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Original Research

Robust Strategic Weight Manipulation Model with an Application to Environmental Assessment

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Abstract

In the increasingly complex and uncertain decision-making circumstances, interest groups and individuals will deliberately set attributes weight to manipulate the expected ranking of alternatives in order to achieve their benefits. However, it is not easy to change the ranking of alternatives, a certain compensation cost should be paid by decision makers. In previous studies, most scholars only considered the existence of unit compensation cost but ignored the uncertainty of compensation cost, which increased the risk of decision-making. In order to address the research gap, we construct two kinds of uncertainty sets in this work to describe the uncertainty of unit compensation cost more accurately. In addition, a robust strategic weight manipulation model is proposed with the presence of unit compensation cost uncertainty based on the robust optimization method to reduce the risk of the model. Furthermore, the proposed robust optimization model is applied to a numerical simulation of environmental assessment. The results show the applicability of the proposed method. Through comparison analysis and sensitivity analysis, we state that the proposed robust model is more scientific and effective than original model. Finally, some interesting conclusions and future research directions are given.

Keywords: robust optimization, strategic weight manipulation, uncertainty set, environmental assessment

Introduction

Ecological and environmental issues have gradually drawn attention from all countries around the world [1]. Accordingly, the concept of "clear waters and lush mountains are mountains of gold and silver" has been put forward by the Chinese government as a guideline for environmental governance. In the process of environmental governance, the design of environmental assessment [2-6] is particularly important in order to effectively evaluate the efficiency of environmental governance. Environmental assessment encourages the consideration of environmental factors in planning and decision-making, ultimately leading to more environmentally compatible production activities. For example, in order to ensure the rationality of location and layout of environmental construction projects, so as to enable the efficient operation of the environmental supply chain [7] and to guide the design of environmental protection measures, it is very important to carry out scientific assessment of environmental construction projects. Only in this way can the purpose of strengthening environmental management be achieved. To some extent, environmental assessment

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is actually a multi-attribute decision-making (MADM) problem [8-9]. The location schemes of environmental construction projects to be planned are the alternatives, the factors that affect environmental governance are multiple attributes, and the staff of environmental management departments are decision makers. Therefore, this paper focuses on the problem of multi-attribute decision-making in environmental assessment.

The decision method that evaluates multiple attributes to obtain the ranking of alternatives is called MADM [10-11]. Decision-makers evaluate each attribute in MADM, and the weights of attributes are obtained. In the actual evaluation process, decision-makers may express their opinions dishonestly in order to obtain more individual benefits, which is called strategic manipulation or non-cooperative behavior [12]. Nevertheless, the strategic manipulation or the non-cooperative behavior is rarely discussed in previous methods such as AHP model, TOPSIS model, VIKOR model, BWM model and FMEA model [13-17]. The strategic weight manipulation model can help decision-makers achieve the purpose of manipulating the alternative ranking [18-19]. However, it is not easy to manipulate the ranking of the alternative. A certain compensation cost needed to be paid by decision makers. Generally, decision makers are expected to achieve their goal of manipulating the alternatives ranking by minimizing the compensation cost. Decision-making in real life tends to be more and more complex and uncertain [20-26], and the interference of uncertain factors on decision-making can't be ignored. Consequently, the compensation cost of the decision makers is not a fixed value. And the decision makers can't measure the compensation cost with a specific value, which often fluctuates within a certain range. The uncertainty of compensation cost is still rarely considered in previous studies. In order to cope with the fluctuation of compensation cost, the robust optimization method is introduced for modeling in this paper.

Robust optimization fully takes into account the uncertainty in the modeling process and reduces the decision risk caused by uncertain factors. And the variable is described in the form of set. In MADM, stochastic programming [27-28] and fuzzy programming [29-30] are commonly utilized to cope with the uncertainty parameters. However, the probability distribution function for random parameters needed to be known in advance in stochastic programming. Fuzzy programming requires the fuzzy membership function of parameters to be determined in advance. For some subjective and objective reasons, probability distribution function and fuzzy membership function are not easy to obtain completely. Compared with these two methods, robust optimization does not require the probability distribution of uncertain parameters and the fuzzy membership function of uncertain parameters. The key of robust optimization is to select an appropriate uncertainty set to characterize the random parameters and meet the realization of all constraints in the worst case [31-34]. Robust optimization has been widely applied in group decision-making [35-38], facility location [39-42], portfolio management [43-45] and other fields. However, few literatures have applied robust optimization method to strategic weight manipulation for environmental assessment. Hence, in order to investigate the construction of environmental assessment projects under uncertain circumstances, we provide two kinds of uncertainty sets to describe the uncertain compensation cost more accurately, so as to eliminate the serious influence of uncertainty factors as much as possible. We build a robust optimization model to mathematize the strategic weight manipulation problem in environmental assessment, which can significantly improve the robustness and reduce the risk of the model.

