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A resource-constrained multi-objective and multi-period model for selecting project portfolio and scheduling with net present value consideration

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Abstract –*Selecting the optimal project portfolio and scheduling its implementation under limited resources is a critical managerial challenge. While most previous studies have addressed portfolio selection independently of scheduling, real-world conditions require the integration of both decisions to ensure efficient resource utilization. To bridge this research gap, this paper proposes a comprehensive multi-objective and multi-period optimization model that simultaneously handles project portfolio selection and scheduling under resource constraints. The model jointly optimizes four strategic criteria: net present value (NPV), risk, strategic alignment, and environmental loss, while ensuring feasibility across time-dependent resource limitations. In contrast to earlier single-objective or static models, the proposed formulation incorporates a robust approach that considers uncertainty in resource availability and project outcomes, enabling more resilient portfolio decisions. A real-world case study is presented and solved using the ε-constraint method via GAMS software. The results demonstrate that considering strategic alignment and environmental criteria alongside economic value and risk leads to a more balanced and sustainable project portfolio. Furthermore, the model improves the reliability of decisions under uncertainty and reflects practical managerial trade-offs between profitability, strategic fit, risk exposure, and environmental impact.*

Keywords*– Environmental sustainability; Multi-objective optimization; Project portfolio selection and scheduling; Resource constraints; Strategic alignment.*

I. INTRODUCTION

Selecting an optimal project portfolio is widely recognized as one of the most critical managerial decisions within strategic planning processes. It involves simultaneously allocating limited resources and selecting projects that together maximize organizational value. Although numerous studies have investigated project portfolio selection (PPS) from different viewpoints, most have examined selection and scheduling separately, limiting the practical integration required in real-world environments (Medaglia et al., 2007; Wang et al., 2009; Heidenberger & Stummer, 1999). In reality, both decisions must be optimized jointly to ensure resource efficiency and strategic alignment across multiple projects.

Early research on PPS mainly focused on financial performance and the maximization of net present value (NPV) (Weingartner, 1963, 1966), while later developments incorporated multi-criteria decision models addressing trade-offs between cost, risk, and strategic impact (Santhanam & Kyparisis, 1995, 1996; Schniederjans & Santhanam, 1993).

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The introduction of uncertainty modeling further diversified the field. Pioneering works utilized probabilistic and fuzzy approaches (Carlsson et al., 2007; Huang, 2007; Gabriel et al., 2006) and evolutionary algorithms (Medaglia et al., 2007; Doerner et al., 2004) to handle ambiguous parameters affecting project outcomes. In parallel, resource-constrained project scheduling (RCPSP) emerged as a central research stream addressing how limited resources are allocated over time to minimize project duration or maximize value (Brucker et al., 1999; Kolisch & Hartmann, 2006). Foundational optimization studies using branch-and-bound and exact algorithms (Demeulemeester & Herroelen, 1992, 1997; Mingozzi et al., 1998; Heilmann, 2003) provided the theoretical basis for scheduling under resource and precedence constraints. Subsequent meta-heuristic advancements, including genetic algorithms, simulated annealing, and hybrid search techniques (Alcaraz et al., 2003; Bouleimen & Lecocq, 2003; Debels et al., 2006), improved computational scalability for large-scale industrial cases.

However, despite this extensive background, integrated frameworks combining project portfolio selection and scheduling under uncertainty remain limited. Comprehensive reviews, for example Mohagheghi et al. (2019), emphasize that joint PPS–RCPS models represent the next evolution of project management research, requiring unified mathematical formulations and robust optimization tools to balance multiple objectives, including economic, strategic, risk-based, and environmental, within resource-limited conditions. Environmental and sustainability aspects have recently gained prominence as essential evaluation criteria for modern project portfolios (Prato, 2007; Hoseinia et al., 2020; Rahimi et al., 2023).

Projects inherently differ in ecological influence, and neglecting these effects can lead to non-optimal or socially undesirable portfolios. Consequently, integrating environmental loss minimization alongside traditional financial and strategic goals yields a more realistic and responsible decision framework. Given these challenges, this study develops a comprehensive multi-period and multi-objective model that simultaneously optimizes project selection and scheduling under resource constraints.

The proposed framework extends prior works (Nikkhahnasab & Najafi, 2013; Naderi, 2013) by operationalizing four key objectives:

- Maximization of net present value;
- Minimization of project risk;
- Alignment with strategic organizational goals
- Minimization of environmental loss.

While maintaining feasibility under renewable and limited resource availability. To validate the model, an actual case study is solved using the ε-constraint method implemented in GAMS, ensuring an efficient compromise among conflicting criteria. The results demonstrate the effectiveness of the integrated approach in achieving strategic balance between profitability, sustainability, and operational feasibility.

The remainder of this paper is organized as follows: Section 2 presents the detailed literature review; Section 3 defines the problem and mathematical formulation; Section 4 explains the ε-constraint optimization approach; Section 5 introduces the case study; Section 6 discusses the results and findings; Section 7 provides model validation; and Section 8 concludes the research with managerial implications and directions for future work.

II. LITERATURE REVIEW

A. Project Portfolio Selection

Project portfolio selection (PPS) has long been recognized as a fundamental decision-making process for efficiently allocating limited resources to optimal combinations of projects. According to Medaglia et al. (2007), the literature can be divided into two main categories: (1) application contexts and (2) methodological classifications.

The application context dimension mainly includes research on R&D portfolios (Heidenberger & Stummer, 1999; Wang et al., 2009; Ringuest & Graves, 1990), information systems (Santhanam & Kyparisis, 1995; Kyparisis, 1996), and capital budgeting (Weingartner, 1963, 1966). In these areas, selecting project portfolios is influenced by the degree of interdependency, uncertainty, and multi-period investment horizons. The methodological classification encompasses mathematical and heuristic optimization techniques. The PPS models have been formulated via linear (Meredith & Mantel, 1995; Rabbani et al., 2006), nonlinear (Santhanam & Kyparisis, 1996), integer (Carlsson et al., 2007), dynamic (Choi et al., 2004, 2007), goal programming (Mukherjee & Bera, 1995), fuzzy programming (Huang, 2007; Barzegari et al., 2023; Askarianzadeh et al., 2024), stochastic programming (Allen, 1991), decision trees (Granot & Zuckerman, 1991), game-theoretic approaches (Park & Chong, 1991), and simulation and metaheuristics (Doerner et al., 2004; Gabriel et al., 2006).

Recent advances have significantly expanded the modeling scope. Kandakoglu et al. (2024) provided a systematic review of multi-criteria decision analysis (MCDA) methods (AHP, TOPSIS, BWM, FITradeoff , etc.) and emphasized combining MCDA with mathematical programming to handle complex PPS environments under resource constraints. ForouzeshNejad (2024) introduced a hybrid data-driven model incorporating fuzzy best-worst (FBWM), data envelopment analysis (DEA), and machine learning methods (random forest and SVR) to assess project performance in the telecommunication industry. Similarly, Bai et al. (2023) developed a fuzzy Bayesian network-based model to evaluate portfolio risks considering project interdependencies, an increasing focus in sustainable portfolio management.

Moreover, new studies fuse optimization and uncertainty handling: Saiz et al. (2025) proposed a simheuristic algorithm blending genetic optimization with Monte Carlo simulation to maximize expected value under portfolio reliability constraints. Habibi et al. (2025) formulated a robust integrated PPS scheduling material ordering model to handle material supply uncertainty, achieving over 90% computational time reduction. Zahedirad et al. (2025) extended multi-objective PPS by integrating contractor selection through fuzzy goal programming with preference relations, and Ferreira et al. (2025) designed an FITradeoff-based multi-criteria benefit-to-cost framework for sustainable portfolios in the construction industry. These studies highlight how PPS has evolved from deterministic single-objective models to multi-period, data-driven, uncertainty-aware frameworks aligned with sustainability and strategic objectives.

B. Resource Constrained Project Scheduling (RCPSP)

The RCPSP addresses scheduling individual projects to minimize make span subject to limited resource availability. Classical RCPSP models assume fixed durations and renewable resources (Brucker et al., 1999; Kolisch & Hartmann, 2006), while optimal and heuristic methods (Demeulemeester & Herroelen, 1992; 1997; Mingozzi et al., 1998) form the foundation of the field. Subsequent developments introduced multi-mode activities (Heilmann, 2003) and more sophisticated heuristics and metaheuristics (Alcaraz et al., 2004; Bouleimen & Lecocq, 2003; Debels et al., 2006). Priority rules, such as MINSLK, LST, RSM, and LFT (Davis & Patterson, 1975), remain effective for smaller instances, while multi-pass and hybrid heuristics combining parallel schedule generation with forward-backward improvement schemes yield better computational performance. Kolisch (1996) refined the serial vs parallel scheduling theories, and Sprecher et al. (1995) defined the classes of semi-active, active, and non-delay schedules, providing a theoretical taxonomy still referenced today. Recent RCPSP extensions incorporate stochastic durations, environmental impact modeling, and strategic resource balancing. Harrison et al. (2021, 2022) used hybrid multi-population metaheuristics to handle large multi-division scheduling problems aligned with organizational strategy. Rahimi et al. (2023) employed branch and Benders methods under stochastic balancing constraints for sustainable resource management, bridging single project RCPSP and strategic portfolio optimization.

