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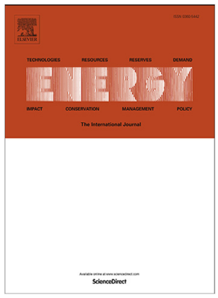


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# A Distributionally Robust Ordinal Priority Approach for Nuclear Energy Technology R&D Portfolio Selection under Scenario Uncertainty

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**Abstract**

A Selecting appropriate nuclear energy technology (NET) R&D portfolios is essential for shaping the national nuclear energy landscape, supporting global carbon reduction efforts, and advancing the UN Sustainable Development Goal for affordable and clean energy. However, research on NET R&D portfolio selection (NET-R&D-PS) remains limited and fails to adequately address the scenario uncertainty. Thus, this study proposes a distributionally robust ordinal priority approach (OPA-DR) for NET-R&D-PS under scenario uncertainty that affects the importance of evaluation attributes. Although the alternative rankings under possible scenarios and their corresponding nominal distributions would be provided, the high uncertainty of future R&D scenarios renders the nominal distributions unreliable. To address this, this study introduces an ambiguity set based on Kullback-Leibler (KL) divergence for OPA-DR, with ambiguity set sizes designed for large- and small-sample problems, characterizing all possible attribute ranking distributions derived from the nominal distribution. This study develops an efficient exact solving algorithm for OPA-DR, requiring only the solution of a one-dimensional equation and the calculation of the optimal solution in closed form with polynomial time complexity, making it suitable for large-scale problems. This study analyzes the OPA-DR sensitivity under varying utility functions and constraint perturbations. The effectiveness of OPA-DR is validated by the NET-R&D-PS for China 2030 Vision Plan, providing insights for scenario analysis, attribute selection, and portfolio selection.

*Keywords:* Nuclear energy technology, R&D portfolio selection, Scenario uncertainty, Multi-attribute decision-making, Distributionally robust ordinal priority approach

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## 1. Introduction

Nuclear power is essential in addressing global energy demands, combating climate change, and achieving the United Nations Sustainable Development Goal 7 (SDG7, Affordable and Clean Energy) (Yu et al., 2025). As a clean energy source, nuclear power significantly reduces greenhouse gas emissions, helping to mitigate climate change. With its reliable and stable power generation capacity, nuclear energy technology (NET) ensures a sustainable energy supply, meets affordable demand, supports economic growth, and drives social development (Collet et al., 2025). Current NET R&D process typically includes four stages and twelve steps, posing considerable technical challenges (Zhang et al., 2019). Sovacool et al. (2014) analyzed the costs of 180 nuclear reactors, of which 64 projects exceeded budgets by over \$1 billion, with 14 projects surpassing \$5 billion in additional costs, and 10 projects exceeding 400% cost overruns, resulting in an average project cost increase of 117%. This underscores the importance of the strategic planning of NET R&D portfolio selection (NET-R&D-PS) in the advancement of the nuclear energy sector (Mancuso et al., 2017).

In the decision-making process of NET-R&D-PS, decision-makers (DMs) must balance multiple factors such as environmental impact, safety design, and economic viability (Yüksel and Dinçer, 2022; Liao et al., 2025). These factors often conflict, as enhancing safety may raise costs, while reducing costs may harm environmental sustainability. DMs must navigate these trade-offs, considering long-term goals and broader societal impacts, which means effective NET-R&D-PS decision-making requires subjective judgment and careful evaluation of the interdependencies between these competing objectives (Yasir Mehboob et al., 2024). Moreover, the uncertainty surrounding the future of NET R&D is another critical aspect of the planning process. Scenario uncertainty is particularly significant in this context, as it can substantially influence the decision-making outcomes (Wang et al., 2024; Zhou et al., 2025). For example, the pace of advancements in other clean energy technologies, such as solar, wind, and hydrogen, could reduce the demand for nuclear power, while breakthroughs in nuclear fusion or other innovations could boost its potential. The prospects for nuclear technology exports also play a crucial role, as global demand and favorable international markets could improve economic feasibility. However, market fluctuations and regulatory changes pose risks to profitability. DMs must navigate these uncertainties alongside the technical complexities of nuclear energy, considering the evolving landscape of clean energy and market dynamics

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(Dong et al., 2025).

NET-R&D-PS is a critical application of project portfolio selection (PPS) problems in the nuclear energy domain, yet it has received limited attention in current research. Current quantitative-based PPS studies primarily categorize into two types for identifying the optimal portfolio (Kandakoglu et al., 2024). One approach involves evaluating projects using multi-attribute decision-making (MADM) technique and then selecting the best portfolio based on constrained project generation (Debnath et al., 2017; Zhang et al., 2020; Wu et al., 2019; Tavana et al., 2020). The other approach generates feasible portfolios first based on constraints, such as project interactions, resource dependencies, and implementation feasibility, followed by evaluation using MADM to determine the optimal portfolio (Tavana et al., 2013; Urli and Terrien, 2010; Song et al., 2021). Although some studies address input data (e.g., evaluation scores, semantic values or pairwise comparison values) uncertainty through grey system theory (Bhattacharyya, 2015) and fuzzy theory (Demircan Keskin, 2020), they often overlook the impact of scenario uncertainty on the evaluation model, which typically exceeds the uncertainties in specific project or portfolio input performance. Another non-negligible source of uncertainty in this input data is the fact that decision analysts typically do not have the level of confidentiality to access detailed NET R&D data. Wang et al. (2021) suggests that using ranking data for decision-making can effectively deal with data inaccessibility and uncertainty, a perspective not yet explored in current PPS studies. Notably, ordinal priority approach (OPA) is a novel MADM method employing linear programming (Ataei et al., 2020). It uses ranking data that reflects expert preferences as decision data, offering a potentially powerful foundation for NET-R&D-PS. By solving a linear programming model, OPA concurrently assigns weights to experts, attributes, and alternatives, enabling ranking without requiring data standardization, expert opinion aggregation, or predetermined weights (Wang, 2024a; Cui et al., 2025). However, the original OPA model and its current extensions do not account for the scenario uncertainty in NET-R&D-PS, which is a key concern for DMs.

To address the above limitations, this study proposes a distributionally robust OPA (OPA-DR) for NET-R&D-PS under scenario uncertainty based on distributionally robust optimization (DRO) paradigm. In NET-R&D-PS, the attribute rankings are associated with the scenarios faced by NET-R&D, each with corresponding realization probabilities, forming the nominal distribution of attribute rankings. The proposed approach employs a Kullback-Leibler (KL) divergence-based ambiguity set with the set size designed for both small- and large-sample cases. To effectively solve the KL divergence-based OPA-DR for practical usage, we develop a solution algorithm with polynomial time complexity, suitable for large-scale problems. The main contribution are:

- Methodological contribution: This study introduces a distributionally robust extension of OPA to address scenario uncertainty, presenting a novel formulation in the OPA literature. Based on OPA properties, this study identifies the basis for distinguishing small-scale from large-scale scenarios and introduces an optimization-based approach for determining ambiguity sets in large-scale scenarios, along with a statistics-based approach for small-sample cases. Unlike commonly used reformulation techniques for the KL divergence-based DRO, this study presents an efficient solving algorithm based on the structural properties of OPA, only requiring the solution of a one-dimensional equation and the calculation of the optimal solution through a closed-form expression.
- Theoretical contribution: This study presents the closed-form solution of OPA-DR, analyzing performance differences among OPA-DR, robust OPA, and stochastic OPA based on nominal distribution. In addition, this study conducts a theoretical sensitivity analysis on the optimal weight disparity scalar and weights of OPA-DR from various utility functions for ranked alternatives, and constraint perturbations. The proven results can be similarly applied to the sensitivity analysis of other OPA models.
- Practical contribution: This study presents a decision-making method aligned with NET-R&D-PS practices. The method is demonstrated through the application of the NET-R&D-PS in China's 2030 Vision Plan, offering insights for scenario analysis, attribute selection, and final portfolio outcomes in NET-R&D-PS.

The remaining parts of this paper are organized as follows: Section 2 reviews the related literature. Section 3 gives the preliminaries. Section 4 proposes OPA-DR for NET-R&D-PS. Section 5 demonstrates the proposed approach using the NET-R&D-PS of China 2030 Vision Plan. Section 6 provides conclusions and future research directions.

## 2. Literature Review

NET-R&D-PS refers to the process of determining the portfolio of NET R&D projects of the nuclear system (reactors and associated post-combustion processes) to promote the advancement and application of NET (Zhang et al., 2019; Li et al., 2024). NET-R&D-PS is a specialized application of the PPS problem within the decision analysis domain. Existing PPS analysis methods are primarily qualitative and quantitative (de Souza et al., 2021). Of these, quantitative analysis is particularly valued for its objectivity and accuracy, with numerous successful instances highlighting its efficacy. This study will concentrate on quantitative-based PPS (Mahmoudi et al., 2022b). Current quantitative approaches are generally divided into two categories (Kandakoglu et al., 2024). The first involves evaluating individual projects and then assembling the optimal portfolio. The second involves generating all possible portfolios from projects and then assessing these to select the best option. The primary distinction between these methods is the focus on decision units; the first emphasizes individual project assessment, while the second centers on portfolio evaluation.

In the first type, MADM technique is initially used to evaluate each project comprehensively, followed by transforming the problem into a 0-1 knapsack problem to identify the optimal portfolio (Kandakoglu et al., 2024). Specifically, the performance or ranking obtained in the first stage is integrated into the additive objective function in the second stage, subject to resource constraints. The primary advantage of this type is its ability to evaluate individual project performance across multiple attributes, thus improving understanding of how each project impacts the overall portfolio. Common MADM methods in this context include AHP (Martins et al., 2017), ANP (Jung and Seo, 2010), DEMATEL (Hajiagha et al., 2022), TOPSIS (Tavana et al., 2020), PROMETHEE (Wu et al., 2018), ELECTRE-TRI (Mavrotas et al., 2003), MABAC (Debnath et al., 2017), and MAUT (Liesiö et al., 2023). Debnath et al. (2017) proposed a hybrid approach combining DEMATEL and MABAC to manage the genetically modified agriculture investment portfolio. They used DEMATEL to assign attribute weights and MABAC to integrate DMs' preferences, resulting in portfolio ranking. Zhang et al. (2020) presented a fuzzy VIKOR multi-objective optimization model for military weapon portfolio selection. This process involves three stages: the first derives attribute weights using fuzzy semantic values, the second applies VIKOR to obtain comparative scores over time, and the final stage uses a multi-objective optimization model to select the optimal portfolio. Wu et al. (2019) determined attribute weights through the interval type-2 fuzzy analytic hierarchy process and then employed the non-dominated sorting genetic algorithm-II to select the optimal distributed energy generation portfolio under budget constraints. Tavana et al. (2013) developed a VIKOR-based mixed integer linear programming approach for network security project portfolio selection, considering project synergies, human resource capabilities, and employee training opportunities. Additionally, some studies addressed decision-making uncertainty by integrating grey system theory (Bhattacharyya, 2015; Nowak et al., 2020) and fuzzy theory (Wu et al., 2018; Demircan Keskin, 2020; Zolfaghari and Mousavi, 2021) to improve MADM input data.

In the second type, all feasible portfolios are generated by considering relevant constraints, followed by an evaluation to identify the optimal one (Kandakoglu et al., 2024). The main advantage of this approach is its ability to address project interactions and offer deeper insights into portfolio differences. In the first stage, feasible or Pareto-optimal portfolios are generated using constraint-based methods that consider factors like project interactions, resource dependencies, and implementation feasibility, without incorporating expert preferences. The second stage involves MADM analysis to rank non-dominated portfolios or select the best compromise portfolio. Among MADM methods, DEA is the predominant technique for analyzing feasible portfolios in the second stage (Tavana et al., 2013; Urli and Terrien, 2010), with a smaller subset utilizing the SMAA approach (Song et al., 2021, 2019). Tavana et al. (2013) proposed a fuzzy multidimensional multiple-choice knapsack model to generate feasible portfolios and apply DEA to filter a manageable set of implementable alternatives. Song et al. (2021) developed four heuristic algorithms based on SMAA for project portfolio selection and scheduling in engineering management.

Existing research on PPS has gained attention across various fields, but research specifically focused on NET-R&D-PS remains relatively scarce. Current studies on PPS still overlook scenario uncertainty in decision-making. Most existing research addresses uncertainty in decision data provided subjectively by experts, using grey system theory and fuzzy theory. However, these studies fail to account for future scenario uncertainty, a broader and more significant source of uncertainty in portfolio selection (Jain et al., 2014). Scenario uncertainty not only complicates long-term performance estimation of projects or portfolios but can also fundamentally alter the importance of attributes (Liesiö et al., 2023; Wang et al., 2022). This is particularly critical in strategic decisions such as NET-R&D-PS. For example, in scenarios involving future nuclear energy exports, the economic attribute becomes more important than security, compared to a scenario without exports. This shift in evaluation structure, driven by scenario uncertainty, is more impactful than the range of fuzziness in expert input data. Additionally, due to the safety classification constraints in NET R&D projects, decision analysts often cannot access precise evaluation data and must rely on expert opinions. This reliance introduces subjectivity and potential biases into the decision-making process. However, empirical evidence suggests that using ranking data as model inputs results in more robust decision outcomes when handling input data uncertainty (Mahmoudi and Javed, 2023). DM only needs to specify "which is better than which" without indicating the degree of dominance or exact values (Wang et al., 2021). Thus, using ranking data for NET-R&D-PS may offer a promising approach, though current research has not explored this aspect.