The main contributions and the originality of this study can be summarized as follows: Firstly, the uncertainty of compensation cost in real life is taken into account, which enriches the uncertainty factors in the model and reduces decision risks. We utilize robust optimization method to deal with cost uncertainty and supplement the research gap in this area. Secondly, this paper describes the disturbance of compensation cost by introducing budgeted uncertainty set and polyhedron uncertainty set, which can describe the uncertainty of unit compensation cost more accurately. We construct the robust optimization model and equivalently transform the robust model into a convex optimization problem that can be easily solved in polynomial time by using duality theory. Finally, through a simulation application of environmental assessment, we show that our proposed method is more practical than deterministic optimization method. We also discuss some parameters and analyze the impact of their changes on the model.

The rest of this paper is arranged as follows: Section 2 proposes material and methods; Section 3 are results and discussion of case study; Section 4 concludes and presents future research directions.

Material and Methods

Data

The material used in this paper is the data for simulation. Industrial development and population growth have led to a sharp increase in global waste production. Waste incineration can obtain a certain amount of energy while effectively reducing the amount of waste [46]. In the environmental construction project location of municipal solid waste oxy-fuel incineration power plant, we comprehensively consider the five indicators $\{a_1, a_2, a_3, a_4, a_5\}$ that including economic input, environmental improvement, financial returns, social benefits and technical support. And ten location alternatives $\{x_1, x_2, ..., x_9, x_{10}\}$ to be planned.

Table 1. Initial data of numerical simulation.

Alternatives	a_1	a_2	a_3	a_4	a_5
x_1	699	92	15000	85	79122
x_2	571	74	12000	73	26823
x_3	285	79	13500	80	32663
x_4	57	51	9000	71	8148
x_5	1722	39	7000	62	5060
x_6	1824	61	10000	79	12500
x_7	579	98	16500	98	85259
x_8	1755	88	18000	76	142000
x_9	655	80	14000	91	42443
x_{10}	800	82	13000	84	23426

Table 2. Standardized data of numerical simulation.

Alternatives	a_1	a_2	a_3	a_4	a_5
x_1	0.6367	0.8983	0.7273	0.6389	0.4592
x_2	0.7091	0.5932	0.4545	0.3056	0.8411
x_3	0.8710	0.678	0.5909	0.5000	0.7984
x_4	1	0.2034	0.1818	0.2500	0.9774
x_5	0.0577	0	0	0	1
x_6	0	0.3729	0.2727	0.4722	0.9457
x_7	0.7046	1	0.8636	1	0.4143
x_8	0.0390	0.8305	1	0.3889	0
x_9	0.6616	0.6949	0.6364	0.8056	0.727
x_{10}	0.5795	0.7288	0.5455	0.6111	0.8659

For benefit indicators, the standardized process is shown in Eq. (1).

$$r_{ij} = \frac{s_{ij} - \min_i(s_{ij})}{\max_i(s_{ij}) - \min_i(s_{ij})} \tag{1}$$

For cost indicators, the standardized process is shown in Eq. (2).

$$r_{ij} = \frac{\max_i(s_{ij}) - s_{ij}}{\max_i(s_{ij}) - \min_i(s_{ij})} \tag{2}$$

where s_{ij} indicates the attributes value of an alternative $x_i \in \{x_1, x_2, ..., x_m\}$ with respect to $a_i \in \{a_1, a_2, ..., a_n\}$.

Table 1 shows the initial data of different indicators under different alternatives. And Table 2 shows the standardized data normalized by Eq. (1) and Eq. (2). Besides, a_1 and a_5 are cost indicators. a_2, a_3 and a_4 are benefit indicators.

Methods

The ranking order is determined by comparing the score $D(x_i)$ of the alternative x_i, which ranks first with the higher value. When comparing the ranking of alternative x_i, $(i \in I = \{1, 2, ..., m\})$ and alternative x_l, $(l \in I = \{1, 2, ..., m\})$, in order to calculate the ranking of alternative x_i, we only need to find out the number of alternatives that meet the cardinality set. $H = \{x_l | D(x_i) > D(x_l)\}$, $(i \neq l)$ Suppose $p(x_l)$ represents the ranking of the alternative x_i, then $p(x_l) = |H| + 1$.