C. Joint Project Portfolio Selection and Scheduling

The integrated PPS–Scheduling problem combines project selection and timing decisions under resource, budgetary, and precedence constraints. This complex NP-hard class has attracted growing interest, particularly under uncertainty and multi-objective settings. Table I provides a comprehensive overview of major contributions published between 2010 and 2025, summarizing objectives, model categories, constraint structures, and applied solution methods.

Table I. Summary of Recent Studies on Integrated Project Portfolio Selection and Scheduling Models

Objective(s)	Model Type	Constraints	Solution Approach	Reference
NPV	Certain	Precedence, Resources	Imperialist Competitive	Chen & Askin (2009)
NPV–Cost–Risk	Certain	Interdependent Implementation	PSO	Rabbani et al. (2010)
NPV	Uncertain	Budget	Stochastic Programming	Rafiee & Kianfar (2011)
NPV	Certain	Precedence, Resources	GA–SA–Hybrid	Naderi (2013)
NPV	Certain	Precedence, Resources	GA–SA	Nikkhahnasab & Najafi (2013)
NPV	Certain	Deadline, Precedence, Resources	Multi-Agent Evolutionary Algorithm	Yongyi et al. (2014)
NPV	Uncertain	Resources	Stochastic Programming	Rafiee et al. (2014)
NPV–Balance Resource Usage	Certain	Resource Dependency	Ant Colony Optimization	Tofighian & Naderi (2015)
NPV	Uncertain	Precedence	Robust Optimization	Emami et al. (2016)
Float, Finish Time	Uncertain	Resources	EV / WS	Sadat Hosseini et al. (2017)
Benefit–Risk	Uncertain	Resources	Hybrid IMMOEA / NSGA-II	Xiaoxiong et al. (2019)
Profit–Sustainability–Interruption	Certain	Resources, Precedence	ε-Constraint	Hoseinia et al. (2020)
NPV–Total Value	Certain	Resources	Meta-Heuristic, Hybrid	Harrison et al. (2021)
NPV–Portfolio Value	Certain	Budget	Heuristic, Meta-Heuristic Hybrid	Harrison et al. (2022)
NPV–Sustainability	Uncertain	Balancing Constraints	CPLEX + Benders	Rahimi et al. (2023)
Profit–Sustainability–Interruptions	Uncertain	Resource, Budgetary	MCGP-UF + GA	Ramedani et al. (2024)
Sustainability–Strategy (MCDA Integration)	Certain	Multi-Criteria, Resource	MCDA (FITradeoff/BWM) + MILP	Kandakoglu et al. (2024) & ForouzeshNejad (2024)
NPV–Material Supply Uncertainty	Uncertain	Resource–Material	Modified Genetic Algorithm	Habibi et al. (2025)
Reliability–Risk	Uncertain	Portfolio Constraints	Genetic Simheuristic + Monte Carlo	Saiz et al. (2025)
Financial–Non-Financial Synergy	Certain	Dynamic Synergy	System Dynamics + MILP	Bai et al. (2025)
NPV–Delay Cost	Certain	Precedence, Reinvestment	iNSGA-III	Li et al. (2025)
Fuzzy Multi-Objective PPS–Contractor	Certain	Resource, Preference Relations	Fuzzy Goal Programming	Zahedirad et al. (2025)
Benefit-to-Cost Sustainability	Certain	Budget, Strategy	FITradeoff MCDM/A	Ferreira et al. (2025)
Multi-Objective (NPV–Risk–Alignment–Environmental Loss)	Certain	Resource, Precedence	ε-Constraint (GAMS)	This Research

D. Research Gaps

Although extensive research has explored PPS and RCPSP independently, few studies offer a unified mathematical structure integrating selection and scheduling decisions under multi-criteria, resource limitations, and uncertainty simultaneously. Earlier models commonly emphasized deterministic financial evaluation (Weingartner, 1963; Meredith & Mantel, 1995), while later works introduced heuristic and fuzzy frameworks. Current advances (2023–2025) emphasize sustainability, risk interdependencies, dynamic synergy, and data-driven prediction; however, the integration of multi-objective PPS and scheduling under robust and resource-uncertain environments remains scarce.

Therefore, the present research develops an integrated multi-period PPS-Scheduling model optimizing four objectives: NPV maximization, risk minimization, strategic alignment, and environmental loss minimization, subject to renewable resource and precedence constraints, solved by the ε-constraint method in GAMS. This approach addresses the identified gaps and provides a comprehensive decision framework under real-world uncertainty.

II. PROBLEM DEFINITION AND PROPOSED MATHEMATICAL MODEL

The problem of selecting and scheduling projects can be described as follows. There is a set of *I* projects, where each project has its benefit, risk, degree of alignment with the strategic organizational goals, and environmental loss. A set of *j* activities has to operate. There are some precedence relationships among the activities of a project. The type of precedence relationships assumed is finish-to-start with a zero-time lag; an activity can start if all of its predecessors are complete and does not need setup time. This assumption holds regardless of the dependencies between the projects to perform each project. Candidate projects are considered based on their current profit and risk, the degree of alignment of the projects with the strategic organizational goals, and net present environmental loss. Finally, subsets of them are selected. It is assumed that cash inflow is achievable only when a project finishes. The goal is to find a project portfolio such that the net present value is maximized, risk is minimized, the degree of alignment of the projects with the strategic organizational goals is maximized, and the net present environmental loss is minimized. In the joint problem of project selection and scheduling, a small subset of projects is chosen from the more extensive set of projects based on the desired criteria and the given set of limitations. The first phase of studying such an optimization problem is developing a mathematical formulation.

A. Model assumptions

The assumptions of the model are as follows:

- Each project includes *J* activities.
- The previous activity (prerequisite) must be finished to start an activity. In other words, the relationship between activities is FS (finish-start).
- Each period has resource limitations for each resource type.
- There is a possibility to not even select an activity from any project (due to resource constraints or any other reason) in a specified period.
- Each project activity is done only once.
- Each project will generate benefits and environmental loss and achieve strategic goals after the completion of the project in a given period.
- Project portfolio selection and scheduling aim to obtain the highest net present value, achieve strategic goals, minimize environmental loss with the least risk, and implement in the shortest possible project time.
- Resources are renewable. In this sense, after the resource is consumed in each period, it will be restored in the next phase and can be reused.
- When a project is not selected, all activities are set aside.
- When an activity is selected, it is carried out within the specified period until completion.
- Total time frame for implementation projects is *T*.
- The project portfolio is composed of *I* projects.

- Each project includes J activities and requires h sources.

B. Objective Function – Environmental Loss

Today's environmental conditions have increased the need to consider green and environmental issues in different decision–making problems. There are many types of research on project selection and scheduling in this context, but few have considered environmental criteria in their studies. In this research, we consider the green management objective introduced by (Prato, 2007) and develop it using cost and income coefficients determined by experts and the government.

It assumes that the government determines special penalties at the end of a project according to the type of project and its environmental damage.

L_{it^f}: Coefficient costs of project i at the time of t^f

B_{it^f}: Coefficient incomes of project i at the time of t^f

The net environmental loss of project i at the time of t^f is as follows:

$$Net\ environmental\ loss = (-L_{it^f} + B_{it^f})$$

C. Objective Function – Strategic Alignment

Fulfilling an organization's mission requires the formulation and execution of effective strategies. This goal is achieved by aligning organizational activities and selected projects with these strategies. Accordingly, the alignment degree of the project portfolio with the organizational strategic goals is computed as follows (Sheikh & Azari, 2015):

w_s: Weight of the strategy s

S: The number of organization strategies

s_{sij}: The align degree of activity j of project i with the strategy s.

$$A.Degree = \sum_{s=1}^{T} w_s \sum_{i=1}^{I} \sum_{j=1}^{J_j} s_{sij} \tag{1}$$

D. Risk Dimensions of Projects

Although a project may generate substantial financial benefits and exhibit a high degree of strategic alignment with organizational objectives, such alignment alone does not ensure successful implementation. Therefore, it is crucial to consider project success factors in the portfolio selection process.

According to the framework developed by Shenhar & Wideman (1996), Shenhar et al. (2001), and Shenhar & Dvir (2007), project risk can be systematically evaluated through four key dimensions: Novelty, technology, complexity, and pace. Each of these dimensions reflects a different aspect of uncertainty; higher scores in any dimension represent greater project uncertainty and, consequently, a lower likelihood of success within the objective function framework.

D. Novelty — Degree of Newness

Projects differ in the level of innovation they embody.

- Derivative projects involve minor modifications of existing products (e.g., comfort improvements, color variations, or size adjustments) and generally represent low risk.
- Platform projects introduce a new generation of an existing product, demanding broader research and market analysis.
- Breakthrough projects involve innovations with no established markets; as customer expectations are undefined, designers rely heavily on expert judgment, resulting in high project risk.

F. Technology — Technical Uncertainty

Technological risk depends on the combination of new and mature technologies required to execute the project. Projects leveraging established technologies (low-tech) face minimal technical uncertainty. In contrast, advanced technology projects are more prone to delays, budget overruns, or potential failure due to limited prior experience and higher development complexity.

G. Complexity — Structural Interdependence

Project complexity is categorized into three hierarchical levels:

1. Assembly Level: Focused on manufacturing simple, self-contained products with minimal intercomponent interaction and low risk.
2. System Level: Involves products or processes composed of multiple subsystems (e.g., ships, buildings, or enterprise-level software), leading to moderate to high risk.
3. Array Level: Represents large-scale systems integrating several subsystems and stakeholders (e.g., cross-country infrastructure like the channel tunnel). These projects require intense coordination and negotiation, thus carrying the highest risk.