## 3. Preliminary

### 3.1. Ordinal Priority Approach

OPA is an effective MADM technique for MADM with incomplete information (Ataei et al., 2020). Unlike conventional methods, OPA uses ordinal rankings, discussed in Section 2, as inputs, allowing for the simultaneous calculation of weights for experts, attributes, and alternatives through a linear programming model (Wang, 2024c). It eliminates the need for data normalization, expert opinion aggregation, and pre-determined decision weights (Wang, 2024b). Consequently, its straightforward data collection process, ease of implementation, and dependable results have led to its widespread application in areas such as supplier selection (Mahmoudi et al., 2022b; Wang et al., 2025), blockchain obstacle analysis (Sadeghi et al., 2023), and performance evaluation (Mahmoudi et al., 2022a; Cui et al., 2025). However, OPA and its current extensions do not account for scenario uncertainty when attribute rankings are given across different scenarios with nominal probability distributions.

Given a set of experts $\mathcal{I}$, attributes $\mathcal{J}$, and alternatives $\mathcal{K}$, DM initially assigns the ranking $t_i$ for expert $i \in \mathcal{I}$. Subsequently, each expert $i \in \mathcal{I}$ independently provides the ranking $s_{ij}$ for each attribute $j \in \mathcal{J}$ and the ranking $r_{ijk}$ for each alternative $k \in \mathcal{K}$ under each attribute $j \in \mathcal{J}$. Define the following sets:

$$\mathcal{X}^1 := \{(i,j,k,l) \in \mathcal{I} \times \mathcal{J} \times \mathcal{K} \times \mathcal{K} : r_{ijl} = r_{ijk} + 1, r_{ijk} \in [K-1]\},$$
$$\mathcal{X}^2 := \{(i,j,k) \in \mathcal{I} \times \mathcal{J} \times \mathcal{K} : r_{ijk} = K\},$$
$$\mathcal{Y} := \{(i,j,k) \in \mathcal{I} \times \mathcal{J} \times \mathcal{K}\}.$$

Based on the ordinal ranking data, OPA identifies the maximum weight disparity among alternatives with consecutive rankings, while reflecting experts' preferences within the normalized weight space, as shown in Equation (1) (Ataei et al., 2020).

$$
\begin{aligned}
\max_{\boldsymbol{w},z} \quad & z \\
\text{s.t.} \quad & z \leq t_i s_{ij} r_{ijk}(w_{ijk} - w_{ijl}) && \forall (i,j,k,l) \in \mathcal{X}^1 \\
& z \leq t_i s_{ij} r_{ijk}(w_{ijk}) && \forall (i,j,k) \in \mathcal{X}^2 \\
& \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} w_{ijk} = 1 \\
& w_{ijk} \geq 0 && \forall (i,j,k) \in \mathcal{Y}
\end{aligned} \tag{1}
$$

The variable $z$ can be regarded the weight disparity scalar of OPA. After solving Equation (1) for $z^\star$ and $\boldsymbol{w}^\star$, the weights of experts, attributes, and alternatives, denoted as $W^{\mathcal{I}}$, $W^{\mathcal{J}}$, and $W^{\mathcal{K}}$, are then given by:

$$
\begin{aligned}
W_i^{\mathcal{I}} &= \sum_{j=1}^{J} \sum_{k=1}^{K} w_{ijk}^\star, && \forall i \in \mathcal{I}, \\
W_j^{\mathcal{J}} &= \sum_{i=1}^{I} \sum_{k=1}^{K} w_{ijk}^\star, && \forall j \in \mathcal{J}, \\
W_k^{\mathcal{K}} &= \sum_{i=1}^{I} \sum_{j=1}^{J} w_{ijk}^\star, && \forall k \in \mathcal{K}.
\end{aligned} \tag{2}
$$

Without loss of generality, map the alternative index $k$ to the ranking index $r$ corresponding to their ranking position $r_{ijk}$ with $R = K$, and define $\mathcal{E} := \mathcal{I} \times \mathcal{J} \times \mathcal{R}$. Wang (2024a) provides the equivalent reformulation of the OPA model in Equation (1), which can be interpreted as deriving weights based on rank order centroid (ROC) weights for alternatives (i.e., a specific utility function for ranked alternatives) within a normalized decision space.

**Lemma 1** (Wang (2024a))**.** *The OPA model in Equation (1) has the following equivalent reformulation:*

$$
\begin{aligned}
\max_{\boldsymbol{w},z} \quad & z, \\
\text{s.t.} \quad & R u_r^{ROC} z \leq t_i s_{ij} w_{ijr}, && \forall (i,j,r) \in \mathcal{E}, \\
& \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} w_{ijr} = 1, \\
& w_{ijr} \geq 0, && \forall (i,j,r) \in \mathcal{E},
\end{aligned} \tag{3}
$$

*where* $u_r^{ROC} = \frac{1}{R}\left(\sum_{h=r}^{R} \frac{1}{h}\right)$ *for any* $r \in \mathcal{R}$.

The dual problem of Equation (3) is shown in Equation (4).

$$\begin{aligned}
&\min_{\lambda,\gamma}\ \lambda \\
&\text{s.t. } t_i s_{ij}\gamma_{ijr} \le \lambda && \forall (i,j,r)\in\mathcal{E} \\
&\quad \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} Ru_r^{ROC}\gamma_{ijr} = 1 \\
&\quad \gamma_{ijr} \ge 0 && \forall (i,j,r)\in\mathcal{E}
\end{aligned} \tag{4}$$

For clarity in subsequent discussions, rewrite the OPA model in Equation (3) as:

$$\max_{z,\boldsymbol{w}\in\mathcal{W}} \{z : \boldsymbol{f}(z) \le \boldsymbol{g}(\boldsymbol{w})\}. \tag{5}$$

where $[\boldsymbol{f}(z)]_{ijr} = f_{ijr}(z) = Ru_r^{ROC} z$ and $[\boldsymbol{g}(\boldsymbol{w})]_{ijr} = g_{ijr}(w_{ijr}) = t_i s_{ij} w_{ijr}$ for all $(i,j,r)\in\mathcal{E}$ and

$$\mathcal{W} := \left\{ w_{ijk} \in \mathbb{R}_+^{I\times J\times K} : \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} w_{ijr} = 1, w_{ijr} \ge 0, \forall (i,j,r)\in\mathcal{E} \right\}.$$

### *3.2. Problem Statement*

This study considers NET-R&D-PS where DM needs to choose the optimal portfolio from a set of optional NET R&D portfolios $\mathcal{H} := \{1,2,\cdots,H\}$, indexed by $h$. Each portfolio consists of $b$ projects chosen from a set of projects $\mathcal{K} := \{1,2,\cdots,K\}$, indexed by $k$. If portfolio $h$ contains project $k$, then $x_{hk} = 1$; otherwise, $x_{hk} = 0$. Additionally, a set of attributes $\mathcal{J} := \{1,2,\cdots,J\}$, indexed by $j$, and a set of experts $\mathcal{I} := \{1,2,\cdots,I\}$, indexed by $i$, are assigned to evaluate the projects. For input data, DM initially provides an importance ranking for each expert $i \in \mathcal{I}$, denoted as $t_i \in \mathcal{I}$. Then, each expert $i \in \mathcal{I}$ ranks each project $k \in \mathcal{K}$ across each attribute $j \in \mathcal{J}$, yielding ranks $r_{ijk} \in \mathcal{R} := \{1,2,\ldots,R=K\}$. The attribute rankings are influenced by potential future scenarios that NET R&D may encounter. Let $\tilde{\boldsymbol{s}}$ denotes the uncertain attribute rankings. DM provides a finite set of scenarios $\mathcal{L} := \{1,2,\ldots,L\}$, indexed by $l$, with corresponding attribute rankings $s_{jl} \in \mathcal{J}$ for each $j \in \mathcal{J}$ and $l \in \mathcal{L}$, associated with nominal probabilities $\boldsymbol{p}_l = \hat{\mathbb{P}}[\tilde{\boldsymbol{s}} = \boldsymbol{s}_l]$. Notably, due to the highly specialized nature of the NET R&D portfolio, the number of feasible portfolios is generally small (less than 20) and is predetermined by experts.

## 4. Distributionally Robust Ordinal Priority Approach

The nominal distribution of scenario faced by NET R&D occurrences is difficult to determine objectively and is typically estimated subjectively using expert judgment, leading to considerable uncertainty (Kandakoglu et al., 2024). This motivates to adopt the DRO modeling paradigm to extend OPA (namely, distributionally robust OPA, OPA-DR) for addressing NET-R&D-PS. Specifically, OPA-DR incorporates an ambiguity set, i.e., a family of probability distributions with limited yet common distributional information derived from the nominal distribution, and evaluates the decision outcome based on its worst-case expected performance across any distribution within the ambiguity set. Let $\mathscr{F}(\hat{\mathbb{P}}, \theta)$ denote the ambiguity set derived from the nominal distribution $\hat{\mathbb{P}}$ with the ambiguity set size $\theta$. The unified framework for OPA-DR is given by:

$$\max_{z, \boldsymbol{w} \in \mathcal{W}} \left\{ z : \boldsymbol{f}(z) \leq \mathbb{E}_{\tilde{s}_j \sim \mathbb{P}_j}[\boldsymbol{g}(\boldsymbol{w}, \tilde{s}_j)], \forall \mathbb{P}_j \in \mathscr{F}(\hat{\mathbb{P}}, \theta), \forall j \in \mathcal{J} \right\}. \tag{6}$$

Notably, Equation (6) is an infinite-dimensional optimization problem, since its ambiguity set contains infinitely possible realizations of probability distribution. Thus, for OPA-DR, the key to our success is designing the ambiguity set based on the nominal distribution for the NET R&D scenario and further determing the effective algorithm for solving Equation (6).

### 4.1. Ambiguity Set Construction

Building upon the nominal distribution for the NET R&D scenario, we adopt a distance-based formulation to quantify distributional ambiguity. Specifically, we employ the KL divergence to measure the proximity between probability distributions. The underlying assumption is that the worst-case distribution is absolutely continuous with respect to the nominal one, sharing the same finite support set (Ben-Tal et al., 2013). This setup provides the foundation for developing solving algorithms and identifying the worst-case distribution, offering insights into managerial decision-making. To begin with, we introduce the definition of the KL divergence.

**Definition 1.** The KL divergence of $\mathbb{P}$ with resepect to $\hat{\mathbb{P}}$ in discrete distribution with $L$ scenarios is given by:

$$D_{KL}(\mathbb{P}, \hat{\mathbb{P}}) = \sum_{l=1}^{L} p_l \phi_{KL} \left( \frac{p_l}{\hat{p}_l} \right), \tag{7}$$

where $\phi_{KL}(t) = t \log t - t + 1$ and $t > 0$.

