optimization model. To ensure consistency across different criteria, the data were normalized and standardized, and all parameters were aligned based on their contribution as either benefit-type or cost-type criteria.

The project portfolio selection problem was then formulated as a multi-objective optimization problem. The objective functions were defined to maximize economic performance, represented by return on investment, while minimizing environmental impact and operational risk. In addition, social impact and acceptance were incorporated as positive objectives to ensure sustainable decision-making. Constraints such as budget limitations, risk thresholds, and strategic balance among different project types were also considered in the model formulation.

Due to the complexity and nonlinearity of the problem, metaheuristic algorithms were employed to obtain optimal or near-optimal solutions. These algorithms are particularly suitable for large-scale, multi-objective optimization problems where traditional exact methods are inefficient. In this study, algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Non-dominated Sorting Genetic Algorithm II (NSGA-II) were utilized to explore the solution space and identify optimal project portfolio combinations.

The optimization model was implemented using MATLAB/Python, where the decision matrix derived from the scoring system in Table 2 was used as the input, and the objective functions were defined based on weighted criteria. The output of the model includes optimal project selection, ranking of projects, and trade-off analysis between competing objectives such as profitability, risk, and sustainability.

Finally, to validate the robustness of the model, sensitivity analysis was conducted by varying key parameters such as the weights of environmental criteria, risk factors, and economic indicators. In addition, different decision-making scenarios, including risk-averse, profit-oriented, and sustainability-focused approaches, were analyzed to evaluate the stability and adaptability of the optimization results.

Overall, this methodology provides a comprehensive and systematic framework for project portfolio optimization in the oil and gas sector and demonstrates the effectiveness of metaheuristic algorithms in handling complex multi-criteria decision-making problems.

Table 2. Scoring of Project Parameters

No.	Project Name	Main Activity	Contract Type	Complexity	Environmental Sensitivity	Social Impact
1	Nargesi	Upstream Production	EPC	Medium	Medium	Positive
2	Gachsaran 1 and 2	Infrastructure	EPC	Medium	Low	Neutral
3	Sohrab	Upstream-Midstream	IPC	High	High	Positive
4	Paydar Gharb 3	Infrastructure	IPC	Low	High	Neutral
5	Dalpari	Upstream Production	IPC	Medium	Low	Neutral
6	Cheshmeh Khosh	Transportation and Storage	IPC	Medium	Medium	Positive
7	Paydar Shargh	Upstream Production	IPC	Low	Low	Neutral
8	Bibi Hakimeh	Extraction and Transportation	EPC	Medium	Low	Positive
9	Aghajeri	Upstream-Midstream	EPC	Medium	Medium	Neutral
10	Masjed Soleiman	Upstream-Midstream	EPC	Medium	Medium	Positive
11	Aban	Upstream Production	IPC	Low	Low	Neutral
12	Ramin	Infrastructure Development	IPC	Medium	Medium	Positive
13	Lali Bengestan	Upstream-Midstream	EPC	Medium	Medium	Positive
14	Amir Kabir Petrochemical	Downstream Petrochemical	EPC	High	High	Positive
15	Azadegan North	Upstream Infrastructure	EPC	Medium	Medium	Positive
16	Azadegan South	Upstream Infrastructure	EPC	Medium	Medium	Positive
17	Sepehr and Jofeir	Upstream Infrastructure	IPC	High	Medium	Neutral
18	Yadavaran	Upstream Production	IPC	High	High	Positive
19	Marun Development	Midstream Pipelines	EPC	Medium	Medium	Positive
20	Ahvaz Oilfield Expansion	Upstream Production	EPC	Medium	Medium	Neutral
21	Karoun Refinery	Downstream Refinery	EPC	High	High	Positive
22	Shadegan Gas Injection	Midstream Gas Injection	IPC	Medium	Medium	Positive
23	Dezful Petrochemical	Petrochemical Complex	EPC	High	High	Positive
24	Omidieh Pipeline	Pipeline Construction	EPC	Medium	Low	Neutral

25	Jask Export Terminal	Export Terminal	IPC	High	High	Positive
26	West Karoun Facilities	Upstream Facilities	IPC	Medium	Medium	Positive
27	Parsian Storage Tanks	Storage Facilities	EPC	Medium	Medium	Neutral
28	Bandar Imam Expansion	Petrochemical Expansion	EPC	High	High	Positive
29	Abadan Refinery Upgrade	Refinery Rehabilitation	EPC	High	High	Positive
30	South Pars Utilities	Utilities and Infrastructure	IPC	Medium	Medium	Positive
31	Karanj Oilfield	Upstream Production	EPC	Medium	Medium	Neutral
32	Darkhovin Development	Upstream Production	IPC	Medium	Medium	Positive
33	Sirri Offshore Support	Offshore Support Facilities	EPC	High	High	Neutral
34	Kharg Island Terminal	Export and Storage	EPC	High	High	Positive
35	Farashband Gas Project	Gas Processing	IPC	Medium	Medium	Positive
36	Lamerd Petrochemical	Downstream Industrial	EPC	High	High	Positive
37	Kish Gas Development	Offshore Gas Extraction	IPC	High	Medium	Positive
38	Arvand Petrochemical	Petrochemical Facilities	EPC	High	High	Positive
39	Salman Offshore Project	Offshore Production	IPC	High	High	Neutral
40	Hegmataneh Pipeline	Pipeline and Transportation	EPC	Medium	Low	Neutral
41	Chalous Gas Field	Offshore Gas Development	IPC	High	High	Positive
42	Tondgouyan Expansion	Petrochemical Expansion	EPC	High	High	Positive
43	Kupal Oilfield	Upstream Production	EPC	Medium	Medium	Neutral
44	Mahshahr Storage Complex	Storage and Export	EPC	Medium	Medium	Positive
45	Ilam Gas Refinery	Gas Refining	IPC	Medium	Medium	Positive
46	Hengam Offshore Field	Offshore Extraction	IPC	High	High	Positive
47	Dez Pipeline Network	Transportation Infrastructure	EPC	Medium	Low	Neutral
48	Pars Petro Refinery	Refinery and Facilities	EPC	High	High	Positive
49	Ramshir Gas Facilities	Gas Facilities	IPC	Medium	Medium	Positive
50	Bahregansar Offshore	Offshore Infrastructure	IPC	High	High	Neutral
51	Arash Gas Project	Offshore Gas Development	IPC	High	High	Positive
52	Falat Continental Shelf	Offshore Facilities	EPC	High	High	Neutral
53	North Dezful Expansion	Upstream Production	EPC	Medium	Medium	Positive
54	Karun West Petrochemical	Petrochemical Development	EPC	High	High	Positive

These projects provide a suitable basis for evaluating project portfolio management using metaheuristic algorithms and allow for a comparison of key characteristics. For input into the optimization model, the attributes of each project were converted into a numerical scoring matrix, in which questionnaire responses were standardized on a 1-to-4 scale. This matrix serves as the primary input for the metaheuristic algorithms, and subsequent analyses are conducted based on it. Table 2 presents the numerical scoring matrix of the projects used for the metaheuristic-based project portfolio management.

Table 3. Numerical project scoring matrix for the meta-heuristic project portfolio management algorithm

Project	TechnicalType	IndustrialType	TechnicalComplexity	Location	Accessibility	Budget	ROI_Duration	ProjectDuration	EnvironmentalSensitivity	EnvironmentalCompliance	NaturalRisk	SafetyCompliance	SocialImpact	SocialAcceptance	ContractType	InnovativeTech
Nargesi	3	3	2	2	2	3	2	2	2	3	3	4	3	2	3	1
Gachsaran 1and2	3	2	2	2	3	3	2	2	1	3	1	3	2	2	3	1
Sohrab	3	3	3	2	3	3	3	3	3	3	4	4	3	4	3	1
PaydarGharb3	3	2	1	2	3	3	2	2	3	4	2	4	2	2	3	1
Dalpari	3	3	2	2	2	3	1	2	1	3	2	3	2	2	3	1
Cheshmeh Khosh	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
PaydarShargh	3	3	1	2	2	3	1	2	1	3	2	3	2	3	3	1
BibiHakimeh	3	3	2	2	2	3	2	3	1	3	2	3	3	3	3	1
Aghajeri	3	3	2	2	2	3	2	3	2	3	2	3	2	3	3	1
MasjedSoleiman	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
Aban	3	3	1	2	2	3	1	2	1	3	2	3	2	3	3	1
Ramin	3	2	2	2	2	3	2	3	2	3	2	3	3	3	3	1
LaliBengestan	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1