In multi-attribute decision-making, the attributes weight will be manipulated strategically by decision-makers to realize their interest. Assuming that the manipulator wants to change the ranking of alternative x_l, we define the expected ranking of manipulator is $p^*(x_l)$, it is obvious that $p^*(x_l) = p(x_l)$. Suppose the attribute weight vector before manipulation is $\omega^0 = (\omega_1^0, ..., \omega_j^0 ..., \omega_n^0)^T$, $(j \in J = \{1, 2, ..., n\})$, the weight vector after manipulation is $\omega = (\omega_1, ..., \omega_j ..., \omega_n)^T$. The attribute weight deviation in manipulation process is $d_j = |\omega_j^0 - \omega_j|$. Assuming that the unit compensation cost is c_j, the total cost paid by the decision-makers to manipulate the attribute weight is $c^T d$. Moreover, an infinite constant M and a 0-1 variable y_{il} are introduced in this paper.

The original nominal model we built is as follows:

$$\begin{aligned} \min \quad & c^T d \\ s.t. \quad & \sum_{j=1}^{n} \omega_j r_{ij} > \sum_{j=1}^{n} \omega_j r_{ij} - (1 - y_{il}) M, \forall i \in I \\ & \sum_{j=1}^{n} \omega_j r_{ij} \leq \sum_{j=1}^{n} \omega_j r_{ij} + y_{il} M, \forall i \in I \\ & \sum_{j=1, i \neq l}^{m} y_{il} + 1 = p^*(x_l), \forall l \in I \\ & \left| \omega_j^0 - \omega_j \right| \leq d, \forall j \in J \\ & \sum_{j=1}^{n} \omega_j = 1, \forall j \in J \\ & y_{il} \in \{0,1\}, \forall i \in I, \forall l \in I \\ & 0 \leq \omega_j \leq 1, \forall j \in J \end{aligned} \tag{3}$$

The objective is to minimize the cost to be compensated by the decision makers to change the weight of environmental factors. The specific constraints are as follows. The first constraint and the second constraint represent the comprehensive evaluation score comparison between the location alternative x_i, $(i \in I)$ and x_l, $(l \in I)$. We utilize an infinite constant M and a 0-1 variable y_{il}, when $y_{il} = 1$, we have $D(x_i) > D(x_l)$. On the contrary, when $y_{il} = 0$, then $D(x_i) \leq D(x_l)$. The third constraint represents the expected ranking of alternative x_l. The fourth constraint indicates the attribute a_j weight deviation in manipulation process is less than or equal to d_j. The fifth constraint indicates that the sum of attributes weight is 1. The sixth constraint is the 0-1 variable. The seventh constraint represents that the weight of the attribute a_j is greater than 0 and not greater than 1.

However, model (3) does not take into account the uncertainty of compensation cost, which is not robust. Due to the fluctuation of compensation cost in the actual situation, the fluctuation is often accompanied by the decision risk. The decision risk cannot be completely eliminated. Accordingly, we introduce budgeted uncertainty set and polyhedron uncertainty set to characterize the disturbance of compensation cost.

The dynamics of model (3) are investigated and the main results are listed as Proposition 2.1 and Proposition 2.2 as follows.

Proposition 2.1 Inspired by the method proposed by Bertsimas and Zhang et al. [47-48], in order to further reduce the uncertainty of compensation cost in modeling and improve the computational efficiency, we introduce uncertain budget to reduce the range of uncertain scenario set and optimize the computational results. Simultaneously, we do not need the probability distribution of uncertain parameters, and the decision does not depend on the historical data [49-50]. Therefore, the above model (3) is transformed into a robust counterpart model:

$$\begin{aligned}
\min \quad & \underline{c}^T d + z\Gamma + \sum_{g=1}^{G} q_g \\
s.t. \quad & \sum_{j=1}^{n} \omega_j r_{ij} > \sum_{j=1}^{n} \omega_j r_{lj} - (1 - y_{il})M, \forall i \in I \\
& \sum_{j=1}^{n} \omega_j r_{ij} \le \sum_{j=1}^{n} \omega_j r_{lj} + y_{il}M, \forall i \in I \\
& \sum_{i=1, i\ne l}^{m} y_{il} + 1 = p^*(x_l), \forall l \in I \\
& \left|\omega_j^0 - \omega_j\right| \le d, \forall j \in J \\
& \sum_{j=1}^{n} \omega_j = 1, \forall j \in J \\
& z + q_g \ge \tilde{c}^T d \\
& q_g \ge 0 \\
& z \ge 0 \\
& y_{il} \in \{0,1\}, \forall i \in I, \forall l \in I \\
& 0 \le \omega_j \le 1, \forall j \in J
\end{aligned} \tag{4}$$

where z and q_g are the dual variables in the dual problem.