It is easy to verify that $\phi_{KL}(t)$ is a convex function on $t > 0$, with the conjugate function $\phi^*_{KL}(s) = e^s - 1$. The KL divergence satisfies $D_{KL}(\mathbb{P}, \hat{\mathbb{P}}) \geq 0$, with equality holding if and only if $\mathbb{P} = \hat{\mathbb{P}}$. However, it is important to note that the KL divergence is asymmetric and does not satisfy the triangle inequality. To avoid pathological cases, following standard assumptions in (Ben-Tal et al., 2013), we assume that:

$$\phi_{KL}(0) < \infty, \quad 0 \cdot \phi_{KL}\left(\frac{0}{0}\right) = 0, \quad 0 \cdot \phi_{KL}\left(\frac{t}{0}\right) = \lim_{\varepsilon \to 0} \varepsilon \cdot \phi_{KL}\left(\frac{t}{\varepsilon}\right) = t \lim_{s \to \infty} \frac{\phi_{KL}(s)}{s}, \quad t > 0.$$

We now consider how to determine the ambiguity set size $\theta$ in the KL divergence-based OPA-DR problem. Inspired by Blanchet et al. (2019), we choose the ambiguity set as the minimum KL ball containing at least one distribution that yields the same optimal solution as the true problem. Specifically, let $(z^\star, \boldsymbol{w}^\star)$ denote the optimal solution under the true distribution $\mathbb{P}^\star$. The set of distributions preserving this optimality is then defined as:

$$\mathcal{P}(z^\star, \boldsymbol{w}^\star) := \left\{ \mathbb{P} : (z^\star, \boldsymbol{w}^\star) \in \arg \min_{z, \boldsymbol{w} \in \mathcal{W}} \{ z : f(z) \leq \mathbb{E}_{\tilde{\boldsymbol{s}} \sim \mathbb{P}}[g(\boldsymbol{w}, \tilde{\boldsymbol{s}})] \} \right\}. \tag{8}$$

Since $\mathbb{P}^\star \in \mathcal{P}(z^\star, \boldsymbol{w}^\star)$ by construction, we can determine the ambiguity set size $\theta$ by minimizing the KL divergence from $\mathcal{P}(z^\star, \boldsymbol{w}^\star)$ to $\hat{\mathbb{P}}$:

$$\theta = \min_{\mathbb{P} \in \mathcal{P}(z^\star, \boldsymbol{w}^\star)} D_{KL}(\mathbb{P}, \hat{\mathbb{P}}). \tag{9}$$

However, since the true optimal solution $(z^\star, \boldsymbol{w}^\star)$ is not accessible, we replace it with the empirical optimal solution $(z_N^\star, \boldsymbol{w}_N^\star)$ when the amount of sample is sufficient, which is obtained by solving the following problem:

$$\min_{z, \boldsymbol{w} \in \mathcal{W}} \{ z : f(z) \leq \mathbb{E}_{\tilde{\boldsymbol{s}} \sim \mathbb{P}_N}[g(\boldsymbol{w}, \tilde{\boldsymbol{s}})] \}, \tag{10}$$

where $\mathbb{P}_N$ represents the empirical distribution. Under mild conditions, replacing $(z^\star, \boldsymbol{w}^\star)$ with $(z_N^\star, \boldsymbol{w}_N^\star)$ provides a good approximation (Shapiro et al., 2023).

**Remark 1.** From Equation (8), we notice that the determination of scenario scale acutally correlates with the number of attributes. Specifically, when $L \leq J$, the KL divergence-based OPA-DR problem in Equation (6) can be considered a small scale problem. This follows from the fact that Equation (8) is equivalent to find a probability distribution set that satisfies the KKT conditions leading to $(z^\star, \boldsymbol{w}^\star)$. Following the KKT condition of OPA provided by Wang (2024a), we have:

$$\mathcal{P}(z^\star, \boldsymbol{w}^\star) \Leftrightarrow \mathcal{P} := \left\{ \mathbb{P} : \sum_{l=1}^{L} p_l s_{jl} = \mathbb{E}_{\tilde{s}_j \sim \mathbb{P}_N}[\tilde{s}_j], \forall j \in \mathcal{J} \right\}, \tag{11}$$

where the left-hand side represents the constant sample average of each attribute ranking. Thus, when $L \leq J$, the feasible distribution set reduces to a singleton. In such small-scale problems, expert judgments of scenario probabilities are assumed to be reliable and capable of handling the limited scope, which implies that the statistics-based approach can determine the ambiguity set size $\theta$.

Note that a commonly used class of test statistics is defined by $\phi_{KL}$:

$$T^L_{\phi_{KL}}(\hat{\mathbb{P}}, \mathbb{P}) = \frac{2L}{\phi''_{KL}(1)} D_{\phi_{KL}}(\hat{\mathbb{P}}, \mathbb{P}), \tag{12}$$

where $\hat{\mathbb{P}}$ is the nominal distribution with $L$ finite samples.

The following proposition provides the ambiguity set size for the small-sample case constructed by the sample size $L$ and the significance level $\rho$.

**Proposition 1.** *Given the nominal distribution with L scenarios, significance level $\rho$, and attribute number $J$, when $L \leq J$, the ambiguity set size $\theta$ of the KL divergence-based OPA-DR problem in Equation (6) is given by:*

$$\theta = \frac{\phi''_{KL}(1)\rho}{2L}. \tag{13}$$

The following algorithm gives the procedure to determine the ambiguity set size $\theta$ for the KL divergence-based OPA-DR problem in Equation (6), which considers small-sample and normal cases.

**Algorithm 1** Specifing the ambiguity set size $\theta$

1: **Input:** Nominal distribution $\hat{\mathbb{P}}$ with $L$ scenario, attribute number $J$, and significance level $\rho$.
2: **Output:** Ambiguity set size $\theta$.
3: **Initialization:** $\theta \leftarrow 0$ and $\mathcal{P} := \emptyset$.
4: **if** $L \leq J$ **then**
5: Calculate through statistics-based approach $\theta \leftarrow \dfrac{\phi''_{KL}(1)\rho}{2L}$.
6: **else**
7: Let $\mathcal{P} := \left\{\mathbb{P} : \sum_{l=1}^{L} p_l s_{jl} = \mathbb{E}_{\tilde{s}_j \sim \mathbb{P}_N}[\tilde{s}_j], \forall j \in \mathcal{J}\right\}$.
8: Calculate through optimization-based approach $\theta \leftarrow \min_{\mathbb{P} \in \mathcal{P}} D_{KL}(\mathbb{P}, \hat{\mathbb{P}})$.
9: **end if**
10: **return** $\theta$.

Based on the above discussion, we obtain the KL divergence ambiguity set for the OPA-DR problem in Equation (6):

$$\mathscr{F}_{KL}(\hat{\mathbb{P}}, \theta) := \left\{ \mathbb{P} \in \Xi : D_{KL}(\mathbb{P}, \hat{\mathbb{P}}) \leq \theta, \sum_{l=1}^{L} p_l = 1, p_l \geq 0, \forall l \in \mathcal{L} \right\}. \tag{14}$$

*4.2. Algorithm Design and Closed-Form Analysis*

In this section, we design an effective algorithm for solving the KL divergence-based OPA-DR problem based on its structural properties. To begin with, we transform Equation (6) into the following equivalent form:

$$\begin{aligned}
&\max_{z, \boldsymbol{w}} \ z, \\
&\text{s.t. } Ru_r^{ROC} z \leq \min_{\mathbb{P}_j \in \mathscr{F}_{KL}(\hat{\mathbb{P}}, \theta)} \mathbb{E}_{\tilde{s}_j \sim \mathbb{P}_j}[t_i \tilde{s}_j w_{ijr}], \quad \forall (i,j,r) \in \mathcal{E}, \\
&\sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} w_{ijr} = 1, \\
&w_{ijr} \geq 0, \qquad \forall (i,j,r) \in \mathcal{E}.
\end{aligned} \tag{15}$$

The following lemma presents the worst-case distribution for the KL divergence-based OPA-DR problem in Equation (15).

**Lemma 2.** *For each $j \in \mathcal{J}$, the worst-case distribution $\mathbb{P}_j^\star$ of the KL divergence-based OPA-DR problem in Equation (15) takes the following form:*

$$p_{jl}^\star = \frac{\hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j^\star}\right)}{\sum_{l=1}^{L} \hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j^\star}\right)}, \quad \forall l \in \mathcal{L}, \tag{16}$$

*where $\alpha_j^\star > 0$ is the unique solution to the following KL divergence constraint:*

$$\sum_{l=1}^{L} \frac{\hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right)}{\sum_{l=1}^{L} \hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right)} \log\left( \frac{\exp\left(\frac{s_{jl}}{\alpha_j}\right)}{\sum_{l'=1}^{L} \hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right)} \right) = \theta. \tag{17}$$

Equation (17) can be efficiently computed by one-dimensional search methods, such as bisection. The following theorem provides the closed-form solution of the KL divergence-based OPA-DR problem in Equation (15) given the worst-case distribution.

**Theorem 1.** *Given the worst-case distributions $\mathbb{P}_j^\star$ for all $j \in \mathcal{J}$, the closed-form solution of the KL divergence-based OPA-DR problem in Equation (15) is given by:*

$$z^\star = \left( \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \frac{Ru_r^{\mathrm{ROC}}}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \right)^{-1}, \tag{18}$$

*and*

$$w_{ijr}^\star = \frac{Ru_r^{ROC} z^\star}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}}, \quad \forall (i,j,r) \in \mathcal{E}. \tag{19}$$

Following the similar proof of Theorem 1, it can be verified that the optimal weight disparity scalar for OPA-DR is smaller than that of the stochastic OPA based on nominal distribution and larger than that of the robust OPA proposed by (Mahmoudi et al., 2022b; Wang, 2024b). Thus, it indicates that, in the uncertain extension of OPA, robustness against parameter uncertainty leads to a tendency for balance, reflecting the DMs' aversion to ambiguity rather than a focus on performance quality. By Lemma 2 and Theorem 1, the KL divergence-based OPA-DR problem in Equation (15) can be efficiently solved using the algorithm outlined below, without relying on the reformulations commonly used to convert the problem into a convex optimization, which becomes a burden as the problem size grows. After applying Algorithm 2, the optimal weights $w_{ijr}^\star$ are mapped to $w_{ijk}^\star$ based on project rankings. Finally, Equation (2) is used to compute the weights for experts, attributes, and projects. Portfolio weights are aggregated according to project affiliation.

### *4.3. Theoretical Sensitivity Analysis*

The sensitivity analysis of OPA-DR mainly consists of two parts: utility function analysis and constraint perturbation analysis. Notably, the latter mainly focuses on the presence of noise in the weight disparities of the alternatives with consecutive rankings.

We begin with the utility function sensitivity analysis by dering the closed-form solution of the OPA-DR problem under the worst-case distributions. Consider the following utility function sensitivity problem:

$$\begin{aligned} \max_{z, \boldsymbol{w} \in \mathcal{W}} \quad & z, \\ \text{s.t.} \quad & Ru_r^{\delta} z \le t_i \left( \sum_{l=1}^{L} p_{jl}^\star s_{jl} \right) w_{ijr}, \qquad \forall (i,j,r) \in \mathcal{E}, \end{aligned} \tag{20}$$

---

**Algorithm 2** Solving the KL divergence-based OPA-DR problem

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1: **Input:** Nominal distribution $\hat{\mathbb{P}}$ with $L$ scenario, ambiguity set size $\theta$, expert ranking $t_i$ for all $i \in \mathcal{I}$, attribute ranking $s_{jl}$ for all $j \in \mathcal{J}$ and $l \in \mathcal{L}$, and project number $R$.

2: **Output:** Optimal weight $\boldsymbol{w}^\star$ and optimal weight disparity scalar $z^\star$.

3: **Initialization:** $z^\star \leftarrow 0$, $\boldsymbol{w}^\star \leftarrow \mathbf{0}$, $\alpha_j^\star \leftarrow 0$, and $p_{jl}^\star \leftarrow \frac{1}{|L|}$ for all $j \in \mathcal{J}$ and $l \in \mathcal{L}$.

4: **for** $j \in \mathcal{J}$ **do**

5: Solving the following equation through bisection method

$$\alpha_j^\star \leftarrow \arg_{\alpha_j} \left\{ \sum_{l=1}^{L} \frac{\hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right)}{\sum_{l=1}^{L} \hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right)} \log\left( \frac{\exp\left(\frac{s_{jl}}{\alpha_j}\right)}{\sum_{l=1}^{L} \hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right)} \right) = \theta \right\}.$$

6: **for** $l \in \mathcal{L}$ **do**

7: Calculate the worst-case probability $p_{jl}^\star \leftarrow \dfrac{\hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j^\star}\right)}{\sum_{l'=1}^{L} \hat{p}_{l'} \exp\left(\frac{s_{jl'}}{\alpha_j^\star}\right)}$.

8: **end for**

9: **end for**

10: Calculate the optimal weight disparity scalar $z^\star \leftarrow \left( \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \dfrac{R u_r^{\mathrm{ROC}}}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \right)^{-1}$.

11: **for** $(i, j, r) \in \mathcal{E}$ **do**

12: Calculate the optimal weight $w_{ijr}^\star \leftarrow \dfrac{R u_r^{\mathrm{ROC}} z^\star}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}}$.

13: **end for**

14: **return** $\boldsymbol{w}^\star$ and $z^\star$.

---

where the utility function $\boldsymbol{u}^\delta$ for ranked alternatives satisfying monotonicity condition $u_r^\delta > u_{r+1}^\delta$ for all $r = 1, \ldots, R-1$; and normalization condition $\sum_{r=1}^R u_r^\delta = 1$.

Let $z^\star(\delta)$ and $\boldsymbol{w}^\star(\delta)$ denote the optimal solution of Equation (20). The following corollary gives the utility function sensitivity analysis results.

**Corollary 1.** *For the utility function sensitivity problem in Equation (20), we have:*

$$z^\star(\boldsymbol{u}^\delta) = z^\star, \tag{21}$$

*and*

$$|w_{ijr}^\star - w_{ijr}^\star(\boldsymbol{u}^\delta)| = \frac{Rz^\star}{t_i \sum_{l=1}^L p_{jl}^\star s_{jl}} \left| u_r^{ROC} - u_r^\delta \right|, \quad \forall (i,j,r) \in \mathcal{E}. \tag{22}$$

Corollary 1 indicates that the optimal weight disparity scalar remains constant for any utility function with monotonicity and normalization properties. Also, the difference in optimal weights is determined by the difference in utility functions.

