Joint Optimization of Robust Portfolio Selection and Risk Response in R&D Project Management

Chao Fang, *Member*, *IEEE*, Si Li, and Yue Shi

***Abstract*—Selecting appropriate research and development (R&D) projects under budget constraints is a critical yet challenging task for enterprises. During development, these projects are inevitably exposed to risky events, which may lead to performance loss, turning the optimal "here-and-now" selection decisions into suboptimal operational outcomes. We propose a joint optimization framework for project portfolio selection and risk response in uncertain environments, explicitly accounting for their interdependencies and budget trade-offs. A two-stage robust optimization (TSRO) model is developed to protect against worst-case scenarios. A key feature is a decision-dependent budgeted uncertainty set capturing the endogenous dependence of performance loss on portfolio selection decisions, together with a non-linear function characterizing the effects of risk response. We devise a tailored solution method to transform the original complex model into a single-level mixed-integer linear program solvable with off-the-shelf solvers. Extensive numerical experiments are conducted based on a 50-project R&D case. The proposed TSRO model consistently outperforms benchmark methods, particularly under worst-case scenarios. Sensitivity analyses further reveal that optimal solutions are highly responsive to the decay rate (representing the risk response effectiveness) while remaining relatively robust to the residual rate of failed projects' values. Moreover, the results suggest that under tight budgets, managers should prioritize a smaller set of projects with intensive risk response, whereas with generous budgets, a broader portfolio becomes optimal. Overall, this study offers an integrated framework that not only enhances decision quality in project portfolio management but also provides actionable insights for balancing selection and risk response.**

***Index Terms*—project portfolio selection, risk response, joint optimization, two-stage robust optimization, R&D management**

***Managerial relevance statement*—This study provides managers with a practical framework to improve decision-making in R&D portfolio management under uncertainty. Traditional approaches often optimize project selection and risk response separately, neglecting their interdependence and leading to suboptimal results when risky events occur. Our TSRO model addresses this gap by jointly optimizing selection and risk response, balancing budget allocation between initiating projects and mitigating risks. For managers, the key implication is that resource allocation strategies should adapt to budget conditions: when budgets are tight, prioritizing fewer projects with stronger risk response is more effective, whereas larger budgets allow for a broader portfolio. Importantly, TSRO not only protects against worst-case outcomes but also encourages proactive investment in high-risk, high-return projects with targeted risk responses—opportunities that might be overlooked by separate optimization methods. Sensitivity analyses further show that optimal solutions are strongly shaped by risk response effectiveness and available budget, but remain relatively stable with respect to the residual value of failed projects. These findings equip managers with actionable insights to design resilient and high-performing portfolios, and provide a flexible tool adaptable across industries where project uncertainty is prevalent.**

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I. INTRODUCTION

RESEARCH and development (R&D) projects drive economic growth by spurring innovation, invention, and progress [1]. However, budget constraints prevent enterprises from launching all candidate projects simultaneously. Extensive empirical and numerical evidence highlight the significance of selecting the "right" projects to maximize returns, sustain competitive advantage, and pursue strategic objectives [2-4]. The R&D project portfolio selection aims to identify a subset of candidate projects that best serve organizational targets under budget constraints [5]. However, the selected portfolios frequently perform below expectations in practice [4, 6, 7]. The Biotechnology Innovation Organization reported that the probability of successfully commercializing a new drug falls below 10% [8]. Such unforeseen performance losses typically stem from risky events like emerging technologies or regulatory reforms [9]. Rapid societal evolution amplifies these uncertainties, making them increasingly difficult to anticipate [10]. Effective risk response can mitigate the negative impacts of risky events during project development [11]. Decision makers (DMs) allocate risk response budget to implement resilience strategies, mitigating performance losses [12].

In practice, DMs select a project portfolio in the planning stage based on the estimated values of each candidate. In the operational stage, risk response strategies are applied to the selected projects to mitigate the adverse effects of risky events. Recognizing the interdependence between project portfolio selection and risk response is critical. First, risk response strategies can only be applied to the selected projects. Second, risk response modifies project risk profiles, directly influencing portfolio selection criteria. Third, budget allocation requires strategic tradeoffs: portfolio expansion constrains risk response budget, while excessive risk response investment limits high-potential project initiation. However, most existing studies address portfolio selection and risk response separately, potentially resulting in suboptimal performance. Therefore, a joint optimization framework for these two domains becomes vital to reconcile their interdependence.

The project portfolio selection problem has been extensively studied. Early works formulate it as an integer programming problem with binary selection decisions [13, 14]. Subsequent research expands to multi-criteria integer programming [15, 16] and multi-objective integer programming [17, 18] to address diverse organizational needs. However, these works typically treat portfolio selection as a deterministic optimization problem, ignoring the uncertainty of R&D projects [19], such as market volatility, technical bottlenecks, and unforeseen disruptions [20].

The uncertainty in project development has attracted considerable interest in the literature. Bai et al. [21] optimize project portfolios by considering the interdependencies in project failure risks. Liesiö and Salo [22] propose a scenario-based model to characterize different risk levels, aiding DMs in project selection with incomplete information. The real options approach is used to value projects under uncertainty by modeling investment opportunities as a portfolio of real options, such as deferral, expansion, and abandonment options [23-25]. Project value uncertainties in this approach are typically modeled using stochastic processes [26], e.g., geometric Brownian motion [24]. Stochastic programming (SP) is a popular method to address uncertainty in project portfolio selection [27, 28]. For example, Salo et al. [29] combine multi-stage stochastic programming with conditional value-at-risk to deal with endogenous uncertainty in the project portfolio. Song et al. [30] propose a stochastic multi-attribute acceptability analysis to consider the project portfolio selection and scheduling problem. Ahmadi and Ghasemi [31] focus on the financial assets, and employ stochastic approaches and chance constraint programming to capture the uncertain return rate, balancing return and risk in a multi-period portfolio optimization model. It should be noted that the approaches mentioned above require exact probability distributions, stochastic processes, or predefined scenario sets with assigned probabilities to characterize uncertain parameters. However, given the innovative nature, inherent risks, and information scarcity of R&D projects, DMs often lack sufficient data to obtain such information effectively. Robust optimization (RO) is a distribution-free approach for modeling uncertainty that enables managers to adjust their risk tolerance levels [32]. RO seeks optimal solutions under worst-case scenarios. This characteristic makes RO more suitable for R&D project management with limited information than distribution-based approaches (e.g., SP) in such contexts [17]. A RO model incorporating the Tchebycheff procedure is proposed to account for uncertainty and facilitate DMs involvement in balancing multiple objectives [33]. RO combined with machine learning is a new attempt and has been successfully applied in the Korean BK21 plan for selecting innovative R&D projects [34]. Shen et al. [35] consider uncertain implementation capability and develop a bi-objective RO model to minimize costs and maximize benefits. However, existing RO studies on project portfolio selection primarily focus on risks while overlooking the endogenous dependence between risks and selection decisions. Moreover, they fail to incorporate flexibility in risk response, likely leading to overly conservative solutions.

The goal of risk response is to mitigate the adverse effects of risky events on the selected projects [12]. Numerous existing studies focus on exploring optimal risk response strategies for predetermined projects, aiming to either maximize effectiveness with the fixed budget [36, 37] or minimize implementation costs [38, 39]. Indeed, determining risk response budgets before project implementation is critical for ensuring response effectiveness. Common practice allocates a fixed share (e.g., 10%, 20%, or 30%) of the total budget to risk response, commonly based on managerial experience and risk preference. However, such allocations sometimes prove insufficient to counteract the adverse impacts of risky events, potentially causing project disruptions. Conversely, overly conservative DMs may allocate excessive budget to risk response, diverting resources from high-potential project initiation and causing inefficient resource allocation. Dillon et al. [40] develop a decision-support framework to optimize risk response budget for the given projects, proposing an exponential function to characterize the risk response effects with fixed initial risk estimates. They further extend this to a multi-stage model in [41]. However, these models only focus on the fixed projects with estimated risks, overlooking interactions between project selection and risk response, thereby hindering integrated budget allocation. Moreover, risk estimation may not be accurate in practice, resulting in suboptimality.

Existing methods primarily enable separate optimization of either project portfolio selection or risk response strategies. This mode of optimization inherently fails to achieve global optimality and efficient budget allocation through its disregard for the critical interdependence between these two decisions. In addition, obtaining information on the distribution of project uncertainty is difficult in practice, and inaccurate estimation would introduce suboptimal performance. Research on joint optimization of robust portfolio selection and risk response in uncertain environments remains scarce.

This paper develops a joint optimization framework for robust R&D project portfolio selection and risk response under risk environments with limited budgets. In this framework, we formulate a two-stage robust optimization (TSRO) model to hedge against worst-case performance loss: the first stage selects projects while reserving risk response budget, and the second stage allocates this reserved budget to mitigate the worst-case performance loss. TSRO features a decision-dependent budgeted uncertainty set (DDBU) to cover all possible realizations of uncertain performance loss. The risk response effect is characterized by an exponential function and incorporated into TSRO's objective function. We apply the piecewise approximation technique to linearize this exponential function, and leverage the minmax and duality theorems to reformulate the resulting approximated model into a single-level mixed-integer linear program (MILP) solvable with off-the-shelf solvers. The proposed model is validated through a 50-project R&D case and sensitivity analysis.

The main contributions of this study are threefold. First, we propose a joint optimization framework for project portfolio selection and risk response that explicitly reconciles their complex interdependence, which separate optimization methods fail to address. Second, we introduce a TSRO model that alleviates the practical challenge of lacking distribution information on R&D project uncertainty. The model integrates a DDBU capturing the endogenous dependence of uncertainty on selection decisions with a non-linear risk response function, resulting in a challenging structure. To address this, we design a tailored solution method that reformulates the problem into a tractable MILP suitable for practical-scale problems. Third, we demonstrate the model's performance advantage through a 50-project R&D case study, with sensitivity analyses validating its robustness and adaptability across diverse operational contexts, thereby underscoring its practical utility.

The remainder of the paper is organized as follows. Section II introduces the problem statement and a TSRO model that jointly considers the project selection and risk response problem. In Section III, we employ the piecewise linear approximation and reformulation techniques to transform TSRO to a solvable single-level MILP problem. A 50-project R&D case study is provided to illustrate how to use the proposed model in Section IV. Section V discusses the results and offers managerial implications. We conclude the study and suggest potential research directions in Section VI.

II. PROBLEM STATEMENT AND MODEL FORMULATIONS

The problem of interest is a two-stage decision-making for R&D project portfolio selection and risk response with the total budget B. Let $\mathcal{N}$ denote the set of all candidate R&D projects up to $|\mathcal{N}|$. The first stage considers a portfolio selection problem where DMs select projects from all candidates to initiate. Here, y_i is a binary decision variable in the first stage, where $y_i = 1$ means project i is selected and $y_i = 0$, otherwise. The fixed basic cost c_i covers all development costs except risk response investment.

During development, ongoing projects may experience uncertain performance losses due to risky events [4, 9, 22]. We introduce a normalized metric $\mathbf{p} \in [0,1]^{|\mathcal{N}|}$ to measure the uncertain performance losses for all projects. A higher value of p_i reflects a larger negative impact on the performance of project i. Specifically, a complete operational failure (i.e., non-performance) of project i occurs at $p_i = 1$, while a target-aligned performance (i.e., anticipated performance benchmark) is achieved when $p_i = 0$. We model the uncertain performance loss $\mathbf{p}$ within a decision-dependent budgeted uncertainty set $\mathcal{P}(\boldsymbol{y})$, which is given by

$$\mathcal{P}(\boldsymbol{y}) = \left\{ \mathbf{p} \in [0,1]^{|\mathcal{N}|} \middle| \begin{array}{c} p_i = p_i^M + \delta_i p_i^D, \\ |\delta_i| \le y_i, \\ \sum_{i\in\mathcal{N}} |\delta_i| \le \Gamma \end{array} \right\}. \quad (1)$$

The two parameters p_i^M and p_i^D in (1) respectively denote the most likely value of the performance loss p_i and the largest deviation from p_i^M, which are the most easily available information of uncertainty in practice [42]. Note that p_i^M and p_i^D can be obtained through historical data, structured expert judgment, or targeted pilot experiment results. The auxiliary variable $\delta_i \in [-1,1]$ measures the normalized deviation of p_i from its most likely value p_i^M, which is denoted by $\delta_i = \frac{p_i - p_i^M}{p_i^D}$. A larger value of $|\delta_i|$ indicates a larger deviation of the performance loss for project i. The constraint $|\delta_i| \le y_i$ makes the uncertainty rely on the binary decision $y_i \in \{0,1\}$ in the first stage. If $y_i = 1$, indicating project i is selected in the portfolio, then the performance loss of project i has a chance to be deviated from p_i^M; otherwise (i.e., $y_i = 0$), δ_i is enforced to be zero. For example, in Roche's Alzheimer pipeline, when an investigational drug named gantenerumab was advanced to Phase III trials (y_i=1), unforeseen target-mechanism failure led to a performance loss deviation ($\delta_i > 0$), evidencing 6-8% efficacy lower than expectation [1]. Conversely, abandoning another drug named crenezumab (y_j=0) prevented further performance deviation ($\delta_j = 0$)[2]. We bound the sum of $|\delta_i|$ for all projects using a budget Γ, which describes the risk tolerance of DMs [32]. A larger value of Γ allows more potential deviations in $\mathbf{p}$, indicating that DMs are more reluctant to take risks. When $\Gamma = 0$, the uncertainty set collapses to a single point $\mathbf{p} = (p_i^M)_{i\in\mathcal{N}}$. It is important to note that $\mathcal{P}(\boldsymbol{y})$ is equivalent to the decision-independent budgeted uncertainty set [32] if $\mathbf{y} = \mathbf{1}$.

In the second stage, DMs are tasked with allocating risk response budget $\mathbf{x}$ for the selected projects to mitigate performance loss [9]. Following [41, 43, 44], we assume that risk response investment exponentially reduces performance loss, formulated as

$$\mathbf{p}'(\mathbf{p},\mathbf{x}) = \mathbf{p}e^{-\sigma\mathbf{x}}, \quad (2)$$

where $\mathbf{p}'(\mathbf{p},\mathbf{x})$ represents the residual performance loss after risk response, and $\sigma \ge 0$ is the decay rate, reflecting the risk response effectiveness. Under a zero risk response investment ($x_i = 0$), $p_i' = p_i$. As x_i approaches infinity, p_i' converges to zero.

The return of project i depends on its residual performance loss p_i', expressed as $r_i - (r_i + l_i)p_i'$ [25], where r_i represents the maximum attainable return with anticipated performance (p_i' =0), while l_i quantifies the economic loss from complete operational failure ($p_i' = 1$). The loss $l_i = (1-\varphi)c_i$ incorporates the residual rate φ, which captures residual value derived from failed projects through reusable resources [45].

To consider the worst-case scenario within the DDBU $\mathcal{P}(\boldsymbol{y})$, a TSRO model is introduced, addressing both project portfolio selection and risk response problems, as detailed below:

[TSRO]

$$\max_{\mathbf{y}} \min_{\mathbf{p}\in\mathcal{P}(\boldsymbol{y})} \max_{\mathbf{x}} \sum_{i\in\mathcal{N}} [r_i - (r_i + l_i)p_i'(p_i, x_i)]y_i \quad (3)$$

[1] https://www.fiercebiotech.com/biotech/roches-anti-amyloid-antibody-gantenerumab-fails-phase-3-alzheimers-trials

[2] https://www.alzforum.org/therapeutics/crenezumab

$$\text{subject to } \sum_{i\in\mathcal{N}} c_i y_i + \sum_{i\in\mathcal{N}} x_i \le B, \quad (4)$$

$$x_i \le M y_i \quad \forall i \in \mathcal{N}, \quad (5)$$

$$y_i \in \{0,1\} \quad \forall i \in \mathcal{N}, \quad (6)$$

$$x_i \ge 0 \quad \forall i \in \mathcal{N}. \quad (7)$$

The objective function (3) represents the portfolio returns under the worst-case performance loss. Constraint (4) caps the total cost (including the basic cost and the risk response investment) at the preset budget B. Constraint (5) permits the risk response investment in project i only if it is selected, with M representing a sufficiently large number. TSRO enables joint optimization of project portfolio selection and risk response for robust R&D project management by protecting against the worst-case scenario.

