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INTEGRATED PROJECT PORTFOLIO SELECTION AND SCHEDULING UNDER FUZZY-STOCHASTIC UNCERTAINTY: A MULTI-AGENT MULTI-OBJECTIVE OPTIMIZATION APPROACH

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Original research

A B S T R A C T

This study proposes a multi-objective fuzzy–stochastic programming model for simultaneous project portfolio selection, scheduling, and allocation within a multi-agent organizational structure, integrating economic, environmental, and resilience objectives. Fuzzy numbers represent uncertainty in project construction and execution times, while stochastic scenarios capture variability in future conditions. Small instances were evaluated using the ε-Constraint method and BARON in GAMS, whereas larger instances were solved using NSGA-II and MOPSO. NSGA-II closely matched exact reference solutions for small instances and handled problems with up to 40 projects, 8 agents, and 4 scenarios. MOPSO achieved better MID values, whereas NSGA-II performed better in the number of Pareto solutions, crowding distance, and computational time. Sensitivity analysis showed that higher discount rates reduced economic value by 32.6%, while higher reinvestment rates increased it by up to 86.9%. The model supports integrated portfolio decisions under uncertainty.

1. INTRODUCTION

Project-oriented organizations must select an appropriate set of candidate projects and determine their implementation schedules in order to achieve strategic objectives. Limited financial and operational resources, numerous candidate projects, interdependencies among decisions, conflicting objectives, and changing environmental conditions have made project portfolio selection and scheduling an important and complex problem in project management and operations research.

Project selection and implementation timing are not independent decisions: selecting a project affects the resources available to other projects across periods, while scheduling can alter the economic and operational consequences of the selected portfolio. Accordingly, an integrated treatment of project portfolio selection and scheduling can provide a more appropriate framework for resource allocation and decision making in project-oriented organizations. A major challenge is uncertainty in information and decision conditions. In practice, project construction and execution durations cannot

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always be predicted precisely and may depend on incomplete information, expert judgment, and implementation conditions. Moreover, parameters affecting portfolio performance may vary across future states. Ignoring these uncertainties can cause model results to diverge from real decision environments. Therefore, approaches capable of representing different types of uncertainty are important in project portfolio selection and scheduling models. (Ranjbar et al., 2022; Shafahi & Haghani, 2018; Vega-Hidalgo et al., 2026).

Fuzzy logic and stochastic programming are two common approaches for handling uncertainty, each representing a different uncertainty source. Fuzzy logic is suitable for ambiguity arising from imprecise information and expert estimates, whereas stochastic approaches represent variability in future conditions through scenarios with specified probabilities. Integrating these approaches in a single model can therefore capture both ambiguity in time estimates and variability in future conditions. In this study, project construction and execution times are modeled as fuzzy parameters, while parameters dependent on future conditions are incorporated through stochastic scenarios.

In addition to uncertainty, the objectives used in project portfolio selection are important. Economic criteria alone may not capture all consequences of project implementation. Growing attention to environmental impacts and the need to maintain satisfactory performance under changing conditions have brought environmental and resilience considerations alongside economic objectives. Hence, project portfolio selection and scheduling can be formulated as a multi-objective problem involving trade-offs among higher economic value, lower environmental impacts, and greater resilience. Consistent with the scope of this study, the economic and environmental dimensions of sustainability, together with economic and environmental resilience, are considered; the social dimension is outside the scope of the model. (Aghileh et al., 2024; Panadero et al., 2018; Perez et al., 2018; Wu et al., 2021).

Furthermore, projects in large organizations are typically implemented by different organizational units or executing agents that may differ in capacity, cost, execution time, and other constraints. Thus, in addition to selecting projects and determining their start times, assigning an appropriate executing agent to each project can affect overall portfolio performance. A multi-agent structure makes it possible to represent differences among executing units and allocate projects according to their characteristics, capacities, and constraints. In this study, an agent refers to an organizational executing agent or unit rather than an artificial-intelligence agent; the multi-agent structure is represented through parameters, allocation variables, and agent-related constraints in the mathematical model. The central research problem is therefore to develop an integrated framework for project selection, scheduling, and allocation when decisions are simultaneously affected by resource limitations, differences among executing agents, uncertainty, and conflicting economic, environmental, and resilience objectives. To address this problem, a multi-objective fuzzy–stochastic mathematical programming model is proposed in which project selection, project start times, and assignment of selected projects to executing agents are determined jointly. The three objectives are to maximize the expected economic value of the project portfolio, minimize environmental impacts, and maximize economic and environmental resilience. This structure enables the interactions among major portfolio decisions and their consequences under different uncertainty conditions to be examined. (Farshchian & Heravi, 2018; Fu & Zhou, 2021; Li et al., 2020; Wang et al., 2024).

2. LITERATURE REVIEW AND RESEARCH GAP

2.1. Project portfolio selection and scheduling

Project portfolio selection and project scheduling are major decision problems in project management and operations research. Their purpose is to determine an appropriate set of projects and their implementation times subject to resource limitations and organizational objectives. As the number of candidate projects, resource constraints, and decision complexity have increased, project portfolio selection has evolved beyond a purely economic focus into a multi-objective problem. Some studies have focused on portfolio selection using mathematical programming, multi-criteria decision-making methods, and metaheuristic algorithms, while others have addressed project scheduling and resource allocation. However, project selection and scheduling are interdependent because selecting a project affects resource consumption over time and its implementation schedule can influence the economic and operational consequences of the portfolio. This has motivated the development of integrated models that determine selection and scheduling decisions simultaneously. (Ranjbar et al., 2022; Shafahi & Haghani, 2018; Vega-Hidalgo et al., 2026; Wang & Song, 2016).

2.2. Modeling uncertainty in project portfolio selection and scheduling

A key characteristic of real project portfolio selection and scheduling problems is uncertainty in some information and decision parameters. Project durations, economic conditions, and other future-dependent factors may not be adequately represented by predetermined deterministic values. Ignoring such conditions may cause model outcomes to deviate from the actual decision environment.

Fuzzy logic and stochastic programming are widely used in the literature to address uncertainty. Fuzzy logic represents ambiguity caused by imprecise information and expert estimates, whereas stochastic programming captures variability in future conditions through scenarios with occurrence probabilities. Because these approaches address different aspects of uncertainty, their combination can simultaneously represent parameter ambiguity and scenario-based variability. Nevertheless, compared with separate fuzzy or stochastic approaches, such a combined structure has received less attention in integrated project portfolio selection and scheduling. (Hu et al., 2026; Perez et al., 2018; Tavana et al., 2020; Wu et al., 2021).

2.3. Multi-agent structure, economic and environmental considerations, and resilience

In project-oriented organizations, projects may be implemented by different executing units or agents that differ in operational characteristics, capacities, costs, project execution times, and associated constraints. Consequently, assigning selected projects to executing agents becomes part of the decision problem in addition to selection and scheduling. A multi-agent structure can represent these differences and allocate projects according to agent capacities and constraints. Sustainability and resilience considerations have also become increasingly important in portfolio decisions. Evaluating projects solely on economic criteria may fail to capture environmental consequences or the ability of a portfolio to maintain satisfactory performance under changing conditions. Accordingly, some studies have incorporated economic, environmental, and resilience criteria into project evaluation. However, as the comparison of prior studies indicates, simultaneous consideration of these dimensions together with integrated selection and scheduling, a multi-agent structure, and fuzzy–stochastic uncertainty remains limited. (Gholami et al., 2025; Fu & Zhou, 2021; Li et al., 2020; Mahmoudi et al., 2022).