Consider the following constraint perturbation sensitivity problem:

$$\begin{aligned} \max_{z, \boldsymbol{w}} \ & z, \\ \text{s.t. } & t_i \left( \sum_{l=1}^L p_{jl}^\star s_{jl} \right) w_{ijr} - R u_r^{ROC} z \geq \varepsilon_{ijr}, && \forall (i,j,r) \in \mathcal{E}, \\ & 1 - \sum_{i=1}^I \sum_{j=1}^J \sum_{r=1}^R w_{ijr} = \epsilon, \\ & w_{ijr} \geq 0, && \forall (i,j,r) \in \mathcal{E}. \end{aligned} \tag{23}$$

The perturbed parameters can be positive or negative, thus the perturbation problem results from the original problem by tightening or relaxing each inequality weight disparity constraints by $\varepsilon_{ijr}$, and changing the righthand side of the equality normalization constraint by $\epsilon$. Let $z^\star(\boldsymbol{\varepsilon}, \epsilon)$ and $\boldsymbol{w}^\star(\boldsymbol{\varepsilon}, \epsilon)$ denote the optimal solution of Equation (23). The following corollary gives the constraint perturbation sensitivity analysis results.

**Corollary 2.** *For the constraint perturbation perturbation problem in Equation (23), we have:*

$$z^\star(\boldsymbol{\varepsilon}, \epsilon) = \left( 1 - \epsilon - \sum_{i=1}^I \sum_{j=1}^J \sum_{r=1}^R \frac{\varepsilon_{ijr}}{t_i \sum_{l=1}^L p_{jl}^\star s_{jl}} \right) z^\star, \tag{24}$$

*and*

$$w^{\star}_{ijr}(\boldsymbol{\varepsilon}, \epsilon) = \frac{Ru_r^{ROC} z^{\star}(\boldsymbol{\varepsilon}, \epsilon)}{t_i \sum_{l=1}^{L} p^{\star}_{jl} s_{jl}}, \quad \forall (i, j, r) \in \mathcal{E}. \tag{25}$$

Corollary 2 shows that when reducing the normalization scale (equality constraint) or tightening the weight disparity constraints (inequality constraints), a smaller optimal weight disparity scalar is obtained.

### *4.4. Implementation Steps*

In this section, we outlines the implementation steps, notes, and algorithmic time complexity of the KL divergence-based OPA-DR model for NET-R&D-PS. The following procedure details the implementation steps.

When applying the proposed model for NET-R&D-PS, it is important to note that, after defining the decision elements, project rankings are assigned independently by each expert, without group discussion, reflecting individual preferences. Attribute rankings for each scenario and their associated probabilities are determined through group judgment to ensure reliability. Expert rankings are provided by DM based on factors such as educational background, job grade, and work experience. For large-scale scenarios, we recommend first clustering or reducing the scenarios, followed by expert group discussions to determine occurrence probabilities. This is because, when faced with complex decision analyses, increasing information load can scatter experts' cognitive resources (such as attention and memory), leading to imprecise judgments or biases and resulting in systematic deviations. Additionally, the proposed model allows for tied rankings, where the weight difference between tied alternatives is zero. In individual decision-making, the proposed model can be formulated without parameters and constraints related to multiple experts.

The time complexity analysis of the proposed model focuses on a comprehensive evaluation of Algorithms 1 and 2. Specifically, for small-scale problems (i.e., when $L \leq J$), the time complexity of Algorithms 1 is $O(1)$; as the problem size increases, its time complexity becomes $O(LJ + J^3)$. For Algorithm 2, its time complexity is $O(IJR+JL)$. Therefore, the overall time complexity of the proposed model exhibits a piecewise characteristic: for small-scale problems, the overall complexity is $O(IJR+JL)$; for large-scale problems, the overall complexity is $O(\max(J^3, IJR, JL))$. In general, the time complexity of the proposed model is polynomial, effectively avoiding the intractability risks associated with exponential or factorial complexities. This characteristic makes it suitable for solving most practical engineering problems, maintaining good applicability even in larger-scale scenarios.

**Procedure 1** Implementation steps of the KL divergence-based OPA-DR model for NET-R&D-PS

1: **Step 1: Identify decision elements.**
2: Determine the expert set $\mathcal{I}$, project set $\mathcal{K}$, and portfolio set $\mathcal{H}$ involved in the NET-R&D-PS decision-making process.
3: Identify the attribute set $\mathcal{J}$ according to the NET-R&D-PS objectives.
4: Identify the scenario set $\mathcal{L}$ that NET R&D would face.
5: **Step 2: Obtain the input data.**
6: Assign important ranking $t_i$ for each expert $i \in \mathcal{I}$.
7: Determine the nominal distribution $\hat{\mathbb{P}}$ for the NET R&D scenario.
8: **for** all scenario $l \in \mathcal{L}$ **do**
9: Assign important ranking $s_{jl}$ for each attribute $j \in \mathcal{J}$.
10: **end for**
11: **for** all expert $k \in \mathcal{K}$ **do**
12: Assign important ranking $r_{ijk}$ for each alternative $k \in \mathcal{K}$ under each attribute $j \in \mathcal{J}$.
13: **end for**
14: **Step 3: Calculate the decision weights.**
15: Determine the ambiguity set size based on Algorithm 1.
16: Solve the worst-case distribution and optimal weights based on Algorithm 2.
17: Calculate the decision weights for experts, attributes, projects, and portfolios.
18: **Step 4: Result analysis and validation.**
19: Determine the NET-R&D-PS decision based on the decision weights and sensitivity analysis.

## 5. Illustrative Demonstration for China 2030 Vision Plan

### *5.1. Case Description and Scenario Setting*

This study selects NET-R&D-PS of China's 2030 Vision Plan as a case study. It focuses on nuclear fission technology, including related reactors and fuel reprocessing processes. Reactors are classified as burner, breeder, or burner-breeder based on their breeding ratio. Fuel reprocessing techniques include once-through, separation and purification, and partial removal of fission products. This study identifies 18 pioneering NET R&D projects, covering five nuclear system types and nine practical applications, as detailed in Table 2. The composition of the alternative portfolio, comprising five optional projects, is presented in Table 1. K1–K4 are classified as small modular and compact reactors, typically designed for propulsion, space power, and isotope production. Project K5 is identified as a combustion reactor with separation–purification, reflecting its reliance on fuel burning coupled with reprocessing. K6–K7 belong to high-temperature gas-cooled reactors, which are well suited for hydrogen production and process heat applications. K8–K11 correspond to fast breeder reactors, characterized by their breeding capability and utilization in both power generation and fissile material production. K12–K15 represent hybrid combustion–breeding reactors, which integrate the features of both combustion and breeding to support multiple energy outputs. Finally, K16–K18 are classified as advanced molten salt reactors, featuring online fuel circulation and partial neutron poison removal.

This study evaluates potential NET R&D scenarios for 2030 based on two key factors: the potential for exportability of NET and the potential for disruptive breakthroughs in other clean energy technologies (OCET). Given China's global nuclear strategy, outlined by the National Energy Administration in 2013 and later adopted as a national policy, China is actively promoting NET in international markets (Liddle and Sadorsky, 2017; Zhang et al., 2019). Beyond NET, OCET may serve as substitutes, making it vital to evaluate their potential for disruptive breakthroughs when developing NET R&D strategies. The following are the four identified scenarios.

- Scenario 1 (S1): No export of NET, with no breakthroughs in OCET. Domestic NET R&D should prioritize addressing national energy demands and achieving substantial sustainability improvements. Given its relative maturity and contribution to meeting non-proliferation objectives, NET will emerge as a more reliable option compared to OCET, considering their intermittency and economic limitations. Thus, sustainability becomes crucial in NET R&D.
- Scenario 2 (S2): No export of NET, with breakthroughs in OCET. In this case, China must reassess its NET R&D path. With the rise of OCET, NET must increasingly focus on cost-effectiveness to remain competitive in the energy market. This requires reducing costs, enhancing R&D efficiency, and continuously optimizing operational and maintenance models.
- Scenario 3 (S3): Export of NET, with no breakthroughs in OCET. The export of China's NET

Table 1: Alternative portfolio and project composition

| | H1 | H2 | H3 | H4 | H5 | H6 | H7 | H8 | H9 | H10 | H11 | H12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| K1 | - | - | - | ✓ | ✓ | ✓ | ✓ | - | - | - | - | - |
| K2 | - | - | - | - | - | ✓ | - | ✓ | - | - | - | - |
| K3 | - | - | - | ✓ | - | - | - | - | ✓ | - | - | ✓ |
| K4 | ✓ | ✓ | ✓ | - | ✓ | - | - | - | - | ✓ | ✓ | - |
| K5 | - | - | - | - | - | - | ✓ | ✓ | - | - | - | - |
| K6 | - | - | - | - | - | - | - | - | - | - | ✓ | - |
| K7 | - | - | - | - | - | - | - | - | ✓ | - | - | ✓ |
| K8 | - | - | - | - | - | - | - | - | - | ✓ | - | - |
| K9 | ✓ | ✓ | - | ✓ | ✓ | - | ✓ | - | - | - | - | - |
| K10 | - | - | ✓ | - | - | ✓ | - | - | - | ✓ | ✓ | - |
| K11 | - | - | - | - | - | - | ✓ | ✓ | - | - | - | - |
| K12 | - | - | - | - | - | - | - | ✓ | - | ✓ | - | - |
| K13 | - | ✓ | - | - | - | - | ✓ | - | - | - | - | - |
| K14 | - | - | - | - | - | - | - | ✓ | - | ✓ | - | - |
| K15 | ✓ | ✓ | - | ✓ | ✓ | ✓ | - | - | ✓ | - | - | - |
| K16 | ✓ | - | ✓ | - | - | - | - | - | ✓ | - | ✓ | ✓ |
| K17 | ✓ | ✓ | ✓ | ✓ | ✓ | - | - | - | ✓ | - | ✓ | ✓ |
| K18 | - | - | ✓ | - | - | ✓ | - | - | - | - | - | ✓ |

has gained significant attention but raises concerns about nuclear proliferation. Therefore, China must ensure that NET exports do not contribute to misuse or abuse, taking sufficient measures to prevent proliferation. Additionally, without breakthroughs in OCET, issues of intermittency and economic viability remain. Given the high costs associated with nuclear projects, collaboration with international partners on cost-effective NET is essential to ensure long-term stability and mutual economic and environmental benefits.

- Scenario 4 (S4): Export of NET, with breakthroughs in OCET. In this context, NET faces competitive pressures from OCET, making economic efficiency a priority in China's NET

R&D. Cost reduction and efficiency improvements are key to maintaining competitiveness in the clean energy market. While economic efficiency will be a primary focus, safety and sustainability will remain critical, although they may become secondary considerations in the face of economic competition.

Table 2: NET R&D project and practical application

| Project type | Project ID | NET application: Electricity generation | Hydrogen production | Process heat | Marine propulsion | Integrated island utilization | Integrated remote inland utilization | Spacecraft power | Isotope production | Military materiel production |
|---|---|---|---|---|---|---|---|---|---|---|
| Combustion & single pass | K1 | ✓ | - | - | - | ✓ | ✓ | - | ✓ | - |
| | K2 | - | - | - | ✓ | - | - | ✓ | - | - |
| | K3 | - | - | - | ✓ | ✓ | ✓ | ✓ | - | - |
| | K4 | - | - | - | ✓ | - | - | ✓ | ✓ | - |
| Combustion & separation-purification | K5 | ✓ | - | - | - | ✓ | - | - | - | - |
| | K6 | - | ✓ | ✓ | - | - | - | - | - | - |
| | K7 | - | ✓ | ✓ | - | - | - | - | - | - |
| Breeding & separation-purification | K8 | - | - | - | - | - | - | - | - | ✓ |
| | K9 | - | - | - | - | - | - | - | - | ✓ |
| | K10 | - | - | - | - | - | - | - | - | ✓ |
| | K11 | ✓ | - | - | - | - | - | - | - | - |
| Combustion-breeding & single pass | K12 | - | ✓ | ✓ | - | - | - | - | - | - |
| | K13 | ✓ | - | - | - | ✓ | ✓ | - | - | - |
| Combustion-breeding & separation-purification | K14 | ✓ | - | ✓ | - | - | - | - | - | - |
| | K15 | ✓ | ✓ | ✓ | - | - | - | - | - | - |
| Combustion-breeding & partial neutron poison removal | K16 | ✓ | ✓ | ✓ | - | ✓ | ✓ | - | - | - |
| | K17 | ✓ | ✓ | ✓ | - | ✓ | ✓ | - | - | - |
| | K18 | ✓ | ✓ | ✓ | - | ✓ | ✓ | - | - | - |

### 5.2. Assessment Attribute

This study selects six attributes for project evaluation in NET-R&D-PS, primarily based on GIF R&D Outlook for Generation IV Nuclear Energy Systems (Pioro and Rodriguez, 2023). These attributes include sustainability, economic viability, safety, proliferation resistance, technological compatibility, and feasibility of implementation.