Proof 2.1 According to the definition of budgeted uncertainty set, it is assumed that the probability distribution of the unit compensation cost is unknown, but the upper and lower bounds of the value interval are known. Here, $\underline{c}$ is used to denote the lower bound of the uncertain parameter c. The length of the compensation cost change interval is denoted by $\tilde{c}$, and the compensation cost interval can be expressed as $[\underline{c}, \underline{c} + \tilde{c}]$. Then, the set of all possible scenarios for the compensation cost can be presented by $\{c|\underline{c} \le c \le \underline{c} + \tilde{c}\}$.The optimal solution for robust optimization is the optimal objective function value that is still feasible under all uncertainties. However, if all uncertain parameters are considered as the worst case, the solution would be too conservative. Here, ε_g is utilized to denote the deviation agree between the actual compensation cost and the lower bound (i.e., Eq. (5)):

$$\varepsilon_g = \frac{c - \underline{c}}{\tilde{c}} \tag{5}$$

Obviously, $\varepsilon_g \in [0,1]$.

Denote the uncertainty budget by Γ, then we have

$$\sum_{g=1}^{G} \varepsilon_g \le \Gamma \tag{6}$$

where Γ belongs to $[0,G]$, indicates the number of uncertain parameters in the planning period of environmental construction project (i.e., Eq. (6)). If Γ is integer, it is interpreted as the maximum number of parameters that can deviate from their nominal values. All uncertain parameters are taken to their worst case if and only if Γ is equal to zero (i.e., the unit compensation cost is the lower bound). Similarly, if and only if Γ is the maximum value, all uncertainty parameters are likely to take their best case (i.e., the unit compensation cost is the upper bound). Therefore, the size of the uncertainty scenario set can be adjusted to strike a balance between optimality and robustness by changing the value of the uncertainty budget.

Based on the above considerations, the compensation cost in model (3) can be rewritten as the following model:

$$\begin{aligned}
\min \quad \max \quad & \left[c^T d \left| \sum_{g=1}^{G} \varepsilon_g \le \Gamma \right. \right] \\
s.t. \quad & \sum_{j=1}^{n} \omega_j r_{ij} > \sum_{j=1}^{n} \omega_j r_{lj} - (1 - y_{il})M, \forall i \in I \\
& \sum_{j=1}^{n} \omega_j r_{ij} \le \sum_{j=1}^{n} \omega_j r_{lj} + y_{il}M, \forall i \in I \\
& \sum_{i=1, i\ne l}^{m} y_{il} + 1 = p^*(x_l), \forall l \in I \\
& \left|\omega_j^0 - \omega_j\right| \le d, \forall j \in J \\
& \sum_{j=1}^{n} \omega_j = 1, \forall j \in J \\
& \sum_{g=1}^{G} \varepsilon_g \le \Gamma \\
& \varepsilon_g \le 1 \\
& \varepsilon_g \ge 0 \\
& y_{il} \in \{0,1\}, \forall i \in I, \forall l \in I \\
& 0 \le \omega_j \le 1, \forall j \in J
\end{aligned} \tag{7}$$

The robust model (7) cannot be solved directly. Since the uncertain parameter is included in the objective function, the scenario where the uncertain parameter maximizes the objective function is the worst-case scenario. We want to find an optimal solution that maximizes the objective function of the worst-case scenario. Consider the following linear programming:

$$\begin{aligned}
\max \quad & \left(\underline{c}^T d\right) + \tilde{c}^T d \\
s.t. \quad & \sum_{j=1}^{n} \omega_j r_{ij} > \sum_{j=1}^{n} \omega_j r_{lj} - (1 - y_{il}) M, \forall i \in I \\
& \sum_{j=1}^{n} \omega_j r_{ij} \le \sum_{j=1}^{n} \omega_j r_{lj} + y_{il} M, \forall i \in I \\
& \sum_{i=1, i \ne l}^{m} y_{il} + 1 = p^*(x_l), \forall l \in I \\
& \left|\omega_j^0 - \omega_j\right| \le d, \forall j \in J \\
& \sum_{j=1}^{n} \omega_j = 1, \forall j \in J \\
& \sum_{g=1}^{G} \varepsilon_g \le \Gamma \\
& \varepsilon_g \le 1 \\
& \varepsilon_g \ge 0 \\
& y_{il} \in \{0,1\}, \forall i \in I, \forall l \in I \\
& 0 \le \omega_j \le 1, \forall j \in J
\end{aligned} \tag{8}$$

Obviously, the strong dual theory holds in above model (8). The primal problem and the dual problem can obtain the same objective function values. Therefore, the robust model can be reformulated based on the strong dual theory, and we can have the equivalent model (4).

Therefore, the model based on budgeted uncertainty set is proved 2.1.

Proposition 2.2 If Z is a polyhedron uncertainty set which is defined as $Z_{polyhedron} = \{\zeta \in R^G : \|\zeta\|_\infty \le 1, \|\zeta\|_1 \le \Gamma\}$, where Γ is an uncertain level parameter, the robust optimization form of model (3) can be represented as

$$\begin{aligned}
\min \quad & \underline{c}^T d + \sum_{g=1}^{G} \left|z_g\right| + \Gamma \max_g \left|q_g\right| \\
s.t. \quad & \sum_{j=1}^{n} \omega_j r_{ij} > \sum_{j=1}^{n} \omega_j r_{lj} - (1 - y_{il}) M, \forall i \in I \\
& \sum_{j=1}^{n} \omega_j r_{ij} \le \sum_{j=1}^{n} \omega_j r_{lj} + y_{il} M, \forall i \in I \\
& \sum_{i=1, i \ne l}^{m} y_{il} + 1 = p^*(x_l), \forall l \in I \\
& \left|\omega_j^0 - \omega_j\right| \le d, \forall j \in J \\
& \sum_{j=1}^{n} \omega_j = 1, \forall j \in J \\
& z_g + q_g \ge -\tilde{c}^T d \\
& y_{il} \in \{0,1\}, \forall i \in I, \forall l \in I \\
& 0 \le \omega_j \le 1, \forall j \in J
\end{aligned} \tag{9}$$

Proof 2.2 According to $Z_{polyhedron} = \{\zeta \in R^G : \|\zeta\|_\infty \le 1, \|\zeta\|_1 \le \Gamma\}$, the cone representation becomes $Z = \zeta \in R^G : P_1\zeta + p_1 \in K^1, P_2\zeta + p_2 \in K^2\}$, where

- $P_1\zeta \equiv [\zeta; 0]$, $p_1 = [0_{G\times 1}; 1]$ and $K^1 = \{[\mathbf{z}; t] \in R^G \times R : t \ge \|\mathbf{z}\|_\infty\}$, whence
$K_*^1 = \{[\mathbf{z}; t] \in R^G \times R : t \ge \|\mathbf{z}\|_1\}$;
- $P_2^* \zeta \equiv [\zeta; 0]$, $p_2 = [0_{G\times 1}; \Gamma]$ and $K^2 = K_*^1 = \{[\mathbf{z}; t] \in R^G \times R : t \ge \|\mathbf{z}\|_1\}$, whence $K_*^2 = K^2$.

Setting $y^1 = \{z; \tau_1\}$, $y^2 = \{q_t; \tau_2\}$, with one-dimensional τ and L-dimensional z, q_g, we have the following systems of constraints:

$$\begin{cases}
\tau_1 + \Gamma\tau_2 + \underline{c}^T d \le B \\
(z+q)_g = -\tilde{c}_g^{\,T} d \\
\|z\|_1 \le \tau_1 \\
\|q_t\|_\infty \le \tau_2
\end{cases}$$

τ_1, τ_2, z, q_g, d are variables among them. We can eliminate the τ variables, then we can obtain a representation of $c^T d \le B, \ \forall (c = \underline{c} + \sum_{g=1}^{G} \zeta_g \tilde{c} : \zeta \in Z)$ and $Z^{polyhedron} = \{\zeta \in R^G : \|\zeta\|_\infty \le 1, \|\zeta\|_1 \le \Gamma\}$ by the following system of constraints in variables z, q_g, d:

$$\begin{cases}
\sum_{g=1}^{G} \left|z_g\right| + \Gamma \max_G \left|q_g\right| + \underline{c}^T d \le B \\
(z+q)_g = -\tilde{c}_g^{\,T} d
\end{cases}$$

Therefore, the model based on polyhedron uncertainty set is proved in detail.

Results and Discussion

The Results of Numerical Simulation

We choose the alternative x_5 as an example to research. We let the ranking from 1 to 10, and let $\Gamma = 1$. Input data into model (3), the uncertain factors in real life are not taken into account in this case. We can observe that the compensation cost decrease as the ranking of x_5 goes down (see Fig. 1). When the ranking of x_5 is 10, the decision maker does not need to pay compensation cost, which indicates that the initial ranking of the alternative x_5 is equal to 10. As the ranking of alternative x_5 rises, the compensation cost for decision makers become higher, which means that the ranking become more difficult to manipulate.

On the other hand, we strategically set the ranking of alternatives x_1, x_2, x_5 and x_8 in the same way. The corresponding results are shown in Table 3.

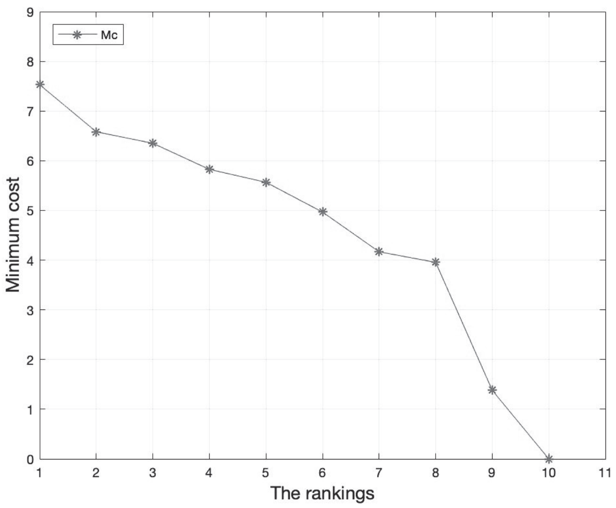

Fig. 1. Minimum cost of different rankings for alternative x_5

As can be seen from Table 3, the minimum compensation cost required by the budgeted uncertainty set model and the polyhedron uncertainty set model is higher than that required by the original nominal model. Because our proposed method takes into account the uncertainty existing in real life and optimizes the objective function in the worst case. Moreover, the weight allocation results of the budgeted uncertainty set model are consistent with those of the nominal model. However, the number of attributes weight changes of the polyhedron uncertainty set model is large, indicating that the effect of the budgeted uncertainty set model is relatively stable. In particular, when the expected ranking of alternative x_1 is 1, none of the three models has a solution, which indicates that the ranking of the alternative can't be manipulated arbitrarily.

Discussion of Data Results

Comparison Analysis

Next, we still take the alternative x_5 as an example, and let the ranking from 1 to 10, while $\Gamma = 1$. The results obtained by deterministic model (3) and robust optimization model (4) are compared (see Fig. 2). It can be shown that the robust optimization model with budgeted uncertainty set can better reflect the uncertainty factors faced by decision makers in actual decision-making activities and reduce the risk of decision making without increasing much cost. In the process of location alternatives planning of environmental construction projects, staff should fully consider the impact of environmental uncertainties, so as to more effectively evaluate the efficiency of environmental governance and finally achieve more environmentally compatible human activities.

In addition, we also compare the results obtained from the polyhedron uncertainty set model (9) and the budgeted uncertainty set model (4) (see Fig. 3). The cost required by the polyhedron uncertainty set model is too high, although the worst-case solution is optimized, but the decision result is too conservative. In contrast, the uncertainty set of budget reduces the scope of the uncertain scenario set. The decision makers can achieve the purpose of manipulating the ranking of environmental construction project location

Table 3. The results of manipulating particular alternatives under different models.

Alternatives	$p^*(x_1)$	Model	Mc	ω
x_1	2	(3)	0.8409	(0.2, 0.2701, 0.2, 0.2, 0.1299)
		(4)	0.8760	(0.2, 0.2701, 0.2, 0.2, 0.1299)
		(9)	1.4045	(0.2, 0.2453, 0.2453, 0.1547, 0.1547)
x_2	4	(3)	0.8795	(0.2637, 0.2, 0.2, 0.1184, 0.2179)
		(4)	0.9203	(0.2637, 0.2, 0.2, 0.1184, 0.2179)
		(9)	1.8893	(0.2609, 0.1391, 0.2, 0.1391, 0.2609)
x_5	5	(3)	5.3190	(0.1376, 0, 0.1675, 0, 0.6949)
		(4)	5.5664	(0.1376, 0, 0.1675, 0, 0.6949)
		(9)	15.1490	(0.1376, 0, 0, 0, 0.6887)
x_8	9	(3)	0.2563	(0.2, 0.2, 0.1767, 0.2, 0.2233)
		(4)	0.2679	(0.2, 0.2, 0.1767, 0.2, 0.2233)
		(9)	0.5458	(0.2, 0.1824, 0.1824, 0.2176, 0.2176)
x_1	1	(3)	No solution	No solution
		(4)	No solution	No solution
		(9)	No solution	No solution

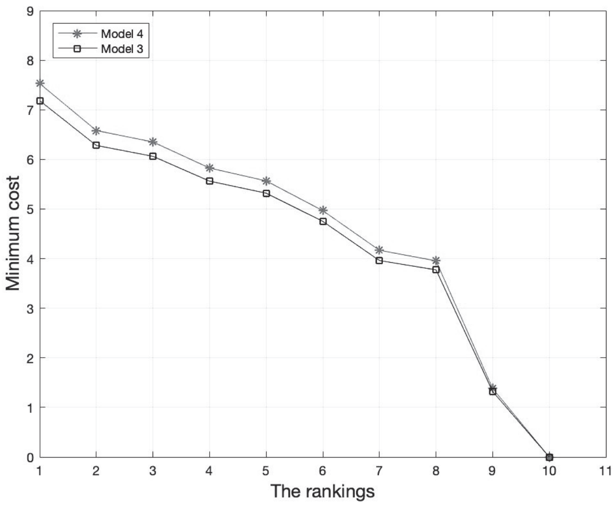

Fig. 2. Minimum cost of different rankings for two models.

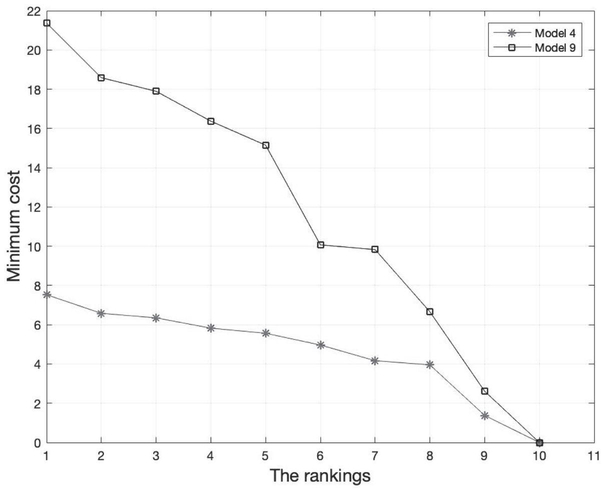

Fig. 3. Minimum cost of different rankings for two uncertain models.

alternatives with less uncertain cost, while the risk of decision making is reduced and the calculation result is optimized.

Sensitivity Analysis

The impact of uncertainty level on the compensation cost required by the decision makers to manipulate the target alternative is worth investigating. At different levels of uncertainty, the decision makers may have different compensation costs to manipulate the ranking of alternatives. Next, we research the impact of uncertainty level on the ranking of different alternatives. We take alternatives x_4, x_7 and x_{10} as examples, and we make the ranking of the three alternatives are equal to 3. We investigate the influence of uncertainty level parameters Γ on the minimum compensation cost in two robust optimization models. Suppose Γ changes from 1 to 6. The data obtained by solving model (4) and model (9) are shown in Table 4 and Table 5.

To facilitate observation, we visualize the data in the above table as Fig. 4 and Fig. 5.

Fig. 4 and Fig. 5 show that the uncertainty level parameter Γ has no influence on the results of model (4), which indicates that the budgeted uncertainty set narrows the range of uncertain scenario set. The budgeted uncertainty set significantly reduces the decision risk brought by uncertain factors, and it also optimizes the calculation results. As for model (9), when the uncertainty level Γ is from 1 to 3, the minimum compensation cost for the decision makers increases slowly with the uncertainty level Γ increase, which means that the difficulty of manipulating the ranking of alternatives increases slowly. However, the

Table 4. Minimum compensation cost under different levels Γ of model (4).

Alternatives	$p^*(x_1)$	Different uncertain levels					
		$\Gamma = 1$	$\Gamma = 2$	$\Gamma = 3$	$\Gamma = 4$	$\Gamma = 5$	$\Gamma = 6$
x_4	3	2.5386	2.5386	2.5386	2.5386	2.5386	2.5386
x_7	3	1.6283	1.6283	1.6283	1.6283	1.6283	1.6283
x_{10}	3	0.5689	0.5689	0.5689	0.5689	0.5689	0.5689

Table 5. Minimum compensation cost under different levels Γ of model (9).

Alternatives	$p^*(x_1)$	Different uncertain levels					
		$\Gamma = 1$	$\Gamma = 2$	$\Gamma = 3$	$\Gamma = 4$	$\Gamma = 5$	$\Gamma = 6$
x_4	3	3.5314	3.5998	3.6567	3.6567	3.6567	3.6567
x_7	3	3.1415	3.2023	3.2529	3.2529	3.2529	3.2529
x_{10}	3	1.2929	1.3179	1.3388	1.3388	1.3388	1.3388

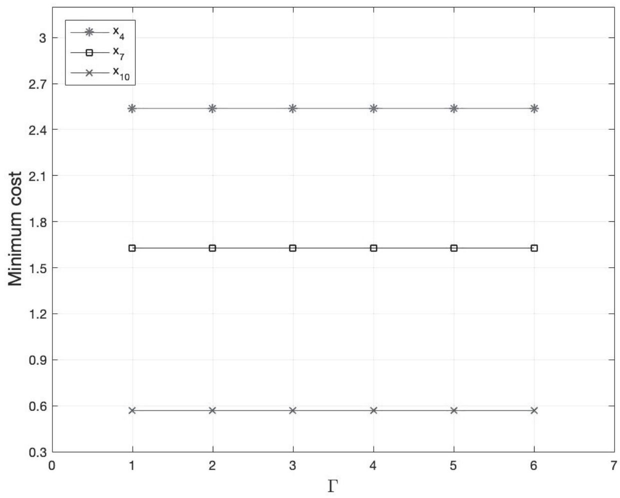

Fig. 4. The tendency of cost under different uncertain levels Γ for model (4).

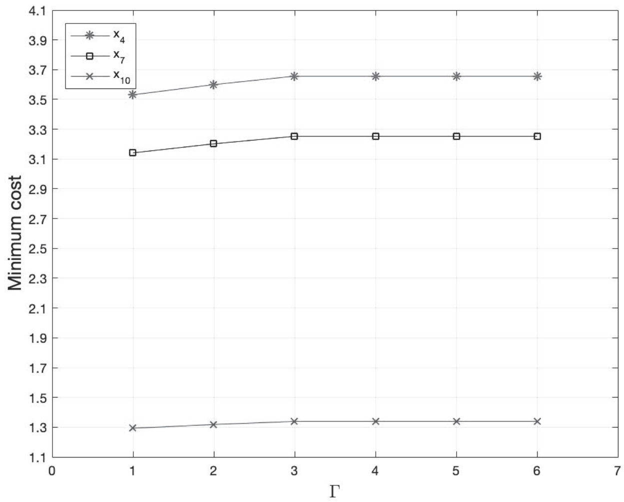

Fig. 5. The tendency of cost under different uncertain levels Γ for model (9).

weight manipulation cost result of model (9) becomes a constant when $\Gamma \geq 3$, which means that the solution result of model (9) reaches convergence with the increase of uncertainty level. Model (9) can also fully take into account the uncertainty factors in decision making and reduce the risks faced by decision makers.

Conclusions

In this study, the uncertainty in the unit compensation costs of decision makers is taken into account. In order to describe the uncertainty characteristics of unit compensation cost more accurately, we construct budgeted uncertainty set and polyhedron uncertainty set. Through a robust optimization approach, we build a robust strategic weight manipulation model to reduce the risks faced by decision makers in uncertain circumstances. Moreover, the case of environmental assessment shows that the robust optimization model is more effective than original model. Some interesting conclusions can be drawn from the case study:

(1) The robust optimization model takes into account the uncertainty of compensation costs in the strategic weight manipulation. The robust model which reduces the risk of decision makers and achieves satisfactory results even in the worst case. However, the solution result of the robust optimization model is more conservative than that of the original model.

(2) The comparison between Fig. 2 and Fig. 3 shows that the budgeted uncertainty set robust optimization model can better reflect the actual uncertainty factors without increasing much cost. The budgeted uncertainty model reduces the range of uncertain scenario set, it reduces the uncertain risk in decision making and optimizes the calculation result. In other words, the budgeted uncertainty set is less conservative than the polyhedron uncertainty set.

(3) According to the data results in Table 3, the ranking of alternatives can't be manipulated arbitrarily. In the strategic weight manipulation, the decision makers can't arbitrarily interfere with the decision-making process, which also shows that the strategic weight manipulation model is practical and has a certain scientific nature.

(4) The changes of uncertain parameters of budgeted uncertainty set will not affect the model. However, in the polyhedron uncertainty set, with the increase of uncertainty level parameters, the cost of the model increases slowly and then tends to converge. Therefore, the two uncertainty models in this paper can better reflect the uncertainty factors in actual decision-making.

To sum up, after considering the uncertainty of compensation cost, a robust strategic weight manipulation model is proposed in this paper to reduce the risk in decision-making. In an application of environmental assessment, our method can effectively evaluate the rationality of location and layout of environmental construction projects, so as to better guide the design of environmental protection measures. However, the paper has some limitations. In future research, we can make full use of historical data to further reduce the conservatism of the model, that is, we can introduce the distributionally robust optimization theory to deal with the cost uncertainty. In addition, the impact of big data on decision-making is becoming more and more valuable [51]. In the future, we can investigate the cost changes in strategic weight manipulation under the background of big data. Machine learning plays an increasingly important role in decision-making [52]. In the future research, we can consider machine learning methods to determine the weight of attributes, which will make the calculation of initial weight more scientific.

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Declaration of Competing Interest

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.

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