2.4. Research gap

The review and comparison of previous studies show that the main components addressed in this research—including project portfolio selection, scheduling, multi-agent structures, fuzzy and stochastic uncertainty, economic and environmental considerations, and resilience—have each been studied in different contexts. However, prior studies combine these components in different ways, and a substantial share considers only a subset simultaneously. Specifically, first, some studies address project selection and scheduling independently or with limited integration. Second, uncertainty modeling has mainly focused on either fuzzy or stochastic approaches, with fewer studies combining both in integrated selection and scheduling. Third, multi-agent structures that explicitly represent differences among executing agents alongside selection and scheduling decisions have been considered in relatively few studies. Fourth, although economic, environmental, and resilience criteria have been investigated separately or jointly, their simultaneous integration with the other dimensions is limited. Accordingly, the research gap does not arise from the complete absence of any individual component, but from the limited integration of all these dimensions within a single decision framework. The present study addresses this gap by developing a multi-objective fuzzy–stochastic mathematical programming model that jointly determines project selection, scheduling, and assignment to executing agents while incorporating economic, environmental, and economic/environmental resilience objectives. Temporal uncertainty is modeled using fuzzy logic and changing future conditions are represented through stochastic scenarios. (Farahmand-Mehr & Mousavi, 2025; Ghasemi et al., 2025; Harrison et al., 2022; Hu et al., 2026; Mozhdehi et al., 2024; Türk et al., 2025) (Table 1).

Table 1. Review of the literature

Integrated model	Resilience	Economic	Environmental	Fuzzy–stochastic	Stochastic	Fuzzy	Multi-agent	Scheduling	Project portfolio selection	Year	Study
✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	2020	Li et al.
✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	2021	Fu & Zhou
✗	✓	✓	✗	✗	✗	✗	✗	✗	✓	2022	Mahmoudi et al.
✓	✗	✓	✗	✗	✗	✗	✗	✓	✓	2022	Ranjbar et al.
✓	✗	✓	✗	✗	✗	✗	✗	✓	✓	2022	Harrison et al.
✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	2024	Mozhdehi et al.
✗	✗	✓	✗	✗	✗	✗	✓	✓	✗	2024	Wang et al.
✓	✓	✓	✓	✗	✗	✓	✓	✓	✓	2025	Gholami et al.
✗	✓	✗	✗	✗	✗	✗	✗	✓	✗	2025	Farahmand-Mehr & Mousavi
✗	✓	✓	✗	✗	✗	✗	✗	✓	✗	2025	Ghasemi et al.
✗	✗	✓	✗	✗	✗	✗	✗	✓	✗	2025	Türk et al.
✗	✗	✓	✗	✗	✓	✗	✗	✓	✗	2026	Hu et al.
✓	✗	✓	✗	✗	✗	✗	✗	✓	✓	2026	Vega-Hidalgo et al.
✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	**2026**	Present study

A comparative review of the literature indicates that project portfolio selection and scheduling research has gradually evolved from deterministic and predominantly economic models toward multi-objective, sustainability-oriented, and uncertainty-based frameworks. Some studies have examined project selection and scheduling in an integrated manner, while others have used fuzzy, stochastic, or hybrid approaches to address uncertainty. More recent studies have also paid increasing attention to sustainability, resilience, and multi-agent structures. (Acquaye et al., 2026; Khalili-Damghani & Sadi-Nezhad, 2013; Mohagheghi et al., 2016).

Despite these developments, prior studies generally cover only part of the problem dimensions. Some focus on integrating selection and scheduling, some address fuzzy or stochastic uncertainty, and others introduce sustainability or resilience criteria into portfolio selection. Even studies closest to the present work, which incorporate multi-agent structures, fuzzy logic, or environmental resilience into project portfolio selection and scheduling, do not simultaneously cover all dimensions considered here. Thus, the gap addressed in this research is not the independent absence of each component in the literature, but the limited simultaneous integration of these components within a unified decision framework. The proposed multi-objective fuzzy–stochastic mathematical programming model jointly performs project selection, scheduling, and assignment to executing agents while simultaneously considering economic, environmental, and economic/environmental resilience objectives. Uncertainty in time-related parameters is represented using fuzzy logic, whereas changes in future conditions are modeled through stochastic scenarios.

3. PROPOSED MODEL

3.1. Problem definition and model framework

Based on the gaps identified in the literature, this study develops a multi-objective fuzzy–stochastic mathematical programming model for simultaneous project portfolio selection and scheduling within a multi-agent structure. The organization faces a set of candidate projects with different costs, durations, economic values, environmental impacts, and resilience characteristics. Because financial resources and execution capacity are limited, not all projects can be implemented simultaneously. The model therefore selects suitable projects, determines their start times, and assigns the selected projects to executing agents in an integrated manner.

The multi-agent structure is introduced to represent differences among organizational executing units or agents. Each agent has specific capacities and operational characteristics, and projects are assigned through decision variables and related constraints. Differences among agents may also affect project costs and execution durations. Thus, the executing agent is not merely an assignment variable; its selection can influence scheduling, cash flows, and ultimately portfolio performance. Two distinct sources of uncertainty are separated in the model. Uncertainty in project construction and execution durations is represented by triangular fuzzy numbers, whereas changes in future conditions and environment-dependent parameters are represented through stochastic scenarios with specified occurrence probabilities. The fuzzy–stochastic approach therefore captures both ambiguity in time estimates and variability in future conditions. The proposed model simultaneously pursues three conflicting objectives: maximizing the expected economic value of the project portfolio, minimizing environmental impacts, and maximizing the economic and environmental resilience of the portfolio. Consequently, rather than producing a single solution based on one criterion, the model provides a set of nondominated solutions that enables decision makers to examine trade-offs and choose a solution consistent with organizational priorities.

3.2. Model assumptions

The following assumptions are adopted to formulate the mathematical model and define the problem framework:

1. The set of candidate projects, planning horizon, time periods, and executing agents are known in advance.
2. Each project may be selected or rejected, and only selected projects enter the scheduling and agent-assignment processes.
3. Each selected project starts in exactly one time period and is assigned to one executing agent.
4. Executing agents have limited capacities, and the number of projects assigned to an agent cannot exceed its specified capacity.
5. Project cost and execution duration may be adjusted according to the characteristics of the assigned executing agent; therefore, agent selection can affect project cost and completion time.
6. Project construction and execution durations are uncertain and are represented by triangular fuzzy numbers.
7. Changes arising from future conditions are incorporated through a set of stochastic scenarios with specified occurrence probabilities.
8. The organization has limited financial resources, and financing facilities may be used within the limits defined by the model.
9. Project cash flows over the planning horizon are considered and the time value of money is represented by a discount rate. The salvage value of selected projects at the end of the planning horizon is also included in the financial calculations.
10. Project environmental impacts are incorporated through model components such as pollutant emissions and waste generation.

11. Portfolio resilience is evaluated in economic and environmental dimensions, and the corresponding project-level resilience indices are considered under scenario conditions.
12. All selected projects must be completed within the planning horizon, considering their start times, construction durations, and execution durations.