Sustainability (A1) refers to the long-term development of the NET industry through improved nuclear fuel efficiency, advanced reactor and fuel cycle technologies, and better waste management and disposal methods (Stamford and Azapagic, 2011). Considering sustainability in the NET R&D portfolio helps reduce dependency on uranium resources, minimize environmental impacts during nuclear energy production, and decrease radioactive waste volume and toxicity, thereby extending the environmental impact timeline. In the questionnaire for expert evaluation, the scope of this attribute is defined to include: the extent to which an alternative contributes to higher fuel utilization and reduced resource consumption; the technological maturity and feasibility of advanced reactor or fuel cycle deployment; and the effectiveness of radioactive waste treatment, storage, and final disposal.

Economic viability (A2) focuses on reducing the lifecycle costs of NET systems through technological innovation and management optimization, addressing challenges such as high initial investments, long construction periods, and substantial policy and market risks during implementation (Carlsson et al., 2012). Improvements in uranium utilization, modular reactor designs, fixed-price contracts, and international cooperation enhance NET competitiveness and adaptability. For expert evaluation, this attribute is framed in terms of: the ability of an alternative to reduce both capital and operational expenditures; its potential to shorten construction schedules and improve project delivery efficiency; and its competitiveness relative to other available energy technologies.

Safety (A3) ensures the secure and reliable operation of nuclear power plants, enhanced through technological innovation and design improvements (Carlsson et al., 2012). It focuses on three main areas: reliable reactivity control, effective residual heat removal, and robust containment, forming a comprehensive safety framework. Safety is a critical evaluation criterion for NET R&D portfolios due to its direct impact on operational safety, public health, and environmental protection. The evaluation scope for this attribute covers: the capability of an alternative to maintain stable and controllable reactor operations under normal and abnormal conditions; the adequacy and resilience of heat removal mechanisms to prevent core damage; the integrity and reliability of containment systems against internal failures or external hazards; and the overall effectiveness of safety design features in mitigating accident risks.

Proliferation resistance (A4) ensures that NET and materials are used exclusively for peaceful purposes, preventing their misuse in nuclear weapons production or other non-peaceful activities (Yoo et al., 2017). This involves implementing design, operational, and management innovations to reduce the risk of illegal transfer or theft of nuclear materials while ensuring the safe, reliable, and effective use of NET. Proliferation resistance is an essential evaluation criterion for NET R&D portfolio selection due to NET's dual potential for both economic and social development, as well as the risk of misuse that could jeopardize human security. In the questionnaire, this attribute is assessed in terms of: the effectiveness of material accounting and control measures to prevent unauthorized access; the robustness of physical protection and monitoring systems against diversion or theft; the extent to which fuel cycle design minimizes the attractiveness of materials for weaponization; and the adequacy of institutional and regulatory frameworks that reinforce non-proliferation objectives.

Technical compatibility (A5) highlights the importance of shared technological features and processes across various NET R&D projects (Carlsson et al., 2012). This is achieved by evaluating similarities in key areas such as reactor technology, materials, and reprocessing processes. High technical compatibility facilitates technology transfer, supports sustained platform development and upgrading, and lowers barriers to future technological transitions. It also enhances the flexibility of NET systems and enables integration with existing infrastructures, thereby reducing the need for new facilities as well as initial construction costs and operational risks. Experts are asked to consider this attribute with reference to: the extent of similarity in fundamental reactor designs and system architectures; the degree of material and component standardization across projects; the ease of integrating reprocessing and fuel cycle processes into existing infrastructures; and the potential of technical commonality to facilitate future technology transfer and platform upgrading.

Implemental feasibility (A6) assesses the viability of a NET proposal from theoretical research to practical application (Li et al., 2024). This assessment ensures that selected solutions are scientifically, technologically, economically, and socially viable. The primary goal is to identify and select NET proposals with strong implementation prospects based on solid research, which should address critical development challenges, demonstrate smooth industrial applicability, and align with national strategic objectives. The scope of evaluation for this attribute is articulated through: the maturity of the underlying scientific research and the credibility of supporting evidence; the readiness of technological pathways for scale-up and demonstration; the feasibility of integration into existing industrial infrastructures and supply chains; and the alignment of the proposal with broader socio-economic needs and national strategic priorities.

### *5.3. Data Source*

This study involves five nuclear energy experts who collaborate in NET-R&D-PS. The experts were selected based on their significant contributions to both research and management in China's advanced nuclear energy technology system, demonstrating deep domain knowledge and practical experience. Their relative importance is ranked as E5 > E3 > E2 > E4 > E1. The probabilities for the four possible NET R&D scenarios in China by 2030, along with the corresponding attribute rankings under each scenario, were determined through a structured expert panel discussion. During this discussion, experts jointly assessed the likelihood of each scenario, considering both quantitative data and qualitative insights, and reached a consensus on the normalized probabilities shown in Table 3. Subsequently, each expert independently ranked the NET R&D projects with respect to multiple attributes, as summarized in Table B.1. Notably, the number of scenarios ($L = 4$) is fewer than the number of evaluation attributes ($J = 6$), which is considered a small-sample scenario. As discussed in Section 4.2, judgments from expert discussion are relatively reliable in such cases. Therefore, a statistics-based approach is used to determine the ambiguity set size, with a commonly applied significance level of $\rho = 0.95$.

Table 3: Nominal distribution of potential scenarios and corresponding expected attribute rankings

| | Probability | A1 | A2 | A3 | A4 | A5 | A6 |
|---|---|---|---|---|---|---|---|
| S1 | 0.2972 | 1 | 4 | 3 | 6 | 5 | 2 |
| S2 | 0.3243 | 4 | 1 | 5 | 6 | 2 | 3 |
| S3 | 0.2162 | 6 | 5 | 3 | 1 | 4 | 2 |
| S4 | 0.1621 | 5 | 3 | 6 | 2 | 4 | 1 |
| Expected ranking | - | 3.7021 | 3.0804 | 4.1343 | 4.2694 | 3.6478 | 2.1618 |

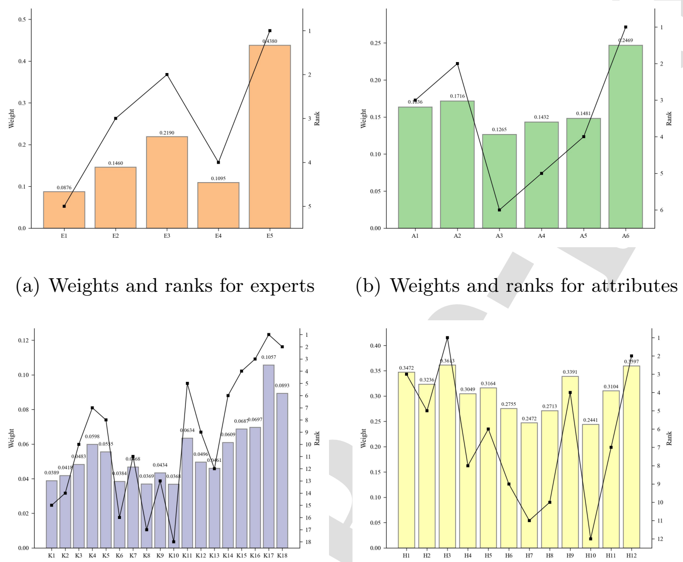
### 5.4. Result Analysis

This study applies Algorithms 1 and 2 to solve the OPA-DR problem in this case study, which involves 5 experts, 6 attributes, 18 projects, and 4 scenarios. In terms of problem size, it comprises a total of 571 variables, including 6 variables $\alpha$, 24 worst-case probability variables $p_{jl}$, 540 weight variables $w_{ijr}$, and 1 weight disparity scalar $z$. The problem is defined by 547 equations: 6 KL-divergence equations for $\alpha$, 1 equation for the weight disparity scalar, and 540 equations for the weights $w_{ijr}$. As indicated by Algorithm 2, the procedure runs in polynomial time and can be solved efficiently, typically in less than one second on a standard computer for this case study. Table 4 shows the resulting worst-case distributions for each attribute. The results highlight distinct worst-case distributions: S1 dominates A1, A3, and A6; S2 dominates A2 and A5; and S3 dominates A4.

Table 4: Worst-case distribution and corresponding expected attribute rankings

| | S1 | S2 | S3 | S4 | Worst-case expected ranking |
|---|---|---|---|---|---|
| A1 | 0.5202 | 0.2676 | 0.1081 | 0.1041 | 2.7597 |
| A2 | 0.2364 | 0.5525 | 0.1334 | 0.0776 | 2.6311 |
| A3 | 0.4318 | 0.1925 | 0.3142 | 0.0615 | 3.5695 |
| A4 | 0.1836 | 0.2004 | 0.3833 | 0.2327 | 3.1526 |
| A5 | 0.1546 | 0.5530 | 0.1671 | 0.1253 | 3.0487 |
| A6 | 0.2963 | 0.1586 | 0.2156 | 0.3295 | 1.8292 |

Figure 1 shows the weights for each expert, attribute, project, and portfolio. For expert weights, E5 has the highest at 0.4380, followed by E3 at 0.2190, E2 at 0.1460, E4 at 0.1095, and E1 at 0.0876. Regarding attribute weights, A6 has the highest weight of 0.2469, making it the most critical factor. Despite strong performance in other areas, substantial execution challenges may hinder successful implementation, thus playing a key role in NET R&D project evaluation. A2 ranks second with a weight of 0.1716. Given the significant financial investment in NET R&D projects, their economic feasibility directly impacts funding and long-term development. Excessive costs or insufficient returns can considerably affect project progress. A1 ranks third with a weight of 0.1636. This attribute is vital for NET R&D, as it involves long-term nuclear fuel supply and waste disposal, making it a critical factor. A5 holds the fourth position with a weight of 0.1481. Evaluating the compatibility of NET with existing systems and infrastructure is crucial, as incompatibility may result in high costs or failure to integrate with the current energy system. A4 ranks fifth with a weight of 0.1432, and A3 is sixth with a weight of 0.1265.



(a) Weights and ranks for experts (b) Weights and ranks for attributes

(c) Weights and ranks for projects (d) Weights and ranks for portfolios

Figure 1: Calculation results

Regarding project weights, the top eight NET R&D projects are ranked as follows: K17, K18, K16, K15, K11, K14, K4, and K5. Among these projects, K14 and K15 focus on combustion-breeding & separation-purification, and K16, K17, and K18 are for combustion-breeding & partial neutron poison removal. K4 is the optimal for combustion & single pass type, K5 is for combustion & separation-purification, and K11 is for breeding & separation-purification. The results indicate that combustion-breeding approaches generally outperform pure combustion or breeding in NET-R&D-PS. As for portfolio weights, the top four NET R&D portfolios are H3 (0.3613), H12 (0.3597), H1 (0.3472), and H9 (0.3391). H3, made up of K4, K10, K16, K17, and K18, covers projects in combustion & single pass, breeding & separation-purification, and combustion-breeding & partial neutron poison removal. Its applications span all nine use cases, making it a well-balanced NET R&D portfolio. It performs particularly well in A1, A2, and A3, while its performance in A5 is relatively weaker compared to other portfolios. H12, consisting of K3, K7, K16, K17, and K18, is also a relatively balanced portfolio but lacks coverage in isotope production and military material manufacturing. Compared to H3, it performs worse in A1, A2, A3, and A6, but outperforms in A4 and A5. H1, composed of K4, K9, K15, K16, and K17, shares the same balanced structure as H3. It particularly excels in A6, demonstrating a strong capacity in addressing execution-related challenges. H9, made up of K3, K5, K15, K16, and K17, is structurally similar to H12 and also lacks applications in isotope and military material domains. While it underperforms in A1, A3, and A6 relative to H3, H12, and H1, it shows a distinct advantage in A5, highlighting its strength in system compatibility.

### 5.5. Model Validation

#### 5.5.1. Sensitivity Analysis of Significance Level

This section analyzes the sensitivity of OPA-DR to changes in the significance level, which directly affects the size of the ambiguity set. Experiments are performed for significance levels of 0.85, 0.90, 0.925, 0.95, and 0.99, respectively. Figure 2 and Table 5 display the worst-case distributions and their associated expected attribute rankings.