III. SOLUTION METHOD

The TSRO model cannot be directly solved using prevailing decomposition-based algorithms (e.g., Benders decomposition, column-and-constraint generation) [42, 46, 47] due to the exponential risk response function, and the compounded interactions among decision-dependent uncertainty, first-stage decision, and second-stage decision on the objective function. Our approach first approximates the exponential risk response function via piecewise linearization, and then reformulates the resulting DDBU-based model as a solvable single-level MILP. This reformulation enables the TSRO to be efficiently solved with off-the-shelf solvers, thereby facilitating large-scale applications while alleviating computational burden.

A. Piecewise Linear Approximation

We first linearize the exponential term $e^{-\sigma x_i}$ in the risk response function (2) via the piecewise linear approximation, which is a common practice in the literature [48-50]. For $x_i \ge 0$, $e^{-\sigma x_i}$ is approximated as follows:

$$1 + \gamma_{i,1} x_i - \sum_{k=1}^{|\mathcal{K}|-1} (\gamma_{i,k} - \gamma_{i,k+1}) z_{i,k} \quad \forall i \in \mathcal{N}, \quad (8)$$

$$x_i - z_{i,k} \le \bar{x}_{i,k} \quad \forall i \in \mathcal{N}, k \in \mathcal{K}, \quad (9)$$

$$z_{i,k} \ge 0 \quad \forall i \in \mathcal{N}, k \in \mathcal{K}, \quad (10)$$

where $\mathcal{K} = \{1, \ldots, |\mathcal{K}|\}$ is the set of sampling segments, $\bar{x}_{i,k}$ is the sampling points, and $\gamma_{i,k} = \frac{e^{-\sigma \bar{x}_{i,k}} - e^{-\sigma \bar{x}_{i,k-1}}}{\bar{x}_{i,k} - \bar{x}_{i,k-1}}$ denotes the slope between the two points $(\bar{x}_{i,k}, e^{-\sigma \bar{x}_{i,k}})$ and $(\bar{x}_{i,k-1}, e^{-\sigma \bar{x}_{i,k-1}})$. The approximated form of $e^{-\sigma x_i}$ is given in (8). Constraints (9) and (10) ensure that the auxiliary variable $z_{i,k}$ is the excess risk response investment allocated to project i over the breakpoint $\bar{x}_{i,k}$. Fig. 1 illustrates an example with two breakpoints. It is intuitive that an increased value of $|\mathcal{K}|$ corresponds to a more accurate approximation of $e^{-\sigma x_i}$ [51]. Appendix A proves that the approximation error is $O\left(\frac{1}{|\mathcal{K}|^2}\right)$, and converge to 0 as $|\mathcal{K}| \to \infty$.

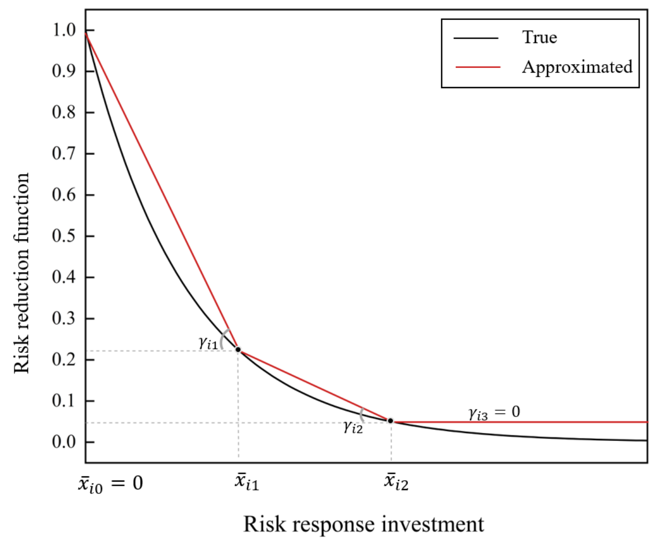

Fig. 1. Illustration of $e^{-\sigma x_i}$ approximation with two breakpoints

B. Reformulation of TSRO-PL with DDBU

Though the computational complexity of the exponential term is solved, the objective function (3) is still non-linear due to the product of the first-stage selection decision y_i and residual performance loss $p_i'(p_i, x_i)$. Combining the approximated formulation and analyzing the relationship between the decision variables, TSRO using the piecewise linear approximation technique (TSRO-PL) is given by:

[TSRO-PL]

$$\max_{\mathbf{y}} \sum_{i\in\mathcal{N}} r_i y_i + \min_{\mathbf{p}\in\mathcal{P}(\mathbf{y})} \max_{\mathbf{x},\mathbf{z}} \sum_{i\in\mathcal{N}} -(r_i + l_i) p_i \Big[y_i + \gamma_{i,1} x_i - \sum_{k=1}^{|\mathcal{K}|-1} (\gamma_{i,k} - \gamma_{i,k+1}) z_{i,k} \Big] \quad (11)$$

s.t. (4)- (7), (9), (10).

We reformulate TSRO-PL with DDBU as a single-level MILP using both the minmax theorem [52] and the duality theorem, and present the formal statement in Proposition 1. Based on the minmax theorem [52], the minmax operators in the second-stage problem of TSRO-PL can be switched. The innermost minimization problem can be dualized into a maximization problem, resulting in a single-level MILP formulation solvable efficiently by state-of-the-art solvers, e.g., Gurobi®.

Proposition 1. TSRO-PL with DDBU defined in (1) is equivalent to the following single-level optimization problem:

$$\max_{\mathbf{y},\mathbf{x},\mathbf{z},\boldsymbol{\lambda}} \sum_{i\in\mathcal{N}} r_i y_i + p_i^M (r_i + l_i) \Big[-y_i - \gamma_{i,1} x_i + \sum_{k=1}^{|\mathcal{K}|-1} (\gamma_{i,k} - \gamma_{i,k+1}) z_{i,k} \Big] - \lambda_i^1 y_i - \lambda^2 \Gamma \quad (12)$$

$$\text{s.t. } \lambda_i^1 + \lambda^2 \le p_i^D (r_i + l_i) \Big[-y_i - \gamma_{i,1} x_i + \sum_{k=1}^{|\mathcal{K}|-1} (\gamma_{i,k} - \gamma_{i,k+1}) z_{i,k} \Big] \quad \forall i \in \mathcal{N}, \quad (13)$$

$$\boldsymbol{\lambda} \ge 0, \quad (14)$$

(4)-(7), (9), (10),

where λ_i^1, λ^2 denote the dual variables of the constraints in uncertainty set (1). The proof is given in Appendix B.

TABLE I
THE CASE STUDY DATA (ADAPTED FROM [53])

Project ID i	Basic cost c_i	Maximum return r_i	Estimated performance loss $\hat{p}_i$	Project ID i	Basic cost c_i	Maximum return r_i	Estimated performance loss $\hat{p}_i$
1	83	94	0.4	26	97	103	0.5
2	71	136	0.2	27	73	124	0.4
3	77	121	0.5	28	99	136	0.5
4	90	158	0.4	29	87	120	0.2
5	99	144	0.2	30	88	100	0.5
6	75	102	0.5	31	79	119	0.1
7	97	118	0.3	32	88	95	0.4
8	80	112	0.3	33	87	122	0.2
9	94	127	0.2	34	81	157	0.2
10	73	110	0.2	35	75	117	0.4
11	74	119	0.3	36	73	135	0.5
12	85	111	0.3	37	74	99	0.5
13	88	123	0.2	38	99	153	0.3
14	73	101	0.5	39	75	121	0.4
15	82	102	0.5	40	72	98	0.4
16	74	108	0.3	41	81	143	0.3
17	85	109	0.4	42	99	112	0.3
18	79	112	0.4	43	94	127	0.4
19	77	135	0.2	44	88	123	0.3
20	75	174	0.5	45	75	130	0.4
21	95	113	0.3	46	87	122	0.4
22	77	113	0.2	47	87	120	0.4
23	82	94	0.3	48	77	113	0.4
24	72	97	0.3	49	73	110	0.4
25	80	164	0.4	50	79	119	0.2

Note: The basic cost and return are in US$ million.

IV. CASE STUDY

Using data from a research laboratory as referenced in [53], we illustrate the application of the proposed model. This case involves 50 large-scale and long-term R&D projects within the same frontier technological domain, composed of relatively higher-risk, higher-return basic research projects alongside lower-risk, lower-return applied research projects [53]. The objective is to optimize portfolio returns by selecting and developing projects under budget constraints. All numerical experiments in this study are coded in Python using Gurobi 12.0.0 for solving, and executed on a PC with 2.90 GHz Intel i5-10400F CPU and 16GB RAM, operating under Windows 11.

A. Dataset and Parameter Settings

Table I shows a subset of project properties used in our numerical experiments, including basic cost, return, and estimated performance loss. We set the decay rate $\sigma = 0.05$, the residual rate $\varphi = 0.4$, and the total budget $B = 0.4 \sum c_i$. Setting the total budget as a proportion of the aggregate costs of the 50 projects mitigates the influence of inter-industry cost magnitude differences, thereby enhancing the cross-domain generalizability. Alternative values of σ, φ, and B are examined in Section V. For the piecewise linear approximation procedure, we set $|\mathcal{K}|$=100 segments with 101 breakpoints spaced 1 unit apart. We conduct preliminary experiments to test different values of $|\mathcal{K}|$, as shown in Appendix C. The results indicate that $|\mathcal{K}|$=100 optimally balances approximation precision and computational efficiency.

B. Experiment Design

To demonstrate the utility of joint optimization for robust R&D project management, we compare the proposed TSRO model with two benchmarks. The first is a separate deterministic optimization model (SDO) that optimizes project portfolio selection and risk response separately, formulated in Appendix D. In SDO, DMs need to select projects based on the estimated values within budget $(1-\theta)B$, where θ denotes the subjectively predetermined share of the total budget B allocated to risk response. This benchmark highlights the core distinction between joint and separate optimization. The second benchmark is a two–stage stochastic programming (TSSP) model shown in Appendix E. In TSSP, DMs must assume a probability distribution for the uncertain performance loss $\mathbf{p}$ to maximize expected portfolio returns. While both TSSP and TSRO employ the joint optimization framework, they differ in the approaches to model uncertainty. To ensure tractability, SDO and TSSP approximate the exponential risk response function using the piecewise linear approximation method, as detailed in (8)-(10). We conduct out-of-sample experiments to simulate real-world values of performance loss and evaluate the proposed model's validity. Our experimental procedure follows the steps established in [42], enabling independent verification and reproducibility.

Step 1. Define the true distribution of uncertain performance loss. Suppose that the uncertain performance loss p_i follows a Beta distribution $Beta(\alpha_i, \beta_i)$ [54]. However,

TABLE II
THE OUT-OF-SAMPLE RESULTS OF TSRO, TSSP, AND SDO

Model	Parameter	Portfolio returns		Portfolio size	Risk response budget (%)	Response efficacy	
		Average	5%			Average	5%
TSRO	Γ=5	1973.26*	1916.51	16	21.92%	72.92%	70.70%
	Γ=10	1969.69	1917.55*	16	23.51%	74.91%	72.88%
	Γ=15	1941.50	1904.67	15	28.20%	82.07%	80.53%
TSSP		1965.41	1886.34	17	16.57%	62.20%	59.47%
SDO	θ=0%	1594.50	1425.52	20	0.30%	2.57%	2.01%
	θ=10%	1855.73	1755.22	18	10.29%	44.87%	41.87%
	θ=20%	1889.56#	1834.15#	16	20.22%	69.89%	67.51%
	θ=30%	1715.46	1691.79	14	30.27%	85.27%*	84.10%*

Note: * represents the best results of all models, # represents the best result of SDO model among all values of θ.

in practice, DMs lack knowledge of the true distribution. The only available information of the uncertain performance loss is the most likely value and the largest deviation. Thus, to estimate these parameters, we draw fifty independent samples from $Beta(\alpha_i, \beta_i)$ for each project i. We let the most likely value p_i^M be the sample average, and the largest deviation p_i^D be the maximum observed deviation among these samples. In this experiment, we set $\alpha_i = 10\hat{p}_i, \beta_i = 10 - 10\hat{p}_i$, enforcing $\mathbb{E}(p_i) = \hat{p}_i$ with variance $\frac{\hat{p}_i(1-\hat{p}_i)}{11}$. In Section V, we change the value of α_i and β_i to test model robustness under varied uncertainty scenarios.

Step 2. Obtain the optimal first-stage solutions. We examine three risk tolerance levels of DMs by setting the uncertainty budget $\Gamma \in \{5, 10, 15\}$ in TSRO. For SDO, four values of the reservation proportion $\theta \in \{0\%, 10\%, 20\%, 30\%\}$ are considered. For TSSP, we generate 50 scenarios, each representing an independent possible realization of p_i sampled from the triangular distribution $T(p_i^L, p_i^M, p_i^U)$ [42, 55, 56], where $p_i^L = \max\{0, p_i^M - p_i^D\}$ and $p_i^U = \min\{1, p_i^M + p_i^D\}$. This triangular distribution is adopted under the premise that DMs can estimate both the most likely value and the largest deviation, which suffice to parametrize the distribution. TSSP is solved by using the simple average approximation (SAA) method [57]. We solve the TSRO, SDO, and TSSP to obtain their optimal first-stage solutions, i.e., the portfolio selection decisions $\mathbf{y}^*$.

Step 3. Generate out-of-sample scenarios and solve the second-stage problem. We generate 10,000 realizations of p_i from $Beta(\alpha_i, \beta_i)$ for each project $i \in \mathcal{N}$. Given the first-stage solutions $\mathbf{y}^*$ obtained in **Step 2** and each performance loss realization, the second-stage problem transforms into a deterministic problem. We then solve this second-stage problem of three models to derive the optimal risk response decisions $\mathbf{x}^*$.

Step 4. Determine out-of-sample performance measures. For all three models, we calculate both the average and 5% percentile of the portfolio returns and the response efficacy among the 10,000 realizations generated in **Step 3**. Portfolio returns directly equal the objective value in TSRO and TSSP, whereas SDO requires summing stage 1 and stage 2 objective values. The response efficacy is defined as $\frac{\sum(r_i+l_i)[p_i - p_i'(p_i, x_i^*)]y_i^*}{\sum(r_i+l_i)p_i y_i^*}$. The averages and 5% percentiles for portfolio returns and response efficacy serve as estimators for their expected values and 5th percentiles under the true performance loss distribution.

C. Results and Analyses

Table II presents both the average and 5% percentile out-of-sample results for three models, where portfolio size signifies the number of the selected projects and risk response budget (%) represents its share of the total budget. Both TSRO and TSSP consistently outperform SDO by delivering higher portfolio returns across all cases. This finding underscores the advantage of the joint optimization for portfolio selection and risk response in R&D project management. Furthermore, under moderate risk tolerance (Γ=5 and 10), TSRO achieves higher portfolio returns than TSSP in both average and 5% percentile metrics. Under high risk tolerance (Γ=15), TSRO yields lower average returns but higher 5% percentile returns than TSSP, indicating its conservative advantage in the worst-case scenario. Note that TSRO considers the worst-case returns among all possible realizations in DDBU, and the 5% percentile closely aligns with the worst-case outcomes. These findings confirm TSRO's superior robustness against performance loss uncertainty relative to TSSP, particularly in the worst case. DMs can tune Γ via cross-validation with better out-of-sample performance for practical implementation [58]. The relatively small gap between TSRO and TSSP results from two key reasons: their shared joint optimization framework and the triangular distribution's close approximation of the Beta distribution, which enhances the predictive accuracy of TSSP.

Compared with other models, except for SDO-θ=30%, TSRO favors selecting fewer projects while allocating a larger share of the budget to risk response. Counterintuitively, heightened risk aversion (higher Γ) reduces portfolio size, contrasting with the classical investment diversification principle [59]. This strategy yields higher response efficacy. In contrast, SDO-θ=0% which totally neglects risk response during portfolio selection, shows minimal response efficacy, revealing the severe limitation of the separate optimization in risk management. It is worth noting that although reserving a similar proportion of the budget for risk response (approximately 20%), TSRO substantially outperforms SDO-θ=20% in both portfolio returns and response efficacy. Thus, the joint optimization demonstrates clear superiority over separate optimization, even under comparable risk response budgets.

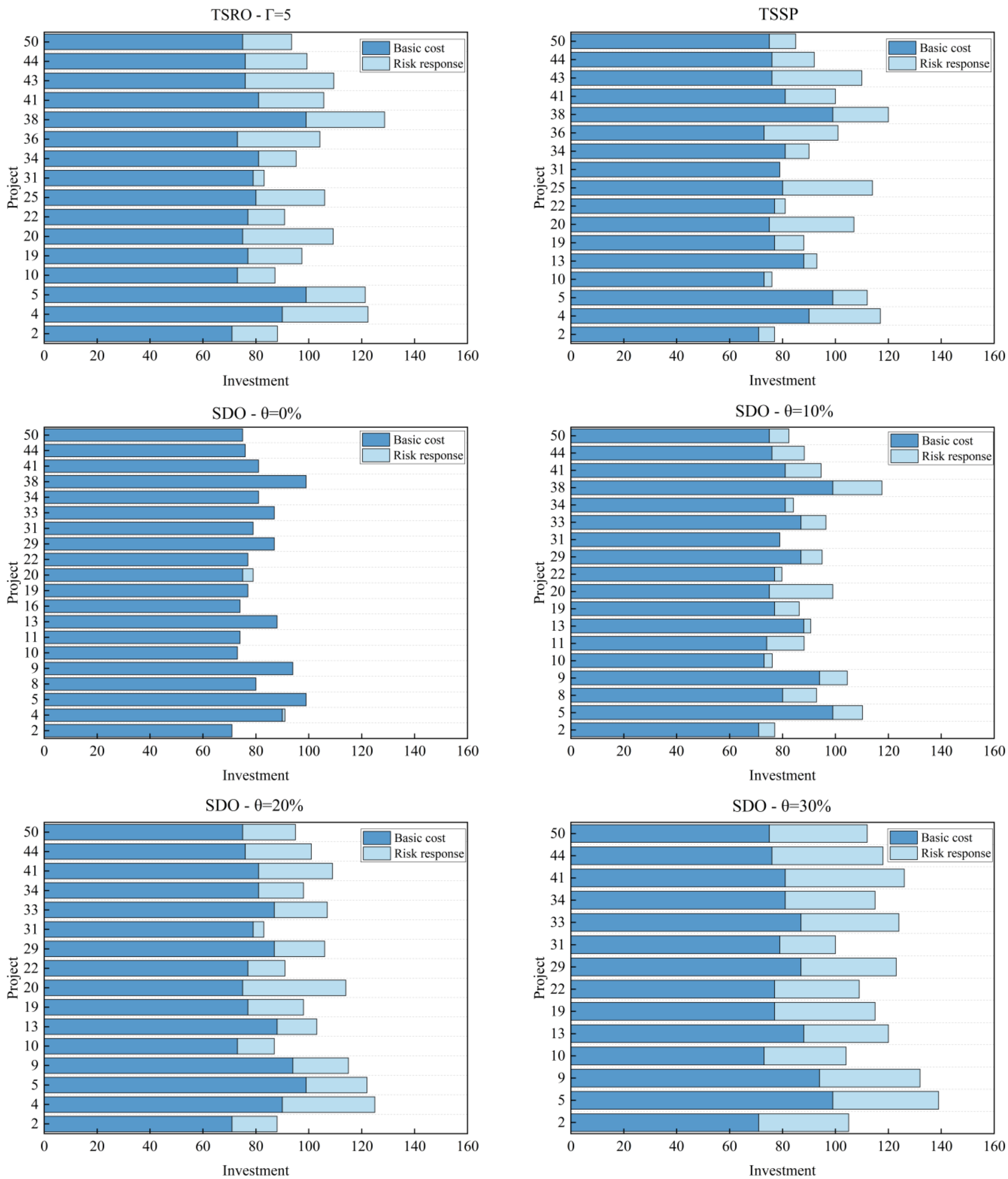

Fig. 2. The optimal budget allocation for selected projects of different models

To shed light on why TSRO performs better, Fig. 2 details the expenditure composition of the selected projects. The joint optimization and the separate optimization show distinct selection patterns. Specifically, TSRO and TSSP consistently select projects 25, 36, and 43, while SDO systematically excludes them across all θ levels. These projects exhibit higher-risk but also higher-return characteristics, and the strategic priority of project 43 is evidenced in [53]. This divergence reveals a critical deficiency of the separate optimization: its tendency to exclude high-potential projects whose risks could be effectively mitigated via targeted responses. By overemphasizing current conditions and neglecting future risk-response opportunities, the separate optimization fails to capture valuable projects that the joint optimization can strategically accommodate.

TABLE III
THE OUT-OF-SAMPLE RESULTS OF TSRO, TSSP, AND SDO ($\boldsymbol{\alpha} = 5\widehat{\mathbf{p}}$, $\boldsymbol{\beta} = 5 - 5\widehat{\mathbf{p}}$)

Model	Parameter	Portfolio returns		Portfolio size	Risk response budget (%)	Response efficacy	
		Average	5%			Average	5%
TSRO	Γ=5	1987.43*	1920.82*	16	22.11%	74.72%	71.87%
	Γ=10	1962.02	1912.17	15	26.55%	81.69%	79.38%
	Γ=15	1912.01	1877.37	14	31.06%	87.48%*	85.70%*
TSSP		1980.87	1908.97	17	17.42%	65.40%	62.31%
SDO	θ=0%	1568.25	1379.92	20	0.43%	3.82%	2.98%
	θ=10%	1822.24	1713.21	18	10.48%	47.70%	43.96%
	θ=20%	1859.03#	1798.72#	16	20.28%	71.98%	68.81%
	θ=30%	1722.22	1694.42	14	30.27%	86.85%#	84.94%#

Note: * represents the best results, # represents the best result of SDO model among all values of θ.

TABLE IV
THE PORTFOLIO RETURNS OF TSRO, TSSP, AND SDO WITH DIFFERENT σ

	σ	TSRO	TSSP	SDO-θ=0%	SDO-θ=10%	SDO-θ=20%	SDO-θ=30%
AVG.	0.01	1581.72*	1574.76	1573.07	1571.02	1524.91	1403.33
	0.02	1677.40*	1670.32	1578.76	1661.98	1656.82	1531.97
	0.03	1799.21*	1760.29	1584.21	1736.50	1754.20	1616.79
	0.04	1889.99*	1888.29	1589.45	1800.17	1829.73	1675.00
	0.05	1973.26*	1965.41	1594.50	1855.73	1889.56	1715.46
	0.06	2034.21*	2031.19	1585.24	1896.23	1933.05	1742.20
	0.07	2095.80*	2093.51	1604.15	1948.46	1976.09	1763.55
	0.08	2140.63*	2139.31	1600.46	1983.09	2005.44	1776.94
	0.09	2182.21*	2171.30	1613.28	2022.69	2032.60	1787.16
	0.1	2213.83*	2210.25	1617.69	2054.37	2053.13	1793.99
5%	0.01	1424.24*	1407.04	1401.19	1426.40	1401.16	1309.14
	0.02	1559.57*	1530.54	1407.97	1530.20	1556.26	1464.64
	0.03	1710.82*	1631.15	1413.92	1615.86	1671.76	1569.15
	0.04	1822.42*	1796.69	1420.14	1689.79	1762.05	1641.38
	0.05	1916.51*	1886.34	1425.52	1755.22	1834.15	1691.79
	0.06	1998.63*	1992.20	1450.21	1824.86	1898.01	1728.82
	0.07	2046.65*	2037.74	1436.12	1864.69	1939.08	1751.91
	0.08	2100.49*	2097.49	1435.57	1908.59	1975.58	1768.75
	0.09	2148.15*	2116.40	1446.42	1952.84	2008.06	1781.44
	0.1	2185.46*	2161.87	1451.29	1990.81	2033.15	1789.97

Note: AVG. and 5% denote the average and 5% percentile portfolio returns, respectively; * represents the best results.

V. DISCUSSION

To assess the robustness and adaptability of TSRO across diverse real-world scenarios, we conduct sensitivity analyses by varying the value of key parameters in both the experimental setting and the model. These configurable parameters allow the model to reflect domain-specific characteristics, thereby enhancing its practical relevance. In this section, unless explicitly specified otherwise, Γ defaults to 5.

A. Impact of Beta Distribution's Parameter

The variance of beta-distributed performance loss in the experiment design is $\frac{\alpha\beta}{(\alpha+\beta+1)(\alpha+\beta)^2}$. To simulate scenarios with a higher probability of performance loss deviation, that is, greater performance loss volatility, we set $\boldsymbol{\alpha} = 5\widehat{\mathbf{p}}$, $\boldsymbol{\beta} = 5 - 5\widehat{\mathbf{p}}$ with expectation $\widehat{\mathbf{p}}$ and variance $\frac{\widehat{\mathbf{p}}(1-\widehat{\mathbf{p}})}{6}$. Numerical results in Table III demonstrate the superiority of joint optimization: TSRO and TSSP outperform SDO in portfolio returns, and TSRO-Γ=15 provides the highest response efficacy. Under higher performance loss variance (vs. Table II's baseline), TSRO and TSSP allocate a greater risk response budget.

B. Impact of Decay Rate σ

In practice, the decay rate σ in (2) reflects how sensitively performance loss recovers to risk response. DMs can estimate the decay rate σ based on industry context, historical data from comparable projects, or expert evaluations [41]. We conduct experiments with $\sigma \in \{0.01, 0.02, \ldots, 0.1\}$. Table IV confirms TSRO's dominance: it outperforms TSSP and SDO in both average and 5% percentile portfolio returns across all tested values of σ. Notably, the performance advantage is more pronounced at the 5% percentile than the average level, underscoring TSRO's superior robustness in the worst-case scenarios. Furthermore, the performance gap between TSRO and SDO widens as σ increases, highlighting the limitations of the separate optimization when risk response effectiveness is high.

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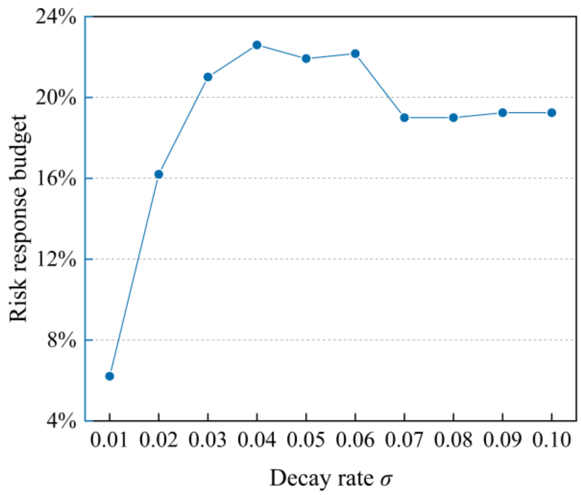
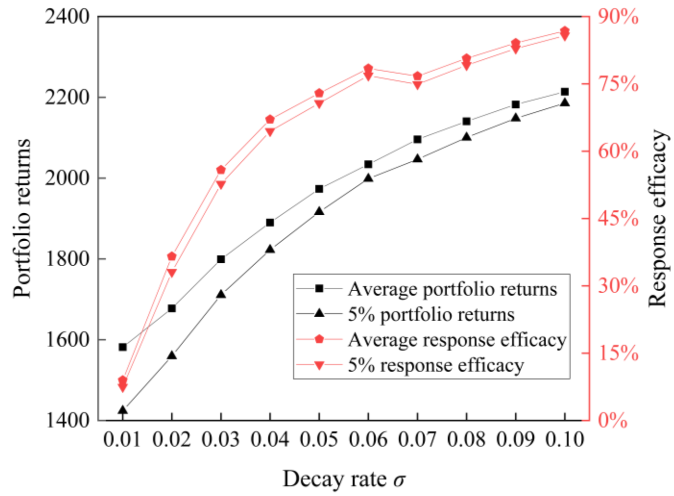


(a)



(b)

Fig. 3. The optimal results of TSRO with different decay rate σ

TABLE V
THE PORTFOLIO RETURNS OF TSRO, TSSP, AND SDO WITH DIFFERENT φ

	φ	TSRO	TSSP	SDO-θ=0%	SDO-θ=10%	SDO-θ=20%	SDO-θ=30%
AVG.	0	1923.80*	1901.14	1408.30	1724.90	1768.81	1698.09
	0.1	1935.27*	1917.99	1454.85	1747.43	1804.01	1702.43
	0.2	1946.74*	1929.46	1501.40	1769.96	1824.78	1706.78
	0.3	1958.21*	1947.43	1547.95	1832.45	1878.21	1711.12
	0.4	1973.26*	1965.41	1594.50	1855.73	1889.56	1715.46
	0.5	1985.52*	1983.40	1641.06	1879.01	1900.92	1719.81
	0.6	2001.48*	1987.49	1687.63	1902.30	1912.28	1724.16
	0.7	2019.24*	2000.54	1734.19	1925.60	1923.65	1728.51
	0.8	2036.15*	2025.54	1780.76	1948.92	1935.03	1732.86
5%	0	1862.93*	1814.43	1208.76	1608.23	1705.79	1670.07
	0.1	1876.58*	1834.49	1263.07	1635.32	1743.85	1675.50
	0.2	1890.21*	1843.46	1317.07	1662.40	1766.22	1680.93
	0.3	1903.86*	1864.89	1371.25	1727.50	1820.30	1686.36
	0.4	1916.51*	1886.34	1425.52	1755.22	1834.15	1691.79
	0.5	1931.18*	1907.76	1479.76	1782.96	1848.01	1697.23
	0.6	1934.81*	1901.12	1533.71	1810.79	1861.88	1702.66
	0.7	1954.84*	1910.42	1587.88	1838.59	1875.76	1708.10
	0.8	1974.91*	1939.91	1641.81	1866.51	1889.64	1713.55

Note: AVG. and 5% denote the average and 5% percentile portfolio returns, respectively; * represents the best results.

We further explore the impact of the decay rate on risk response decisions and portfolio performance for TSRO. Fig. 3 (a) shows that optimal solutions are highly responsive to the variance of decay rate. To be specific, when the decay rate σ is low, indicating limited recoverability, DMs allocate less budget to risk response because substantial risk response investments only yield a small risk response effect. As σ grows moderately to 0.04, each incremental response investment can significantly reduce performance loss, leading to an increased risk response budget. Beyond σ=0.06, however, the optimal risk response budget declines from peak levels observed at $\sigma \in \{0.03, \ldots, 0.06\}$ and stabilizes.

Fig. 3 (b) indicates that higher σ values yield diminishing marginal returns for portfolio returns and response efficacy. When the decay rate is high, DMs should prioritize other factors to improve portfolio performance. Notice that increasing σ progressively narrows the gap between average and 5% percentile values for both portfolio returns and response efficacy. This convergence occurs because higher σ enhances risk response effectiveness, offsetting performance loss fluctuations. Consequently, TSRO delivers increasingly consistent outcomes as the decay rate improves. Comparing Fig. 3 (a) and (b), it can be observed that despite a shrinking risk response budget (σ from 0.04 to 0.05), response efficacy increases. This is because the efficacy gains from a higher σ outweigh the negative impact of budget reduction.

C. Impact of Residual Rate φ

We conduct experiments across residual rate $\varphi \in \{0.0, 0.1, \ldots, 0.8\}$. The residual rate can be specified using historical data from analogous projects or expert assessments. The outperformance of TSRO is demonstrated in Table V. It's interesting that a higher residual rate φ narrows the TSRO-SDO gap at θ=0% but amplifies their differential at θ=30%. This implies diminishing importance of risk response when failure generates high residual value.

TABLE VI
THE PORTFOLIO RETURNS OF TSRO, TSSP, AND SDO WITH DIFFERENT B

	B	TSRO	TSSP	SDO-θ=0%	SDO-θ=10%	SDO-θ=20%	SDO-θ=30%
AVG.	0.2	1042.97*	1039.27	870.79	950.45	948.71	896.50
	0.3	1526.81*	1520.35	1223.26	1422.98	1384.92	1360.29
	0.4	1973.26*	1965.41	1594.50	1855.73	1889.56	1715.46
	0.5	2397.88*	2389.21	1905.74	2227.75	2308.72	2180.73
	0.6	2804.43*	2798.08	2114.71	2591.77	2699.39	2579.88
5%	0.2	1015.82*	999.84	770.90	889.94	917.11	881.74
	0.3	1488.66*	1478.02	1095.66	1348.86	1346.41	1340.89
	0.4	1916.51*	1886.34	1425.52	1755.22	1834.15	1691.79
	0.5	2342.10*	2328.50	1727.20	2116.04	2249.12	2151.89
	0.6	2754.46*	2744.54	1910.25	2469.72	2632.04	2548.84

Note: AVG. and 5% denote the average and 5% percentile portfolio returns, respectively; * represents the best results.

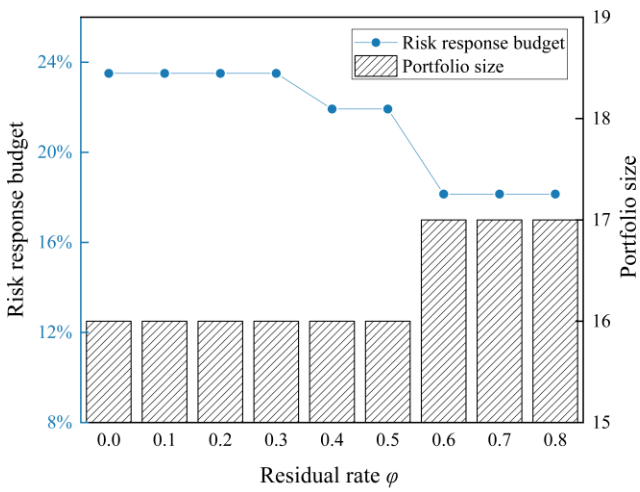


Fig. 4. The optimal solutions of TSRO with different residual rate φ

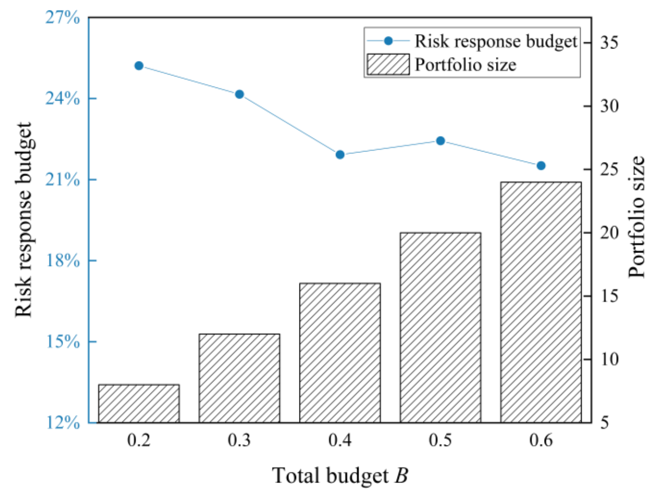


Fig. 5. The optimal solutions of TSRO with different total budget B

Fig. 4 illustrates that a higher residual rate φ correlates with a stable or declining risk response budget. A higher φ reduces project failure costs, attenuating the need for risk response. The consistent or expanding portfolio size with rising φ reflects enterprises' willingness to undertake more projects. This indicates that higher failure residual value through enhanced organizational learning and resource reuse reduces risk aversion and encourages more project initiation. TSRO's solution stability at specific ranges of φ ensures solution robustness in project selection and budget reservation despite minor φ variations—a critical advantage given the practical difficulty of precise estimation.

D. Impact of Total Budget B

We analyze how the total budget B affects the optimal solutions by examining five values within the range $\{0.2\sum c_i, 0.3\sum c_i, \ldots, 0.6\sum c_i\}$. The total budget is typically appropriated from the enterprise and determined by financial capacity. Table VI confirms TSRO's consistent superiority over TSSP and SDO, delivering higher portfolio returns in both average and 5% percentile metrics.

As shown in Fig. 5, the risk response budget share decreases overall with fluctuations, and portfolio size grows as the total budget increases. This pattern suggests that resource allocation strategies should adapt to budget conditions: when budgets are tight, prioritizing fewer projects with stronger risk response is more effective, whereas larger budgets allow for a broader portfolio. It's worth noting that maintaining a fixed risk response budget share with different total budgets isn't the optimal policy, resulting in inferior performance.

VI. CONCLUSIONS

Risky events pose a significant challenge to R&D project management, often rendering today's optimal portfolio selection decisions into tomorrow's inferior performance. This study develops a joint optimization framework integrating robust portfolio selection with risk response in uncertain environments, explicitly considering their interdependencies and budget trade-offs. We formulate a TSRO model to protect against worst-case scenarios. A distinctive feature of the model is the DDBU, which captures the endogenous link between performance loss and portfolio selection decisions, combined with a non-linear function that characterizes risk response effects. With all parameters specified, DMs can apply our tailored solution method to derive optimal project portfolio composition and risk response budget allocation. A 50-project R&D case demonstrates the superiority of the proposed approach over benchmark methods, while sensitivity analyses confirm its robustness and adaptability across diverse operational contexts, offering actionable insights for designing resilient and high-performing portfolios.

This study assumes independence among candidate R&D projects. Future research would incorporate project interdependencies [60], including cross-project risk correlations and interactive risk response effects. In practice, R&D projects typically span multiple years and require dynamic risk management adaptations. The proposed model can be extended into a multi-stage framework, enabling adaptive risk response adjustments over project lifecycles. Additionally, alternative functional forms for risk response effects may be adopted, with our linear approximation methodology still applicable. Finally, while our validation is based on a research laboratory case, broader cross-industry generalization can be achieved by acquiring domain-specific datasets in future work.

APPENDIX

Appendix A. Error Bound of Piecewise Linear Approximation

We assume segments are uniformly partitioned in $[0, x_i^{max}]$, where x_i^{max} is the maximum value that x_i can take. The approximation of $e^{-\sigma x_i}$ for any given value $x_i \in \left[\bar{x}_{i,k-1}, \bar{x}_{i,k}\right]$, $\forall k \in \mathcal{K}$, is expressed by $e^{-\sigma \bar{x}_{i,k-1}} + \gamma_{i,k}\left(x_i - \bar{x}_{i,k-1}\right)$, and $\gamma_{i,k}$ is rewritten as

$$-\frac{|\mathcal{K}|}{x_i^{max}} e^{-\sigma \bar{x}_{i,k-1}} \left(1 - e^{-\sigma \frac{x_i^{max}}{|\mathcal{K}|}}\right).$$

The error of the piecewise linear approximation in the k-th segment can be expressed as

$$ERR(k) \coloneqq \gamma_{i,k}\left(x_i - \bar{x}_{i,k-1}\right) + e^{-\sigma \bar{x}_{i,k-1}} - e^{-\sigma x_i}. \tag{15}$$

By taking the first derivative of (15), we can get $x_i^* = -\frac{1}{\sigma} \ln \frac{-\gamma_{i,k}}{\sigma}$ as the maximum point. Thus, $e^{-\sigma x_i^*} = \frac{|\mathcal{K}|}{\sigma x_i^{max}} e^{-\sigma \bar{x}_{i,k-1}} \left(1 - e^{-\sigma \frac{x_i^{max}}{|\mathcal{K}|}}\right)$. For notational brevity, we define

$$e^{s_{|\mathcal{K}|}} \coloneqq e^{\sigma x_i^* - \sigma \bar{x}_{i,k-1}} = \frac{\frac{\sigma x_i^{max}}{|\mathcal{K}|}}{1 - e^{-\sigma \frac{x_i^{max}}{|\mathcal{K}|}}}, \tag{16}$$

which is not related to k. Thus, the maximum error is given by

$$ERR(k)_{max} = e^{-\sigma \bar{x}_{i,k-1} - s_{|\mathcal{K}|}}\left(e^{s_{|\mathcal{K}|}} - s_{|\mathcal{K}|} - 1\right). \tag{17}$$

We notice that $ERR(k)_{max}$ is a decreasing function of k, since $\bar{x}_{i,k}$ increases when k increases. Thus, the maximum error occurs in the first segment, which means $k = 0$. From the Taylor's expansion of $e^{-\sigma \frac{x_i^{max}}{|\mathcal{K}|}}$, we derive that $e^{-s_{|\mathcal{K}|}}=1$ as $|\mathcal{K}| \to \infty$. As for the last term, we have $e^{s_{|\mathcal{K}|}} - s_{|\mathcal{K}|} - 1 = O\left({s_{|\mathcal{K}|}}^2\right)$. Then with the same approach,

$$\begin{aligned} s_{|\mathcal{K}|} &= \ln \frac{1 - e^{-\sigma \frac{x_i^{max}}{|\mathcal{K}|}}}{\frac{\sigma x_i^{max}}{|\mathcal{K}|}} \\ &= \ln\left[1 - \frac{1}{2!}\sigma \frac{x_i^{max}}{|\mathcal{K}|} + o\left(\frac{1}{|\mathcal{K}|}\right)\right] \\ &= -\frac{1}{2!}\sigma \frac{x_i^{max}}{|\mathcal{K}|} + o\left(\frac{1}{|\mathcal{K}|}\right). \end{aligned} \tag{18}$$

Thus, ${s_{|\mathcal{K}|}}^2$ has the same order of $\frac{1}{|\mathcal{K}|^2}$, together with the above formulation of $e^{s_{|\mathcal{K}|}} - s_{|\mathcal{K}|} - 1$, we conclude that

$$ERR(k)_{max} = O\left(\frac{1}{|\mathcal{K}|^2}\right), \tag{19}$$

which implies that the maximum error of the piecewise linear approximation converges to 0 as $|\mathcal{K}| \to \infty$.

Appendix B. Proof of Proposition 1

Proof. It can be seen that the objective function of the second-stage problem, shown in (11), is both linear in $(\mathbf{x}, \mathbf{z})$ and $\mathbf{p}$. Also, the uncertainty set $\mathcal{P}(\boldsymbol{y})$ defined in (1) is bounded and continuous in $\mathbf{p}$, and the second-stage problem is continuous and complete recourse. The conditions of the minmax theorem [52] are satisfied, making it equivalent to switching the operation order of the second-stage problem. By substituting the min-max operation with the max-min, TSRO-PL with the DDBU is equivalent to the following bi-level optimization:

[TSRO-PL1]

$$\begin{gathered} \max_{\mathbf{y},\mathbf{x},\mathbf{z}} \sum_{i \in \mathcal{N}} r_i y_i + p_i^M (r_i + l_i) \left[-y_i - \right. \\ \left. \gamma_{i,1} x_i \sum_{k=1}^{|\mathcal{K}|-1} \left(\gamma_{i,k} - \gamma_{i,k+1}\right) z_{i,k}\right] + \min_{\boldsymbol{\delta}} \sum_{i \in \mathcal{N}} p_i^D (r_i + l_i) \\ \left[-y_i - \gamma_{i,1} x_i + \sum_{k=1}^{|\mathcal{K}|-1} \left(\gamma_{i,k} - \gamma_{i,k+1}\right) z_{i,k}\right] \delta_i \end{gathered} \tag{20}$$

$$\text{s.t.} -\delta_i \geq -y_i \quad \forall i \in \mathcal{N}, \tag{21}$$

$$-\sum_{i \in \mathcal{N}} \delta_i \geq -\Gamma, \tag{22}$$

$$\delta_i \geq 0 \quad \forall i \in \mathcal{N}, \tag{23}$$

(4)-(7), (9), (10).

We further transform the bi-level optimization TSRO-PL1 into a single-level optimization by dualizing the innermost minimization problem. Let λ_i^1, λ^2 denote the dual variables of (21) and (22), respectively. The dual of the inner problem of TSRO-PL1 is given as follows:

$$\max_{\boldsymbol{\lambda}} \sum_{i \in \mathcal{N}} -\lambda_i^1 y_i - \lambda^2 \Gamma \tag{24}$$

s.t. (13), (14).

Therefore, by replacing the inner minimization problem with its dual, we have the single-level optimization, which is equivalent to TSRO-PL with DDBU.

Appendix C. Approximation Error with Different $|\mathcal{K}|$

TABLE VII
THE MAXIMAL APPROXIMATION ERRORS AND OPTIMAL SOLUTIONS UNDER FOUR VALUES OF $|\mathcal{K}|$

$\|\mathcal{K}\|$	$ERR(1)_{max}$	Portfolio size				Risk response budget (%)			
		TSRO			TSSP	TSRO			TSSP
		Γ=5	Γ=10	Γ=15		Γ=5	Γ=10	Γ=15	
20	6.91E-03	17	17	17	18	16.57%	16.57%	18.09%	12.85%
50	1.19E-03	16	16	15	17	21.92%	23.51%	28.20%	16.57%
100	3.05E-04	16	16	15	17	21.92%	23.51%	28.20%	16.57%
200	7.72E-05	16	16	15	17	21.92%	23.51%	28.20%	16.57%

We conduct the preliminary experiments by considering four values of $|\mathcal{K}|$, i.e., $|\mathcal{K}| \in \{20,50,100,200\}$, to choose an appropriate value of $|\mathcal{K}|$ before computational studies. Table VII shows the maximal approximation errors and the optimal solutions under four values of $|\mathcal{K}|$. The column "$ERR(1)_{max}$" represents the maximal approximation error, which is proven in Appendix A. The approximation error keeps decreasing as $|\mathcal{K}|$ increases, and it is not greater than 3.05E-04 with $|\mathcal{K}| = 100$. The optimal solutions of TSRO and TSSP keep stability for $|\mathcal{K}| \geq 50$. We thus choose $|\mathcal{K}| = 100$ in the computational studies to balance the approximation precision and the computation efficiency.

Appendix D. Separate Deterministic Optimization Models (SDO)

The separate deterministic models, one of the benchmark models described in Section IV, are formulated as follows:

The first-stage model:

[SDO-1]

$$\max_{\mathbf{y}} \sum_{i\in\mathcal{N}}[r_i - p_i^M(r_i + l_i)]\, y_i \tag{25}$$

$$\text{s.t. } \sum_{i\in\mathcal{N}} c_i y_i \leq (1-\theta)B, \tag{26}$$

(6).

The second-stage model:

[SDO-2]

$$\max_{\mathbf{x}} \sum_{i\in\mathcal{N}}(r_i + l_i)[p_i^M - p_i'(x_i, p_i)]y_i^* \tag{27}$$

$$\text{s.t. } \sum_{i\in\mathcal{N}} x_i \leq B - \sum_{i\in\mathcal{N}} c_i y_i^*, \tag{28}$$

(5), (7),

where y_i^* is the optimal solution determined in the first-stage model.

The SDO-1 involves selecting a project portfolio within a budget $(1-\theta)B$ to maximize the estimated portfolio returns, and the SDO-2 allocates the remaining budget to the selected projects with the objective of maximizing performance regain.

Appendix E. Two-stage Stochastic Programming Model (TSSP)

The two-stage stochastic programming model, one of the benchmark models described in Section IV, is formulated as follows:

[TSSP]

$$\max_{\mathbf{y},\mathbf{x}} \sum_{\omega\in\Omega}\sum_{i\in\mathcal{N}} \phi_\omega[r_i - (r_i + l_i)p_i'(x_i^\omega, p_i^\omega)]\, y_i \tag{29}$$

$$\text{s.t. } \sum_{i\in\mathcal{N}} c_i y_i + x_i^\omega \leq B \quad \forall\omega \in \Omega, \tag{30}$$

$$x_i^\omega \leq M y_i \quad \forall i \in \mathcal{N}, \omega \in \Omega, \tag{31}$$

$$x_i^\omega \in \mathbb{R}_+ \quad \forall i \in \mathcal{N}, \omega \in \Omega, \tag{32}$$

$$\sum_{\omega\in\Omega} \phi_\omega = 1, \tag{33}$$

(6),

where $\omega \in \Omega$ represents a scenario that is unknown when the first-stage decision $\mathbf{y}$ are made and is known when the second-stage decision $\mathbf{x}$ are made, independently happening with a probability $\phi_\omega = \frac{1}{|\Omega|}$. Ω is a set of all scenarios.

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