3.3. Sets, parameters, and decision variables

To present the mathematical structure of the model, the sets and indices, parameters, and decision variables are first defined. The main notation used in the model is presented in the following tables (Table 2, Table 3 and table 4).

a) Sets and Indices

Table 2. Sets and indices(a)

Index	Description
i=1…N	Index of candidate projects
t=1…T	Index of time periods
y=1…Y	Index of years in the planning horizon
s =1…S	Index of uncertainty scenarios
ag =1…AG	Index of executing agents
g	Index of objective evaluation criteria/components
l	Index of financing/loan types
q=1.2.3	Index of triangular fuzzy-number components: lower bound, most likely value, and upper bound

(b) Main Model Parameters

Table 3. Main model parameters

Parameter	Definition
Ps	Occurrence probability of scenario s
w_g^E	Weight of criterion g in the economic dimension
w_g^{Env}	Weight of criterion g in the environmental dimension
w_g^{Res}	Weight of criterion g in the resilience dimension
NCF_{gts}	Net cash flow for criterion g in period t and scenario s
SV_{igs}	Salvage value of project i for criterion g under scenario s
r	Discount rate
$Emission_{igs}$	Pollutant emissions of project i for criterion g under scenario s
$waste_{igs}$	Waste generated by project i for criterion g under scenario s
$RecoverableWaste_{igs}$	Recoverable/reusable waste of project i for criterion g under scenario s
RES_{igs}^{Eco}	Economic resilience index of project i for criterion g under scenario s
RES_{igs}^{Env}	Environmental resilience index of project i for criterion g under scenario s
α^{Eco}	Importance coefficient of economic resilience
α^{Env}	Importance coefficient of environmental resilience
Cap_{ag}	Capacity of executing agent ag
M	Sufficiently large positive number used in logical constraints
Q_{il}	Number of repayment periods for loan type l for project i

(c) Main Decision and Auxiliary Variables

Table 4. Main decision and auxiliary variables

Variable	Description
x_i	Binary selection variable for project i; 1 if selected, 0 otherwise
X_{it}	Binary scheduling variable; 1 if project i starts in period t
$z_{i,ag}$	Binary assignment variable; 1 if project i is assigned to agent ag
ST_i	Start time of project i
FN_{is}	Completion time of project i under scenario s

F_{ilt}	Amount of loan type l received for project i in period t
TM_{it}	Loan principal repaid for project i up to period t
TI_{its}	Loan interest for project i up to period t under scenario s

3.4. Mathematical formulation

The proposed model is formulated as a multi-objective mathematical programming model that simultaneously addresses economic, environmental, and resilience objectives. The principal decisions include project selection, determination of the start time of selected projects, and assignment of selected projects to executing agents. Because multiple scenarios are considered, expected objective values are calculated using the occurrence probability of each scenario.

Objective 1: Maximization of Project Portfolio Economic Value
The first objective maximizes the economic value of the project portfolio. By considering discounted project cash flows and residual values at the end of the planning horizon, the objective seeks the most economically beneficial combination of projects. Because economic conditions are uncertain in real environments, economic calculations are performed for all plausible scenarios and their expected values are incorporated according to scenario probabilities.

$$\max Z1 = \sum_{s=1}^{S} Ps\left[\sum_{g\in G^{E}} \boldsymbol{w_g^E} \sum_{t=1}^{T} \frac{NCF_{gts}}{(1+r^1)^{\mathrm{t}}} + \sum_{i=1}^{N} \frac{SV_{isg}\mathrm{x}_i}{(1+r^1)^{T}}\right]$$

In this objective, net cash flows over the planning horizon are converted to present values using the discount rate, and the salvage values of selected projects are included at the end of the planning horizon. To account for uncertainty in future conditions, the economic outcome of each scenario is weighted by its probability. Thus, the first objective seeks the project combination that creates the maximum expected economic value for the portfolio.

Objective 2: Minimization of Environmental Impacts
Maximizing economic benefits alone cannot satisfy sustainable-development requirements. The second objective therefore minimizes the environmental impacts of selected projects. It incorporates pollutant emissions, waste generation, and other environmental consequences into the decision process so that project selection is not based solely on economic profitability.

$$Min_{Z2} = \sum_{s=1}^{S} \mathrm{Ps} \sum_{i=1}^{N} x_i \sum_{\mathrm{g}\in G^{Env}} \boldsymbol{w_g^{Env}} \left(Emission_{\ igs} + waste_{igs} - RecoverableWaste_{igs}\right)$$

Pollutant emissions and generated waste are treated as adverse environmental outcomes, while recyclable, redesign able, or saleable waste is deducted from total adverse impacts. Environmental criterion weights and scenario probabilities are also incorporated in the expected environmental impact of the portfolio. Accordingly, the model favors projects that, alongside the other objectives, impose a lower environmental burden.

Objective 3: Maximization of the Resilience Index
In project-oriented environments, an organization's ability to cope with disruptions and recover performance is a key success factor. Therefore, the third objective maximizes the resilience index of the project portfolio. In this study, resilience combines economic and environmental components and is calculated for each project and organizational agent.

$$Max\ Z_3 = \sum(g\in G^{Res})\ w\_g^{Res} \sum(s=1 \ldots S)\ P\_s \sum(i=1 \ldots N)\ x\_i\ (\alpha^{Eco}\ RES\_igs^{Eco} + \alpha^{Env}\ RES\_igs^{Env})$$

In this objective, the economic and environmental resilience scores of each project are aggregated using their respective importance coefficients and then weighted by resilience-criterion weights and scenario probabilities to calculate expected portfolio resilience. Only selected projects contribute to portfolio resilience. Baseline resilience scores are determined before optimization and used as model input parameters; therefore, the model maximizes overall portfolio resilience by selecting an appropriate project combination. The three objectives are inherently conflicting: higher economic value may be accompanied by greater environmental impacts, while projects with higher resilience do not necessarily generate the highest economic return. The model is therefore solved as a multi-objective problem and produces a set of nondominated solutions for examining trade-offs among objectives.

3.5. Model constraints

To link project selection, scheduling, and allocation decisions and ensure solution feasibility, the model includes operational, temporal, financial, and environmental constraints. These constraints can be classified into seven main groups. First, selection and scheduling constraints link project selection to project start times and ensure that only selected projects enter the implementation plan and that each selected project starts in a specified period. Second, executing-agent assignment and capacity constraints link project selection to agent allocation, ensure that every selected project is assigned to an appropriate agent, and enforce limited agent capacities. Because executing agents differ in their characteristics, the effect of the assigned agent on project cost and duration is represented through adjustment parameters, directly linking agent assignment to selection and scheduling. Third, project time constraints determine the start and completion times of selected projects based on start periods, construction durations, and execution durations. Since time parameters are uncertain, construction and execution durations are modeled fuzzily and completion-time relations are defined for different fuzzy parameter values; these constraints also prevent project completion beyond the planning horizon. Fourth, financial and cash-flow constraints control the financial feasibility of the portfolio throughout the planning horizon. They include initial financial resources, investment and execution costs, cash inflows and outflows, receipt and repayment of financing, loan principal and interest, reinvestment rates, and cash balances. Fifth, tax and environmental constraints calculate income tax, carbon tax, and waste-related costs or taxes in the relevant periods and incorporate them into cash flows; revenue from saleable or recoverable waste is treated as an inflow where applicable. Sixth, financing and loan-repayment constraints control the use of credit resources, principal repayment, and interest calculations and prevent borrowing beyond specified limits. Finally, fuzzy-uncertainty constraints represent different construction and execution durations and preserve the logical ordering of triangular fuzzy-number components. Collectively, these constraints ensure that solutions satisfying the economic, environmental, and resilience objectives are also feasible with respect to project selection and scheduling, agent assignment, execution capacity, time, financing, cash flow, tax obligations, and uncertainty.