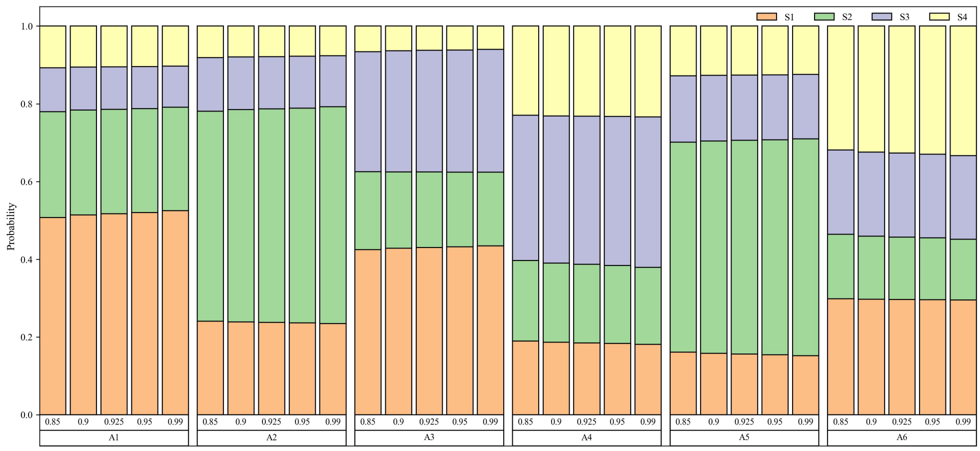



Figure 2: Worst-case distribution under different significant levels

Figure 2 illustrates that, for the worst-case distribution, as the significance level increases, the probability of the optimal scenario for each attribute also rises. Moreover, Table 5 shows that with

Table 5: Worst-case expected attribute rankings of model validation

| $\rho$ | A1 | A2 | A3 | A4 | A5 | A6 |
|---|---|---|---|---|---|---|
| 0.75 | 2.8655 | 2.7356 | 3.6292 | 3.2783 | 3.1157 | 1.8664 |
| 0.85 | 2.8110 | 2.6818 | 3.5983 | 3.2135 | 3.0812 | 1.8472 |
| 0.90 | 2.7850 | 2.6561 | 3.5837 | 3.1826 | 3.0647 | 1.8381 |
| 0.95 | 2.7597 | 2.6311 | 3.5695 | 3.1526 | 3.0487 | 1.8292 |
| 0.99 | 2.7400 | 2.6116 | 3.5585 | 3.1291 | 3.0362 | 1.8222 |

an increasing significance level, the worst-case expected rankings for all attributes shift toward lower values. The optimal weight disparity scalar of OPA-DR decreases consistently as the significance level increases, in line with the closed-form solution from Theorem 1. Regarding the results for projects and portfolios, the final rankings remain consistent across different significance levels. This observation highlights the numerical stability of OPA-DR with respect to the significance level, enabling DMs to choose appropriate levels based on their risk preferences without concern for significant changes in the optimal solution.

*5.5.2. Perturbation Analysis of Project Rankings*

This section conducts a perturbation analysis of OPA-DR in relation to project rankings, assessing the impact of ranking deviations on the final outcomes, which demonstrates the reliability of OPA-DR in the face of uncertainties in expert judgments. Specifically, perturbed samples are generated by adding Gaussian noise to original expert-provided project rankings, resulting in normal distributions centered around each ranking with standard deviations of 1/4, 1/3, and 5/12. This setting follows the empirical rule that approximately 99.7% of data in a normal distribution falls within three standard deviations of the mean, and thus these standard deviations yields perturbation radii $\sigma$ of 0.75, 1, and 1.25, respectively. The following stopping condition are defined to assess the perturbation outcomes:

$$\begin{aligned}
&\|(\arg\max_{k\in\mathcal{K}} p^m_{k,1},\ldots,\arg\max_{k\in\mathcal{K}} p^m_{k,R})^\top - (k^\star_1,\ldots,k^\star_R)^\top\|_2 = 0,\\
&\|(\max_k p^m_{k,1},\ldots,\max_k p^m_{k,R})^\top\|_2 \geq d,
\end{aligned}$$

where $p^m_{k,r}$ is the probability that alternative $k$ is assigned to rank $r$ at iteration $m$, $k^*_r$ denotes the $r$-th ranked alternative in the reference solution, and $d = 2.1213$ corresponds to the $\ell_2$ norm of the constant vector $(1/2, \ldots, 1/2)$ in 18 dimensions. The first condition ensures convergence of the final ranking to the original ranking after a specified number of iterations. The second condition requires that the convergence probability meets a minimum threshold. A maximum of 2000 iterations is allowed for convergence, with at least 100 iterations required for statistical reliability.

The simulation results show that for radii $\sigma = 0.75$ and $\sigma = 1$, OPA-DR converges within 100 and 883 iterations, respectively, while for radius $\sigma = 1.25$, simulation fails to meet the stopping condition and reaches the maximum iteration limit of 2000. This failure primarily occurs because the last three projects do not consistently converge to the original rankings, though it does not affect the final outcomes.

Figure 3 shows ranking results and associated probabilities for different perturbation levels. The bar plot reveals that as the radius increases, the maximum probability of each project achieving optimal decreases. For $\sigma = 0.75$, most alternatives show high confidence with probabilities near 1, whereas for $\sigma = 1.25$, many probabilities fall below 0.6, indicating a marked decline in prediction certainty. The case for $\sigma = 1$ lies between the above two cases. As for project rankings, the cases $\sigma = 0.75$ and $\sigma = 1$ present the identical project rankings with the original rankings, while $\sigma = 1.25$ shows some minor fluctuations in the rankings. Among all 18 projects, the top 15 rankings remain consistent across difference radii. Specifically, for $\sigma = 1.25$, K1 drops from 15th to 16th, K6 rises from 16th to 15th, and K8 moves from 17th to 18th, with most changes confined to adjacent positions. This is due to the fact that the projects with reversed rankings have nearly identical original weights and relatively low rankings.

Figure 4 illustrates the distributions of portfolio weights for different perturbation radii, which display Gaussian-like patterns consistent with the sampling strategy. It also indicates that as the perturbation radius increases, weight variability intensifies, reflecting reduced consensus across the simulated rankings. Overall, based on the above findings, OPA-DR demonstrates considerable stability to project ranking perturbations, with the ranking structure remaining stable even under higher noise, although the convergence speed and confidence may decline in uncertain decision-making contexts.

*5.5.3. Comparison Analysis*

This section conducts comparison analysis of OPA-DR to validate its rationality, with the benchmark methods of robust OPA (OPA-R), stochastic OPA (OPA-S) based on nominal distribution,

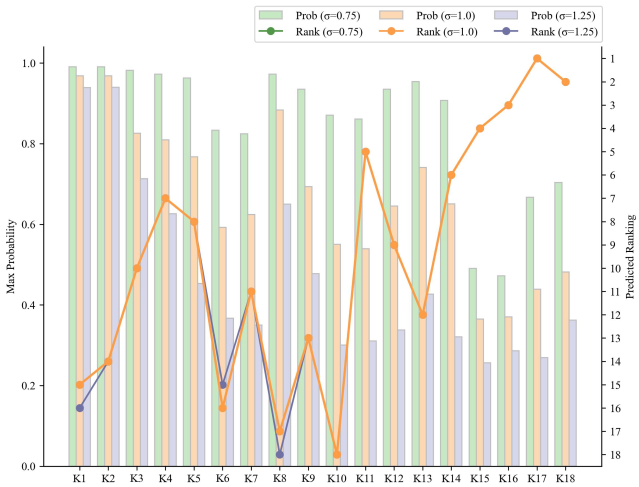



Figure 3: Ranking results and associated probabilities under different perturbation levels

and OPA for each scenario. Specifically, the following benchmark models are constructed:

- OPA-R considers the case where the true attribute rankings lie within the support sets constructed from the four scenarios and optimizes against the worst-case ranking (Mahmoudi et al., 2022b; Wang, 2024c):

$$\max_{z,\boldsymbol{w}\in\mathcal{W}} \left\{ z : Ru_r^{ROC} z \leq t_i \min_{l\in\mathcal{L}} \{s_j^l\} w_{ijr}, \forall (i,j,r)\in\mathcal{E} \right\}.$$

- OPA-S treats attribute rankings as random variables following the nominal distribution $\hat{\mathbb{P}}$ in Table 3 and optimizes based on expected rankings:

$$\max_{z,\boldsymbol{w}\in\mathcal{W}} \left\{ z : Ru_r^{\mathrm{ROC}} z \leq t_i \mathbb{E}_{\tilde{s}_j\sim\hat{\mathbb{P}}}[\tilde{s}_j] w_{ijr}, \forall (i,j,r)\in\mathcal{E} \right\}.$$

- OPA is applied to each scenario, treating them as determination problems. For each scenario $l \in \mathcal{L}$, the formulation is:

$$\max_{z,\boldsymbol{w}\in\mathcal{W}} \left\{ z : Ru_r^{\mathrm{ROC}} z \leq t_i s_{jl} w_{ijr}, \forall (i,j,r)\in\mathcal{E} \right\}.$$

Figure 5 illustrates the weight results for attributes, alternatives, and portfolios, highlighting differing attitudes toward uncertainty across frameworks. In general, the results of OPA-DR, OPA-R, and OPA-S fall within the envelope defined by the OPA results of four scenarios. For attributes,

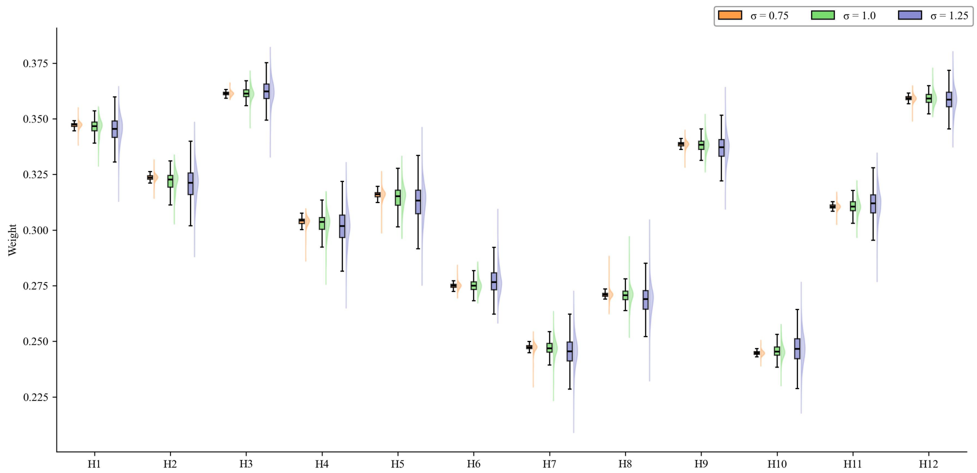
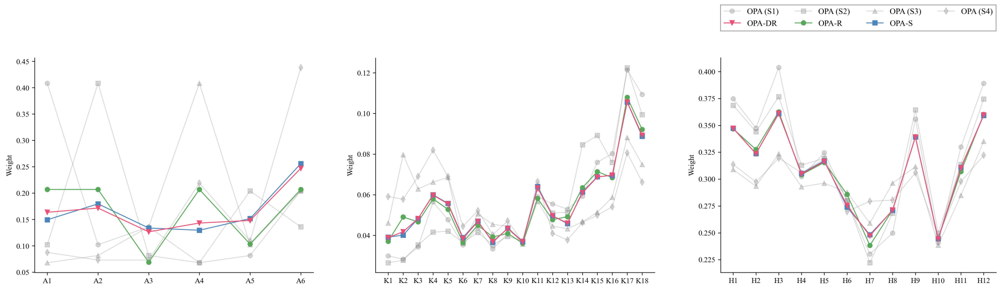



Figure 4: Distributions of alternative weights under different perturbation levels

OPA assigns the highest weight to the top-ranked attribute in each scenario, which is optimal for a deterministic future but lacks robustness against scenario uncertainty. In contrast, OPA-R assigns equal weights to the attributes ranked first in each scenario, namely A1, A2, A4, and A6, ensuring robustness but introducing over-conservatism. OPA-S, however, aligns the attribute weight results with the expected rankings based on the nominal distribution. OPA-DR, in turn, provides attribute weight results that strike a balance between OPA-S and OPA-R, avoiding both excessive conservatism and overreliance on the nominal distribution. Regarding projects and portfolios, the relationships among OPA-DR, OPA-R, and OPA-S are similar to that of the attribute results and fall within the range defined by the OPA results of the four scenarios. However, the OPA results for each scenario show variation, especially for K17 and K18, which exhibit significant shifts in their weight distributions, indicating that the original OPA model is highly sensitive to scenario-specific inputs.