AmirKabir Petrochemical	3	3	3	2	2	3	3	3	3	3	3	4	3	3	3	2
Azadegan North	3	2	2	2	2	3	2	3	2	3	2	3	3	3	3	1
AzadeganSouth	3	2	2	2	2	3	2	3	2	3	2	3	3	3	3	1
SepehrJofeir	3	2	3	2	3	3	3	3	2	3	3	4	2	3	3	1
Yadavaran	3	3	3	2	3	3	3	3	3	4	3	4	3	4	3	2
MarunDevelopment	2	2	2	2	2	3	2	2	2	3	2	3	3	3	3	1
AhvazExpansion	3	3	2	2	2	3	2	2	2	3	2	3	2	3	3	1
KarounRefinery	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
ShadeganInjection	2	2	2	2	2	3	2	2	2	3	2	3	3	3	3	1
DezfulPetrochemical	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
OmidiehPipeline	2	2	2	2	2	3	2	2	1	3	1	3	2	2	3	1
JaskTerminal	3	3	3	2	3	3	3	3	3	4	3	4	3	4	3	2
WestKaroun	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
ParsianStorage	2	2	2	2	2	3	2	2	2	3	2	3	2	3	3	1
BandarImam	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
AbadanUpgrade	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
SouthPars Utilities	2	2	2	2	2	3	2	3	2	3	2	3	3	3	3	1
Karanj	3	3	2	2	2	3	2	2	2	3	2	3	2	2	3	1
Darkhovin	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
SirriOffshore	3	3	3	3	3	3	3	3	3	4	4	4	2	3	3	2
KhargTerminal	3	3	3	2	3	3	3	3	3	4	3	4	3	4	3	2
Farashband	2	3	2	2	2	3	2	2	2	3	2	3	3	3	3	1
LamerdPetrochemical	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
KishGas	3	3	3	3	3	3	3	3	2	4	3	4	3	4	3	2
ArvandPetrochemical	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
SalmanOffshore	3	3	3	3	3	3	3	3	3	4	4	4	2	3	3	2
HegmatanehPipeline	2	2	2	2	2	3	2	2	1	3	1	3	2	2	3	1
ChalousGas	3	3	3	3	3	3	3	3	3	4	4	4	3	4	3	2
Tondgouyan	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
Kupal	3	3	2	2	2	3	2	2	2	3	2	3	2	2	3	1
MahshahrStorage	2	2	2	2	2	3	2	2	2	3	2	3	3	3	3	1
IlamRefinery	2	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
HengamOffshore	3	3	3	3	3	3	3	3	3	4	4	4	3	4	3	2
DezPipeline	2	2	2	2	2	3	2	2	1	3	1	3	2	2	3	1
ParsPetroRefinery	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
RamshirFacilities	2	3	2	2	2	3	2	2	2	3	2	3	3	3	3	1
Bahregansar	3	3	3	3	3	3	3	3	3	4	4	4	2	3	3	2
ArashGas	3	3	3	3	3	3	3	3	3	4	4	4	3	4	3	2
FalatContinental	3	3	3	3	3	3	3	3	3	4	4	4	2	3	3	2
NorthDezful	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
KarunWest Petrochemical	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2

The results presented in Table 1 are derived from a standardized numerical scoring system applied to all 54 projects considered in this study. This system converts qualitative questionnaire responses and expert judgments into quantitative values ranging from 1 to 4, thereby enabling their direct use as inputs for the metaheuristic optimization model. The scoring framework was consistently applied across the entire dataset to ensure comparability, reliability, and analytical robustness.

For all projects, the scoring criteria were defined as follows. The technical project type was classified into upstream, midstream, and downstream activities, assigned scores of 3, 2, and 1, respectively. The project category, including industrial, infrastructure, and service types, was scored as 3, 2, and 1, respectively. Technical complexity was evaluated at three levels, where high complexity received a score of 3, medium complexity 2, and low complexity 1.

Geographical location was categorized into onshore and offshore conditions, with scores of 2 and 3, respectively, reflecting the higher complexity and risk typically associated with offshore projects. Accessibility was evaluated based on site conditions, with easy access scored as 1, moderate access as 2, and difficult access as 3. The total project budget was classified into three ranges, where projects above \$5 million were assigned a score of 2, those between \$0.5 million and \$5 million were scored as 3, and projects below \$0.5 million received a score of 1, reflecting relative financial prioritization.

The return on investment (ROI) period was categorized into short-term (less than 3 years), medium-term (3–7 years), and long-term (greater than 7 years), with corresponding scores of 1, 2, and 3. Similarly, project duration was classified as short, medium, and long, with scores of 1, 2, and 3, respectively.

Environmental sensitivity was assessed at three levels (low, medium, high) with scores of 1, 2, and 3. Compliance with environmental regulations was evaluated on a four-level scale, where poor, medium, good, and excellent compliance were assigned scores of 1, 2, 3, and 4, respectively. Natural risk was categorized into low, medium, and high levels with scores of 1, 2, and 3. Compliance with safety standards followed a similar four-level classification, ranging from poor (1) to excellent (4).

Societal impact was evaluated as negative, neutral, or positive, corresponding to scores of 1, 2, and 3, respectively. Social acceptance was classified into low, medium, and high levels with scores of 1, 2, and 3. The contract type, including EPC and IPC, was assigned a score of 3 for both categories due to their comparable strategic importance in large-scale oil and gas projects, while other contract types were assigned a score of 2.

Finally, the level of modern technology utilization was assessed based on the extent of implementation of advanced tools such as BIM, IoT, and digital monitoring systems. Projects with minimal or no use of such technologies were scored as 1, those with moderate usage as 2, and projects with extensive implementation as 3.

This unified scoring system was applied consistently to all 54 projects, resulting in a comprehensive decision matrix that enables direct comparison across multiple criteria. The use of a standardized numerical framework ensures compatibility with metaheuristic optimization algorithms and enhances the reliability of the analysis. Furthermore, this approach facilitates sensitivity analysis and supports multi-objective decision-making in project portfolio optimization.

To assess the reliability and internal consistency of the scoring system, Cronbach's alpha coefficients were calculated for all criteria based on the responses collected from experts. The results of this analysis are presented in Table 3, confirming the robustness and validity of the evaluation framework.

Table 4. Cronbach's Alpha Coefficient for Each Criterion

Project	TechType (α=0.85)	Category (α=0.80)	Complexity (α=0.88)	Location (α=0.75)	Access (α=0.82)	Budget (α=0.90)	ROI (α=0.87)	Duration (α=0.83)	EnvSens (α=0.86)	EnvComp (α=0.89)	Risk (α=0.84)	Safety (α=0.88)	SocialImpact (α=0.80)	Acceptance (α=0.82)	Contract (α=0.78)	Tech (α=0.77)
Nargesi	3	3	2	2	2	3	2	2	2	3	3	4	3	2	3	1
Gachsaran1&2	3	2	2	2	3	3	2	2	1	3	1	3	2	2	3	1
Sohrab	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1
PaydarWest3	3	2	1	2	3	3	2	2	3	4	2	4	2	2	3	1
Dalpari	3	3	2	2	2	3	2	2	2	3	2	3	2	2	3	1
CheshmehKhosh	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1

PaydarShargh	3	3	2	2	3	3	2	2	3	3	2	3	2	3	3	1
BibiHakimeh	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1
Aghajari	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1
MasjedSoleiman	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1
Aban	3	3	2	2	3	3	2	2	3	3	2	3	2	3	3	1
Ramin	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1
LaliBengestan	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1
AmirKabir	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
AzadeganNorth	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1
AzadeganSouth	3	3	2	2	3	3	3	3	3	3	3	4	3	4	3	1
SepehrJofeir	3	2	2	2	3	3	3	3	2	3	3	4	2	3	3	1
Yadavaran	3	3	3	2	3	3	3	3	3	4	3	4	3	4	3	2
Marun	2	2	2	2	2	3	2	2	2	3	2	3	3	3	3	1
Ahvaz	3	3	2	2	2	3	2	2	2	3	2	3	2	3	3	1
KarounRefinery	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
Shadegan	2	2	2	2	2	3	2	2	2	3	2	3	3	3	3	1
DezfulPetro	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
Omidieh	2	2	2	2	2	3	2	2	1	3	1	3	2	2	3	1
Jask	3	3	3	2	3	3	3	3	3	4	3	4	3	4	3	2
WestKaroun	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
Parsian	2	2	2	2	2	3	2	2	2	3	2	3	2	3	3	1
BandarImam	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
Abadan	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
SouthPars	2	2	2	2	2	3	2	3	2	3	2	3	3	3	3	1
Karanj	3	3	2	2	2	3	2	2	2	3	2	3	2	2	3	1
Darkhovin	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
Sirri	3	3	3	3	3	3	3	3	3	4	4	4	2	3	3	2
Kharg	3	3	3	2	3	3	3	3	3	4	3	4	3	4	3	2
Farashband	2	3	2	2	2	3	2	2	2	3	2	3	3	3	3	1
Lamerd	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
Kish	3	3	3	3	3	3	3	3	2	4	3	4	3	4	3	2
Arvand	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
Salman	3	3	3	3	3	3	3	3	3	4	4	4	2	3	3	2
Hegmataneh	2	2	2	2	2	3	2	2	1	3	1	3	2	2	3	1
Chalous	3	3	3	3	3	3	3	3	3	4	4	4	3	4	3	2
Tondgouyan	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
Kupal	3	3	2	2	2	3	2	2	2	3	2	3	2	2	3	1
Mahshahr	2	2	2	2	2	3	2	2	2	3	2	3	3	3	3	1
Ilam	2	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
Hengam	3	3	3	3	3	3	3	3	3	4	4	4	3	4	3	2
DezPipeline	2	2	2	2	2	3	2	2	1	3	1	3	2	2	3	1
ParsPetro	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2
Ramshir	2	3	2	2	2	3	2	2	2	3	2	3	3	3	3	1
Bahregansar	3	3	3	3	3	3	3	3	3	4	4	4	2	3	3	2
Arash	3	3	3	3	3	3	3	3	3	4	4	4	3	4	3	2
Falat	3	3	3	3	3	3	3	3	3	4	4	4	2	3	3	2
NorthDezful	3	3	2	2	2	3	2	3	2	3	2	3	3	3	3	1
KarunWestPetrochemical	3	3	3	2	2	3	3	3	3	4	3	4	3	4	3	2

Table 3 presents the finalized scoring matrix of the 54 selected projects, evaluated across sixteen criteria with validated reliability coefficients (Cronbach's alpha ranging from 0.75 to 0.90). The matrix reflects a consistent and structured transformation of qualitative project characteristics into quantitative values, enabling their direct application in the optimization model.

A general observation from Table 3 indicates that the majority of projects are categorized as upstream (score = 3), highlighting the dominance of extraction and production activities in the studied portfolio. Midstream projects (score = 2) are fewer and are mainly associated with transportation and infrastructure systems, while downstream projects are limited but exhibit higher complexity and environmental sensitivity.

From the perspective of project category, most projects fall within industrial (score = 3) and infrastructure (score = 2) classes, confirming that the dataset primarily represents large-scale engineering developments. The technical complexity values are generally concentrated in the medium (2) to high (3) range, indicating that the majority of projects involve sophisticated design, execution challenges, and advanced engineering requirements.

In terms of geographical characteristics, most projects are located in onshore environments (score = 2), while offshore projects (score = 3), such as Sirri, Salman, Hengam, and Chalous, exhibit higher risk and operational difficulty. Accessibility scores further support this observation, as many projects are associated with moderate to difficult access (scores 2 and 3), reflecting real-world constraints in remote oilfield locations.

Economic indicators reveal that almost all projects fall into the high-budget category, which is consistent with the capital-intensive nature of the oil and gas sector. The return on investment (ROI) values vary between medium (2) and long-term (3), suggesting a balanced mix of short- and long-term strategic investments. Similarly, project duration is predominantly medium to long, aligning with typical project lifecycles in this industry.

Environmental indicators show that most projects have medium to high environmental sensitivity (scores 2 and 3), particularly in downstream and offshore developments. However, environmental compliance scores are generally high (3–4), indicating strong adherence to environmental regulations. Natural risk values range from low to high depending on project location and type, while safety compliance consistently shows high scores (3–4), reflecting the critical importance of safety standards in the industry.

From a social standpoint, the majority of projects demonstrate neutral to positive social impacts (scores 2–3) and moderate to high social acceptance (scores 2–4). This suggests that, despite environmental and operational challenges, these projects contribute positively to regional development, employment, and infrastructure.

Regarding contractual structure, both EPC and IPC contract types are uniformly assigned a score of 3, indicating their equal strategic importance within the portfolio. Additionally, the level of modern technology utilization is predominantly low to moderate (scores 1–2), highlighting a potential gap and opportunity for future digital transformation in project execution.

Overall, the distribution of scores in Table 3 confirms that the dataset is both diverse and balanced, encompassing a wide range of project conditions, risk levels, and investment characteristics. This heterogeneity is essential for the effective implementation of metaheuristic optimization algorithms, as it enables comprehensive trade-off analysis between economic performance, risk management, environmental sustainability, and social acceptance. Furthermore, the acceptable range of Cronbach's alpha values demonstrates the internal consistency and reliability of the evaluation framework, supporting the validity of subsequent optimization results.

The results obtained from the application of the Genetic Algorithm (GA) for optimizing the oil and gas project portfolio demonstrate the capability of the model to identify an optimal combination of projects based on multiple conflicting criteria, including economic, social, environmental, and risk-related factors.

In the initial phase of the analysis, eighteen projects were evaluated as a pilot dataset. The GA employs a population-based search mechanism in which each candidate solution represents a specific combination of selected and non-selected projects. Through iterative processes involving selection, crossover, and mutation, the algorithm converges toward an optimal or near-optimal portfolio configuration.

The output of the algorithm, denoted as best_solution, is represented as a binary decision vector (e.g., [1, 0, 1, 0, …]), where a value of "1" indicates that a project is selected, and "0" indicates that it is excluded from the portfolio. For example, a solution such as [1, 0, 1, 0] implies that projects such as Nargesi and Sohrab are included in the optimal portfolio, while projects like Gachsaran 1 & 2 and Paydar Gharb 3 are excluded. This selection is determined based on the maximization of the objective function.

The objective (fitness) function is formulated as a composite index that simultaneously maximizes benefits and minimizes risks. Specifically, the overall portfolio score, denoted as fitness(best_solution), is calculated based on four main components:

- Economic index: Represents the financial attractiveness of the portfolio, typically calculated based on budget allocation and return on investment (ROI) of the selected projects.

- Social index: Reflects the overall societal contribution of the portfolio, including social impact and public acceptance of the selected projects.
- Environmental index: Accounts for environmental considerations by combining environmental sensitivity and the level of compliance with environmental regulations.
- Risk index: Captures the inherent uncertainties and challenges associated with the projects, primarily based on technical complexity and natural risk factors.

These indices are incorporated into a weighted objective function, allowing decision-makers to adjust the relative importance of each criterion according to strategic priorities. The GA therefore identifies project combinations that achieve an optimal trade-off between profitability, sustainability, and risk mitigation.

Overall, the results confirm that the proposed optimization framework is effective in handling multi-criteria decision-making problems in project portfolio management and can support strategic planning in the oil and gas industry by providing balanced and data-driven portfolio solutions.

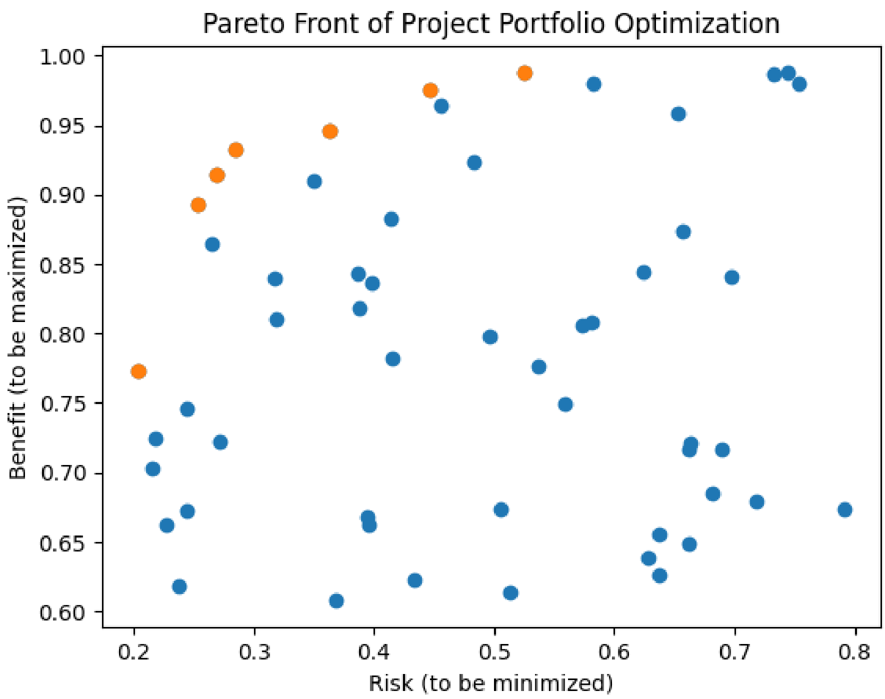

Figure 1. Pareto Front of Project Portfolio Optimization

Figure 1 illustrates the Pareto front obtained from the multi-objective optimization of the oil and gas project portfolio using the Genetic Algorithm. In this study, the portfolio selection problem is formulated as a conflicting multi-objective decision-making problem, where two main objectives are considered simultaneously: (i) maximization of overall project benefit (economic and social performance), and (ii) minimization of overall project risk (technical and natural risk).

Each point in the solution space represents a feasible portfolio configuration, where a subset of the 54 candidate projects is selected. The horizontal axis corresponds to the aggregated risk index, while the vertical axis represents the aggregated benefit index. Due to the inherent trade-off between these objectives, improvement in one objective generally leads to deterioration in the other, which results in a set of non-dominated (Pareto-optimal) solutions rather than a single optimal solution.

The Pareto front, highlighted in Figure 1, consists of those solutions that are not dominated by any other solution in the search space. In other words, for any solution on the Pareto front, there is no alternative solution that simultaneously provides higher benefit and lower risk. These solutions therefore represent the most efficient trade-offs between conflicting objectives.

From a decision-making perspective, the Pareto front provides a flexible set of optimal alternatives, allowing decision-makers to select the most appropriate portfolio configuration based on strategic preferences and risk tolerance levels. For instance, solutions located toward the upper-left region of the Pareto front correspond to high-benefit but relatively higher-risk portfolios, whereas solutions toward the lower-right region represent more conservative portfolios with reduced risk but lower overall benefit.

The distribution of solutions along the Pareto front confirms the effectiveness of the Genetic Algorithm in exploring the search space and identifying diverse optimal trade-offs. Furthermore, the smooth and well-distributed nature of the front indicates good convergence behavior and population diversity preservation throughout the optimization process.

Overall, the results presented in Figure 1 balancing competing criteria in complex project portfolio selection problems, providing decision-makers with a robust set of optimal solutions for strategic planning in the oil

3-3. Pareto Front Analysis

The presented figure depicts a **three-dimensional Pareto front** derived from the multi-objective optimization of the project portfolio, highlighting the inherent trade-offs among objectives.

3-3-1. Chart Axes

- **X-axis – Economic Index**: Represents the economic performance of the project portfolio. Higher values indicate greater profitability and returns; the optimization goal is to **maximize this index**.
- **Y-axis – Social Index**: Measures social performance, including positive impacts on the community, job creation, and improvements in quality of life. The objective is to **maximize social benefits**.
- **Z-axis – Environmental Index**: Reflects environmental sustainability and positive effects such as pollution reduction or optimal resource use. This index is also considered for **simultaneous maximization**.

All three indices are treated as multi-objective goals, and the Pareto front highlights the balance among them.

3-3-2. Point Colors and Risk Index

- The **color of each point** indicates the **Risk Index** associated with the portfolio.
- The **color bar** on the right defines the scale: dark purple/blue represents **low (desirable) risk**, whereas light green/yellow indicates **high (undesirable) risk**.
- Consequently, the point colors provide a visual cue about the risk level of each project combination, aiding in the rapid interpretation of trade-offs.

3-3-3. Meaning of Points on the Pareto Front

- Each point in the three-dimensional space represents a **portfolio** with a specific combination of selected projects.
- **Coordinates (X, Y, Z)** correspond to the values of the economic, social, and environmental indices, respectively.
- **Point color** reflects the portfolio’s risk level as interpreted through the color bar.

This structure transforms the Pareto front into an interactive tool for exploring potential solutions.

3-3-4. General Analysis of the Pareto Front

- **Distribution of points**: Points in the lower-left region (low index values) indicate weaker performance across the three objectives but are often associated with **lower risk** (darker colors). Conversely, points in the upper-right region (high index values) demonstrate stronger performance but **bear higher risk** (lighter colors).
- **Trade-offs**: The Pareto front reveals the intrinsic conflicts among objectives. Portfolios with higher economic, social, and environmental indices usually exhibit increased risk, whereas low-risk portfolios tend to show weaker performance in key objectives. This characteristic underscores the multi-objective nature of the optimization, where improvement in one objective (e.g., economic) may come at the expense of another (e.g., risk).

The Pareto front provides a set of **non-dominated solutions**, each representing a unique combination of economic, social, environmental, and risk indices. This tool enables decision-makers to select an appropriate portfolio based on **strategic priorities** such as profitability or risk reduction.

- **Managerial Implications**: Decision-makers must balance the **maximization of performance indices** with the **minimization of risk**. No single solution can simultaneously optimize all objectives; instead, the Pareto front offers a variety of options suitable for different managerial scenarios.

- **Applications**: This analysis is valuable for **complex project management**, **strategic planning**, and **resource allocation** in organizations pursuing both sustainability and profitability simultaneously.

Overall, the Pareto front serves as a powerful tool for multi-objective analysis, supporting informed decision-making under complex and multidimensional conditions. Table 5 presents the output resulting from the selection of the optimal project portfolio.

Table 5. Output from decision-making for the optimal project portfolio

Risk	Fitness	Environmental_Sensitivity	First_Portfolio_ID	Count	Portfolio_ID	Risk_norm	Fitness_norm	EnvSens_norm
0.013889	234.5288	2.153846	89	1	89	0	0.93673	0.292308
0.014085	247.7462	2.214286	39	1	39	0.002817	1	0.328571
0.014706	233.4058	2.538462	94	1	94	0.011765	0.931354	0.523077
0.015385	234.5186	2.230769	60	1	60	0.021538	0.93668	0.338462
0.016949	186.3975	2.3	68	1	68	0.044068	0.706329	0.38
0.016949	208.5997	2.583333	38	1	38	0.044068	0.812609	0.55
0.017241	214.5519	2	56	1	56	0.048276	0.841101	0.2
0.017241	217.0537	2.333333	14	1	14	0.048276	0.853077	0.4
0.017544	196.8479	2.363636	58	1	58	0.052632	0.756353	0.418182
0.017857	193.2061	2.363636	76	1	76	0.057143	0.738921	0.418182
0.017857	199.9145	2.454545	11	1	11	0.057143	0.771033	0.472727
0.018182	183.5782	2.4	84	1	84	0.061818	0.692833	0.44
0.018182	203.1244	2.333333	67	1	67	0.061818	0.786399	0.4
0.018519	198.8661	2.454545	21	1	21	0.066667	0.766015	0.472727
0.018868	173.0351	2.4	53	1	53	0.071698	0.642364	0.44
0.018868	181.8037	2.4	16	1	16	0.071698	0.684338	0.44
0.018868	190.8372	2.454545	59	1	59	0.071698	0.727581	0.472727
0.018868	194.7376	2	24	1	24	0.071698	0.746252	0.2
0.019231	175.6301	2.2	65	1	65	0.076923	0.654786	0.32
0.019608	177.8948	2.3	98	1	98	0.082353	0.665627	0.38
0.019608	183.2556	2.7	78	1	78	0.082353	0.691289	0.62
0.019608	190.2614	2.272727	28	1	28	0.082353	0.724825	0.363636
0.019608	193.2969	2.454545	87	1	87	0.082353	0.739355	0.472727
0.02	162.8346	2.666667	90	1	90	0.088	0.593535	0.6
0.02	177.2149	2.3	22	1	22	0.088	0.662372	0.38
0.020408	165.0437	2.444444	57	1	57	0.093878	0.604109	0.466667
0.020408	193.3958	2.272727	80	1	80	0.093878	0.739829	0.363636
0.020408	196.7599	2.363636	55	1	55	0.093878	0.755932	0.418182
0.020833	143.74	2	4	1	4	0.1	0.50213	0.2
0.020833	160.997	2.333333	25	1	25	0.1	0.584738	0.4
0.020833	164.5048	1.777778	72	1	72	0.1	0.60153	0.066667
0.020833	183.2513	2.4	97	1	97	0.1	0.691268	0.44
0.020833	185.7198	2.3	27	1	27	0.1	0.703084	0.38
0.021277	160.9652	2.333333	42	1	42	0.106383	0.584586	0.4
0.021277	168.2945	2.333333	62	1	62	0.106383	0.619671	0.4
0.021277	178.5318	2.3	73	1	73	0.106383	0.668676	0.38
0.021739	144.6207	2.5	99	1	99	0.113044	0.506346	0.5
0.021739	145.4341	2.5	63	1	63	0.113044	0.51024	0.5
0.021739	157.5298	2	52	1	52	0.113044	0.568141	0.2
0.021739	172.0544	2.3	95	1	95	0.113044	0.637669	0.38
0.022222	143.3623	2.375	29	1	29	0.12	0.500322	0.425
0.022222	178.0801	2.3	37	1	37	0.12	0.666514	0.38
0.022727	142.0893	2.125	40	1	40	0.127273	0.494228	0.275
0.022727	148.9128	2.5	51	1	51	0.127273	0.526892	0.5
0.022727	155.4955	1.777778	12	1	12	0.127273	0.558403	0.066667
0.022727	161.9869	2.666667	6	1	6	0.127273	0.589477	0.6
0.022727	162.5366	2.444444	31	1	31	0.127273	0.592108	0.466667
0.022727	175.1941	2.2	64	1	64	0.127273	0.652699	0.32

0.022727	175.7698	2.4	79	1	79	0.127273	0.655454	0.44
0.023256	158.9353	2	66	1	66	0.134884	0.574869	0.2
0.02381	141.9211	2	20	1	20	0.142857	0.493423	0.2
0.02381	146.9926	2	8	1	8	0.142857	0.5177	0.2
0.02381	147.2791	2.5	70	1	70	0.142857	0.519072	0.5
0.02381	150.932	1.875	35	1	35	0.142857	0.536558	0.125
0.02381	154.219	2.333333	30	1	30	0.142857	0.552292	0.4
0.02381	155.565	2	33	1	33	0.142857	0.558735	0.2
0.02381	156.5989	2.333333	3	1	3	0.142857	0.563685	0.4
0.02381	164.0558	2.555556	15	1	15	0.142857	0.59938	0.533333
0.02439	139.4387	2.25	85	1	85	0.15122	0.48154	0.35
0.02439	141.7227	3.25	45	1	45	0.15122	0.492474	0.95
0.02439	142.3422	2.375	13	1	13	0.15122	0.495439	0.425
0.02439	146.2028	1.75	18	1	18	0.15122	0.513919	0.05
0.02439	146.3084	2.75	88	1	88	0.15122	0.514425	0.65
0.02439	157.7085	2.222222	10	1	10	0.15122	0.568996	0.333333
0.025	122.6858	1.857143	77	1	77	0.16	0.401345	0.114286
0.025	138.7306	2.125	1	1	1	0.16	0.478151	0.275
0.025	141.4663	2.625	48	1	48	0.16	0.491246	0.575
0.025	146.7056	2	75	1	75	0.16	0.516326	0.2
0.025	148.7122	2.5	61	1	61	0.16	0.525932	0.5
0.025	148.8247	2.5	43	1	43	0.16	0.52647	0.5
0.025641	138.8444	1.75	81	1	81	0.169231	0.478695	0.05
0.025641	141.642	2.25	9	1	9	0.169231	0.492087	0.35
0.025641	147.6818	2.125	71	1	71	0.169231	0.520999	0.275
0.026316	126.642	2.285714	54	1	54	0.178947	0.420283	0.371429
0.026316	137.5032	1.875	44	1	44	0.178947	0.472275	0.125
0.026316	139.1701	2.375	2	1	2	0.178947	0.480254	0.425
0.026316	142.8562	2	19	1	19	0.178947	0.4979	0.2
0.027027	128.3245	2.714286	17	1	17	0.189189	0.428338	0.628571
0.027027	147.4407	3	49	1	49	0.189189	0.519845	0.8
0.027778	127.9807	3.142857	96	1	96	0.2	0.426691	0.885714
0.027778	132.4106	2.142857	47	1	47	0.2	0.447897	0.285714
0.027778	132.9635	2	41	1	41	0.2	0.450544	0.2
0.027778	141.6157	2.125	26	1	26	0.2	0.491961	0.275
0.028571	112.4721	2.666667	82	1	82	0.211429	0.352453	0.6
0.028571	122.5044	2.285714	7	1	7	0.211429	0.400477	0.371429
0.029412	112.3189	1.666667	36	1	36	0.22353	0.35172	0
0.029412	131.8913	2.285714	34	1	34	0.22353	0.445411	0.371429
0.029412	144.1504	3	92	1	92	0.22353	0.504095	0.8
0.030303	108.4465	2	100	1	100	0.236364	0.333183	0.2
0.030303	109.8718	2.166667	74	1	74	0.236364	0.340005	0.3
0.03125	118.2524	2.142857	69	1	69	0.25	0.380123	0.285714
0.03125	122.8058	2	32	1	32	0.25	0.40192	0.2
0.033333	123.2197	2.142857	23	1	23	0.28	0.403901	0.285714
0.035714	86.32374	2.6	86	1	86	0.314286	0.227283	0.56
0.035714	107.1163	3.333333	46	1	46	0.314286	0.326815	1
0.035714	108.7198	2.333333	91	1	91	0.314286	0.334491	0.4
0.035714	127.0264	2.142857	5	1	5	0.314286	0.422123	0.285714
0.047619	69.45254	1.75	50	1	50	0.485714	0.146522	0.05
0.066667	70.34318	2.75	83	1	83	0.76	0.150785	0.65
0.083333	38.84382	2.5	93	1	93	1	0	0.5

The data presented in Table 4 represent the output of a code used for analyzing and normalizing the risk, fitness, and environmental sensitivity features of 100 portfolios, evaluated for 18 projects. The dataset includes the original values of Risk, Fitness, and Environmental_Sensitivity, along with their normalized counterparts (Risk_norm, Fitness_norm, EnvSens_norm) scaled to the 0–1 range using MinMaxScaler. Additionally, the Count of each unique combination of features and the First_Portfolio_ID for each combination were calculated. All combinations are unique, and each portfolio appears exactly once. The following is a comprehensive interpretation of the data in continuous text form.

The dataset consists of 100 portfolios, each described by three main features:

- Risk, ranging from 0.013888887 to 0.083333264;
- Fitness, varying between 38.84382351 and 247.7461921;
- Environmental sensitivity, between 1.666666667 and 3.333333333.

Linear normalization was applied to these variables to facilitate comparison among portfolios. The Count column confirms the uniqueness of each portfolio, indicating that each combination appears only once. These data were likely generated within a multi-objective optimization framework to identify the best possible combinations for the 18 projects.

Risk indicates the level of potential hazards associated with each portfolio. Portfolio 89, with a risk of 0.013888887, represents the lowest-risk option, while Portfolio 93, with a risk of 0.083333264, is the highest-risk option. The risk distribution is skewed, with approximately 80% of portfolios having Risk_norm below 0.2, indicating that most portfolios fall into the low-risk category. This focus on low-risk portfolios may reflect a priority to select safer project options.

Fitness, as a measure of portfolio performance or desirability, reaches its maximum in Portfolio 39 (247.7461921) and its minimum in Portfolio 93 (38.84382351). After normalization, Fitness_norm for these portfolios corresponds to 1 and 0, respectively. The distribution of fitness is more uniform compared to risk, although a few portfolios exhibit very high or very low fitness. High-fitness portfolios, such as 39, 89, and 94, are likely to demonstrate superior performance across project evaluation criteria.

Environmental sensitivity, representing portfolio responsiveness to environmental factors, is highest in Portfolio 46 (3.333333333) and lowest in Portfolio 36 (1.666666667). After normalization, EnvSens_norm for these portfolios corresponds to 1 and 0, respectively. Most portfolios display moderate environmental sensitivity, with EnvSens_norm between 0.2 and 0.6. This distribution indicates a general balance regarding environmental impact, although portfolios like 46 may be more vulnerable under unstable environmental conditions.

Examining relationships between variables reveals interesting patterns. There is a strong inverse relationship between risk and fitness. For instance, Portfolio 39, with minimal risk, achieves the highest fitness, whereas Portfolio 93, with the highest risk, has the lowest fitness. This relationship suggests that low-risk portfolios generally perform better. The correlation between risk and environmental sensitivity is less pronounced, though high-risk portfolios, such as 93, exhibit moderate environmental sensitivity. Similarly, high-fitness portfolios like 39 and 89 have moderate environmental sensitivity, indicating that superior performance does not necessarily correlate with high or low environmental sensitivity.

Some portfolios stand out due to their specific characteristics. Portfolio 39, with a risk of 0.013888887, fitness of 247.7461921, and environmental sensitivity of 2.214285714, provides the best balance between low risk and high performance, making it an ideal choice for projects prioritizing safety and efficiency. Portfolio 89, with similar low risk, fitness of 234.5288466, and environmental sensitivity of 2.153846154, is also highly desirable. Conversely, Portfolio 93, with high risk (0.083333264), low fitness (38.84382351), and environmental sensitivity of 2.5, is the least favorable option and should likely be avoided. Portfolio 46, with the highest environmental sensitivity (3.333333333), medium risk, and low fitness, may perform poorly under unstable environmental conditions.

Given that these data were generated to evaluate 18 projects, each portfolio likely represents a specific combination of evaluation criteria for these projects. They were probably produced using a multi-objective optimization algorithm, such as NSGA-II, aiming to minimize risk, maximize fitness, and manage environmental sensitivity. Portfolios such as 39, 89, and 94, with low risk, high fitness, and balanced environmental sensitivity, represent the best options for selection.

For better decision-making, portfolios with low risk and high fitness, like 39 and 89, should be prioritized as they provide strong and stable performance. High-risk portfolios, such as 93, 83, and 50, with low fitness, should only be considered if the project can tolerate higher risk. Additionally, portfolios with high environmental sensitivity, like 46 and 49, may not be suitable for projects in unstable environmental conditions, in which case portfolios with lower sensitivity, like 36 or 81, are preferable.

For a more detailed analysis, scatter plots can be used to visually examine the relationships between risk, fitness, and environmental sensitivity. Calculating Pearson or Spearman correlation coefficients can identify linear or non-linear relationships between variables. Moreover, clustering algorithms such as K-Means can group portfolios based on similarities, and sensitivity analysis can assess the impact of environmental changes on project performance. These analyses can help identify better portfolios and understand the trade-offs among criteria.

In summary, the dataset provides a powerful tool for evaluating and selecting optimal portfolios for the 18 projects. Portfolios 39, 89, and 94, due to their low risk, high fitness, and balanced environmental sensitivity, are the most suitable options for achieving project objectives. These data enable decision-makers to make informed choices considering risk, performance, and environmental sustainability. Additional analyses, such as plotting and statistical calculations, can be conducted separately to enhance the decision-making process.

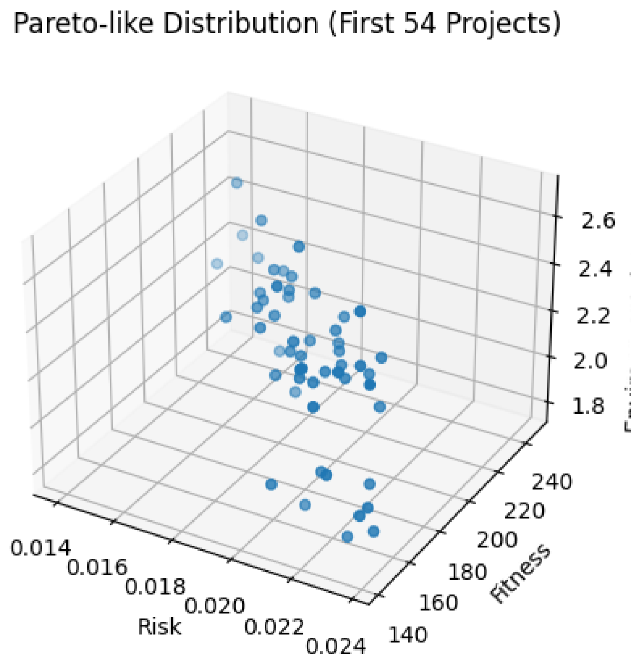

Figure 2. Portfolio evaluation 3D scatter

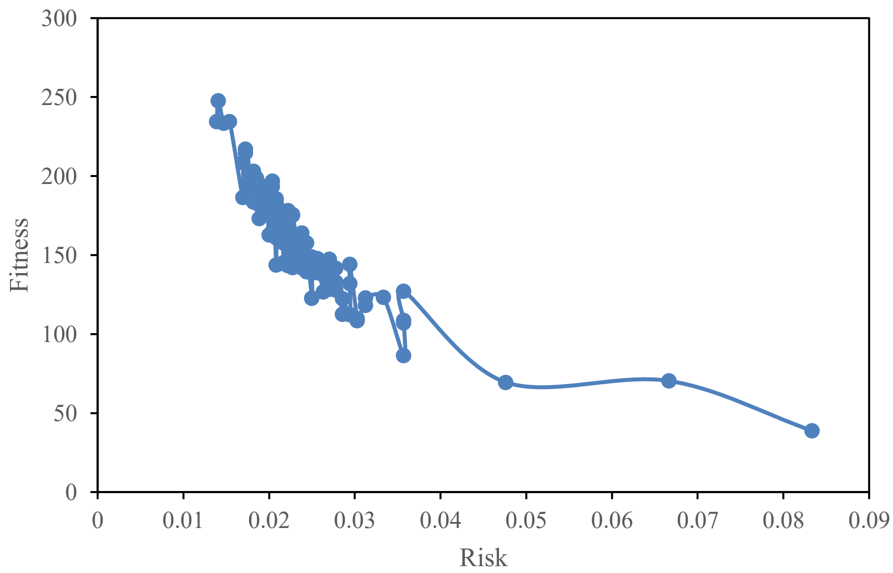

Figure 3. Risk assessment and data output from processing

The data presented consists of about 80 portfolios with two main variables: "Risk" and "Fitness". The risk range is between 0.0139 and 0.0833 and the performance range is between 38.84 and 247.75. By examining the dispersion of the data, it is observed that most of the portfolios are concentrated in the low to medium risk range (0.014 to 0.03) and only a few have high risk, which indicates a left-skewed tendency in risk. In the case of performance, most of the values are between 140 and 200, and a few outliers are observed, which makes Fitness more dispersed than Risk.

By simultaneously analyzing risk and performance, it is found that low-risk portfolios (0.014–0.02) can perform well (Fitness between 230 and 247), while high-risk portfolios (0.05–0.08) often perform poorly (Fitness between 38 and 70). This suggests that the classic "more risk = more return" relationship does not hold in this data set, and that low-risk portfolios may even perform better.

The approximate statistical indicators of the data include a mean risk of ~0.022, a mean Fitness of ~165, a median risk of ~0.02, and a median Fitness of ~165. The standard deviation of risk is approximately 0.012 and the standard deviation of performance is approximately 40, indicating greater concentration of risk and greater dispersion of Fitness. The initial correlation between Risk and Fitness is negative and weak, such that an increase in risk is associated with a decrease in performance on average, which is contrary to the classical risk-return hypothesis.

In this data set, the portfolios with the lowest risk and highest return are considered as the optimal points, for example, a portfolio with a risk of about 0.014 and a return of 247.7 shows the best combination of low risk and return. Therefore, the data suggests that the highest returns are associated with low-risk or low-to-moderate risk portfolios, and increasing risk does not necessarily increase returns. This pattern can indicate low-risk, high-return investment opportunities in this data set and is suitable for scientific and analytical decision-making.

4. Discussion and Conclusion

The present study examined the application of multi-objective metaheuristic optimization to the selection and prioritization of oil and gas construction projects. The findings showed that project portfolio selection in this sector cannot be reduced to a single financial criterion because the attractiveness of each portfolio depends simultaneously on its economic return, social contribution, environmental performance, technical and natural risk, safety requirements, and strategic compatibility. Based on the standardized assessment of the candidate projects, the Genetic Algorithm generated a set of non-dominated portfolio alternatives and identified a balanced solution with an overall score of 2.9, an economic index of 0.85, a social index of 0.75, an environmental index of 0.80, and a risk index of 0.40. The conventional multi-criteria weighting approach produced a portfolio with a higher economic index of 0.90, but this improvement was achieved through a stronger emphasis on profitability and did not provide the same breadth of trade-off alternatives as the metaheuristic model. The Pareto front further demonstrated that portfolios with greater economic, social, and environmental performance generally involved higher risk, whereas more conservative portfolios reduced risk at the expense of overall benefit. These results support the use of a Pareto-based framework for strategic decision-making rather than the selection of a single portfolio based on an aggregated financial score.

The first important finding was the capacity of the Genetic Algorithm to generate a diversified set of efficient portfolio solutions. Instead of prescribing only one combination of projects, the algorithm identified several portfolios that were non-dominated across the principal objectives. This result is important because decision-makers in the oil and gas industry may differ in their priorities and risk tolerance. A profit-oriented organization may prefer a portfolio with a high economic index, whereas a public-sector or sustainability-oriented organization may accept a lower return in exchange for improved environmental compliance, social acceptance, or lower risk. The generation of a Pareto front therefore provides greater decision flexibility than traditional ranking methods. This finding is consistent with the multi-objective framework proposed for industrial research and development portfolios, in which Pareto-efficient solutions enabled the simultaneous consideration of strategic, technical, business, resource, and temporal objectives [8]. It also aligns with scenario-based robust portfolio selection models that produce alternative solutions under different risk and uncertainty conditions rather than assuming that a single portfolio remains optimal under all circumstances [5].

The superior breadth of solutions generated by the metaheuristic approach can be explained by the combinatorial nature of project portfolio selection. When numerous projects are evaluated simultaneously, the number of possible portfolio combinations increases exponentially. Traditional weighting and ranking approaches generally score projects separately and select those with the highest individual values, but such procedures may overlook the effect of project combinations, shared constraints, and interdependencies. In contrast, the Genetic Algorithm evaluates the portfolio as a complete configuration and continuously modifies combinations through selection, crossover, and mutation. This feature makes it possible to identify portfolios whose collective value exceeds what would be expected from the isolated ranking of their constituent projects. The result is consistent with research demonstrating that project interdependencies significantly affect portfolio value and that evolutionary algorithms can outperform conventional optimization procedures when these relationships are incorporated into the model [11]. It is also supported by network-based portfolio models showing that strategic robustness depends on the pattern of relationships among projects and not merely on the quality of individual initiatives [13].

The findings also showed that the portfolio recommended by the multi-criteria weighting method achieved a slightly higher economic index than the balanced Genetic Algorithm solution. This result should not be interpreted as evidence that the conventional method was generally superior. Rather, it reflects the effect of the method’s weighting structure and stronger orientation toward profitability. When economic performance is assigned the greatest importance, the resulting portfolio is likely to concentrate on projects with stronger returns, even if those projects involve greater environmental sensitivity, social challenges, or risk exposure. The metaheuristic solution, by comparison, accepted a modest reduction in the economic index in order to obtain more balanced performance across social, environmental, and risk dimensions. This interpretation is consistent with mathematical programming research in oil and gas companies, which has shown that maximizing net present value alone may generate a different portfolio from one designed to satisfy broader strategic objectives [6]. Similarly, research on environmentally and socially constrained financial portfolios indicates that the inclusion of sustainability criteria can reduce purely financial performance while producing a more responsible and strategically balanced allocation [16].

The relatively high environmental index obtained by the optimized portfolio is particularly meaningful in the context of oil and gas projects. Many of the evaluated projects were characterized by medium or high environmental sensitivity, especially offshore, refinery, petrochemical, and export-related developments. At the same time, environmental compliance was generally assessed at moderate to high levels. The algorithm therefore favored combinations that did not simply avoid environmentally sensitive projects, but instead balanced sensitivity with regulatory compliance and other portfolio benefits. This distinction is important because environmentally sensitive projects may still be strategically necessary, provided that they are accompanied by strong mitigation, monitoring, and compliance systems. The result corresponds with sustainability-oriented project selection models that integrate environmental performance into resource-constrained portfolio selection and scheduling rather than treating environmental criteria as a final screening mechanism [14]. It is also compatible with simulation–optimization research showing that sustainable portfolio management requires explicit analysis of the trade-offs among economic value, environmental effects, and operational constraints [15].

The social index of 0.75 further indicated that the selected portfolio maintained a favorable level of community impact and social acceptance. Oil and gas projects frequently influence employment, local infrastructure, regional development, public services, land use, and community welfare. Consequently, projects that appear economically attractive may face implementation barriers when local concerns are neglected. The optimized portfolio’s social performance suggests that the model was capable of incorporating non-financial benefits into project selection. This finding is aligned with portfolio benefit-evaluation studies showing that the total value of a portfolio should include strategic and non-financial benefits rather than only direct financial returns [4]. Group neural-network models have likewise shown that benefit evaluation becomes more accurate when interactions and collective financial and non-financial outcomes are considered [3]. More recent pruned neural-network models also support the inclusion of synergy, ambidexterity, and multiple benefit dimensions when evaluating project portfolios [21].

The risk index of 0.40 suggests that the optimized solution achieved a relatively controlled level of aggregate risk while preserving substantial economic, social, and environmental value. This finding demonstrates the importance of evaluating risk at the portfolio level. A collection of individually acceptable projects may create excessive aggregate exposure if several projects share similar technical, geographical, financial, or environmental vulnerabilities. The use of a risk-minimization objective enabled the algorithm to avoid portfolios in which high-return projects were excessively concentrated in high-risk categories. This result supports the literature emphasizing that project portfolio risk includes not only project-specific uncertainty but also dependencies, common causes, and cumulative effects [12]. It also agrees with robust optimization models that incorporate risk scenarios and uncertainty into portfolio selection to prevent solutions from becoming infeasible or undesirable when underlying assumptions change [5].

The configuration of the Pareto front provided additional insight into the relationship between benefit and risk. Solutions located in the high-benefit region generally carried greater risk, whereas portfolios with lower risk tended to produce more limited economic, social, or environmental outcomes. This pattern confirms that risk cannot be eliminated without an opportunity cost. The managerial task is therefore not to select the minimum-risk portfolio under all circumstances, but to determine the level of risk that is justified by the expected portfolio benefits. This interpretation is consistent with cash-flow optimization studies in construction project portfolios, where genetic algorithms and particle swarm optimization improved financial performance while requiring decision-makers to consider market conditions and execution uncertainty [7]. It also resembles findings from financial portfolio optimization, where greater expected return is commonly associated with increased risk and where the quality of a solution must be judged using risk-adjusted rather than return-only measures [25, 28].

The distribution of the Pareto solutions also indicated that the Genetic Algorithm maintained adequate population diversity and did not converge prematurely to one narrow region of the search space. This characteristic is essential in multi-objective portfolio optimization because premature convergence would produce a limited set of similar alternatives and reduce the practical value of the model. The broad distribution of non-dominated points suggests that crossover and mutation were effective in exploring different combinations of projects. This result is supported by studies in which genetic algorithms improved the prediction and evaluation of project portfolio benefits by optimizing model parameters and escaping inferior local solutions [4]. Comparable evidence has been reported in hybrid neural-network applications, where evolutionary optimization substantially improved predictive accuracy and portfolio benefit measurement [3, 21].

Although the Genetic Algorithm was central to the generation of the Pareto front, the broader comparison of metaheuristic methods suggests that algorithm selection should depend on the decision problem. Particle Swarm Optimization may reach promising solutions more quickly because of its relatively simple collective search mechanism, while the Genetic Algorithm may provide more extensive exploration and greater diversity through mutation and recombination. Simulated Annealing may be useful when the model requires a simple mechanism for escaping local optima, although its performance depends heavily on the cooling schedule. The study's findings therefore support the comparative use of algorithms rather than the assumption that one method will always dominate. The relevance of algorithmic comparison is also demonstrated by prior research in which particle swarm and genetic algorithms differed in convergence speed and solution quality when optimizing portfolio cash flows [7]. Likewise, competitive evolutionary algorithms have sometimes outperformed standard GA and PSO models when project interdependencies were explicitly represented [11].

The standardized numerical scoring of technical, spatial, economic, temporal, environmental, safety, social, and operational indicators was another strength of the study. The acceptable reliability coefficients for the criteria indicated that the expert-based evaluation framework possessed adequate internal consistency. Converting qualitative judgments into a structured numerical matrix made it possible to integrate diverse project characteristics within the optimization model. This is especially valuable in oil and gas portfolios because several strategically important characteristics, such as social acceptance, environmental sensitivity, accessibility, technical complexity, and innovative technology use, cannot be adequately represented through financial data alone. The use of structured preferences is consistent with industrial portfolio algorithms that translate managerial priorities into formal selection criteria [1]. It also corresponds with approaches combining earned value management and analytic hierarchy procedures to support transparent project reprioritization and resource allocation [9].

The results further imply that digitalization can improve the continuing application of the proposed model. Although the current study used structured questionnaire data and expert assessments, the same framework could be linked to digital dashboards containing real-time information on cost, schedule, safety, environmental compliance, and risk. Such integration would enable dynamic portfolio reassessment as project conditions change. This interpretation is consistent with research on digital PPM in construction, which highlights the potential of digital systems to improve monitoring, collaboration, cost control, and decision quality, despite continuing challenges in infrastructure, integration, security, and organizational readiness [17, 18]. Intelligent portfolio dashboards can further combine value, prioritization, and risk indicators, thereby allowing decision-makers to update portfolio choices as new information becomes available [19]. Machine-learning methods could also be incorporated to predict critical success factors, identify emerging risks, and improve the quality of portfolio inputs [23].

Overall, the study demonstrates that multi-objective metaheuristic optimization provides a more comprehensive basis for oil and gas project portfolio selection than profit-centered ranking alone. The Genetic Algorithm generated a balanced portfolio and a diverse Pareto front, enabling decision-makers to observe how improvements in profitability, social value, and environmental performance may increase risk. The findings also show that the optimal portfolio is conditional on strategic preferences rather than universally fixed. A portfolio selected by a private investor may differ from one preferred by a public client, environmental regulator, or risk-averse organization. This conclusion reflects broader developments in portfolio optimization, including the use of machine learning for volatile assets [29], combined stock and cryptocurrency allocation [30], behavioral models of investor choice [31], few-shot large-language-model optimization [26], and emerging quantum approaches to complex allocation problems [27]. Although these studies concern different asset classes, they similarly indicate that advanced optimization should integrate multiple objectives, uncertainty, computational intelligence, and decision-maker preferences.

This study had several limitations. First, the optimization results depended on expert judgments and standardized scores, which may contain subjectivity despite acceptable reliability coefficients. Second, some financial, environmental, and operational indicators were represented through ordinal categories rather than continuous real-world measurements. Third, the model simplified certain project dependencies and did not fully represent cascading delays, shared contractors, political uncertainty, commodity-price fluctuations, or changes in regulatory conditions. Fourth, the algorithmic outputs were affected by parameter settings, including population size, crossover rate, mutation rate, inertia coefficients, and stopping criteria. Fifth, the analysis primarily represented one sectoral and national context, which may limit the direct generalizability of the resulting weights and portfolio configurations. Finally, although the broader dataset included numerous projects, parts of the optimization process were initially developed and tested on a smaller pilot portfolio, and the findings should therefore be interpreted as evidence of methodological effectiveness rather than a definitive investment prescription.

Future studies should validate the model using continuously updated financial, scheduling, safety, environmental, and operational data from completed and ongoing projects. Researchers should explicitly model technical, resource, cash-flow, and strategic dependencies among projects and examine how project delays or cancellation affect the remaining portfolio. Comparative studies could evaluate NSGA-II, NSGA-III, multi-objective PSO, differential evolution, ant colony optimization, and hybrid genetic–swarm algorithms under identical constraints. Further work should incorporate uncertainty through stochastic programming, fuzzy variables, scenario analysis, and robust optimization. Longitudinal research could examine dynamic portfolio rebalancing across planning and execution stages. Studies should also compare expert-defined weights with weights learned from historical performance data and examine whether machine-learning models improve the prediction of project benefits, risk, cost overruns, and environmental outcomes.

Oil and gas organizations should establish a formal portfolio governance process in which project selection is based on economic, environmental, social, safety, and risk indicators rather than financial return alone. Decision-makers should use the Pareto front as a strategic negotiation tool and select a portfolio according to clearly documented priorities and risk tolerance. Portfolio data should be updated periodically, and projects should be reevaluated when costs, schedules, market conditions, environmental obligations, or strategic objectives change. Organizations should also maintain a centralized digital database integrating project performance, resource use, risk exposure, and sustainability indicators. Before implementation, algorithmic outputs should be reviewed by a multidisciplinary committee comprising project managers, financial analysts, engineers, environmental specialists, safety professionals, and community-relations experts.

Authors' Contributions

Authors equally contributed to this article.

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Declaration of Interest

The authors report no conflict of interest.

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Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] E. E. Cihan, C. A. Uslu, and Ö. Kabak, "Hyper-project portfolio management: Post-merger project portfolios," *Management Decision,* vol. 61, no. 8, pp. 2280-2301, 2023, doi: 10.1108/MD-06-2022-0853.
[2] E. E. Cihan, Ç. Alabaş-Uslu, and Ö. Kabak, "Initial preference algorithm of industrial project portfolio," *Kybernetes,* vol. 52, no. 12, pp. 6025-6048, 2023, doi: 10.1108/K-04-2022-0644.
[3] L. Bai, Y. An, and Y. Sun, "Measurement of project portfolio benefits with a GA-BP neural network group," *IEEE Transactions on Engineering Management,* vol. 71, pp. 4737-4749, 2023, doi: 10.1109/TEM.2023.3236956.
[4] Y. Tian, L. Bai, L. Wei, K. Zheng, and X. Zhou, "Modeling for project portfolio benefit prediction via a GA-BP neural network," *Technological Forecasting and Social Change,* vol. 183, p. 121939, 2022, doi: 10.1016/j.techfore.2022.121939.
[5] A. A. Ramedani, H. Didehkhani, and A. Mehrabian, "Scenario-based optimization robust model project portfolio selection under risk considerations," *Neural Computing and Applications,* vol. 34, no. 23, pp. 20589-20609, 2022, doi: 10.1007/s00521-022-07434-8.
[6] A. Panahi, A. Habibirad, and S. Safari, "Developing a mathematical programming model to determine the optimal portfolio of capital projects in oil and gas companies to achieve the strategic goals," *Petroleum Business Review,* vol. 7, no. 2, pp. 15-30, 2023.
[7] R. Rajabi and S. Haj Yakhchali, "Optimization of cash flow in project portfolio considering market indicators using genetic algorithms and particle swarm optimization," *Journal of Structural and Construction Engineering,* vol. 9, no. 9, pp. 103-120, 2022, doi: 10.22065/jsce.2022.310778.2609.
[8] M. K. Nielsen, A. M. Jacobsen, J. L. Carstensen, M. T. Nielsen, and T. Tambo, "Industrial R&D project portfolio selection method using a multi-objective optimization program: A conceptual quantitative framework," *Journal of Industrial Engineering and Management,* vol. 17, no. 1, pp. 217-234, 2024, doi: 10.3926/jiem.6552.
[9] M. Mombini, M. Babakhani, and M. Sabzehparvar, "Evaluation and prioritization of project portfolios during execution for resource allocation: Approach of earned value management and analytic hierarchy process; case study," in *12th International Conference on Industrial Engineering*, 2015. [Online]. Available: https://civilica.com/doc/516244.
[10] N. Raad, M. Shirazi, and S. Ghodsypour, "Selecting a portfolio of projects considering both optimization and balance of sub-portfolios," *Journal of Project Management,* vol. 5, no. 1, pp. 1-16, 2020, doi: 10.5267/j.jpm.2019.8.003.
[11] M. Poursekazemi, M. Fattahi, S. Mazhari, and B. Asadi, "Optimization of project portfolios with interdependent effects using the imperialist competitive algorithm (ICA)," *Industrial Management Journal,* vol. 5, no. 1, pp. 1-20, 2013, doi: 10.22059/imj.2013.35680.
[12] C. Micán, G. Fernandes, and M. Araújo, "Project portfolio risk management: A structured literature review with future directions for research," *International Journal of Information Systems and Project Management,* vol. 8, no. 3, pp. 67-84, 2020, doi: 10.12821/ijispm080304.
[13] L. Bai, X. Han, H. Wang, K. Zhang, and Y. Sun, "A method of network robustness under strategic goals for project portfolio selection," *Computers & Industrial Engineering,* vol. 161, p. 107658, 2021, doi: 10.1016/j.cie.2021.107658.
[14] A. RezaHoseini, S. F. Ghannadpour, and M. Hemmati, "A comprehensive mathematical model for resource-constrained multi-objective project portfolio selection and scheduling considering sustainability and projects splitting," *Journal of Cleaner Production,* vol. 269, p. 122073, 2020, doi: 10.1016/j.jclepro.2020.122073.
[15] M. Saiz, M. A. Lostumbo, A. A. Juan, and D. Lopez-Lopez, "On the use of simulation-optimization in sustainability aware project portfolio management," in *2020 Winter Simulation Conference (WSC)*, 2020, doi: 10.1109/WSC48552.2020.9383941.
[16] M. Z. Wu, "Portfolio Optimization Under ESG Constraints: Markowitz Model vs. Index Model," *SHS Web of Conferences,* vol. 218, p. 02002, 2025, doi: 10.1051/shsconf/202521802002.
[17] C. C. Wittebrood, "Digitizing project portfolio management in the architecture, engineering & construction industry," TU Delft, 2020.
[18] F. Nsubuga, "Towards digital project portfolio management in construction: Challenges and opportunities for public clients," ed, 2024.
[19] A. Zaidouni, M. A. J. Idrissi, and A. Bellabdaoui, "A PRISMA systematic review for intelligent IS/IT project portfolio dashboard from the value, prioritization and risk perspectives," in *2024 4th International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET)*, 2024, doi: 10.1109/IRASET60544.2024.10548997.
[20] R. A. Pinto, F. Bernardini, and R. M. Marcacini, "aePPM-HC: A method for helping project portfolio management based on topic hierarchy learnings," *International Journal of Business Intelligence and Data Mining,* vol. 18, no. 3, pp. 364-382, 2021, doi: 10.1504/IJBIDM.2021.114469.
[21] L. Bai, S. Liu, Y. An, and Q. Xie, "A pruned GA-BPNN model for project portfolio benefit evaluation considering ambidexterity," *Kybernetes,* 2024, doi: 10.1108/K-04-2024-0982.
[22] Z. Zhu, "Selection of projects for project portfolio using fuzzy TOPSIS and machine learning," ed, 2021.
[23] M. T. Elnabwy, D. Khalaf, E. A. Mlybari, and E. Elbeltagi, "An integrated machine learning approach for evaluating critical success factors influencing project portfolio

management adoption in the construction industry," *Engineering, Construction and Architectural Management,* 2024, doi: 10.1108/ECAM-05-2024-0537.

[24] S. H. Hosseini, H. Shakouri G, A. Kazemi, R. Zareayan, and M. Mousavian H, "A system dynamics investigation of project portfolio management evolution in the energy sector: Case study: An Iranian independent power producer," *Kybernetes,* vol. 49, no. 2, pp. 505-525, 2020, doi: 10.1108/K-12-2018-0688.

[25] P. Lönnrot, "Portfolio optimization with AI: Evaluating Performance Beyond Traditional Techniques," ed, 2025.

[26] L. A. Mantshimuli and J. W. Muteba Mwamba, "Few-Shot Portfolio Optimization: Can Large Language Models Outperform Quantitative Portfolio Optimization? A Comparative Study of LLMs and Optimized Portfolio Allocators," (in English), *Journal of Risk and Financial Management,* vol. 19, no. 5, p. 320, 2026, doi: 10.3390/jrfm19050320.

[27] S. Mohd, M. Dasgupta, F. Akter, M. P. Arunachalam, and S. Sharma, "Quantum computing applications in financial modeling and portfolio optimization," 2025: IEEE, pp. 868-872, doi: 10.1109/CE2CT64011.2025.10939675.

[28] L. M. Moreira, I. L. d. Santos, and P. H. González, "Portfolio Optimization for Pension Purposes: Literature Review," *Journal of Economic Surveys,* vol. 40, no. 1, pp. 45-72, 2025, doi: 10.1111/joes.12702.

[29] D. Song, *Machine Learning for Price Prediction and Risk - Adjusted Portfolio Optimization in Cryptocurrencies* (In Machine Learning and Modeling Techniques in Financial Data Science). 2025, pp. 321-356.

[30] N. Shahbazi and S. Barkhordari, "Optimizing a portfolio comprising selected stocks and cryptocurrencies," *Budget and Finance Strategic Research,* vol. 6, no. 2, pp. 11-35, 2025.

[31] M. Eskandari, A. Mohseni, and M. Ghasemi, "The Effect of Behavioral Biases on Portfolio Optimization of Investors in the Tehran Stock Exchange: An Approach Based on Modern Behavioral Finance," *Accounting, Finance, and Computational Intelligence,* pp. 1-17, 2026.