The complete set of model constraints is presented below.

$$TM_{it} = \sum_{l=1}^{L} \sum_{\theta=0}^{t} \frac{F_{il\theta}}{Q_{il}} \qquad \forall i, t$$

$$TI_{its} = \sum_{l=1}^{L} \sum_{\theta=0}^{t} \frac{(1+r_{is}^{3}).F_{il\theta}}{Q_{il}} - TM_{it} \quad \forall i, t, s$$

$$R_{ts} = \sum_{i=1}^{N} \sum_{\theta=0}^{t} CF_{i\Theta s}\, X_{i\theta}$$

$$\sum_{t=0}^{T} X_{it} = x_i \qquad \forall i$$

$$\sum_{i=1}^{N} z_{i,ag} \leq Cap_{ag} \qquad \forall ag$$

$$ST_i = \sum_{t=0}^{T} t\ X_{it} \qquad \forall i$$

$$FN_{is} = \sum_{t=0}^{T} (t + \tilde{d}_{is}^{1} + \tilde{d}_{is}^{2})\, X_{it} \qquad \forall i, s$$

$$\sum_{t=0}^{T} (t + \tilde{d}_{is}^{1} + Duration_{i,ag,s}) X_{it} \leq T + M(1 - z_{i,ag}) \quad \forall i, ag, s$$

$$\tau_{ys}^{e} = r^{e}(1 + p_e)^{y-1} \sum_{t \in T_y} \sum_{i=1}^{N} \sum_{ag=1}^{AG} \sum_{\theta=0}^{t} Y_{i,ag,s} z_{i,ag} X_{i\theta}$$

$$EX_{t,ag,s} = \sum_{i=1}^{N} \sum_{\theta=0}^{t-1} C_{i,ag,s}\, z_{i,ag} X_{i\theta} \qquad \forall t, ag, s$$

$$CB_{t,s} = CB_{t-1,s}(1 + \mathrm{r}^{2}) + Inflow_{t,s} - outflow_{t,s} - Tax_{t,s}$$

and

$$\Sigma_i \ \Sigma_l \ F_{ilt} + R_{ts} + E_{(t-1,s)}(1+r^2) + \Sigma_a \ \Sigma_i \ \Sigma_{(\theta=0\ldots t)} \ \delta^3_{ia} \ r^w_{ia} \ X_{i\theta} = E_{ts} + \Sigma_{ag} EX_{(t,ag,s)} + \Sigma_i DC_{it} + \Sigma_i IO_i X_{it} + \Sigma_i (TM_{it} + TI_{its}) + (\tau^e_{ys} + \tau^w_{ys}) + \Sigma_i \tau^{re}_{iys}$$

$$\forall s \quad y = \{1 \ldots y-1\}$$

$$\Sigma_i \ \Sigma_l \ F_{ilT} + RT_s + E_{(T-1,s)}(1+r^2) + \Sigma_i \ SV_{is} \ x_i + \Sigma_a \ \Sigma_i \ \Sigma_{(\theta=0\ldots T)} \ \delta^3_{ia} \ r^w_{ia} \ X_{i\theta} = E_{Ts} + \Sigma_{ag} EX_{(T,ag,s)} + \Sigma_i DC_{iT} + \Sigma_i IO_i X_{iT} + \Sigma_i (TM_{iT} + TI_{iTs}) + \tau^e_{Ys} + \tau^w_{Ys} + \Sigma_i \tau^{re}_{iYs}$$

$$DC_{it} = De_i \sum_{\theta=0}^{t} X_{i\theta}$$

$$\tau_{ys}^{w} = \sum_{t \epsilon T_y} \sum_{i=1}^{N} \sum_{\theta=0}^{t} \left[\sum_{k=1}^{K} \delta_{ik}^{1} L_r (1 + pL_r)^{(y-1)} + \sum_{h=1}^{H} \delta_{ih}^{2} S_r (1 + pS_r)^{(y-1)}\right] X_{i\theta} \qquad \forall y, s$$

$$\tau_{iys}^{re} = r^{re} \left[\sum_{t \epsilon T_y}^{y} \sum_{\theta=0}^{t} \left(\sum_{ag=1}^{AG} cinf_{iag,s}\, Z_{i,ag} - De_i\right) X_{i\theta} - \sum_{t \epsilon T_y}^{y} TI_{its}\right] \qquad \forall y, i, s$$

$$F_{ilt} \leq D_l X_{it} \quad \forall i, l, t$$

$$\sum_{ag=1}^{AG} z_{i,ag} = x_i \qquad \forall i$$

$$\sum_{i=1}^{N} IO_i\, X_{i0} \leq \beta$$

$$C_{i,ag,s} = C_{is0}^{0} \times Factor_{ag} \qquad \forall ag, i, s$$

$$Duration_{i,ag,s} = \tilde{d}_{is}^{2} \times Eff_{ag} \qquad \forall ag, i, s$$

$$FN_{isq} = \sum_{t=0}^{T} (t + d_{isq}^{1} + d_{isq}^{2}) X_{it} \qquad \text{q=1, 2, 3}$$

$$d_{is1}^{1} \leq d_{is2}^{1} \leq d_{is3}^{1} \qquad \forall i, s$$

$$d_{is1}^{2} \leq d_{is2}^{2} \leq d_{is3}^{2} \qquad \forall i, s$$

Overall, the above constraints connect the three principal decisions—project selection, implementation timing, and executing-agent assignment—while ensuring the temporal and financial feasibility of the portfolio. Other financial relations include calculations of loan principal and interest, depreciation, income tax, carbon tax, and waste-related costs, which are used in determining cash inflows and outflows.

3.6. Fuzzy-stochastic uncertainty modeling

A central feature of the proposed model is the simultaneous treatment of two types of uncertainty with different characteristics. In real project portfolio selection and scheduling problems, some uncertainty arises from ambiguity in parameter estimation, while another part stems from variability in future conditions. A combined fuzzy–stochastic approach is therefore employed. In the fuzzy component, uncertainty in project construction and execution durations is considered. Because these durations cannot be determined precisely before implementation and are largely based on expert estimates, they are represented by triangular fuzzy numbers. In general, a fuzzy time parameter can be expressed as follows:

$\tilde{d}_{is} = (d_{is}^1, d_{is}^2, d_{is}^3)$

where the three components represent, respectively, the optimistic, most likely, and pessimistic values of the time parameter for project i, with the following ordering relationship:

$d_{is}^1 \leq d_{is}^2 \leq d_{is}^3$

Accordingly, project completion time is calculated for the three fuzzy parameter values, and constraints governing the ordering of fuzzy components ensure consistency of time values in the model. Thus, ambiguity in estimating construction and execution times is directly reflected in scheduling decisions.

In the stochastic component, different future conditions are represented by a set of scenarios s = 1, …, S with occurrence probabilities, such that:

$\sum_{(s=1 \ldots S)} P_s = 1$

Each scenario represents a different possible future state, and parameters dependent on the decision environment are specified accordingly. Scenario effects enter the objective functions and other future-dependent relations, while expected values are calculated by weighting scenario outcomes according to their occurrence probabilities.