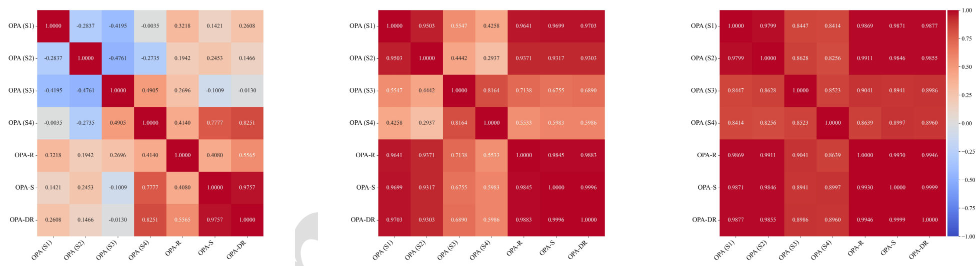
We further calculate the Pearson correlation coefficients between the outcomes of OPA-DR and the other benchmarks, as illustrated in Figure 6. For attribute weights, the OPA results across the four scenarios vary significantly and show negative correlations, with the overall correlation typically below 0.5. Many negative correlations appear in these scenarios, though the correlations between OPA-DR, OPA-S, and OPA (S4) are relatively high. Regarding project and portfolio weights, OPA-




(a) Attribute weight comparison (b) Alternative weight comparison (c) Portfolio weight comparison

Figure 5: Weight outcomes of different approaches

DR exhibits strong correlations with OPA-S (0.9996) and OPA-R (0.9883), outperforming OPA-R and OPA-S in its correlation with other scenarios, and significantly exceeding the correlation of any individual scenario. Overall, OPA-DR provides more stable and balanced weight assignments than benchmark methods, combining the strengths of stochastic and robust approaches to mitigate distributional uncertainty and worst-case scenarios.



(a) Attribute weight correlation (b) Project weight correlation (c) Portfolio weight correlation

Figure 6: Pearson correlation coefficients among the weight outcomes of different approaches

## 6. Conclusion

NET has emerged as a vital means to achieve a clean, efficient, and sustainable global energy supply, with the optimal NET-R&D-PS playing a crucial role in ensuring technological innovation, enhanced safety performance, clean sustainability, and cost-effectiveness maximization. However, current research on NET-R&D-PS, particularly in the nuclear energy sector, is limited and does not adequately address the scenario uncertainties faced by NET R&D. To address this, this study introduces OPA-DR to tackle the NET-R&D-PS problem under scenario uncertainty, which significantly affects attribute rankings. Specifically, OPA-DR enhances the traditional OPA by replacing deterministic attribute rankings with worst-case expected rankings under uncertainty. Additionally, this study proposes an ambiguity set based on KL divergence for OPA-DR to characterize the possible family of distributions within a given nominal distribution for scenarios. In designing the ambiguity set size, it is found that the number of attributes serves as the basis for distinguishing small-scale scenarios (where the number of scenarios is less than the number of attributes). Based on this, we design small-scale scenario ambiguity sets using a statistics-based approach and large-scale scenario ambiguity sets using an optimization-based approach. Subsequently, based on the structural properties of OPA, we propose a solution algorithm that requires solving a one-dimensional equation and analytically calculating the optimal weight using the closed-form solution, making it a polynomial-time algorithm capable of efficiently solving large-scale problems. Finally, this study analyzes the sensitivity of OPA-DR under different alternative utility functions and weight difference constraint perturbations from a theoretical perspective.

This study provides an illustrative demonstration of NET-R&D-PS for China 2030 Vision Plan. The case study identifies eighteen R&D projects and twelve portfolios across five categories of nuclear energy systems, spanning nine applications. Evaluation attributes for the identified NET R&D portfolios include sustainability, economic viability, safety, proliferation resistance, technical compatibility, and implementation feasibility. Considering exportability of NET and breakthrough potential of OCET, four potential NET R&D scenarios for 2030 and their respective probability distributions are determined, along with the attribute importance ranking for each scenario. The results show the worst-case distribution of attributes within the proposed ambiguity set for OPA-DR, which would provide DMs with valuable insights into NET R&D prospects. Additionally, the NET-R&D-PS results identify H3 as the optimal portfolio. H3 demonstrates a balanced and consistently strong performance, covering breeding, separation-purification, combustion, and partial neutron poison removal, with applications spanning all nine use cases. This study validates the model by testing OPA-DR with varying significance levels and project ranking parameters, and compares it with robust OPA and stochastic OPA based on nominal distribution. The results confirm the robustness and stability of the KL divergence-based OPA-DR approach, validating its effectiveness in addressing the MADM-based NET-R&D-PS.

It is important to note that the results and conclusions are derived within a specific context. Therefore, further testing across various NET-R&D-PS scenarios is necessary to confirm their effectiveness. Furthermore, the proposed approach is adaptable to other energy sectors (e.g., renewable energy R&D and hydrogen storage technologies) by following the implementation steps outlined in Section 4.4 and adhering to the provided several notes. Moreover, this study assumes attribute independence, but future research could explore scenarios that incorporate attribute interactions, which are more typical in real-world contexts. This could be achieved using the method proposed by Wang (2024b), which models correlations between indicators in the ranking parameters using an exponential form. In this case, the theoretical proof derived in this study remains consistent. Additionally, while this study proposes different approaches to determine the ambiguity set size to minimize the impact of biased or inconsistent expert opinions, it is recognized that such systematic biases may still persist. To address this, we propose two feasible modeling approaches to improve the proposed approach in the future. The first approach considers a globalized DRO formulation, which ensures no constraint violation for any distribution within a predefined ambiguity set, while allowing potential constraint violations for distributions outside the ambiguity set. This method can smoothly extend to the proposed approach without adding computational cost, handling cases where the true distribution lies outside the ambiguity set constructed by nominal distribution. For further details on globalized DRO modeling, we refer the reader to Liu et al. (2023). The second approach applies Bayesian DRO modeling, treating the nominal distribution provided by experts as the prior and updating the posterior distribution to mitigate bias. For more information on Bayesian DRO modeling, we refer the reader to Shapiro et al. (2023).

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## Appendix A. Technical Proofs

Proof of Proposition 1. Assume the given nominal distribution $\hat{\mathbb{P}}$ is a random sample independently and identically drawn from an unknown distribution $\mathbb{P}$. Based on this, we can conduct the following hypothesis test:

- $H_0$: $\hat{\mathbb{P}}$ is drawn from $\mathbb{P}$;
- $H_1$: $\hat{\mathbb{P}}$ is not drawn from $\mathbb{P}$.

Given a threshold $\rho$, if the test does not reject $H_0$, then $\mathbb{P}$ passes the test and can be regarded as the distribution constructing the ambiguity set. Thus, the ambiguity set of distributions obtained from the test is:

$$\begin{aligned} \mathscr{F}(\hat{\mathbb{P}},\rho) &:= \left\{\mathbb{P} : T^L_{\phi_{KL}}(\hat{\mathbb{P}},\mathbb{P}) \leq \rho\right\}, \\ &:= \left\{\mathbb{P} : \frac{2L}{\phi''_{KL}(1)} D_{\phi_{KL}}(\hat{\mathbb{P}},\mathbb{P}) \leq \rho\right\}, \\ &:= \left\{\mathbb{P} : D_{\phi_{KL}}(\hat{\mathbb{P}},\mathbb{P}) \leq \theta = \frac{\phi''_{KL}(1)\rho}{2L}\right\}. \end{aligned} \tag{A.1}$$

Using the asymptotic distribution of $T^L_{\phi_{KL}}(\hat{\mathbb{P}},\mathbb{P})$ (which converges to a chi-squared distribution with $L-1$ degrees of freedom), the size parameter $\theta$ of the KL divergence ambiguity set can be determined at a significance level $\delta = \mathbb{P}\left(T^L_{\phi_{KL}}(\hat{\mathbb{P}},\mathbb{P}) > \rho | H_0\right)$. Let $\rho = \chi^2_{L-1,1-\delta}$, then the ambiguity set corresponds to the $1-\delta$ confidence region of the true distribution $\mathbb{P}$. Furthermore, noting that $\hat{\mathbb{P}}$ and $\mathbb{P}$ are interchangeable, the convergence result still holds. Therefore, we have the results in Proposition 1. □

Proof of Lemma 2. For any $(i,j,r) \in \mathcal{E}$ and fixed $w_{ijr}$, the expert ranking $t_i$ is a deterministic parameter, leading to:

$$\min_{\mathbb{P}_j \in \mathscr{F}_{KL}(\hat{\mathbb{P}},\theta)} \mathbb{E}_{\boldsymbol{\xi}_j \sim \mathbb{P}_j}[t_i s_j w_{ijr}] \Leftrightarrow t_i w_{ijr} \min_{\mathbb{P}_j \in \mathscr{F}_{KL}(\hat{\mathbb{P}},\theta)} \mathbb{E}_{s_j \sim \mathbb{P}_j}[s_j]. \tag{A.2}$$

Therefore, the worst-case expectation of attribute ranking under the KL-divergence ambiguity set can be determined by solving the following convex optimization problem:

$$\begin{aligned} \min_{\mathbb{P}_j \in \mathbb{R}_+^L} \quad & \sum_{l=1}^{L} p_{jl} s_{jl}, \\ \text{s.t.} \quad & \sum_{l=1}^{L} p_{jl} \log\left(\frac{p_{jl}}{\hat{p}_l}\right) \leq \theta, \\ & \sum_{l=1}^{L} p_{jl} = 1. \end{aligned} \tag{A.3}$$

The Lagrangian of Equation (A.3) is given by:

$$\begin{aligned} \mathcal{G}(\alpha_j, \beta_j, \boldsymbol{p}_j) &= \sum_{l=1}^{L} p_{jl} s_{jl} + \alpha_j \left(\theta - \sum_{l=1}^{L} p_{jl} \log\left(\frac{p_{jl}}{\hat{p}_l}\right)\right) + \beta_j \left(1 - \sum_{l=1}^{L} p_{jl}\right), \\ &= \alpha_j \theta + \beta_j + \sum_{l=1}^{L} p_{jl} \left(s_{jl} - \alpha_j \log\left(\frac{p_{jl}}{\hat{p}_l}\right) - \beta_j\right). \end{aligned} \tag{A.4}$$

where $\alpha_j \geq 0$ and $\beta_j$ are the dual variables.

Note that the KKT conditions are both necessary and sufficient for optimality in convex optimization problems. By taking the derivative with respect to $p_{jl}$ and setting it to zero, for all $l \in \mathcal{L}$, we get:

$$\frac{\partial \mathcal{G}(\alpha_j, \beta_j, \boldsymbol{p}_j)}{\partial p_{jl}} = 0 \Leftrightarrow s_{jl} - \alpha_j \left(1 + \log\left(\frac{p_{jl}}{\hat{p}_l}\right)\right) - \beta_j = 0,$$

which yields:

$$p_{jl} = \hat{p}_l \exp\left(\frac{s_{jl} - \beta_j}{\alpha_j} - 1\right). \tag{A.5}$$

Substituting Equation (A.6) into the normalization condition gives:

$$\sum_{l=1}^{L} \hat{p}_l \exp\left(\frac{s_{jl} - \beta_j}{\alpha_j} - 1\right) = 1 \Rightarrow \exp\left(-\frac{\beta_j + \alpha_j}{\alpha_j}\right) \sum_{l=1}^{L} \hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right) = 1.$$

Define $Z(\alpha_j) = \sum_{l=1}^{L} \hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right)$, yielding:

$$\beta_j = -\alpha_j \log Z(\alpha_j) - \alpha_j. \tag{A.6}$$

Plugging Equation (A.6) into Equation (A.5) provides the form of worst-case distribution:

$$p_{jl} = \frac{1}{Z(\alpha_j)} \hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right), \quad \forall l \in \mathcal{L}. \tag{A.7}$$

According to the KKT condition, the optimal value of $\alpha_j$ can be obtained by solving the following equation:

$$\alpha_j^\star = \arg_{\alpha_j} \left\{ \sum_{l=1}^{L} \frac{\hat{p}_l \exp\left(\frac{s_{jl}}{\alpha_j}\right)}{Z(\alpha_j)} \log\left(\frac{\exp\left(\frac{s_{jl}}{\alpha_j}\right)}{Z(\alpha_j)}\right) = \theta \right\}. \tag{A.8}$$

Note that the function on the left-hand side of Equation (A.8) is strictly decreasing and continuous in $\alpha_j$, ensuring the existence and uniqueness of the optimal solution. Substituting $\alpha_j^\star$ into Equation (A.7) gives the worst-case distribution $\mathbb{P}_j^\star$ that satisfies the KKT condition, which gives the results in Lemma 2. □

Proof of Theorem 1. Given the worst-case distribution $\mathbb{P}_j^\star$, we have OPA-DR in the following form:

$$\begin{aligned}
&\max_{z,\boldsymbol{w}} \ z, \\
&\text{s.t. } Ru_r^{ROC} z \le t_i \left(\sum_{l=1}^{L} p_{jl}^\star s_{jl}\right) w_{ijr}, && \forall (i,j,r) \in \mathcal{E}, \\
&\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} w_{ijr} = 1, \\
&w_{ijr} \ge 0, && \forall (i,j,r) \in \mathcal{E}.
\end{aligned} \tag{A.9}$$

which is a typical linear programming problem. Thus, employing the Lagrange multiplier method, we have:

$$\begin{aligned}
\mathcal{G}(z,\boldsymbol{w},\alpha,\boldsymbol{\beta}) = z + \alpha &\left(1 - \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} w_{ijr}\right) \\
&+ \sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{R} \beta_{ijr}\left(t_i\left(\sum_{l=1}^{L} p_{jl}^\star s_{jl}\right) w_{ijr} - Ru_r^{ROC} z\right).
\end{aligned} \tag{A.10}$$