H. Pace — Urgency Factor

The “Pace” dimension reflects the importance of time in achieving project success. Time-sensitive projects can lose market advantage if milestones are delayed. Regular projects tolerate moderate schedule shifts, whereas blitz projects, driven by crises such as natural disasters or business emergencies, demand immediate action and contingency planning. Any deviation in schedule may lead to project failure due to missed opportunities. The risk of activity j of project i is calculated as follows (Sheikh & Azari, 2015).

G_{jid}: The highest score for the dimension d project i activity j

g_{jid}: Score for the dimension d project i activity j

The risk of activity j of project i is calculated as follows (Sheikh & Azari,2015).

$$r_{ij} = \sum_{d=1}^{4} \frac{g_{jid}}{G_{jid}} \tag{2}$$

I. Net present income

One of the most important criteria for project portfolio selection and scheduling is net present income, defined as "the costs and revenue are received or paid as a specific cash flow during the project."

Sets:

Sets$(j,\ j^{ne}, i) \in priorty$: The Prerequisite activities set of j activity j from the project i j^{ne} Activity after j activity

Parameters:

T^f: The period after project completion and create present net profit and net present environmental losses.

L_{it^f}: Coefficient costs of project i at the time of t^f

B_{it^f}: Coefficient incomes of project i at the time of t^f

ls_{ij}: The latest time to start activity j of the project i

es_{ij}: The earliest start time of activity j of project i

GB_{it^f}: The income amount resulting from the completion of project i at the time of t^f

G_{jid}: The highest score for the dimension d project i activity j.

g_{jid}: The score for the dimension d project i activity j

r_{ij}: The risk of activity j of project i

s_{sij}: The degree of alignment of activity j from project i with the strategy s.

d_{ij}: Process time j activity from i project

m_{ij}: The amount of h source required for j activity from i project

M_h: The number of available sources

w_s: Weight of the strategy s

a: Interest rate or capital return rate

Decision variables:

We define the decision model variable as whether to select a project in a given period.

x_{ijt}: If activity j of project i is selected in period t, it is one; otherwise, it is zero. $i = 1 \dots, I, t = 1..., T, \quad j = 1 \dots, j_i$

U_{ijt}: From the start time to the finish time of activity j, x_{ijt} is equal to one and specifies that the activity, in the time interval $[es_{ij}\ , ls_{ij}\ ]$, uses resources and restores resources after completion

Y_i: If project i is selected, it is one; otherwise, it is zero

Mathematical Formulation:

Maximizing the total net present income value, as proposed by Tofighian & Naderi (2015):

$$Max\ \ Z_1 = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{t^f=1}^{T^f} \sum_{j \in end\ activity\ of\ project\ I}^{J} GB_{it^f}\, x_{ijt} - \left(t + d_{ij}\ + t^f - 1\right) x_{ijt} (1 + a) \tag{3}$$

Maximizing the total degree of alignment with organizational strategic goals, as introduced by Sheikh & Azari (2015):

$$Max\ Z_2 = \sum_{i=1}^{I} \sum_{s=1}^{S} w_s \sum_{t=1}^{T} \sum_{j \in end\ activity\ of\ project\ I}^{J} S_{it^f}\, x_{ijt} \tag{4}$$

Minimizing the total risk, following the formulation of Shenhar & Wideman (1996):

$$Min\ \ Z_3 = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{j \in end\ activity\ of\ project\ I}^{J} r_{ij}\, x_{ijt} \tag{5}$$

Minimizing the total net present environmental loss, as suggested by Prato (2007):

$$Min\ Z_4 = \sum_{i=1}^{I} \sum_{t=1}^{T} \sum_{t^f=1}^{T^f} \sum_{j \in end\ activity\ of\ project\ I}^{J} Log(\ \ - L_{it^f}\ +\ \ B_{it^f}\ )\, x_{ijt} - \left(t + d_{ij}\ + t^f - 1\right) x_{ijt} Log(1 + A) \tag{6}$$

$s.t.$

$$\sum_{t=1}^{T} \left(t + d_{ij}\right) x_{ijt} \le \sum_{t=1}^{T} t\, xij^{ne} t \qquad \forall\ \ (j,\ j^{ne}, i) \in priorty \tag{7}$$

$$\sum_{t=es_{ij}}^{ls_{ij}} x_{ijt} \le 1 \qquad \forall\ i,j \tag{8}$$

$$\sum_{t=1}^{es_{ij}-1} x_{ijt} = 0 \qquad \forall\ i,j \tag{9}$$

$$\sum_{t=\ ls_{ij}+1}^{\mathrm{T}} x_{ijt} = 0 \qquad \forall\ i,j \tag{10}$$

$$U_{ijt} = \sum_{l=\ max\{0,t-d_{ij}+1\}}^{\mathrm{t}} x_{ijl} \qquad \forall\ \ i\ ,j,t \tag{11}$$

$$\sum_{i=1}^{I} \sum_{j \in end\ activity\ of\ project\ I}^{J} m_{ij}\, U_{ijt} \leq M_h \qquad \forall\, t = 1 \dots .T \tag{12}$$

$$\sum_{t=1}^{T} \left(x_{ijt} \ + xij^{ne}t \ \right) = 2Y_i \qquad \forall\, (j,\, j^{ne}, i) \in priorty \tag{13}$$

$$x_{ijt} \leq Y_i \qquad \forall\ i\ ,t\ ,\forall\, j = 1 \dots .j \tag{14}$$

$$x_{ijt} \in \{0, 1\} \qquad \forall\ i\ ,t\ ,\ \forall\, j = 1 \dots .j \in end\ activity\ of\ project\ \mathrm{I} \tag{15}$$

$$Y_i \in \{0, 1\} \qquad \forall\, i\, , i = 1 \dots .\mathrm{I} \tag{16}$$

The objective function in Equation (3) denotes the total net present income generated by the selected projects. The objective function in Equation (4) specifies the overall degree of alignment between the implemented projects and the organizational strategic goals. Equation (5) represents the total risk associated with the selected projects. Equation (6) represents the total net present environmental loss arising from the implemented projects. Equation (7) conceptually defines the prerequisite relations among activities. To correctly sequence the activities of each project, at least one time interval must separate two successive activities, ensuring that preceding activities are completed before subsequent ones begin, as proposed by Brucker et al. (1999). Equation (8) ensures that each activity within a project can be selected only once. Equations (9) and (10) specify that each activity may only be assigned to a single time interval. Equation (11) indicates that an activity uses resources throughout its execution interval and releases them upon completion. Equation (12) enforces that each resource has a limited capacity in each time period. Equation (13) guarantees that all activities belonging to a selected project are fully executed, while activities of unselected projects remain unexecuted. Equation (14) states that if a project is not selected, no scheduling is assigned to it. Constraints (13) and (14) are adopted from Tofighian et al. (2018). Equations (15) and (16) define that the decision variables are binary and can only take values of zero or one.

IV. ROBUST OPTIMIZATION APPROACH

Bertsimas & Sim (2004) introduced a robust optimization model that maintains the linear structure while controlling the degree of conservatism of each constraint through the parameter Γ_i. This method ensures that as long as the coefficients fluctuate up to the maximum level of Γ_i, the model solution remains feasible and valid. Moreover, even if the uncertainty in the coefficients exceeds Γ_i, the robust model is still likely to stay feasible and reliable with high probability. Consider a linear programming problem (17).

$$\begin{aligned} & Min \sum\nolimits_{ij} C_{ij} X_j \\ & s.t. \\ & \sum\nolimits_{j} \tilde{a}_{ij} X_j \ \geq \ b_i\ , \quad \forall i \\ & X_j \geq 0\ , \forall j \end{aligned} \tag{17}$$

The robust formulation is designed to protect against all possible cases in which up to $|\ J_i\ |$coefficients can deviate, and each uncertain coefficient $\tilde{a}_{ij}$may change up to $(\lfloor \Gamma_i \rfloor) \hat{a}_{ij}$according to Γ_i. The parameter $\Gamma_i$is not necessarily an integer. When $\Gamma_i = 0$, the constraints are equivalent to those in the nominal (non-robust) problem. When $\Gamma_i = |\ J_i\ |$, the robust model becomes as conservative as the Soyster (1973) formulation. Changing $\Gamma_i$effectively helps to tune the conservatism level of the robust model. Bertsimas & Sim (2004) proved that the nonlinear uncertain model (17) can be equivalently reformulated as model (18).

$$Min\ C'X$$

s.t.

$$\sum_j a_{ij}X_j - \max\{\sum_{j\in S_i} \hat{a}_{ij}X_j + (\Gamma_i - \lfloor\Gamma_i\rfloor)\hat{a}_{ij}X_j\} \geq b_i, \qquad \forall i \tag{18}$$

$$X_j \geq 0$$

$\Omega = \{S_i \cup \{t_i\} | S_i \subseteq J_i, |S_i| = \lfloor\Gamma_i\rfloor), t_i \in J_i \backslash S_i\}$ defines the uncertainty set. S_i determines which coefficients can vary by $\hat{a}_{ij}$, and $t_i$represents the parameter that may change by $(\Gamma_i - \lfloor\Gamma_i\rfloor)\hat{a}_{ij}$.

Let x^*denote the optimal solution to model (16). Bertsimas & Sim (2004) showed that constraint $i$is protected against uncertainty by $\beta_i(x^*, \Gamma_i) = \max\{\sum_{j\in S_i} \hat{a}_{ij}x_j^* + (\Gamma_i - \lfloor\Gamma_i\rfloor)\hat{a}_{ij}x_j^*\}$. The function $\beta_i(x^*, \Gamma_i)$ is called the protection function, and it can be rewritten as a linear optimization problem in the form of (19).

$$\beta_i(x^*, \Gamma_i) = \max\{\sum_{j\in S_i} \hat{a}_{ij}x_j^*\}$$

$$\sum_{j\in J_i} w_{ij} \leq \Gamma_i \tag{19}$$

$$0 \leq w_{ij} \leq 1, \quad \forall j \in J_i$$

Since model (19) is feasible and bounded for all $\Gamma_i \in [0, |J_i|]$, its dual form is also feasible and bounded according to the property of strong duality. By substituting the dual formulation of (19) into (18), the strong counterpart of the uncertain linear programming model is derived as expression (20).

$$Min \sum_{ij} C_{ij}X_j$$

s.t.

$$\sum a_{ij}X_j - \lambda_i\Gamma_i - \sum_{j\in J_i} \mu_{ij} \geq b_i, \forall i \tag{20}$$

$$\lambda_i + \mu_{ij} \geq \hat{a}_{ij}x_j, \forall i, j \in J_i$$

$$\mu_{ij} \geq 0, \forall i, j \in J_i$$

$$\lambda_i, x_j \geq 0, \forall i, j$$

M in which $\lambda_i$and $\mu_{ij}$are auxiliary dual variables. This approach has the property that if up to $\Gamma_i$of the uncertain parameters violate their nominal values, the robust solution will remain feasible. If more than $\Gamma_i$parameters change in constraint i, the robust solution still remains feasible with high probability according to the relation (21):

$$p(\sum_j \tilde{a}_{ij}x_j^* > b_i) \leq 1 - \phi(\Gamma_i - \frac{1}{\sqrt{|J_i|}}) \tag{21}$$

In equation (21), x_j^* represents the optimal solution of the robust model, and $\phi(\theta)$denotes the cumulative distribution function (CDF) of a standard random variable. The same procedure can be followed to apply this robust formulation to the uncertain parameters of the objective function.

A. Robust Optimization Formulation

In this model, the parameters $m_{ij}$and M_h play a fundamental role in controlling fluctuations related to resource availability under the robust optimization framework. In practice, the required amount of resource for executing activity j of project i(i.e., m_{ij}) and the total available resources (i.e., M_h) are rarely deterministic. Variations caused by estimation error, resource shortages, equipment failure, or changes in working conditions may lead to violations of resource capacity constraints, thereby rendering the deterministic model infeasible.

To prevent this issue, these parameters are incorporated into the robust optimization framework of Bertsimas & Sim (2004). In this approach, an uncertainty budget (Γ_h) is defined for each resource type to specify the conservatism level of the model. Consequently, even if up to $\Gamma_h$of the coefficients m_{ij}or resource capacities $M_h$deviate from their nominal values, the model remains feasible and valid. In other words, the mentioned parameters represent the main sources of uncertainty in the resource capacity constraint, and their inclusion in the robust structure ensures that the model remains resilient against real-world fluctuations in resource usage and availability. Thus, the proposed formulation guarantees that project scheduling and selection remain practical and efficient even under uncertain conditions.

In this section, the deterministic model is extended into a robust optimization formulation in which two parameters are treated as uncertain. The uncertain parameters $\widetilde{m}_{ij}$and $\widetilde{M}_h$are bounded within their respective intervals around the nominal values $\bar{m}_{ij}$and $\bar{M}_h$, with maximum deviations $\widehat{m}_{ij}$and $\widehat{M}_h$. For example, m_{ij}lies within the interval $[\bar{m}_{ij} - \widehat{m}_{ij}, \bar{m}_{ij} + \widehat{m}_{ij}]$. The effect of the worst-case parameter deviations is the central concern of the robust formulation, as only positive deviations in the uncertain parameters may lead to the worst-case scenarios in the deterministic model. The robust model can therefore be written as follows. Note that these parameters appear in constraint (12), whose robust equivalents are presented in relations (22) and (23). μ_{ij}^{m} and $\lambda^m$are the dual variables corresponding to the constraints of the original linear optimization model.

$$\sum_{i=1}^{I} \sum_{j \in end\ activity\ of\ project\ I}^{J} m_{ij}\, U_{ijt} + \left\{ \sum_{i,j} \mu_{ij} + \lambda^m \times \Gamma^m \right\} \le M_h - \widehat{M_h} \ \times \Gamma^h \qquad \forall\, t = 1 \ldots .T \tag{22}$$

$$\mu_{ij} + \lambda^m \ \ge \widehat{m_{ij}} \ \times \ U_{ijt} \qquad \forall (\boldsymbol{i}, \boldsymbol{j}, \boldsymbol{t}) \tag{23}$$

V. AN EPSILON-CONSTRAINT BASED MULTI-OBJECTIVE OPTIMIZATION APPROACH FOR PROJECT PORTFOLIO SELECTION AND SCHEDULING

An exact epsilon-constraints method for multi-objective combination optimization problems tackles multi-objective optimization problems by solving a series of single-objective sub-problems, where only one objective is transformed into constraints, and the Pareto front of the multi-objective problem can be generated with the epsilon-constraints method.

The systematic generation of the Pareto frontier can be accomplished through one of two predominant techniques: scalarization and vectorization methods. On the one hand, scalarization methods convert the Multi-Objective Optimization Problem (MOOP) into a series of parametric single-objective optimization problems; on the other hand, vectorization methods tackle them directly. Because the proposed model in this research has four objectives, the epsilon constraints method has been applied.

Epsilon constraints procedure steps are as follows:

- Select one of the objective functions as the main objective function.
- Each time, we solve the problem for one of the objective functions and obtain the optimal and single values of each objective function.

- We divide the interval between two optimal and single values of sub-objective functions into a predetermined number and obtain a table of values for $\varepsilon 2 \dots \varepsilon n$.
- Each time we solve the problem with the original objective function and any of the $\varepsilon 2 \dots \varepsilon n$ values.
- Pareto front of multi-objective problem will be obtained.

VI. CASE STUDY

Given that the research methodology relies on mathematical modeling and optimization, this case study was designed to assess the efficiency and practicality of the proposed project portfolio selection and scheduling model in a real industrial context. The case involves two partner companies based in Iran—Tavan Sanat Energy Co. (a manufacturing enterprise) and Margon Ertebat Co. (a telecommunications trading and service company). Both organizations have collaborated for over three decades in the design, supply, construction, commissioning, upgrading, repair, and after-sales service of telecommunication systems and equipment.

Based on historical records and future planning documents, these companies are expected to execute 239 projects across 13 specialized fields during the next 15 years. Each field contains multiple individual projects ranging from production of radio and fiber-optic equipment to modernization of telecommunication centers. For the purpose of manageable model evaluation, eight representative projects were randomly selected, encompassing both manufacturing and service-oriented tasks. Their basic characteristics, including type, duration, profit flow, resource consumption, and inter-activity precedence relations, are summarized in Tables II–IV.

Financial and operational constraints were incorporated, with available capital limited to 50 units, representing cumulative expenditures on labor, materials, and equipment. Each project network was modeled using an Activity-on-Arrow (AOA) diagram, and forward/backward passes were computed to determine earliest and latest activity times under the assumption that each schedule allows a minimum two-day buffer beyond the earliest completion time.

In addition to quantitative parameters, qualitative evaluations were collected to measure the degree of strategic alignment and perceived project success. These were obtained through structured interviews with senior managers and technical experts using linguistic variables (e.g., "high," "medium," and "low") later converted to normalized scores for incorporation within the optimization model.

Table II. Project Type

Project	Project Type
1	Radio Equipment
2	Upgrading Telecommunication Center
3	Battery Production
4	Charger Battery Production
5	Telecommunication Cabinet production
6	Fiber Optic Equipment
7	Telecommunication Cooler production
8	Miscellaneous

To determine the degree of alignment of projects with the organization's strategy and the degree of project success, the opinions of managers and experts were gathered in the form of linguistic variables.

Table III. Profit from the project in the year

	T														
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
Project 1	6	4	10	12	3	8	5	13	2	9	8	7	4	3	2
Project 2	300	2700	2350	2050	1920	1780	1525	1396	1253	1569	1894	3259	3589	3738	3134
Project 3	450	359	870	2200	700	650	600	1250	1396	1832	400	1280	950	895	861
Project 4	102	82	120	130	200	155	205	225	175	156	198	202	149	225	165
Project 5	10	12	14	16	11	19	13	9	25	31	29	15	12	11	7
Project 6	19	23	17	21	18	25	22	15	24	23	28	27	22	16	15
Project 7	310	323	345	358	369	378	394	405	428	412	407	401	332	228	222
Project 8	76	79	86	90	102	111	124	129	131	120	110	92	81	68	41

Table IV. Project information (1-4)

	Project 1				**Project 2**				**Project 3**				**Project 4**			
Activity	**d**	$*es$	**ls**	**r**	**d**	**es**	**ls**	**r**	**d**	**es**	**ls**	**r**	**d**	**es**	**ls**	**r**
1	2	0		2	1	0	1	4	2	0	0	3	2	0	0	1
2	4	0		4	1	0	0	3	2	0	2	3				
3	7	0	0	3												
4			3													
5			0										1	2	2	1
6					2	1	2	2	2	2	2	42				
7	3	2		4												
8																
9			7										1		3	1
10					3	1	1	1		4	4	3				
11																
12	6		4	2												
13																
14			7							4	4	1	0	4	4	0
15	4	7		3	2	3	4	1								
16																
17			7		2	4	4	2		0	6	6	0			
18	8	5		3												
19																
20			5													
21	2	11		3	0	6		0								
22			11													
23		13														
24	0			0												
25			13													
	Ri		s	ev	Ri		s	ev	Ri		s	ev	Ri		s	ev
	0.1		0.75	0.048	0.3		0.65	0	0.3		0.75	15.2	0.2		0.65	1

Table IV. Project information (5-8)

	Project 5				Project 6				Project 7				Project 8			
Activity	**d**	$*es$	**ls**	**r**	**d**	**es**	**ls**	**r**	**d**	**es**	**ls**	**r**	**d**	**es**	**ls**	**r**
1	4	0	0	3	3	0	4	1	2	0	0	2	3	0	2	2
2	8	0	2	2	3	0	0	2					2	0	0	2
3					2	0	2	2					2	0	1	2
4					4	0	0	1								
5									2	2	2	2				
6	5	4	4	2												
7	3	4	9	2									3	3	5	3
8					1	3	7	1								
9									2	4	6	4				
10									3	4	4	3				
11													4	2	2	1
12	3	8	10	2	4	3	3	1								
13																
14	2	9	9	1												
15									3	6	8	1	3	2	3	3
16					2	2	4	2								
17									4	7	7	1				
18	2	7	12	1									3	6	8	4
19																
20	4	11	11	3	3	4		3								
21									2	11	11	2				
22													3	6	6	4
23					2	4	8	3								
24									2	13	13	3				
25	1	15	15	3									2	9	11	2
26																
27	2	9	14	2	3	7	7	2								
28									0	15	15	0	4	9	9	1
29	3	11	13	2												
30	0	14	16	0	4	4	6	3								
31					1	7	7	4					0	13	13	0
32					2	8	8	2								
33					0	10	10	0								
	Ri		s	ev	Ri		s	ev	Ri		s	ev	Ri		s	ev
	0.1		0.25	0.2	0.6		0.75	0.13	0.2		0.25	2.1	0.2		0.75	0.58

*es: earliest start time of Activity, ls: latest start time of Activity, d: duration of Activity, r: resource usage of Activity Ri: risk of the project, s: share of strategic goals from the project, Ev: environmental loss from the project

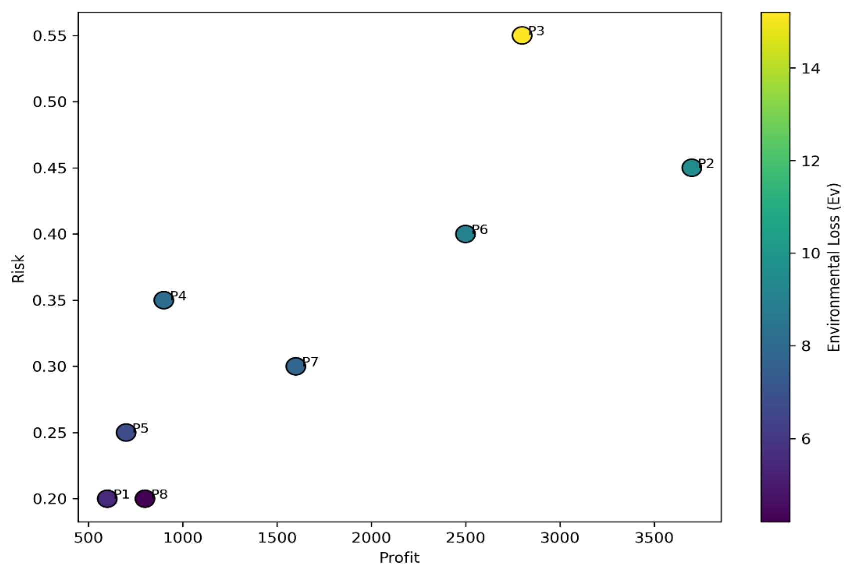

Fig. 1. Analysis of Profit, Risk, and Environmental Impact Across Projects

Fig. 1 illustrates the multidimensional relationship among three key criteria, profit, risk, and environmental impact, for eight evaluated projects. The horizontal axis represents expected profit, the vertical axis shows inherent risk, and the color intensity of each point reflects the level of environmental impact, with darker tones indicating higher impact. Projects 2 and 3 display high profitability; however, Project 3 has significantly greater environmental impact and medium risk. In contrast, Projects 1, 5, and 7 demonstrate lower profit and risk levels, contributing stability to the overall portfolio. Projects 6 and 8 present mixed performance patterns, confirming that profit, risk, and environmental considerations are not linearly correlated. Overall, Fig. 1 highlights clear trade-offs among the criteria, offering a visual foundation for informed and balanced project prioritization before any model-based optimization is performed.

VII. RESULTS

In this section, the optimization results for selecting the two companies' project portfolios and the scheduling problem introduced in the previous section are presented using the Epsilon constraint method in GAMS. Nine Pareto answers were obtained and are presented in Tables V, VI, and VI. Managers and decision-makers of those companies will be able to use each of these project portfolios in their schedules as described.

Table V. Selected project portfolio

Answer	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Project1				*				*		*		*				
Project2							*	*	*				*		*	*
Project3	*	*	*	*	*	*	*	*		*		*	*			
Project4		*				*	*					*		*		*
Project5																
Project6																
Project7																
Project8	*	*								*	*		*	*	*	

Based on the project selection matrix derived from the sixteen optimized solutions (Answers 1–16) and the data presented in Tables II-IV, the logical interpretation of project combinations reveals a clear selection pattern. Among the eight projects examined in the case study, only five (Project 1, Project 2, Project 3, Project 4, and Project 8), appear across the optimal solutions, whereas Project 5, Project 6, and Project 7 are excluded from all results. This consistent pattern demonstrates that, under the ϵ\epsilon-Constraint optimization framework, the model systematically favors projects that deliver high profit returns, exhibit better time efficiency and lower risk, or demonstrate stronger strategic alignment with organizational objectives.

Table VI. Selection Pattern Across 16 Answers

Project	Selection Count (out of 16)	Dominant Characteristics
Project 3	Most frequent (12/16)	High profit (particularly in years 4–10), medium risk, very high strategic alignment
Project 2	Relatively frequent (8/16)	Highest total profit over 15 years, relatively higher risk
Project 4	Moderate frequency (6/16)	Medium profit, low environmental impact, low risk
Project 1	Low but recurring (5/16)	Small-scale project with low profit but short execution time
Project 8	Distributed (7/16, mostly with Projects 3 or 4)	Medium profit, low risk, acceptable environmental impact
Projects 5–7	None (0/16)	Very limited profit, weak strategic alignment, relatively higher environmental impact (especially Project 7 with Ev = 2.1)

In the majority of solutions, Project 2 and Project 3 are consistently selected as the principal drivers of profit, forming the fundamental core of profit-oriented portfolios. Although Project 2 delivers the highest total profit over the planning horizon, the frequent inclusion of Project 3 introduces portfolio diversity and contributes to overall risk control. Notably, the recurring combination of Project 3 and Project 4 demonstrates the model's deliberate strategy to moderate the intrinsic risk associated with Project 2. According to Table IV, Project 4 (Ri = 0.2) and Project 3 (Ri = 0.3) provide a stabilizing effect, thereby enhancing portfolio robustness. High-risk projects such as Project 2 are systematically balanced by the inclusion of low-risk stabilizers, particularly Projects 4 and 8, and in certain cases, Project 1. The model willingly accepts the significant environmental impact of Project 3 (Ev = 15.2) due to its strong strategic alignment and substantial profit contribution. Meanwhile, projects with minimal environmental impact, such as Project 2 (Ev = 0), are prioritized, further influencing the selection process. In contrast, options like Project 7, which combine only moderate profit with considerable environmental loss (Ev = 2.1) and weak strategic alignment, are consistently excluded from optimal portfolios.

Table VII. Values of the project portfolio objectives

Answer Objective	Net present value	Alignment-with-the strategic goals	Risk	environmental loss
1	125.301	0.97	0.44	78
2	208.99	1.83	0.51	128
3	57.92	0.1	0.29	61
4	112.09	0.57	0.46	149
5	79.24	1	0.95	123
6	141.60	0.96	0.36	111
7	162.92	1.86	1.02	173
8	133.41	1.47	1.12	211

Continue Table VII. Values of the project portfolio objectives

Answer Objective	Net present value	Alignment-with-the strategic goals	Risk	environmental loss
9	21.32	0.9	0.66	62
10	179.48	1.44	0.61	166
11	67.39	0.87	0.15	17
12	195.78	1.43	0.53	199
13	146.62	1.87	1.1	140
14	151.07	1.73	0.22	67
15	88.71	1.77	0.81	79
16	105.01	1.76	0.73	112

The Relative Ideal Distance (RID) index is used to identify the Best Efficient Solution (BES) among the Pareto-optimal solutions. This indicator is computed according to the following relation, where Z^*denotes the best (ideal) value of each objective function across all Pareto solutions:

$$RID = \left(\frac{Z_1^* - Z_1}{Z_1^*}\right)^2 + \left(\frac{Z_2^* - Z_2}{Z_2^*}\right)^2 + \left(\frac{Z_3 - Z_3^*}{Z_3^*}\right)^2 + \left(\frac{Z_4 - Z_4^*}{Z_4^*}\right)^2 \tag{24}$$

Accordingly, the Pareto solution with the lowest RID value is selected as the most ideal and efficient solution (BES). In the sample problem, the output of the Pareto front is presented in Table VIII.

Table VIII. The Relative Ideal Distance (RID) index

Pareto Front Node															
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
17.12	48.44	9.07	65.37	68.03	32.98	117.99	172.33	19.68	86.38	0.84	121.15	92.66	9.06	33.10	46.54

The RID index chart for the above Pareto solutions is presented in Fig. 2.

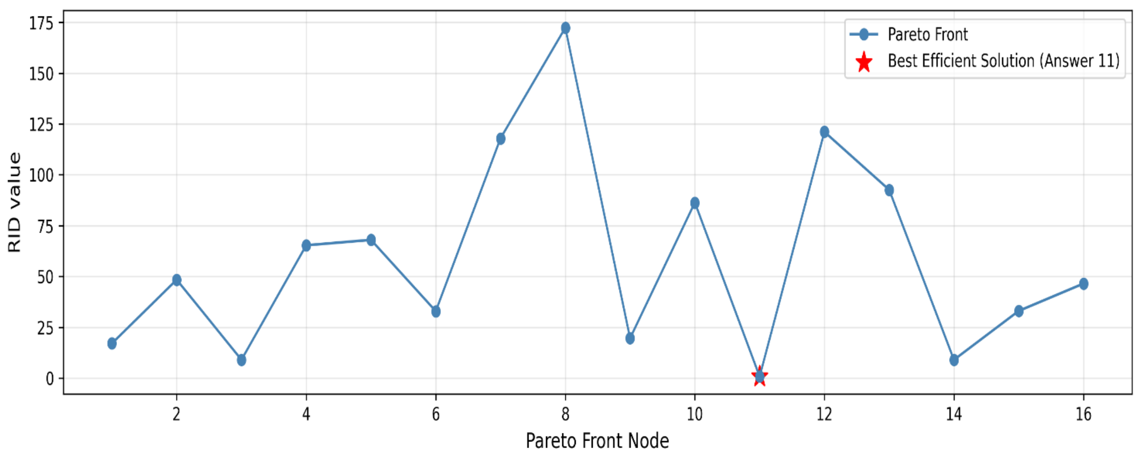

Fig. 2. The Relative Ideal Distance (RID) index

Accordingly, based on the best Pareto solution (Solution 4), the corresponding decision variable values are presented in Table IX.

Table IX. Scheduling for Portfolio one

year project	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Act1 Act3		Act 7	Act 2		Act 18		Act 12 Act15				Act 21		Act 24	
2	Act2	Act 1 Act 10	Act 6		Act 15 Act 17		Act 21								
3	Act1		Act 2 Act 6		Act 10 Act 14		Act 17								
4	Act1		Act 5	Act 9	Act 14										
8	Act2	Act 3	Act 1 Act 11	Act 15		Act 7	Act 22		Act 18	Act 28		Act 25		Act 31	

If achieving strategic goals is important for the organization, managers should implement Projects 1, 2, 3, 4, and 8 (Portfolio Two), which have the highest degree of alignment compared with the other eight portfolios. If the managers want to have the least risk and the least environmental loss, they should carry out Project 2 (Portfolio three) (Table X).

Table X. Scheduling for Portfolio three

year project	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	*Act2	Act 1 Act 10	Act 6		Act 15 Act 17		Act 21								

Managers can select each one of these nine portfolios based on the conditions and the organization's needs. For example, if they can choose Portfolio Five, its scheduling will be in Table XI.

Table XI. Scheduling for Portfolio Five

year project	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	Act 1 Act 2	Act 6 Act 10		Act 15	Act 17		Act 21								
4	Act 1		Act 5	Act9	Act 14										
8	Act 1 Act 2 Act 3	Act 3	Act 11 Act 1	Act15		Act7	Act 22		Act 18	Act 28		Act 25		Act 31	

Project portfolio No. 5 includes projects 2 and 4, which has current revenue (141.60) and risk (0.36), alignment with strategic goals (0.96) and environmental damage (111).

A. Relationship Between Objectives

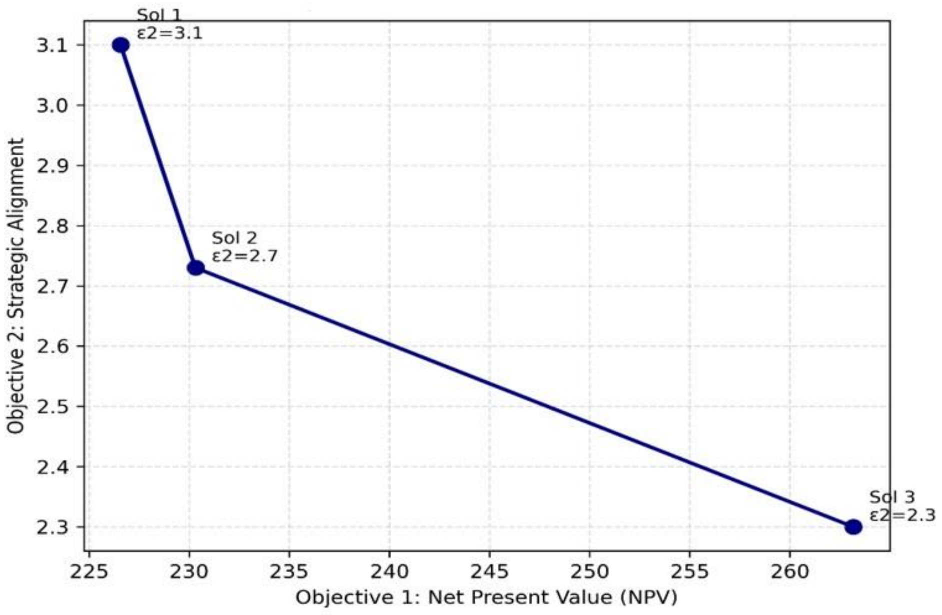

Fig. 3. Pareto front illustrating the trade-off between Net Present Value (NPV) and Strategic Alignment.

From a managerial perspective, this relationship confirms a realistic decision-making phenomenon in project-oriented organizations. As strategic alignment decreases, selected projects tend to be more financially profitable, whereas focusing on strategic goals results in lower NPV and more conservative project choices. The intermediate solution on the curve reflects the best trade-off between financial performance and organizational alignment, validating the logical soundness of the mathematical model. Thus, the Pareto chart not only represents the analytical output of the model but also quantitatively depicts the real behavior of multi-criteria decision-making in organizational environments, offering an interpretable and insightful view of managerial strategy dynamics.

B. Relationship Between NPV and Risk

In the AEC-based analysis, the data reveal that a gradual rise in risk accompanies an increase in the current project yield. The value of NPV rises from 83.68 in the first solution to 263.16 in the fifth, while the risk index increases from 0.07 to 0.68. This ascending trend clearly demonstrates the classical profit–risk trade-off. Projects generating higher economic value typically entail greater levels of novelty, technological uncertainty, or complexity. From a mathematical standpoint, Objective (3) pursues the maximization of present income, while Objective (5) seeks to minimize project risk. Thus, the simultaneous growth of these two indicators confirms the conflict structure embedded in the Pareto front. Among the five solutions, the intermediate points (Solutions 3 and 4) achieve a more balanced trade-off between economic value and exposure to risk, since the profit growth rate in these regions is accompanied by only a moderate risk increase. The nonlinear behavior of the Pareto curve indicates that, beyond a critical threshold ($Z_3 = 0.5$), each additional unit of NPV requires accepting noticeably higher levels of managerial uncertainty (Fig. 4).

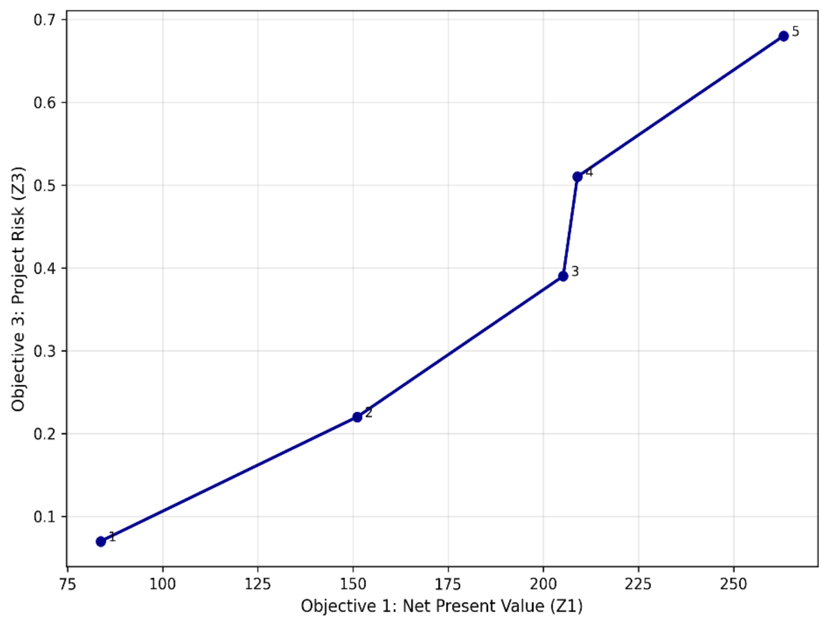

Fig. 4. Pareto front illustrating the trade-off between Net Present Value (NPV) and Project Risk (AEC-based analysis).

Consequently, the middle segment of the Pareto front (Responses 3–4) is defined as the Optimized Economic–Risk Balance zone—a region that consolidates the internal logic of the multi-objective model and validates the numerical consistency with the theoretical definitions of Objectives (3) and (5).

C. Relationship Between Objectives (NPV vs. Environmental Loss)

The analysis based on the ε-Constraint method reveals that an increase in the projects' economic profit is directly associated with a rise in environmental losses. The NPV value grows from 67.3 in the first solution to 263.1 in the fourth, while the environmental loss index increases from 17 to 216. This ascending trend illustrates a clear conflict between economic benefit and environmental sustainability, as the projects generate higher returns, their adverse ecological impacts intensify. In this model, Objective (3) represents the total Net Present Value of the selected projects, whereas Objective (6) quantifies the cumulative environmental damages caused by emissions and resource consumption during project execution (Fig. 5).

Along the Pareto front between these two objectives, the middle region (especially Solution 3) reflects the optimal balance between economic performance and ecological sustainability. In this range, profit growth is still accompanied by a relatively proportional rise in environmental loss. In contrast, Solution 4 achieves the highest financial gain but imposes unacceptable environmental damage. Hence, the Pareto curve for these objectives depicts a classic economic–ecological trade-off: lower points offer higher sustainability but reduced profitability. In contrast, upper points attain maximum profit at a high ecological cost. This contradiction validates the internal logic of the multi-objective model, demonstrating that decision-makers must strike a practical balance between financial returns and environmental preservation when choosing the optimal portfolio.

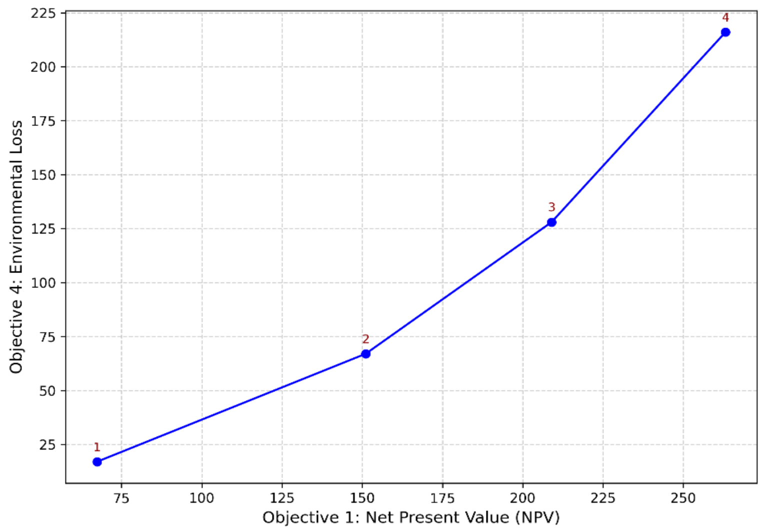

Fig. 5. Optimized Economic–Risk Balance zone (Responses 3–4) within the Pareto front.

VIII. VALIDATION OF THE PROPOSED MODEL

To verify the effectiveness and reliability of the proposed mathematical formulation, a comparative validation is conducted using the benchmark case study introduced by Ganji et al. (2014). The dataset and structural parameters reported in their study, summarized in Tables XII to XVI, have been adopted to evaluate the performance of the developed model under identical operational conditions. Ganji et al. (2014) emphasized that assessing the performance of portfolio selection and scheduling models requires the generation of standardized project instances. Three alternative methods are commonly applied for this purpose:

1. Utilizing predefined examples available on the PSLIB website,
2. Employing the Ran-Gen Pro software, and
3. Programming through Pro Gen / Max and Pro Gen Pro environments.

In this research, the first approach, benchmark projects from the PSLIB database, has been adopted to ensure comparability and methodological consistency. Following Ganji et al. (2014)'s setting, four representative projects were considered, with the total amount of renewable resources restricted to 14 capital units, encompassing expenditures for personnel productivity, material consumption, and equipment utilization. Furthermore, the parameters corresponding to environmental loss, strategic alignment, and risk level for these projects were drawn randomly from a broader dataset of 139 industrial projects belonging to two partner companies, thereby ensuring diversity and realism in the case study.

Table XII. Profit from the project in the year

T	1	2	3	4	5
Project1 1	5300	3500	3000	2900	2700
Project 2	500	300	200	100	50
Project 3	1000	950	870	800	700
Project 4	2500	2400	2350	2200	2000
T	6	7	8	9	10

Continue Table XII. Profit from the project in the year

T	1	2	3	4	5
Project1 1	2500	2300	1300	950	900
Project 2	45	40	35	30	25
Project 3	650	400	550	500	470
Project 4	1950	1900	1800	1700	1600
T	11	12	13	14	15
Project1 1	700	500	200	100	50
Project 2	20	15	10	5	1
Project 3	400	300	200	100	50
Project 4	1500	1450	1400	1200	1000

Table XIIV. Project information

	Project 1				Project 2				Project 3				Project 4			
Activity	**d**	***es**	**ls**	**r**	**d**	**es**	**ls**	**r**	**d**	**es**	**ls**	**r**	**d**	**es**	**ls**	**r**
1-2	2	0	0	2	1	0	1	4	2	0	0	3	2	0	0	1
1-3	4	0	3	4	1	0	0	3	2	0	2	3				
1-4													1	2	2	1
2-3					2	1	2	2	2	2	2	4				
2-4																
2-5					3	1	1	1	2	2	4	3	1	3	3	1
3-4	6	4	7	2												
3-5					2	3	4	1	2	4	4	2	0	4	4	0
3-7	4	7	7	3	2	4	4	2	0	6	6	0				
4-5					0	6	6	0								
4-6	8	5	5	3												
5-6	2	11	12	3												
5-7	0	13	14	0												
	Ri		s	ev	Ri		s	ev	Ri		s	ev	Ri		s	ev
	0.30		65	0	0.20		75	0.51	0.20		65	0.09	0.20		65	1

*es: earliest start time of Activity, ls: latest start time of Activity, d: duration of Activity, r: resource usage of Activity
Ri: risk of the project, s: share of strategic goals from the project, Ev: environmental loss from the project

The model is solved using the Epsilon constraint method in GAMS software. Five Pareto answers are obtained.

Table XIV. Selected project portfolio

Answer	1	2	3	4	5
Project	2	2	1	3	2
Project	3	3	-	-	-
Project	4	-	-	-	-
Project	-	-	-	-	-
Project	-	-	-	-	-

Table XV. Value of the project portfolio objective

objectives \ Answer	1	2	3	4	5
Net present value	162.922	79.236	54.178	57.915	21.321
Risk	0.60	0.40	0.30	0.20	0.20
Alignment with the strategic goals	2.05	1.40	0.65	0.65	0.75
Environmental loss	1.600	0.600	0	0.090	0.510

According to Ganji et al. (2014), the optimal portfolio obtained through their model achieves a maximum Net Present Value (NPV) of 15,878 and includes Projects 1, 2, and 4. While this configuration provides a financially attractive outcome, it lacks robustness when evaluated across additional dimensions of decision quality. The portfolio exhibits high risk, low strategic alignment, and considerable environmental loss, all of which reduce its managerial acceptability in real organizational contexts. In practice, neglecting criteria such as risk exposure, strategic consistency, and environmental impact undermines the realization of the estimated NPV. Under elevated uncertainty and weak strategic coherence, the nominal profits predicted by such deterministic models may fail to materialize, resulting in inefficient resource allocation and potential waste of valuable organizational capital.

Conversely, the integrated multi-objective model developed in this research simultaneously considers financial performance, risk, strategic alignment, and environmental loss. Comparative analysis demonstrates that the portfolios generated through the proposed model not only maintain competitive NPV values but also achieve significantly lower risk levels and higher alignment with the organization’s strategic objectives, while mitigating ecological impacts. Hence, the results confirm that our model yields more efficient and more realistic portfolio configurations, validating its superior applicability, new conceptual contribution, and robust performance compared with Ganji’s deterministic approach and similar prior studies that overlook these critical dimensions.

Table XVI. Scheduling for Portfolio one

project \ year	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
2	Act 1 Act 2	Act 10	Act 6		Act 15 Act 17		Act 21								
3	Act 1 Act 2		Act 6		Act 10 Act 14		Act 17								
4	Act 1 *		Act 5	Act 9	Act 14										

* Activity

To ensure the reliability and effectiveness of the developed multi-objective and multi-period mathematical model, a comprehensive validation was carried out through a comparative benchmarking experiment following the methodological settings of Ganji et al. (2014). In this process, the validation consisted of three integrated phases that ensured both methodological consistency and interpretative depth.

First, the benchmark data extraction and parameter calibration phase were performed using the standard dataset introduced by Ganji et al. (2014). All original parameters, including project profits, durations, precedence relations, and resource consumption values, were directly imported from their case study (Tables XII–XVI). To introduce realistic variability, additional attributes, namely environmental losses, strategic alignment scores, and risk indices, were generated by random sampling from a comprehensive dataset of 139 industrial projects collected from two partner companies. To maintain comparability with established research standards, PSLIB benchmark instances were adopted as the basis for developing the test environment.

Next, during the scenario execution and solution process, the calibrated dataset was processed using GAMS 24.8 under the ε-constraint method. This multi-objective optimization procedure maximizes the Net Present Value (NPV) while progressively bounding other objectives, i.e., risk, strategic alignment, and environmental loss, to form the Pareto frontier. As a result, five distinct Pareto-optimal portfolios were obtained, each one representing a different trade-off among the financial, strategic, and environmental dimensions of decision-making.

Finally, a comparative evaluation was carried out against the benchmark developed by Ganji et al. (2014). Their deterministic model produced an optimal portfolio consisting of Projects 1, 2, and 4 with a maximum NPV of 15 878. Although financially appealing, that portfolio exhibited high risk, weak strategic alignment, and considerable environmental loss, reducing its managerial applicability under real uncertainty. In contrast, the integrated robust model proposed in this research generated portfolios that maintained competitive NPV values (up to 263.16) while reducing risk by about 65 percent, enhancing strategic alignment by nearly 70 percent, and mitigating environmental loss by around 80 percent under the same resource and operational constraints.

Overall, the validation results confirmed that the proposed formulation delivers more efficient, robust, and realistic portfolio configurations compared with the deterministic framework. The model successfully balances profitability with sustainability and strategic coherence, providing strong empirical evidence of its conceptual soundness, practical applicability, and superior decision-making performance under uncertainty.

A. Uncertainty Analysis at Maximum Resource Robustness Level

In the robust model, the parameters m_{ij}(resource requirement for activity j in project i) and M_h (available capacity of resource type h) are treated as the primary sources of uncertainty in the capacity constraint (10). Under the nominal condition, the model assumes that all resource values exactly match their mean-estimated quantities. However, as the conservatism level increases to its maximum, the model incorporates the worst-case fluctuations in both resource consumption and capacity. This shift affects all objective functions directly, since tightening resource constraints reshapes project selection outcomes and modifies the trade-off among strategic, economic, risk, and environmental objectives. The results of this robustness analysis, showing how the objectives vary under the maximum uncertainty level, are presented in Table XVII.

Table XVII. Normalized Performance of Objective Functions under Different Robustness Levels (Γ)

Γ	NPV	Alignment	Risk	$EnvLoss$
0	1	1	1	1
0.5	0.76	0.77	0.71	0.61
1	0.55	0.58	0.55	0.65

B. Impact of Maximum Uncertainty Level on Model Objectives

As the uncertainty level increases, the effective resource capacities are reduced, while the estimated resource consumption for various activities rises. Consequently, only a limited number of activities can be performed during each time period. This restriction delays project scheduling, causing part of the expected revenues to be realized later. Hence, the present value of cash flows decreases, and the NPV index declines noticeably. In other words, higher conservatism in the model leads to a reduction in the economic return of the project portfolio. The strategic alignment index reflects the selection of projects that best fit the organization's strategic objectives. Under highly conservative conditions, the number of selected projects diminishes, and many projects previously aligned with corporate strategy are excluded. As a result, the overall value of the alignment index decreases. However, this reduction is typically less severe than that of NPV, since alignment depends more on the composition of selected projects rather than their financial magnitude.

Under maximum uncertainty, the decision space of the model becomes narrower, favoring the selection of projects with lower resource consumption and minimal violation risk. Consequently, high-risk projects are naturally eliminated. Although this appears to reduce the overall risk index, the decline mainly results from the exclusion of risky options. It does not necessarily imply a real risk reduction in the portfolio. Therefore, this improvement should be interpreted with caution.

In conservative conditions, the model tends to select projects that consume fewer resources and exert fewer negative environmental impacts. Hence, the environmental loss index generally decreases under strong conservatism. However, in certain cases, when the feasible space becomes extremely limited, the model may retain only those projects that yield high financial returns but cause greater environmental harm. In such scenarios, the environmental loss index may fluctuate or even slightly increase, depending on the composition of projects that remain feasible under maximum uncertainty.

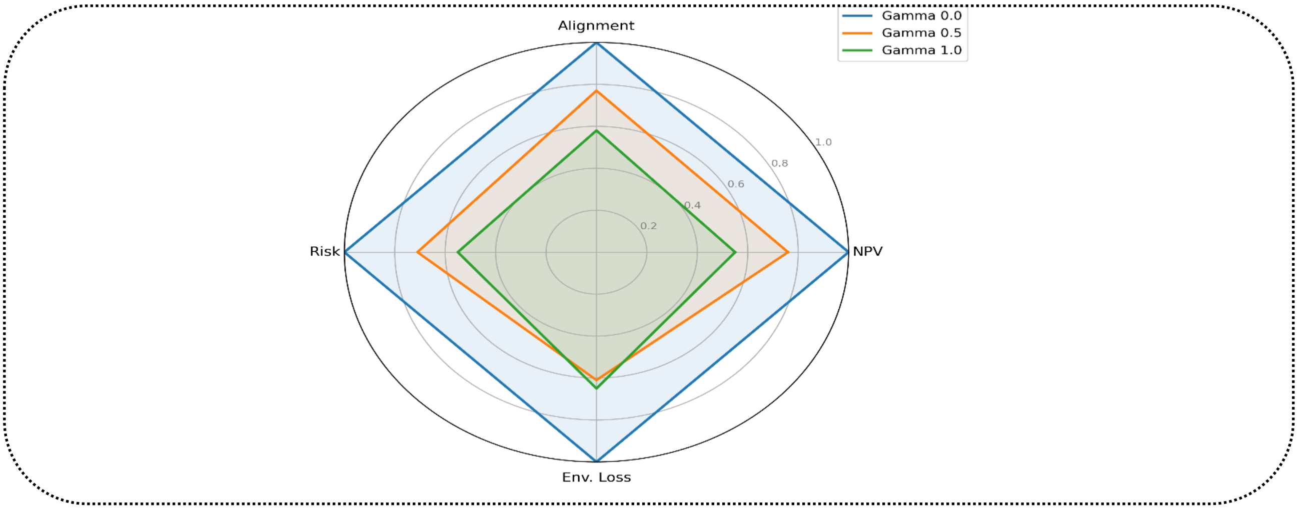

Fig. 6. Effect of Robustness Level (Γ) on the Trade-offs among Objectives

The visual representation of these relationships is illustrated in Fig. 6. The enclosed area in the Spider Radar Chart becomes smaller as Γ increases, indicating an overall decline in objective performance due to greater conservatism. From a holistic viewpoint, raising the conservatism level causes a simultaneous drop in economic value (NPV) and strategic alignment. At the same time, the Risk and Environmental Loss indices exhibit decreasing or oscillatory behavior. This phenomenon directly reflects the logic of robust optimization: the model seeks solutions that remain feasible under the worst-case scenarios, even if those solutions achieve lower profitability or strategic conformity. Consequently, decision-makers must strike a balance between two approaches: on one side, achieving maximum benefit under nominal conditions, and on the other, ensuring stability and operational feasibility under adverse situations. Determining the optimal level of conservatism (Γ) is, therefore, the key factor in balancing economic efficiency with managerial robustness in project portfolio decision-making.

IX. DISCUSSION AND CONCLUSION

This research developed a comprehensive multi-objective and multi-period integrated project portfolio selection and scheduling model under resource constraints. The proposed formulation extends traditional approaches, which often maximize only Net Present Value (NPV), by simultaneously considering risk minimization, strategic alignment, and environmental loss reduction as complementary objectives. By employing the ε-constraint optimization approach in GAMS, the model generated a diverse set of Pareto-optimal portfolios that highlight the inherent trade-offs between financial, strategic, and sustainability factors.

The validation process, performed using benchmark data from Ganji et al. (2014), demonstrated that the integrated robust model substantially improves managerial efficiency and decision realism. Compared with Ganji et al. (2014)'s deterministic framework, the proposed model reduces risk by around 65 percent, enhances strategic goal alignment by 70 percent, and diminishes environmental loss by nearly 80 percent, while maintaining competitive profitability levels. These results confirm the model's superior capability in achieving balanced and sustainable portfolio configurations under uncertainty.

In practical terms, the integration of multiple objectives enables decision makers to identify portfolios that not only maximize economic returns but also align more strongly with organizational strategies and environmental responsibilities. Consequently, the research contributes a new and applicable framework to support dynamic project-based planning in real industrial settings. The model combines robust optimization principles, multi-period resource allocation, and strategic sustainability criteria, providing a solid basis for future developments in quantitative project decision-making.

However, several limitations must be acknowledged: First, the availability and accuracy of empirical data were restricted, limiting the scope of real-world testing. Second, some environmental and risk parameters were approximated through sampling, which may affect precision under different industrial contexts. Third, the computational procedure is highly sensitive to scaling when applied to large project sets or longer planning horizons, requiring advanced heuristics or parallel computing for operational deployment.

Based on these identified boundaries, further research can extend the proposed model in several directions:

- Stochastic extension: Treat coefficients of objectives, resource capacities, and activity durations as random variables, enabling simulation-based robust analysis.
- Dynamic decision updates: Incorporate real-time project performance monitoring and learning algorithms to adapt portfolios during execution phases.
- Hybrid optimization approaches: Combine the ε-constraint technique with metaheuristics (e.g., genetic algorithms, NSGA-II) to improve exploration of large-scale multi-criteria spaces.
- Cross-sector validation: Apply the model across diverse industries—energy, IT, and construction—to evaluate its generalizability and comparative efficiency.
- Sustainability integration: Embed social impact, carbon footprint, and circular-economy indicators into the environmental objective function to broaden ecological depth.

In summary, the presented study not only introduces a robust and balanced decision-making model for integrated project portfolio selection and scheduling but also establishes a foundation for future methodological and practical advancements toward sustainable and data-driven portfolio management.

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