Thus, fuzzy logic represents ambiguity in estimating project construction and execution durations, whereas the scenario-based stochastic approach represents variability in future conditions. Combining the two allows the model to incorporate both sources of uncertainty simultaneously into project selection, scheduling, and allocation, bringing the decision structure closer to the conditions faced by real project-oriented organizations.

4. SOLUTION METHODOLOGY AND EXPERIMENTAL SETUP

Given the multi-objective nature of the proposed model and the increasing computational complexity associated with larger numbers of projects, time periods, executing agents, and uncertainty scenarios, a single solution method is not suitable for all problem sizes. A two-stage solution strategy is therefore adopted. First, small instances are solved using the exact ε-Constraint method and the BARON solver in GAMS to examine model solvability and generate reference solutions for evaluating metaheuristics. Second, two multi-objective metaheuristics, NSGA-II and MOPSO, are used for large-scale instances.

4.1. ε-Constraint method and BARON solver

In multi-objective problems, simultaneous optimization of conflicting objectives requires a mechanism for generating nondominated solutions. In this study, the ε-Constraint method is used to solve small instances exactly. One objective is treated as the primary objective, while the remaining objectives are converted into constraints with specified ε bounds. By gradually varying ε values, a set of efficient solutions is generated and trade-offs among objectives can be examined. The resulting problems are solved in GAMS using BARON. Applying the exact method to small instances not only verifies the consistency and solvability of the mathematical structure but also produces reference solutions used to evaluate the quality of metaheuristic results. As problem size and the number of variables and constraints increase, the computational time of the exact method rises substantially, making large instances difficult to solve within an acceptable time. Multi-objective metaheuristics are therefore used for large-scale problems.

4.2. NSGA-II algorithm

The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is a well-established metaheuristic for multi-objective optimization. It ranks the population into nondominated fronts based on Pareto dominance and uses crowding distance to preserve diversity along the Pareto front. In this study, each NSGA-II solution represents project-selection decisions, start times of selected projects, and assignments to executing agents. After generating the initial population, solutions are evaluated for feasibility and objective values and then ranked using nondominated sorting and crowding distance. New generations are produced using selection, two-point crossover, and segment-reversal mutation, while elitism preserves superior solutions across successive generations.

4.3. MOPSO algorithm

To compare and evaluate NSGA-II, Multi-Objective Particle Swarm Optimization (MOPSO) is also applied. Each particle represents a potential solution, and particles move through the search space based on individual experience and information from superior solutions stored in a repository of nondominated solutions. In the multi-objective version, an external archive retains nondominated solutions and the leader-selection mechanism is designed to guide movement toward desirable regions while preserving Pareto-front diversity. MOPSO is used as a benchmark metaheuristic to compare the two approaches in terms of nondominated-solution quality and diversity as well as computational efficiency.

4.4. Algorithm parameter tuning

Metaheuristic performance depends on the values of control parameters. To reduce subjective parameter selection and obtain an appropriate combination of control settings, the Taguchi design-of-experiments method is used. Different levels of the principal algorithm parameters are evaluated using orthogonal arrays, and suitable parameter combinations are selected based on the experimental results. These values are then used in the final NSGA-II and MOPSO runs.

4.5. Experimental setup and performance evaluation

The computational experiment comprised 20 test instances of increasing scale, ranging from 5 to 40 projects, 1 to 8 executing agents, and 1 to 4 uncertainty scenarios. Small instances were solved with the exact ε-Constraint method and BARON in GAMS to provide reference solutions. NSGA-II and MOPSO were then evaluated using mean ideal distance (MID), the number of nondominated/Pareto solutions, crowding distance, and computational time. Because these indicators measure different aspects of performance, convergence, diversity, solution-set extent, and computational efficiency were considered jointly.

5. RESULTS

The results are reported for the 20 test instances defined in the computational experiment. The increasing dimensions make it possible to evaluate model solvability, the effect of scale on exact solution time, and the performance of the metaheuristic approaches.

5.1. Model validation and solvability assessment

First, the mathematical structure of the model was examined for feasibility and boundedness. All 20 test instances were feasible and bounded; hence, no inconsistency causing infeasibility or unbounded objective behavior was observed in the tested instances. The instances were then solved using the ε-Constraint method and BARON in GAMS to evaluate exact solvability. Instances 1–10 reached optimal solutions within acceptable computational times. From instance 11 onward, the increasing number of variables, constraints, projects, agents, and scenarios caused a substantial increase in computational complexity, and obtaining exact optimal solutions within acceptable time became difficult (Table 5).

Table 5. Solution of test problems at different scales

Computational time	Resilience	Environmental impacts	Net present value of final wealth	Instance
10	950	1006	10456852	1
19	978	1045	10654245	2
26	1005	1076	10849883	3
33	1038	1109	10987582	4
39	1061	1129	11169699	5
47	1096	1168	11345172	6
57	1123	1194	11488647	7
66	1148	1223	11595257	8
76	1172	1251	11740892	9
83	1195	1276	11920000	10
Optimal solution not obtained within acceptable time	—	—	—	11
Optimal solution not obtained within acceptable time	—	—	—	12
Optimal solution not obtained within acceptable time	—	—	—	13
Optimal solution not obtained within acceptable time	—	—	—	14
Optimal solution not obtained within acceptable time	—	—	—	15
Optimal solution not obtained within acceptable time	—	—	—	16
Optimal solution not obtained within acceptable time	—	—	—	17
Optimal solution not obtained within acceptable time	—	—	—	18
Optimal solution not obtained within acceptable time	—	—	—	19
Optimal solution not obtained within acceptable time	—	—	—	20

For the instances solvable exactly, computational time increased from 10 seconds for the first instance to 83 seconds for the tenth. Objective values also changed with problem scale. For example, the economic objective increased from 10,456,852 in the first instance to approximately 11,920,000 in the tenth, while the resilience index increased from 950 to 1,195. The increase in the environmental objective from 1,006 to 1,276 should not be interpreted as an environmental improvement because this objective is minimized; rather, it mainly reflects the larger number of projects and greater problem scale.

These results indicate two points. First, the proposed model is mathematically solvable for the test instances. Second, increasing problem size rapidly increases the computational complexity of the exact method. Metaheuristic methods were therefore necessary for larger instances.

5.2. Validation of NSGA-II against exact solutions

To assess the ability of NSGA-II to approximate reference solutions, its results for small instances were compared with those obtained by the exact method. Differences from the reference solutions ranged from 16 to 100 units for the economic objective and from 1 to 9 units for the environmental objective and resilience index (Table 6).

Table 6. Comparison of the exact ε-Constraint method and NSGA-II

Difference				**NSGA-II**				**Exact ε-Constraint method**				
Computational time	Resilience	Environmental index	Net present value of final wealth	Computational time	Resilience	Environmental	Net present value of final wealth	Computational time	Resilience	Environmental	Net present value of final wealth	Instance
0	1	1	16	10	949	1005	10456836	10	950	1006	10456852	1
1	3	1	42	18	975	1044	10654203	19	978	1045	10654245	2
2	4	2	42	24	1001	1074	10849841	26	1005	1076	10849883	3
3	4	2	46	30	1034	1107	10987536	33	1038	1109	10987582	4
3	4	3	61	36	1057	1126	11169638	39	1061	1129	11169699	5
4	4	3	64	43	1092	1165	11345108	47	1096	1168	11345172	6
4	5	3	83	53	1118	1191	11488564	57	1123	1194	11488647	7
4	7	6	85	62	1141	1217	11595172	66	1148	1223	11595257	8
5	8	7	88	71	1164	1244	11740804	76	1172	1251	11740892	9
5	9	9	100	78	1186	1267	11919900	83	1195	1276	11920000	10
…….	…….	…….	…….	85	1224	1302	12091078	Computational limitation	…….	…….	…….	11
…….	…….	…….	…….	90	1247	1325	12250103	Computational limitation	…….	…….	…….	12
…….	…….	…….	…….	99	1286	1365	12390741	Computational limitation	…….	…….	…….	13
…….	…….	…….	…….	104	1318	1398	12496964	Computational limitation	…….	…….	…….	14
…….	…….	…….	…….	114	1354	1426	12631295	Computational limitation	…….	…….	…….	15
…….	…….	…….	…….	123	1382	1458	12794010	Computational limitation	…….	…….	…….	16
…….	…….	…….	…….	128	1407	1491	12987762	Computational limitation	…….	…….	…….	17
…….	…….	…….	…….	134	1434	1523	13097069	Computational limitation	…….	…….	…….	18
…….	…….	…….	…….	143	1456	1559	13278743	Computational limitation	…….	…….	…….	19
…….	…….	…….	…….	153	1494	1581	13385529	Computational limitation	…….	…….	…….	20

The small differences between the metaheuristic and reference solutions indicate that NSGA-II generated close approximations for instances where exact comparison was possible. This finding provides a basis for using the algorithm on larger instances that cannot be solved exactly within acceptable computational time.

NSGA-II also solved large-scale instances containing up to 40 projects, 8 executing agents, and 4 uncertainty scenarios, demonstrating the applicability of the metaheuristic to problem sizes for which the exact method faces computational limitations.

5.3. Comparison of NSGA-II and MOPSO

After validating the ability of NSGA-II to approximate reference solutions, NSGA-II and MOPSO were compared on large-scale problems (Table 7). Because the problem is multi-objective, algorithm performance was not assessed using a single indicator. Instead, several criteria were used to examine nondominated-solution quality, Pareto-front diversity, and computational efficiency: MID, number of Pareto solutions, crowding distance, and computational time. The algorithms did not perform uniformly across all indicators. MOPSO achieved better MID values, indicating stronger performance under this convergence criterion.

Table 7. Comparison of NSGA-II and MOPSO based on performance indicators

MOPSO				**NSGA-II**				
Computational time	Crowding distance	MID	No. of Pareto points	Computational time	Crowding distance	MID	No. of Pareto points	Problem
11	62	0.79	10	10	70	0.81	10	1
21	69	0.78	15	18	35	0.82	10	2
29	63	0.78	8	24	95	0.81	7	3
34	82	0.79	13	30	64	0.83	16	4
39	58	0.8	16	36	87	0.84	10	5
47	35	0.81	13	43	88	0.85	12	6
56	53	0.8	10	53	52	0.85	8	7
66	52	0.81	16	62	53	0.86	10	8
74	65	0.82	11	71	38	0.87	11	9
82	64	0.82	15	78	37	0.86	7	10
88	94	0.83	8	85	87	0.87	12	11
95	46	0.83	5	90	37	0.88	8	12
104	80	0.84	4	99	72	0.88	5	13
105	101	0.85	4	104	93	0.89	7	14
117	102	0.86	11	114	97	0.90	11	15
124	76	0.87	4	123	70	0.90	8	16
133	92	0.87	5	128	85	0.91	8	17
138	94	0.88	7	134	86	0.92	10	18
144	54	0.89	8	143	44	0.93	9	19
155	88	0.90	7	153	82	0.94	10	20

In contrast, NSGA-II performed better in the number of Pareto solutions, crowding distance, and computational time and generated a more diverse set of nondominated solutions with better computational efficiency. These findings show that selecting an algorithm for a multi-objective problem should not be based solely on superiority in one metric. Although MOPSO's better MID is an advantage in terms of proximity to the ideal point, project portfolio selection and scheduling also require a sufficiently large and diverse set of nondominated alternatives so that decision makers can examine trade-offs. Considering the indicators jointly, NSGA-II provided more balanced overall performance and was selected for subsequent analyses. This choice does not imply that NSGA-II is superior under every criterion; rather, it reflects a joint assessment of nondominated-solution quality and diversity and computational efficiency.

5.4. Pareto-front analysis

To examine trade-offs among the model objectives, Pareto fronts generated from nondominated solutions were analyzed. With three objectives—maximizing economic value, minimizing environmental impacts, and maximizing resilience—it is generally impossible to attain the best value of all three simultaneously; improving one objective may alter performance in the others. Pareto fronts therefore provide a set of efficient solutions from which decision makers can choose according to their priorities (Figure 1, Figure 2 and Figure 3).

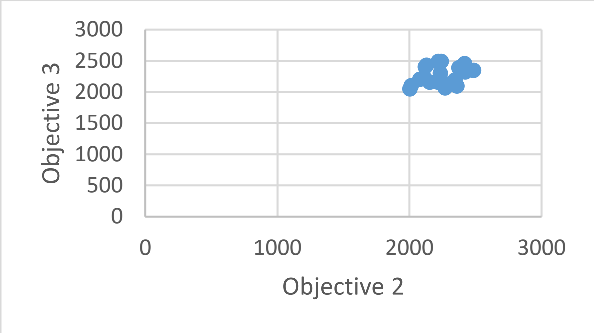

Figure 1. Pareto front of economic and environmental objectives under changes in execution duration

The economic–environmental Pareto front shows that changes in project execution duration affect the balance between these objectives (Figure 1). Solutions generating greater portfolio economic value are not necessarily associated with the lowest environmental impacts. Decision makers therefore face a set of nondominated alternatives with different levels of economic and environmental performance.

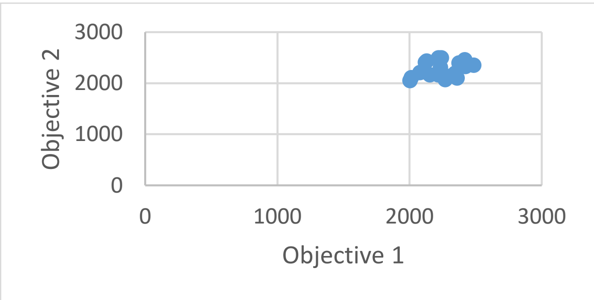

Figure 2. Pareto front of economic and resilience objectives under changes in execution duration

The economic–resilience Pareto front indicates that changes in project execution duration can affect the timing of economic benefits, resource allocation, and portfolio implementation conditions, thereby influencing resilience (Figure 2). A trade-off therefore exists between economic return and resilience, and the final choice depends on decision-maker priorities.

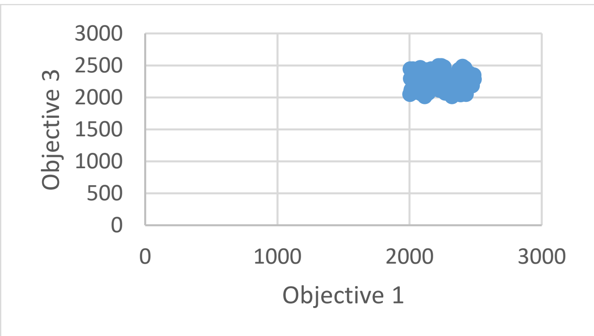

Figure 3. Pareto front of environmental and resilience objectives under changes in execution duration

The environmental–resilience Pareto front likewise shows that the model can generate nondominated solutions that balance lower environmental impacts against higher portfolio resilience (Figure 3). Changes in execution duration can affect both objectives through changes in resource-use patterns and implementation conditions. Achieving satisfactory performance therefore requires selecting a balanced solution from the Pareto alternatives. Overall, the Pareto-front analysis confirms trade-offs among economic, environmental, and resilience objectives. Rather than producing a single solution, the proposed model supplies a set of efficient alternatives and enables selection of a project portfolio consistent with organizational priorities.

5.5. Sensitivity analysis of economic parameters

To examine the stability of model behavior and assess the effects of economic parameters on portfolio decisions, sensitivity analyses were conducted for the discount rate, reinvestment rate, loan interest rate, income tax rate, and carbon tax rate. The results show that changes in financial and policy parameters can affect objective values and, in some cases, the composition of selected projects.
An increase in the discount rate reduced the present value of future cash flows and consequently lowered portfolio economic value. Within the investigated range, the economic value decreased by approximately 32.6%. This result indicates that projects whose benefits are realized mainly in later periods are more sensitive to changes in the discount rate (Figure 4).

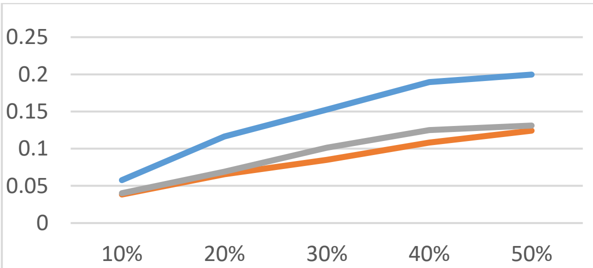

Figure 4. Effect of the discount rate on model objectives

In contrast, a higher reinvestment rate improved portfolio economic value; within the investigated range, net present value increased by approximately 86.9% (Figure 5).

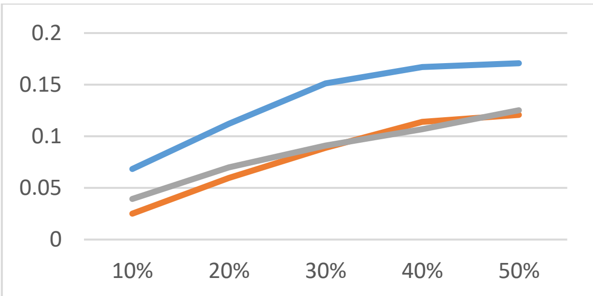

Figure 5. Effect of the reinvestment rate on model objectives

This result reflects the higher return obtained from reinvesting cash flows and the strengthening of financial resources available for continued project implementation. Changes in this parameter can also influence portfolio resilience because greater available financial resources increase flexibility in responding to changing implementation conditions.

The loan-interest-rate analysis showed that higher financing costs reduce both economic performance and portfolio resilience (Figure 6). As the loan interest rate increased from 0% to 50%, economic value decreased from 11,920,000 to 6,905,826 and the resilience index fell from 1,195 to 623. These changes demonstrate the sensitivity of project selection and scheduling decisions to financing costs.

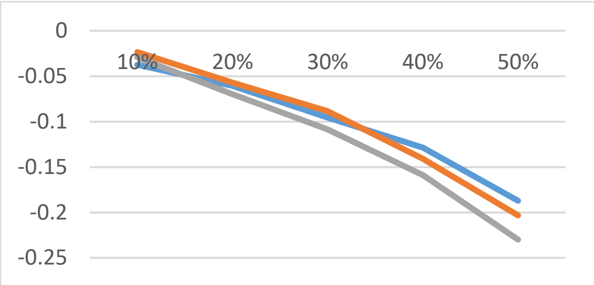

Figure 6. Effect of the loan interest rate on model objectives

Increasing the income tax rate produced a similar pattern. When the rate reached 50%, net present value decreased from 11,920,000 to 7,400,365 and the resilience index from 1,195 to 552 (Figure 7). At the same time, the environmental-impact index decreased from 1,276 to 636. This apparent reduction in environmental impacts mainly results from tighter financial resources, fewer executable projects, and changes in portfolio composition and should not be interpreted as a direct environmental improvement caused by higher income tax. The results indicate that tax policies can influence not only project profitability but also portfolio selection, prioritization, scheduling, and resilience capacity.

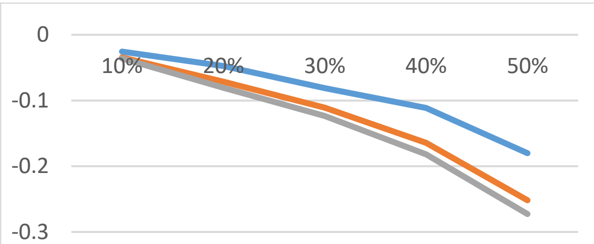

Figure 7. Effect of the income tax rate on model objectives

An increase in the carbon tax rate also had a substantial effect on model performance. As the rate increased from 0% to 50%, portfolio economic value decreased from 11,920,000 to 6,173,230 and the resilience index from 1,195 to 505, while the environmental objective changed from 1,276 to 1,857 (Figure 8). This finding indicates that carbon-emission cost policies can materially affect trade-offs among economic, environmental, and resilience objectives.

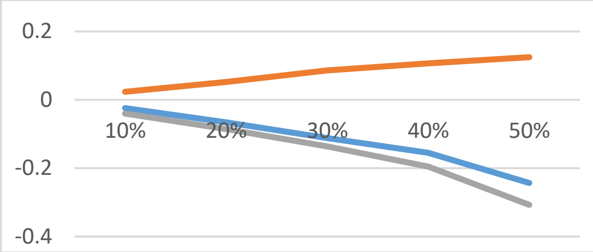

Figure 8. Effect of the carbon tax rate on model objectives

Overall, the sensitivity analysis shows that the proposed model responds meaningfully to changes in economic parameters and that changes in financial and policy conditions can affect not only economic value but also environmental performance, resilience, and the composition of selected projects. This feature enables the consequences of alternative economic and policy scenarios to be assessed before a final portfolio decision is made.

5.6. Uncertainty analysis of project execution duration

To examine the effect of time uncertainty on model performance, changes in project execution durations were analyzed under different scenarios (Figure 9, Figure 10, Figure 11). Because execution duration affects scheduling, cash flows, resource allocation, and overall portfolio performance, changes in this parameter can influence not only scheduling decisions but also the economic, environmental, and resilience objectives. The results show that changes in execution duration alter the economic objective across scenarios. Longer execution can delay cash flows and project benefits and thereby reduce portfolio economic value through the time value of money. Thus, changes in time parameters do more than shift implementation schedules; they can alter the financial performance of the entire portfolio. Execution-duration changes also affect the environmental-impact index because changes in project activity periods can alter the timing of environmental impacts and the selection and scheduling pattern of projects. The third objective is also affected: changes in execution time can alter project-allocation schedules, utilization of agent capacities, and economic and operational conditions, thereby changing the selected portfolio and its resulting resilience. Overall, the analysis shows that execution-duration uncertainty can simultaneously influence economic, environmental, and resilience performance. Differences among scenarios further demonstrate the importance of explicitly accounting for uncertainty in project portfolio selection and scheduling. The proposed fuzzy–stochastic structure therefore enables portfolio behavior to be examined under alternative conditions and solutions to be evaluated against both temporal and scenario-based changes (Table 8).

Table 8. Uncertainty analysis of project execution duration

Resilience			**Environmental impact index**			**Net present value of final wealth**			**Project execution duration**
Scenario 3 – agreement with the West	Scenario 2 – no sanctions	Scenario 1 – continuation of sanctions	Scenario 3 – agreement with the West	Scenario 2 – no sanctions	Scenario 1 – continuation of sanctions	Scenario 3 – agreement with the West	Scenario 2 – no sanctions	Scenario 1 – continuation of sanctions	
1365	1365	1195	1571	1418	1276	14715458	13334547	11920000	0%
1228	1238	1058	1391	1245	1103	14715285	12277964	10729330	10%
1036	1066	866	1210	1111	969	14715151	10604045	9015074	20%
933	925	763	1016	957	815	14714997	9171258	7660535	30%
793	788	623	886	791	649	14714831	8055224	6043746	40%
627	616	457	742	635	493	14714675	6435888	4840312	50%

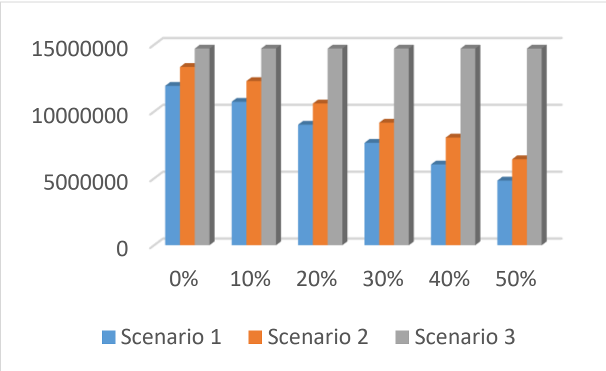

Figure 9. Uncertainty analysis of project execution duration for the first objective

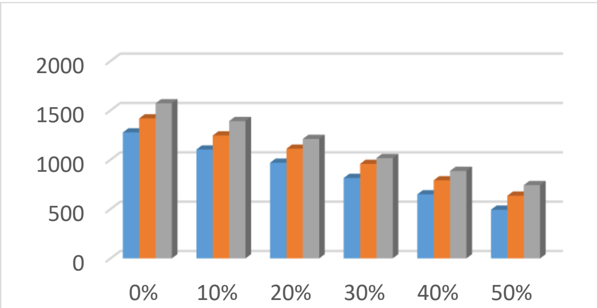

Figure 10. Environmental-impact index under increasing project execution duration across scenarios

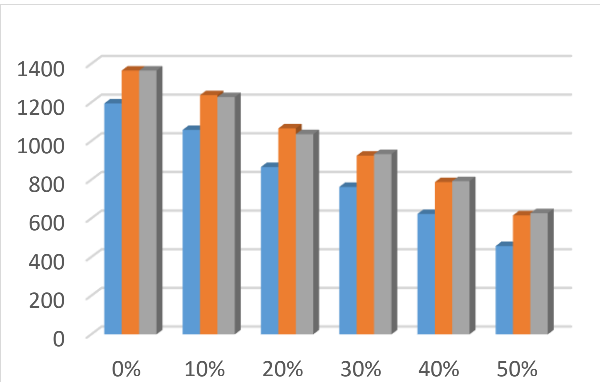

Figure 11. Uncertainty analysis of project execution duration

6. DISCUSSION

The findings support the value of integrating project selection, scheduling, and assignment decisions rather than treating them independently. This is consistent with integrated portfolio-scheduling studies such as Ranjbar et al. (2022) and Vega-Hidalgo et al. (2026), while the present model extends that line of work by simultaneously incorporating organizational executing agents and two distinct forms of uncertainty. The fuzzy representation of construction and execution durations complements earlier fuzzy portfolio models (Perez et al., 2018; Mohagheghi et al., 2016), whereas the scenario-based stochastic component is consistent with the need to represent changing future conditions (Tavana et al., 2020; Hu et al., 2026). The multi-agent structure is also related to decentralized and agent-based project-allocation approaches (Li et al., 2020; Fu & Zhou, 2021), but here agent differences are embedded directly in the joint portfolio optimization model. Finally, the Pareto analysis confirms that economic value, environmental impact, and resilience cannot generally be optimized simultaneously at their individual best values. This result is consistent with the growing emphasis on resilient and sustainability-oriented portfolio decisions (Mahmoudi et al., 2022; Gholami et al., 2025).

6.1. Managerial and practical implications

The proposed model can serve as a decision-support framework for project portfolio managers in project-oriented organizations. One of its main applications is the ability to make integrated decisions on project selection, implementation timing, and assignment of selected projects to executing agents. Rather than examining these decisions independently, decision makers can evaluate their interactions at the portfolio level. The multi-agent structure allows differences in executing-agent capacities and characteristics to be incorporated, enabling managers to determine not only which projects should be implemented but also how they should be allocated among units or agents subject to operational constraints.

This is particularly useful in organizations where project implementation is distributed among multiple units and can support better use of available capacity and improved coordination of portfolio decisions. Moreover, providing a set of nondominated solutions rather than a single solution enables managers to examine trade-offs among economic value, environmental impacts, and resilience and select a solution consistent with organizational strategic priorities. Sensitivity analyses and uncertainty scenarios also allow financial, policy, and temporal changes to be assessed before implementation. Managers can therefore examine the effects of changes in the discount rate, financing costs, related taxes, and project execution durations on portfolio composition and performance and revise decisions as conditions change. Overall, the model provides an analytical decision-support tool for organizations managing multiple projects, particularly in complex, multi-unit, and uncertain environments.

6.2. Research limitations and directions for future research

Despite its capabilities, the proposed model has several limitations. First, fuzzy uncertainty is focused mainly on project construction and execution times, although other parameters such as investment costs, operating costs, project revenues, and resource capacities may also be uncertain in practice. Second, the model considers economic and environmental dimensions together with resilience, while the social dimension of sustainability lies outside the scope of the study. In addition, computational complexity increases with problem size, limiting the use of exact methods for large-scale instances. Future research may extend the fuzzy–stochastic model by incorporating uncertainty in additional parameters, including costs, revenues, and resource capacities. Adding the social dimension alongside economic and environmental dimensions could also provide a more comprehensive framework for sustainable and resilient project portfolio selection and scheduling. From a solution-method perspective, advanced multi-objective algorithms such as NSGA-III and MOEA/D may be investigated and compared, particularly for problems with more objectives and larger dimensions.

7. CONCLUSION

This study proposed a multi-objective fuzzy-stochastic optimization framework for the integrated selection, scheduling, and assignment of project portfolios in a multi-agent organizational structure. The model combines fuzzy temporal uncertainty with stochastic future scenarios and simultaneously considers economic value, environmental impacts, and economic/environmental resilience. Exact ε-Constraint solutions obtained with BARON established reference results for small instances, while NSGA-II and MOPSO enabled larger instances to be addressed. NSGA-II showed the more balanced overall performance when convergence, nondominated-solution diversity, and computational efficiency were considered together, although MOPSO performed better in MID. Sensitivity and uncertainty analyses further showed that financial parameters and execution-time uncertainty can materially change portfolio performance and composition. The main contribution is therefore an integrated decision-support framework that allows managers to examine trade-offs among three conflicting objectives while accounting for differences among executing units and multiple sources of uncertainty.

Conflict of interest
All authors declare that they have no conflicts of interest

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