Following Wang (2024a), we always have:

$$\frac{\partial \mathcal{G}(z,\boldsymbol{w},\alpha,\boldsymbol{\beta})}{\partial \alpha} = \frac{\partial \mathcal{G}(z,\boldsymbol{w},\alpha,\boldsymbol{\beta})}{\beta_{ijr}} = 0, \quad \forall (i,j,r) \in \mathcal{E}, \tag{A.11}$$

which yields:

$$w_{ijr}^\star = \frac{Ru_r^{ROC} z^\star}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}}, \quad \forall (i,j,r) \in \mathcal{H}, \tag{A.12}$$

and

$$\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{r=1}^{K} w_{ijr}^\star = 1. \tag{A.13}$$

Substituting Equation (A.12) into Equation (A.13) yields the closed-form solution of OPA-DR shown in Theorem 1. $\square$

Proof of Corollary 1. By the closed-form solution in Theorem 1, we have:

$$z^\star(\boldsymbol{u}^\delta) = 1 \Bigg/ \left( \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \frac{R u_r^\delta}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \right) = 1 \Bigg/ \left( R \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{1}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \right) = z^\star, \tag{A.14}$$

where the second equality follows from $\sum_{r=1}^{R} u_r^\delta = 1$. It follows that, for any $(i, j, r) \in \mathcal{E}$,

$$|w_{ijr}^\star - w_{ijr}^\star(\boldsymbol{u}^\delta)| = \left| \frac{R u_r^{ROC} z^\star}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} - \frac{R u_r^\delta z^\star(\boldsymbol{u}^\delta)}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \right| = \frac{R z^\star}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \left| u_r^{ROC} - u_r^\delta \right|, \tag{A.15}$$

which gives the results in Corollary 1. $\square$

Proof of Corollary 2. Let $(\lambda^\star, \boldsymbol{\gamma}^\star)$ be optimal for the dual problem of Equation (23):

$$\begin{aligned}
\min_{\lambda, \gamma} \;\; & \lambda, \\
\text{s.t. } & t_i \left( \sum_{l=1}^{L} p_{jl}^\star s_{jl} \right) \gamma_{ijr} \leq \lambda, && \forall (i,j,r) \in \mathcal{E}, \\
& \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \left( \sum_{h=r}^{R} \frac{1}{h} \right) \gamma_{ijr} = 1, \\
& \gamma_{ijr} \geq 0, && \forall (i,j,r) \in \mathcal{E}.
\end{aligned} \tag{A.16}$$

Suppose that $(z, \boldsymbol{w})$ is feasible for the perturbation problem in Equation (23). Then, we have, by strong duality,

$$\begin{aligned}
z^\star &\geq z + \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \gamma_{ijr}^\star \left( t_i \left( \sum_{l=1}^{L} p_{jl}^\star s_{jl} \right) w_{ijr} - R u_r^{ROC} z \right) + \lambda^\star (1 - \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} w_{ijr}), \\
&\geq z + \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \gamma_{ijr}^\star \varepsilon_{ijr} + \lambda^\star \epsilon,
\end{aligned} \tag{A.17}$$

where the last inequality follows from $\gamma_{ijr}^\star \geq 0$ for all $(i, j, r) \in \mathcal{E}$.

Thus, for any $z$ feasible for the perturbation problem, we have:

$$z \leq z^\star - \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \gamma_{ijr}^\star \varepsilon_{ijr} - \lambda^\star \epsilon, \tag{A.18}$$

which yields:

$$z^\star(\boldsymbol{\varepsilon}, \epsilon) \leq z^\star - \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \gamma_{ijr}^\star \varepsilon_{ijr} - \lambda^\star \epsilon. \tag{A.19}$$

Let $\sigma_{ijr} = Ru_r^{ROC}\gamma_{ijr}$ for all $(i,j,r) \in \mathcal{E}$. Following the symmetric argument as the proof of Theorem 1, we have, by Lagrange multiplier method,

$$\lambda^\star = 1 \Big/ \left( \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \frac{Ru_r^{ROC}}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \right) = z^\star, \tag{A.20}$$

and

$$\sigma_{ijr}^\star = \frac{Ru_r^{ROC}\lambda^\star}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}}, \quad \forall (i,j,r) \in \mathcal{E}. \tag{A.21}$$

Thus, we have:

$$\begin{aligned} z^\star(\boldsymbol{\varepsilon}, \epsilon) &\leq z^\star - \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \frac{z^\star}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \varepsilon_{ijr} - z^\star \epsilon, \\ &= \left( 1 - \epsilon - \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{r=1}^{R} \frac{\varepsilon_{ijr}}{t_i \sum_{l=1}^{L} p_{jl}^\star s_{jl}} \right) z^\star. \end{aligned} \tag{A.22}$$

Following the symmetric argument as the proof of Theorem 1, we can conclude that the equality in the upper bound always holds, which gives the results in Corollary 2. □

## Appendix B. Case Study Data

Table B.1: Project ranking under each attribute given by experts

| Expert ID | Project ID | A1 | A2 | A3 | A4 | A5 | A6 | Expert ID | Project ID | A1 | A2 | A3 | A4 | A5 | A6 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| E1 | P1 | 18 | 17 | 18 | 4 | 12 | 3 | E2 | P1 | 16 | 18 | 15 | 5 | 11 | 3 |
| | P2 | 16 | 15 | 17 | 8 | 17 | 7 | | P2 | 17 | 14 | 18 | 8 | 17 | 9 |
| | P3 | 15 | 14 | 7 | 5 | 15 | 10 | | P3 | 15 | 15 | 7 | 1 | 18 | 4 |
| | P4 | 17 | 18 | 11 | 2 | 18 | 8 | | P4 | 18 | 17 | 13 | 6 | 6 | 5 |
| | P5 | 12 | 13 | 16 | 9 | 6 | 4 | | P5 | 13 | 16 | 11 | 9 | 16 | 10 |
| | P6 | 13 | 16 | 12 | 13 | 3 | 9 | | P6 | 14 | 10 | 8 | 10 | 3 | 14 |
| | P7 | 14 | 11 | 8 | 12 | 7 | 18 | | P7 | 11 | 12 | 6 | 15 | 7 | 17 |
| | P8 | 10 | 10 | 3 | 18 | 11 | 17 | | P8 | 12 | 13 | 12 | 16 | 8 | 18 |
| | P9 | 7 | 8 | 9 | 14 | 13 | 5 | | P9 | 10 | 6 | 10 | 18 | 12 | 6 |
| | P10 | 9 | 6 | 13 | 11 | 1 | 11 | | P10 | 4 | 11 | 16 | 17 | 1 | 15 |
| | P11 | 8 | 9 | 15 | 15 | 8 | 14 | | P11 | 8 | 8 | 17 | 13 | 10 | 11 |
| | P12 | 11 | 12 | 14 | 16 | 16 | 1 | | P12 | 9 | 9 | 14 | 12 | 13 | 1 |
| | P13 | 5 | 7 | 6 | 1 | 14 | 15 | | P13 | 7 | 7 | 4 | 2 | 15 | 8 |

**Table B.1 continued from previous page**

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | P14 | 4 | 4 | 5 | 10 | 9 | 12 | | P14 | 5 | 4 | 5 | 14 | 5 | 12 |
| | P15 | 6 | 5 | 10 | 17 | 2 | 2 | | P15 | 6 | 5 | 9 | 11 | 2 | 2 |
| | P16 | 2 | 3 | 4 | 6 | 10 | 13 | | P16 | 2 | 2 | 3 | 4 | 14 | 13 |
| | P17 | 1 | 1 | 2 | 7 | 4 | 6 | | P17 | 1 | 1 | 2 | 7 | 4 | 7 |
| | P18 | 3 | 2 | 1 | 3 | 5 | 16 | | P18 | 3 | 3 | 1 | 3 | 9 | 16 |
| E3 | P1 | 18 | 15 | 16 | 2 | 11 | 3 | E4 | P1 | 18 | 17 | 18 | 2 | 11 | 2 |
| | P2 | 17 | 18 | 12 | 7 | 18 | 4 | | P2 | 17 | 18 | 17 | 7 | 16 | 4 |
| | P3 | 11 | 14 | 7 | 1 | 16 | 9 | | P3 | 16 | 16 | 2 | 8 | 12 | 15 |
| | P4 | 14 | 17 | 17 | 3 | 15 | 5 | | P4 | 12 | 14 | 5 | 6 | 18 | 7 |
| | P5 | 15 | 13 | 13 | 8 | 9 | 11 | | P5 | 15 | 11 | 13 | 17 | 15 | 5 |
| | P6 | 13 | 16 | 5 | 17 | 4 | 6 | | P6 | 13 | 15 | 8 | 10 | 4 | 6 |
| | P7 | 16 | 11 | 11 | 11 | 3 | 18 | | P7 | 14 | 13 | 15 | 9 | 1 | 11 |
| | P8 | 6 | 12 | 9 | 18 | 6 | 17 | | P8 | 5 | 8 | 6 | 18 | 5 | 18 |
| | P9 | 4 | 5 | 10 | 9 | 8 | 7 | | P9 | 6 | 7 | 10 | 15 | 13 | 8 |
| | P10 | 8 | 10 | 14 | 12 | 1 | 13 | | P10 | 10 | 9 | 9 | 13 | 2 | 13 |
| | P11 | 9 | 8 | 18 | 10 | 12 | 14 | | P11 | 8 | 10 | 16 | 16 | 9 | 12 |
| | P12 | 12 | 9 | 15 | 16 | 10 | 1 | | P12 | 7 | 12 | 14 | 11 | 6 | 3 |
| | P13 | 10 | 7 | 6 | 14 | 17 | 12 | | P13 | 9 | 5 | 7 | 3 | 10 | 10 |
| | P14 | 5 | 3 | 3 | 13 | 5 | 15 | | P14 | 4 | 4 | 11 | 14 | 17 | 16 |
| | P15 | 7 | 4 | 4 | 15 | 2 | 2 | | P15 | 11 | 6 | 12 | 12 | 3 | 1 |
| | P16 | 2 | 2 | 2 | 5 | 13 | 10 | | P16 | 2 | 2 | 4 | 5 | 14 | 14 |
| | P17 | 1 | 1 | 1 | 6 | 7 | 8 | | P17 | 3 | 1 | 1 | 4 | 7 | 9 |
| | P18 | 3 | 6 | 8 | 4 | 14 | 16 | | P18 | 1 | 3 | 3 | 1 | 8 | 17 |
| E5 | P1 | 17 | 17 | 17 | 2 | 14 | 1 | E5 | P10 | 9 | 8 | 13 | 11 | 2 | 12 |
| | P2 | 18 | 14 | 18 | 3 | 17 | 4 | | P11 | 10 | 10 | 15 | 12 | 11 | 10 |
| | P3 | 15 | 15 | 5 | 4 | 16 | 11 | | P12 | 11 | 11 | 14 | 15 | 12 | 2 |
| | P4 | 16 | 18 | 12 | 5 | 15 | 5 | | P13 | 8 | 9 | 6 | 1 | 18 | 13 |
| | P5 | 12 | 13 | 16 | 17 | 9 | 6 | | P14 | 5 | 4 | 7 | 9 | 8 | 14 |
| | P6 | 13 | 16 | 4 | 18 | 3 | 7 | | P15 | 6 | 5 | 8 | 10 | 1 | 3 |
| | P7 | 14 | 12 | 9 | 13 | 5 | 16 | | P16 | 2 | 2 | 3 | 7 | 13 | 15 |
| | P8 | 4 | 6 | 10 | 16 | 7 | 17 | | P17 | 1 | 1 | 1 | 8 | 4 | 9 |
| | P9 | 7 | 7 | 11 | 14 | 10 | 8 | | P18 | 3 | 3 | 2 | 6 | 6 | 18 |

## Highlights

**A Distributionally Robust Ordinal Priority Approach for Nuclear Energy Technology R&D Portfolio Selection under Scenario Uncertainty**

Shutian Cui, Fengjing Zhu, Renlong Wang

- Explores nuclear energy technology R&D portfolio selection (NET-R&D-PS) under scenario uncertainty.
- Proposes a distributionally robust ordinal priority approach (OPA-DR) with a Kullback-Leibler divergence-based ambiguity set, applicable to small- and large-sample problems.
- Provides an efficient exact algorithm for solving OPA-DR.
- Presents NET-R&D-PS of China's 2030 Vision Plan as a case study.

**Declaration of interests**

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: