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A TWO-STAGE MATHEMATICAL PROGRAMMING MODEL FOR DISTRIBUTED PHOTOVOLTAIC PROJECT PORTFOLIO SELECTION WITH INCOMPLETE PREFERENCE INFORMATION

Zhiying ZHANG, Huchang LIAO*

Business School, Sichuan University, Chengdu 610064, China

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Abstract. With the rapid growth of the solar photovoltaic (PV) market, many distributed PV power projects are introduced to the market. Selecting a rational project investment portfolio is a complex and challenging task for energy enterprises as both financial and non-financial factors of projects are needed to be considered under limited information and resources. This study presents a two-stage hybrid multi-attribute decision-making and integer programming model for distributed PV project portfolio selection. In Stage I, a multiple attribute group decision-making method based on mathematical programming is used to evaluate the non-financial value of projects under incomplete preference information. Compensative weighted averaging operators with an adjustable parameter are utilized to capture the subjective attitudinal character of an expert in the aggregation process. Then, a rank acceptability index is developed to measure each project's group support degree in non-financial dimension. In Stage II, a bi-objective integer programming model is constructed to optimize project portfolios, which considers both financial and non-financial values of projects under resource, carbon emission and other strategic constraints. The applicability and effectivity of the proposed approach are demonstrated by a case study of a distributed PV project portfolio selection.

Keywords: distributed photovoltaic, project portfolio, multiple attribute group decision making, incomplete preference information.

JEL Classification: C44, D70, D81, L83.

Introduction

Global warming, energy security and economic issues force the switch from traditional energy sources (such as coal, gas, and oil) to new energy sources. Solar energy generation is a new energy source that takes advantage of solar irradiation to provide electricity via photovoltaic (PV) or concentrating solar power systems (Zambrano-Asanza et al., 2021). PV technology

*Corresponding author. E-mail: *liaohuchang@163.com*

has enormous potential for deployment in electrical distribution networks due to its current trends in efficiency improvement, cost reduction, and governmental incentives. The layout of PV power plants can be divided into two types: centralized PV and distributed PV. The centralized PV power plants are usually installed in remote and desolate areas like deserts, and the installation area is large, while distributed solar PV projects are mainly installed in relatively small areas such as households, industrial and commercial rooftops (Wu, Wang, et al., 2019; Wu et al., 2018). Compared with centralized PV projects, distributed PV projects have the advantages of flexible assembly and fast consumption, the development of which is conducive to solving the problem of inconsistency between power generation and load in China. Meanwhile, the construction of distributed PV can ease grid investment pressure as it is close to the demand centre and no additional transmission channels are needed (Zhang et al., 2015).

In recent years, distributed PV has become the policy priority of new energy power generation in China. For example, the "Carbon Peaking Action Plan before 2030", issued by the State Council of China, requires that the roof PV coverage rate of new public institutions and new factory buildings should reach 50% by 2025[1]. The introduction of various policies has greatly stimulated the investment enthusiasm for distributed PV power projects. A large number of distributed PV projects have been reported to the decision-making executives of energy enterprises for approval and implementation. At the same time, due to the continuous decline in costs, more and more energy enterprises are entering the market to find investment opportunities, leading to increasingly fierce competition among enterprises. Project portfolio selection, as one of the most crucial decision-making problems in project management, is choosing multiple projects to meet the strategic objectives of an enterprise under the constraints of resources and some other conditions (Goli et al., 2019; Wu et al., 2018). A proper project portfolio is essential for energy enterprises to create competitive advantages in the highly competitive distributed energy market (Wu, Xu, et al., 2019). Thus, effective tools are needed to help managers in energy enterprises to select the optimal project investment portfolio.

Some scholars used the Mean-Variance Portfolio theory to assist investors to select the optimal energy project portfolio. For example, Shakouri et al. (2015) determined a community-based photovoltaic investment portfolio by applying the Mean-Variance Portfolio theory. Considering the uncertainty of factors, Zhang et al. (2022) evaluated the investment portfolio strategies of an energy enterprise under different policy scenarios using a mean-variance model based on the real options method. These studies sought to create a quantitative decision-support model that mainly relied on economic indicators of projects. In fact, the investment in solar PV projects needs to consider issues of resource condition, economy and sustainability (including society and environment) (Sward et al., 2021). That is to say, an optimal project portfolio should be accepted financially and non-financially (technically). As an effective tool to solve the problem of multiple and conflicting attributes, many MADM techniques have been adopted by scholars to select PV projects (see literature review in Section 1.1). However, the MADM method is mainly used to rank alternatives (Goli & Moham-

[1] http://www.gov.cn/zhengce/content/2021-10/26/content_5644984.htm

madi, 2022). If a project investment portfolio is selected only according to the ranking of alternative projects, the complex requirements, such as the resource constraints and internal relationship of projects are hard to be satisfied simultaneously. It was observed that Wu et al. (2018) combined the MADM method with 0-1 programming for the selection of an appropriate distributed PV project portfolio, which considered the financial and technical feasibility of the project while meeting the resource constraints of energy enterprises. However, in the paper of Wu et al. (2018), the evaluation results of the MADM method are only used to eliminate inferior projects and are not incorporated in the portfolio optimization model, which means that the technical performance of projects is not reflected effectively in the portfolio selection. This is a limitation of the existing literature.

In the MADM process, the final ranking of projects is usually derived by integrating attribute performances and attribute weights. With the increasing complexity of PV projects, there are challenges for experts to provide precise and complete weight information due to time pressure, lack of data and limited knowledge. In other words, the weight information is usually incomplete (Li & Wan, 2013; Zuo et al., 2020). Experts might be able to provide some pairwise comparison information of projects. There may be inconsistency between the ranking orders of projects directly obtained from experts and that indirectly determined by aggregating the performances on multiple attributes. In this sense, deriving a satisfactory ranking of projects with incomplete information on attribute weights and project pairwise comparisons is another challenge. In addition, since attributes can be conflicting, it is often hard for experts to find an ideal project combining all the ideal evaluation values of attributes. That is to say, the decision-making in practical application is a complex outcome of a rigorous analysis considering the compensation effects between attributes (Aggarwal, 2015; Aggarwal & Fallah Tehrani, 2019). For experts with optimistic attitudes, they may take more attention to the attributes of "maximum utility" in the aggregation process; while for the experts who are pessimistic, to avoid investment risks, the negative impact of "minimum utility" attributes attracts their attention more. To the best of our knowledge, existing literature on PV project selection failed to indicate the attitudinal character of an expert in the aggregation process.

To solve the above issues, this study aims to introduce a two-stage hybrid multi-attribute decision-making and integer programming model for distributed PV project portfolio selection with incomplete preference information. In the first stage, a multiple attribute group decision-making method is used to evaluate the non-financial value of projects. The evaluation of the technical feasibility of projects usually involves quantitative and qualitative attributes. As for the expressions of evaluation information, a good trend presented in the existing literature is that a single type of attribute information (either linguistic scales or fuzzy numbers) is evolving into a hybrid form (including crisp data and linguistic variables). Followed by this trend, in this paper, the performance of projects on quantitative attributes is measured in crisp numbers; for the performance of projects on qualitative attributes which is hard to measure in numbers, experts are suggested to score them in linguistic terms as linguistic expressions align well with people's habit of expression. Uncertainty and ambiguity are inevitable in the practical decision-making process, making it a challenge for experts to give precise linguistic evaluations. In this regard, the hesitant fuzzy linguistic term set (HFLTS) (Liao et al., 2015; Rodríguez et al., 2012) is applied. To capture the attitudinal character of an expert in the aggregation process, we use compensative weighted averaging (CWA) operators (Aggarwal, 2015) to aggregate the performances on multiple attributes. Compared with the ordered weighting averaging (OWA) operators which provide different degrees of compensation in aggregation by appropriately choosing the weight vector, the generalization in CWA operators is achieved by providing an adjustable parameter. It is worth noting that different experts have different attitudinal characters, and they may reach different ranking results of projects even under the same investment conditions. Regarding the incomplete preference information, the Linear Programming Technique for Multidimensional Analysis of Preference (LINMAP) method (Srinivasan & Shocker, 1973), based on some pairwise comparisons of alternatives, can generate compromise solutions without a priori specification of attribute weights. As the LINMAP method can reduce the cognitive burden of experts, it has achieved wide extensions and applications (Li & Wan, 2013; Liu et al., 2021; Wan & Dong, 2015; Wan & Li, 2013, 2014, 2015; Wan et al., 2017; Zuo et al., 2020). Inspired by the LINMAP method, a mathematical programming model is set up based on the consistency and inconsistency indices to elicit attribute weights and compensation parameters for different experts. Then, ranks of projects under experts' different preference information and attitudinal characters can be obtained and a rank acceptability index is further developed to measure the group support degree of each project in terms of the non-financial dimensions. In the second stage, based on the support degree of projects derived in the first stage, a bi-objective 0-1 integer programming model is formulated to optimize the financial return and non-financial value for the project portfolio by considering the resource limitation, carbon emission reduction responsibility of enterprises and relationships of projects. The nondominated sorting genetic algorithm II (NSGA-II) (Deb et al., 2002) is adopted to obtain the Pareto-optimal solutions to the project portfolio optimization problem.

In summary, the main contributions of this paper can be summarized as follows:

1) We discussed different degrees of compensation in the aggregation process when evaluating the solar PV projects;
2) We extend the LINMAP method to elicit the compensation parameter and attribute weights, and then, a rank acceptability index is developed to measure the group support degree of each project;
3) In addition to the financial return of projects, our optimization of the distributed PV project portfolio also considers the non-financial value, which makes the obtained portfolio feasible technically and economically.

This paper is organized as follows. Section 1 reviews PV project investment with MADM methods and provides the related basic knowledge. Section 2 describes the research problem. Section 3 presents the methodology for the selection of distributed PV project portfolio in detail. Section 4 tests the proposed model with a case study. The final section concludes the paper.

1. Related work

In this section, a short review of the PV project investment with MADM methods and related knowledge is introduced.

1.1. A short review of photovoltaic project investment

Recently, scholars have carried out abundant valuable research about PV project investment with MADM methods, mainly focusing on the following aspects: 1) risk assessment, 2) single project evaluation, 3) project portfolio selection, 4) site selection. Below, we briefly review the literature on PV project investment in recent years in terms of the MADM techniques, preference information, information expression and research purposes, as shown in Table 1.

Table 1. A short review of solar PV project investment with MADM methods

References	MADM techniques	Information expression	Purposes	Incomplete preferences
Wu et al. (2018)	AHP, PROMETHEE II	Triangular intuitionistic fuzzy number, interval number	Project portfolio selection	
Fang et al. (2018)	Prospect theory, TOPSIS	Rough number	Site selection	
Ozdemir and Sahin (2018)	AHP	1–9 scale	Site selection	
Song et al. (2019)	SMAA	Interval numbers, crisp numbers	Project portfolio selection	√
Wu, Wang, et al. (2019)	TODIM, ANP	HFLTS	Single project evaluation	
Wu, Xu, et al. (2019)	AHP	Internal type-2 fuzzy numbers	Project portfolio selection	
Rediske et al. (2020)	AHP, TOPSIS	1–9 scale, crisp numbers	Single project evaluation	
Wu et al. (2020)	DEMATEL, TODIM	Triangular intuitionistic fuzzy number	Single project evaluation	
Zambrano-Asanza et al. (2021)	AHP	1–9 scale	Site selection	
Gao et al. (2021)	Prospect theory, ANP	Intuitionistic fuzzy sets, interval numbers, crisp numbers	Site selection	
Liang et al. (2021)	Evidential reasoning	linguistic scales	Risk assessment	
Kannan et al. (2021)	BWM, GRA, VIKOR	1–9 scale, 1–5 scale	Site selection	
Wei (2021)	AHP, TOPSIS	Interval type-2 fuzzy numbers	Single project evaluation	

Note: All abbreviations and corresponding explanations can be found in Table A.1 in the Appendix.

Through the literature review, we found that the existing MADM literature on PV project investment mainly focuses on project site selection. The research on project portfolio selection is relatively limited and the project portfolio is selected mainly based on financial benefits. In addition, existing PV project investment studies rarely discussed the different compensation effects between evaluation attributes. More importantly, from the third and fifth columns of Table 1, we can find that many studies used the fuzzy sets to describe the uncertainty of PV project investment but the preference information was complete. Song et al. (2019) used the stochastic multicriteria acceptability analysis (SMAA) method to deal with incomplete preference information when selecting a project portfolio. However, as the weighted averaging operator is used to aggregate evaluations in their paper, the degree of compensation between attributes cannot be changed. Based on the above findings, this study presents a framework for PV project portfolio selection. In contrast to existing studies, this study investigates the following three characteristics simultaneously: 1) The degree of compensation in the aggregation process is adjustable according to the attitudinal character of an expert; 2) The incomplete preference information on attributes is allowed; 3) The support degree of each project in terms of the non-financial dimension is considered when optimizing the project portfolio.

1.2. Basic knowledge

1.2.1. Hesitant fuzzy linguistic term set

A hesitant fuzzy linguistic term set (HFLTS) (Rodríguez et al., 2012), which represents the value of a variable by a set of consecutive ordered finite subset of a given linguistic term set (LTS), is an effective tool to represent the uncertain and hesitant decision-making information. Let $S=\{s_\sigma|\sigma=0,1,\ldots,2\tau\}$ be an LTS. Liao et al. (2015) redefined the HFLTS in a mathematical form as: $H_S=\{<x_i,h_S(x_i)>|x_i\in X\}$, where $h_S(x_i)=\{s^{(k)}(x_i)\,|\,s^{(k)}(x_i)\in S;k=1,2,\ldots,K\}$ with K being the number of all different linguistic terms in $h_S(x_i)$. $h_S(x_i)$, shorten as h_{Si}, is called a hesitant fuzzy linguistic element (HFLE). Different HFLEs have different numbers of linguistic terms. To operate correctly when comparing or computing with HFLEs, linguistic term $\bar{s}$ could be added into the short HFLE until the compared or computed HFLEs have same length, as follows:

$$\bar{s}=\frac{1}{2}({h_{Si}}^{+}\oplus {h_{Si}}^{-}), \tag{1}$$

where ${h_{Si}}^{+}$ and ${h_{Si}}^{-}$ are the maximal term and minimal term in h_{Si}. The hesitant fuzzy linguistic distance between two HFLEs can be calculated by:

$$d(h_{S1},h_{S2})=\left(\frac{1}{K}\sum_{k=1}^{K}\left(\frac{|L_1^{(k)}-L_2^{(k)}|}{2\tau}\right)^{\rho}\right)^{1/\rho}, \tag{2}$$

where h_{S1} and h_{S2} are two HFLEs with $K_1=K_2=K$. $L_1^{(k)}(k=1,2,\ldots,K_1)$ and $L_2^{(k)}(k=1,2,\ldots,K_2)$ are the subscripts of the linguistic terms in h_{S1} and h_{S2}, respectively. When $\rho=2$, $d(h_{S1},h_{S2})$ is called the hesitant fuzzy linguistic Euclidean distance.

1.2.2. Incomplete preference information

In practical decision-making situations, experts may specify some preference information such as weights of attributes and pairwise comparisons of alternatives according to their knowledge and experience. Due to the time pressure, lack of data, and experts' limited expertise in the problem domain, these preferences may be incomplete.

Let $w = \{w_j \mid j \in 1,2,\ldots,n\}$ be the weight vector of attributes and I_G be the index set of attributes. Li and Wan (2013) summarized five basic relations among attribute weights based on a set of all possible attribute weights $\Lambda_0 = \{w_j \mid \sum_{j=1}^{n} w_j = 1, w_j \geq 0, j \in I_G\}$:

1) A weak ranking: $\Lambda_1 = \{w_j \in \Lambda_0 | w_j \geq w_{j_1}, j, j_1 \in I_G, j \neq j_1\}$;
2) A strict ranking: $\Lambda_2 = \{w_j \in \Lambda_0 | \alpha_{jj_1} \leq w_j - w_{j_1} \leq \beta_{jj_1}, j, j_1 \in I_G, j \neq j_1\}$, where α_{jj_1} and β_{jj_1} are two constants such that $0 < \alpha_{jj_1} < \beta_{jj_1}$;
3) A ranking with multiples: $\Lambda_3 = \{w_j \in \Lambda_0 | w_j \geq \mathrm{K}_{jj_1} w_{j_1}, j, j_1 \in j, j \neq j_1\}$, where K_{jj_1} is a constant such that $\mathrm{K}_{jj_1} > 0$;
4) An interval form: $\Lambda_4 = \{w_j \in \Lambda_0 | \alpha_{j_1} \leq w_{j_1} \leq \beta_{j_1}, j_2 \in j\}$, where α_{j_1} and β_{j_1} are two constants such that $0 < \alpha_{j_1} < \beta_{j_1}$;
5) A ranking of differences: $\Lambda_5 = \{w_j \in \Lambda_0 | w_j - w_{j_1} \geq w_{j_2} - w_{j_3}, j, j_1, j_2, j_3 \in I_G, j \neq j_1 \neq j_2 \neq j_3\}$.

Let $A = \{A_i \mid i = 1,2,\ldots,m\}$ be a set of m alternatives and I_A be the index set of alternatives. An expert may provide preferences in terms of pairwise comparisons over alternatives as $\Omega = \{<(A_l, A_z), t\ (l,z)> \mid l, z \in I_A, l \neq z\}$ based on his/her knowledge and experience, where (A_l, A_z) represents an ordered pair of alternatives A_l and A_z that the expert prefers A_l to A_z (denoted by $A_l \succ A_z$) and $t\ (l,z) \in [0,1]$ expresses the intensity that A_l is preferred to A_z. In some situations, experts might not be able to specify all the relations, that is, only partial pairwise comparisons between alternatives are given, *i.e.*, $|\Omega| < C_n^2$, where $|\Omega|$ represents the number of alternative pairs.

2. Problem description and data collection

Suppose that an energy enterprise plans to select a PV portfolio to invest in from a candidate project set $A = \{A_i \mid i = 1,2,\ldots,m\}$. The presented two-stage evaluation framework produces portfolios considering both the financial and non-financial values of projects.

Stage I is to compute projects' support degrees according to their evaluations in the non-financial dimension. The MADM method is adopted. First, based on the literature review in Section 1.1, a set of eight attributes $G_N = \{g_j \mid j = 1,2,\ldots,8\}$ are defined. These attributes reflect the resource condition and sustainability of projects and can be divided into two subsets: quantitative attributes (G_C) and qualitative attributes (G_H), satisfying $G_N = G_C \cup G_H$ and $G_C \cap G_H = \varnothing$. We denote the index sets of G_C and G_H as I_C and I_H, respectively, and the performance of project A_i on attribute g_j as $\overline{v}_{ij}$.

The quantitative attributes are scored in crisp numbers ($\overline{v}_{ij} = \overline{r}_{ij}$), including attribute g_1 (annually average solar radiation), g_2 (average temperature) and g_3 (rooftop available area). The values of g_1 and g_2 can be obtained from the National Aeronautics and Space Administration (NASA) website by inputting the geodetic coordinates system of a PV project; while the value of g_3 (rooftop available area) can be collected from the urban map using Google Earth. Attribute g_4 (project synergy), g_5 (Policy support), g_6 (project extensibility), g_7 (social benefits), and g_8 (future electricity demand) are qualitative attributes. As the qualitative attributes are hard to measure in numerical values, a group of experts $E = \{e_q \mid q = 1,2,\ldots,Q\}$ are invited to score them using the HFLTS ($\overline{v}_{ij}^{q} = \overline{h}_{Sij}^{q} = \{\overline{s}_{Lij}^{q(k)} \mid \overline{s}_{Lij}^{q(k)} \in S, q(k) = 1,2,\ldots,K^q\}$). The descriptions of the attributes are shown in Table 2.

Table 2. Attributes to evaluate the non-financial value of projects

Attributes	Type	Data form	Brief description
Resource condition			
Annually average solar radiation (g_1)	Benefit	Crisp numbers	The amount of power generation
Average temperature (g_2)	Benefit	Crisp numbers	The working temperature of solar cells and batteries
Rooftop available area (g_3)	Benefit	Crisp numbers	The area that can be used to install solar panels
Sustainability			
Project synergy (g_4)	–	HFLTSs	Development experience and resource allocation of existing projects in the same investment region
Policy support (g_5)	–	HFLTSs	The development and investment environment of the region, including government subsidies and the implementation of grid connections, etc.
Project extensibility (g_6)	–	HFLTSs	Possibility of project expansion and investment in other projects
Social benefits (g_7)	–	HFLTSs	Economic traction, job creation and talents cultivation
Future electricity demand (g_8)	–	HFLTSs	Regional demand for PV projects and the increased consumer demand for electricity

After obtaining the data, the candidate PV projects are analyzed and ranked using a mathematical programming-based MADM method which could represent the attitudinal character of experts through an adjustable parameter. Afterwards, regarding the different ranking results of projects caused by experts' divergent preferences and attitudinal characters, we use a rank acceptability index to measure the group support degree of each project in terms of the non-financial dimension.

In Stage II, a bi-objective 0-1 integer programming model is formulated to optimize the financial return and non-financial value for the portfolio by considering the resource limitation, carbon reduction responsibility of enterprises and relationships of projects such as interdependencies. The NPV is used to measure the financial returns of the project.

3. Methodology

In this section, we present the proposed approach for PV project investment portfolio selection in detail.

3.1. Computing support degrees of projects

3.1.1. Normalizing the evaluation matrix

Before the aggregation of performances on multiple attributes, normalization of the evaluation matrix is needed. For the crisp number $\overline{v}_{ij} = \overline{r}_{ij}$, the normalized value $v_{ij} = r_{ij}$ can be computed as:

$$v_{ij} = \begin{cases} \dfrac{\overline{r}_{ij}}{\sqrt{\sum_{i=1}^{m} \overline{r}_{ij}^2}}, & \text{if } G_j (j \in I_C) \text{ is benifit attribute,} \\ \dfrac{1/\overline{r}_{ij}}{\sqrt{\sum_{i=1}^{m} 1/\overline{r}_{ij}^2}}, & \text{if } G_j (j \in I_C) \text{ is cost attribute.} \end{cases} \tag{3}$$

The HFLE $\overline{v}_{ij}^q = \overline{h}_{Sij}^q = \{\overline{s}_{L_{ij}}^{q(k)} \mid \overline{s}_{L_{ij}}^{q(k)} \in S; q(k) = 1,2,\ldots,K^q\}$ given by each expert could be normalized as the same length according to Eq. (1). Then, the synthesized evaluation values $v_{ij} = h_{Sij} = \{s_{L_{ij}}^{(k)} \mid k = 1,2,\ldots,K\}$ of the expert group on qualitative attributes can be calculated by:

$$L_{ij}^{(k)} = \sum_{q=1}^{Q} \varpi_q L_{ij}^{q(k)}, j \in I_H, k = 1,2,\ldots,K, \tag{4}$$

where ϖ_q is the weight of expert e_q.

3.1.2. Aggregating evaluation values considering compensation effect among attributes

To rank the projects, it is necessary to aggregate the performance of projects on multiple attributes to a global value. In the aggregation process, it is hard for experts to find an alternative combining all the ideal values of attributes. For instance, in the decision making of PV project investment, a high utility of *initial investment cost* often correspond to a low utility of *annually capital income*. That is to say, decisions in practical applications are a complex outcome of a rigorous analysis considering the compensation effect between attributes. Existing MADM literature on PV project selection generally adopted the simple additive value functions, e.g., the weighted averaging operator, to integrate the attribute performances. In such cases, the quality of the optimal solution may be impugned by the inability of the simplest additive function to control the degree of compensation between attributes in the aggregation process.

Aggarwal (2015) developed a class of compensative weighted averaging (CWA) aggregation operators, the generalization of which is achieved by providing an additional adjustable parameter, shown as follows:

$$CWA(v_{i1}, v_{i2}, \ldots, v_{in}) = \log_{\lambda_q} \left(\sum_{j=1}^{n} w_j^q (\lambda_q)^{v_{ij}} \right), \quad i \in I_A, \; q \in I_E, \tag{5}$$

where $w^q=(w_1^q,w_2^q,\ldots,w_n^q)^T$ is the weight vector of attributes, satisfying $\sum_{j=1}^{n} w_j^q=1$. I_A and I_E are index sets of projects and experts, respectively. $\lambda_q \in (0,+\infty]$, $\lambda \neq 1$ is the compensation parameter, reflecting the degree of compensation in the aggregation process. By changing the value of λ_q, a broad range of operators can be obtained. When $\lambda \to 0$, for any value of w_j, $CWA(v_{i1},v_{i2},\ldots,v_{in}) \to \min_j(v_{i1},v_{i2},\ldots,v_{in})$; when $\lambda \to 1$, $CWA(v_{i1},v_{i2},\ldots,v_{in}) \to WA(v_{i1},v_{i2},\ldots,v_{in})$, where WA refers to the weighted averaging operator; when $\lambda \to +\infty$, $CWA(v_{i1},v_{i2},\ldots,v_{in}) \to \max_j(v_{i1},v_{i2},\ldots,v_{in})$. As the value of λ moves along the range $\lambda \in (0,+\infty]$, $\lambda \neq 1$, the aggregated value moves from the non-compensatory "minimum" (converges to "and") to the fully compensatory "maximum" (converges to "or"). The parameter λ makes the CWA operator achieve the desired level of "andness" or "orness" in the aggregation process naturally, and can be used to represent the attitudinal character of an expert. $\Psi_1=\{\lambda|0<\lambda<1\}$, $\Psi_2=\{\lambda|\lambda>1\}$, and $\Psi_3=\{\lambda|\lambda \to 1\}$ indicate pessimistic, optimistic and indifferent attitudes of an expert for the projects, respectively. In the following, we use CWA operators to aggregate the performances on multiple attributes.

If the attribute weight vector $w^q=(w_1^q,w_2^q,\ldots,w_n^q)^T$ and the compensation parameter λ_q have been given by experts already, then using Eq. (5), the global value of projects can be worked out and the ranking of projects can be further derived. However, each expert has his/her own preference and attitudinal character. It is difficult to obtain a uniform attribute weight vector and compensation parameter. In addition, due to the limitations of experts' knowledge and time, they are only able to provide partial preference information about attribute weights. Moreover, although an expert's attitudinal character, such as pessimistic and optimistic, can be shaped with his/her previous experiences, values, or priorities about different alternatives, it is hard for an expert to provide a concrete compensation degree between attributes in advance.

The LINMAP method is based on the pairwise comparisons of alternatives. It generates the best compromise alternative as the solution that has the shortest distance to the ideal solution without prior-defined complete attribute weights. Inspired by the LINMAP method, in what follows, a mathematical programming model is constructed to elicit (w^q,λ_q).

3.1.3. Deriving the ranking of projects under incomplete preference information

(1) Calculating consistency and inconsistency indices

Suppose that the positive ideal solution (PIS) is $v^{q+}=(v_1^{q+},v_2^{q+},\ldots,v_n^{q+})$ which is unknown a priori and needs to be determined, where v_j^{q+} is the best performance on attribute $g_j(j=1,2,\ldots,n)$ for expert e_q. If $j \in I_C$, $v_j^{q+}=r_j^+$ is a crisp number; if $j \in I_H$, $v_j^{q+}=h_{Sj}^+$ is an HFLE. Assume that expert e_q provides the incomplete pairwise preference judgments over projects by a set of ordered pairs as:

$$\Omega^q=\{<(A_l,A_z),t^q(l,z)>|\,l,z \in I_A,l \neq z\}, \tag{6}$$

where $t^q(l,z) \in [0,1]$ denotes the truth degree to which the alternative A_l is superior to the alternative A_z. Using Eqs (2) and (5), the square of the CWA-based Euclidean distance between the project pair $(A_l, A_z) \in \Omega^q$ and the PIS $v^{q+} = (v_1^{q+}, v_2^{q+}, \ldots, v_n^{q+})$ can be calculated, respectively, as:

$$D_l^q = \log_{\lambda_q}\Big(\sum_{j\in I_C} w_j^q \lambda_q^{(r_{lj}-r_j^{q+})^2} + \sum_{j\in I_H} w_j^q \lambda_q^{\frac{1}{K}\sum_{k=1}^{K}((L_{lj}^{(k)}-L_j^{q(k)+})/2\tau)^2}\Big), \tag{7a}$$

$$D_z^q = \log_{\lambda_q}\Big(\sum_{j\in I_C} w_j^q \lambda_q^{(r_{zj}-r_j^{q+})^2} + \sum_{j\in I_H} w_j^q \lambda_q^{\frac{1}{K}\sum_{k=1}^{K}((L_{zj}^{(k)}-L_j^{q(k)+})/2\tau)^2}\Big). \tag{7b}$$

For each pair of projects $(A_l, A_z) \in \Omega^q$, if $D_z^q \geq D_l^q$, the project A_l is closer to the PIS than the project A_z, which is to say, $A_l \succ A_z$ ("$\succ$" means preferred to). So the ranking order of projects A_l and A_z determined by D_l^q and D_z^q based on (w^q, λ_q, v^{q+}) is consistent with the preference given by expert e_q. On the contrary, if $D_z^q < D_l^q$, the ranking order of projects A_l and A_z determined by D_l^q and D_z^q based on (w^q, λ_q, v^{q+}) is inconsistent with the preference given by expert e_q. (w^q, λ_q, v^{q+}) should be chosen so that the ranking order and preference for a given ordered pair of projects is consistent.

An index $(D_z^q - D_l^q)^-$ is defined to measure inconsistency between the ranking of projects A_l and A_z determined by D_l^q and D_z^q and the preference given by expert e_q preferring A_l to A_z as follows:

$$(D_z^q - D_l^q)^- = \begin{cases} t^q(l,z)(D_l^q - D_z^q), & \text{if } D_z^q < D_l^q, \\ 0, & \text{if } D_z^q \geq D_l^q. \end{cases} \tag{8}$$

Eq. (8) can be rewritten as $(D_z^q - D_l^q)^- = t^q(l,z)\max\{0, D_l^q - D_z^q\}$. Furthermore, the total inconsistency index of expert e_q is defined as:

$$IC^q = \sum_{(A_l,A_z)\in\Omega^q} (D_z^q - D_l^q)^- = \sum_{(A_l,A_z)\in\Omega^q} t^q(l,z)\max\{0, D_l^q - D_z^q\}. \tag{9}$$

In analogous, consistency index $(D_z^q - D_l^q)^+$ is defined as:

$$(D_z^q - D_l^q)^+ = \begin{cases} t^q(l,z)(D_z^q - D_l^q), & \text{if } D_z^q \geq D_l^q, \\ 0, & \text{if } D_z^q < D_l^q, \end{cases} \tag{10}$$

which can be rewritten as $(D_z^q - D_l^q)^+ = t^q(l,z)\max\{0, D_z^q - D_l^q\}$. Then, the consistency index of expert e_q is defined as:

$$CI^q = \sum_{(A_l,A_z)\in\Omega^q} (D_z^q - D_l^q)^+ = \sum_{(A_l,A_z)\in\Omega^q} t^q(l,z)\max\{0, D_z^q - D_l^q\}. \tag{11}$$

(2) Constructing mathematical programming model based on the LINMAP method

In real decision-making process, the inconsistency index IC^q is supposed to be 0, and the inconsistency index IC^q should not be greater than the consistency index CI^q. In this sense, we construct a mathematical programming model (Model 1) to derive the attribute weight vector w^q and compensation parameter λ_q:

Model 1

$$\min\{IC^q\}$$

$$s.t.\begin{cases} CI^q - IC^q \geq \varepsilon, \\ r_{ij} \leq r_j^{q+} \leq 1,\ i \in I_A,\ j \in I_C, \\ L_{ij}^{(k)} \leq L_j^{q(k)+} \leq 2\tau,\ i \in I_A,\ j \in I_H,\ k = 1,2,\ldots,K, \\ L_j^{q(k)+} \leq L_j^{q(k+1)+},\ j \in I_H,\ k = 1,2,\ldots,K, \\ w^q \in \Lambda^q,\ \lambda_q \in \Psi^q, \end{cases}$$

where ε is a threshold given by experts, showing the degree to which CI^q is greater than IC^q, and the stricter the expert, the larger the value of ε. $r_{ij} \leq r_j^{q+} \leq 1$ and $L_{ij}^{(k)} \leq L_j^{q(k)+} \leq 2\tau$ are used to ensure $v^{q+} = (v_1^{q+}, v_2^{q+}, \ldots, v_n^{q+})$ is the positive idea solution. $L_j^{q(k)+} \leq L_j^{q(k+1)+}$ ensures that the PIS satisfies the context-free grammar of HFLTS (Rodríguez et al., 2012). Λ^q and Ψ^q are the incomplete attribute weight set and compensation preference set for expert e_q, respectively.

Based on Eqs (8)–(11), $CI^q - IC^q$ can be simplified as $CI^q - IC^q = \sum_{(A_l, A_z) \in \Omega^q} \{(D_z^q - D_l^q)^+ - (D_z^q - D_l^q)^-\} = \sum_{(A_l, A_z) \in \Omega^q} t^q(l,z)(D_z^q - D_l^q)$. For $(A_l, A_z) \in \Omega^q$, let $\vartheta_{lz}^q = \max\{0, D_l^q - D_z^q\}$, and then we have $\vartheta_{lz}^q \geq 0$ and $\vartheta_{lz}^q \geq D_l^q - D_z^q$. Thus, Model 1 can be converted to Model 2:

Model 2

$$\min\{\sum_{(A_l, A_z) \in \Omega^q} t^q(l,z)\vartheta_{lz}^q\}$$

$$s.t.\begin{cases} \sum_{(A_l, A_z) \in \Omega^q} t^q(l,z)(D_z^q - D_l^q) \geq \varepsilon, \\ D_z^q - D_l^q + \vartheta_{lz}^q \geq 0,\ (A_l, A_z) \in \Omega^q, \\ \vartheta_{lz}^q \geq 0,\ (A_l, A_z) \in \Omega^q, \\ r_{ij} \leq r_j^{q+} \leq 1,\ i \in I_A,\ j \in I_C, \\ L_{ij}^{(k)} \leq L_j^{q(k)+} \leq 2\tau,\ i \in I_A,\ j \in I_H,\ k = 1,2,\ldots,K, \\ L_j^{q(k)+} \leq L_j^{q(k+1)+},\ j \in I_H,\ k = 1,2,\ldots,K, \\ w^q \in \Lambda^q,\ \lambda_q \in \Psi^q. \end{cases}$$

Solving Model 2, the attribute weight vector, compensation parameter and PIS for each expert can be deduced. The ranking order of projects under individual expert's opinions is generated according to the increasing order of the distances $D_i^q (i = 1,2,\ldots,m,\ q = 1,2,\ldots,Q)$.

3.1.4. Computing the group support degrees of projects

Suppose the ranks of projects under the opinion of expert e_q is $R_q = (R_q^1, R_q^2, \ldots, R_q^m)$. Inspired by the idea of the TOPSIS method, we develop a rank acceptability index to measure the group support degree of each project, computed as:

$$SD_i = \sum_{q=1}^{Q} \varpi_q \frac{|R_q^i - m|}{|R_q^i - 1| + |R_q^i - m|}, \tag{12}$$

where ϖ_q is the weight of expert e_q, and m is the number of projects.

3.2. Establishing multi-objective programming model for project portfolio selection

3.2.1. Objectives and constraints

Maximizing profit is the most commonly used objective function in project portfolio optimization. However, focusing only on the current profits may negatively affect the long-term development of enterprises. Factors such as the availability of resources in the region where the project is located and the sustainability of the investment should be taken into account when making decisions. In this regard, we optimize the project portfolio by maximizing the values of projects in both financial and non-financial dimensions.

The first objective function is to maximize the financial return of the selected portfolio. The NPV is used to measure the financial return of a project, computed as:

$$NPV_i = \sum_{t=1}^{L} [(AR_{it} - AC_{it})(1+r)^{-t}] - IC_i,$$

where AR_{it} and AC_{it} are the annual capital income and annual operation and maintenance cost of project A_i at the tth year, respectively. IC_i denotes the initial investment cost. L represents the life cycle and r is the discount rate. In addition, the group support degree of each project derived from Section 3.1 is used as the coefficient of the second objective function that aims to maximize the total non-financial value of the chosen project portfolio.

It is well known that the traditional constraints are the limited resources as projects in a portfolio often compete with each other for scarce resources. In this paper, the budget limitation (TC) will be taken into account. Besides, to achieve the goals of "carbon peaking" and "carbon neutrality", energy enterprises in China, especially the large power generation enterprises, need to undertake a certain amount of carbon emission quota. Therefore, the required minimum carbon emission reduction CR should be met when selecting the portfolios. CR_i is the carbon emission reduction of project A_i.

Moreover, strategic constraints (SC) that reflect relationships of projects should be considered. Suppose that $X_i = 1$, if the project A_i is chosen; otherwise, $X_i = 0$. These relationships mainly include: 1) Mutually exclusive relationship: $X_a + X_b + \ldots + X_l \le 1$, denoting that at most one of the projects in the set $\{A_a, A_b, \ldots, A_l\}$ can be selected; 2) Interdependence: $X_a \le X_b$, representing that A_b will be considered on the condition that A_b is chosen; 3) Complementary relationship: $X_a = X_b$, which means both A_a and A_b are chosen or neither.

3.2.2. Establishing and solving multi-objective programming model

The bi-objective 0-1 integer programming model for distributed PV project portfolio selection is constructed as follows:

Model 3

$$\max\sum_{i=1}^{m}\left(\sum_{t=1}^{L}[(AR_{it}-AC_{it})(1+r)^{-t}]-IC_i\right)X_i$$

$$\max\sum_{i=1}^{m}SD_iX_i$$

$$s.t.\begin{cases}\sum_{i=1}^{m}X_iIC_i\le TC,\\ \sum_{i=1}^{m}X_iCR_i\ge CR,\\ X\in SC,\\ X_i\in\{0,1\},\ i=1,2,\ldots,m,\end{cases}$$

where $X=\{X_i\,|\,i=1,2,\ldots,m\}$ is the set of decision variables. r is the discount rate and L represents the life cycle of the PV project. In this paper, we assume that there is no preference on the priorities of objectives. To solve the model, the NSGA-II is adopted as it can obtain uniformly distributed Pareto-optimal solutions and has good convergence and excellent robustness (Tirkolaee et al., 2022).

3.3. Procedure of the proposed method

To facilitate the application, steps of the proposed two-stage mathematical programming model for distributed PV project portfolio selection under incomplete preference information are summarized as follows.

Stage I: Group support degree computation

Step 1. Identify the feasible project set $A=\{A_i\,|\,i=1,2,\ldots,m\}$, attribute set $G=\{g_j\,|\,j=1,2,\ldots,n\}$ and form the expert group $E=\{e_q\,|\,q=1,2,\ldots,Q\}$. Then, collect the data of projects over attributes. The performances of quantitative attributes are measured in crisp numbers $\overline{v}_{ij}=\overline{r}_{ij}$; while the qualitative attributes are scored by experts using the HFLTS, expressed as $\overline{v}_{ij}^{q}=\overline{h}_{Sij}^{q}=\{\overline{s}_{Lij}^{q(k)}\,|\,\overline{s}_{Lij}^{q(k)}\in S, q(k)=1,2,\ldots,K^q\}$.

Step 2. Obtain the incomplete preference information of pairwise comparisons between projects Ω^q, attribute weight vector $w^q\in\Lambda^q$ and compensation parameter $\lambda_q\in\Psi^q$ for each expert e_q.

Step 3. Normalize the evaluation matrix using Eqs (1) and (3), and then obtain the synthesized evaluation matrix of qualitative attributes using Eq. (4).

Step 4. Build and solve Model 2 to obtain the attribute weight vector, compensation parameter and PIS $v^{q+}=(v_1^{q+},v_2^{q+},\ldots,v_n^{q+})$.

Step 5. Calculate the distances $D_i^q\,(i=1,2,\ldots,m,\ q=1,2,\ldots,Q)$ of projects from the PIS using Eq. (7a) and generate the ranking order of projects for each expert according to the increasing order of the distances.

Step 6. Calculate the group support degree of each project using Eq. (12).

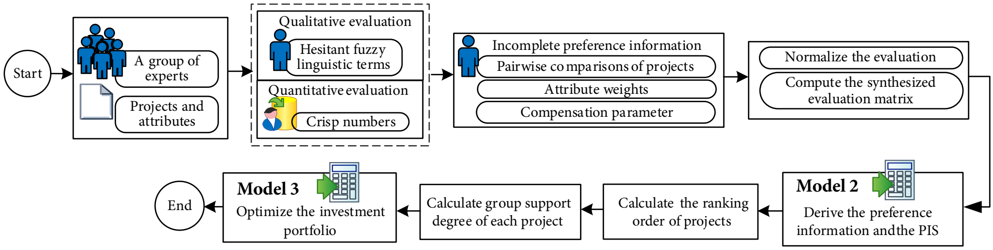

Figure 1. The flowchart of the two-stage mathematical programming model for PV project portfolio selection under incomplete preference information

Stage II: Project portfolio optimization

Step 7. Establish Model 3 to optimize the investment portfolio and solve the model using the NSGA-II.

The flowchart of the proposed method is displayed in Figure 1.

4. An illustrative example

This section refers to an empirical case (adapted from Wu et al., 2018) to illustrate the applicability and computation process of the proposed method.

4.1. Example description and basic data collection

An energy enterprise, which is located in eastern China, plans to invest in distributed PV projects. The enterprise identifies ten investment projects as alternatives based on the investigation, which are located in different cities in Zhejiang province. The investment limit of the enterprise this year is $52*10^6$ CNY, and it needs to complete $8.5*10^3$ t of carbon emission reduction. Due to a lack of funds, the enterprise must conduct a comprehensive evaluation for these ten projects and then selects an optimal portfolio to invest. The evaluation task is assigned to four experts, among which two are project managers in the enterprise and two are scholars with energy engineering background. The scholars need to have at least 5 years of technical expertise and research experience in the field of PV energy. As mentioned in Section 2, eight attributes are defined, among which three are quantitative attributes and five are qualitative attributes, listed in Table 2. Projects' performance on quantitative attributes is measured in crisp numbers, shown in Table 3, while that on qualitative attributes are scored by experts using the HFLTS. The following linguistic term set is used:

$$S = \{s_0 = \text{extreamly poor}, s_1 = \text{very poor}, s_2 = \text{poor}, s_3 = \text{medium poor}, \\ s_4 = \text{fair}, s_5 = \text{medium good}, s_6 = \text{good}, s_7 = \text{very good}, s_8 = \text{extreamly good}\}.$$

The evaluations of qualitative attributes are supposed to be given as shown in Table 4.

Table 3. Performance of projects on quantitative attributes (source: Wu et al., 2018)

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
g_1 (MJ/m^2)	4416.37	4417.41	4539.61	4769.82	4870.36	4390.77	4761.29	4502.05	4792.43	4791.41
g_2 (°C)	17.2	17.2	17	17.3	16.7	16.9	17.4	17.1	17.8	17.8
g_3 (m^2)	14512.02	11296.25	17010.34	10224.63	13660.65	10191.92	13680.21	16098.07	11723.68	18188.42

Table 4. Performance of projects on qualitative attributes (source: created by the authors)

Experts	Attributes	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
e_1	g_4	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_6\}$	$\{s_4\}$	$\{s_6\}$	$\{s_4,s_5\}$
	g_5	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_6,s_7\}$	$\{s_5\}$	$\{s_5,s_6\}$
	g_6	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_7,s_8\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$
	g_7	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_7\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_4,s_5\}$	$\{s_6\}$
	g_8	$\{s_4,s_5\}$	$\{s_6\}$	$\{s_5,s_6\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_5\}$	$\{s_5,s_6\}$	$\{s_4\}$	$\{s_6,s_7\}$	$\{s_4,s_5\}$
e_2	g_4	$\{s_7\}$	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_6\}$	$\{s_3,s_4\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$
	g_5	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_6,s_7\}$	$\{s_6,s_7\}$	$\{s_6\}$	$\{s_6\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_5\}$	$\{s_4\}$
	g_6	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_7\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_5\}$
	g_7	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_6,s_7\}$	$\{s_6\}$	$\{s_5,s_6\}$	$\{s_7\}$	$\{s_6\}$	$\{s_6,s_7\}$	$\{s_5\}$	$\{s_5,s_6\}$
	g_8	$\{s_4,s_5\}$	$\{s_6\}$	$\{s_5,s_6\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_6,s_7\}$	$\{s_4,s_5\}$
e_3	g_4	$\{s_5\}$	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_6,s_7\}$	$\{s_3,s_4\}$	$\{s_6\}$	$\{s_4,s_5\}$
	g_5	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_6,s_7\}$	$\{s_5\}$	$\{s_5,s_6\}$
	g_6	$\{s_6,s_7\}$	$\{s_5\}$	$\{s_5\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_7\}$	$\{s_4,s_5\}$	$\{s_5\}$	$\{s_5\}$
	g_7	$\{s_5,s_6\}$	$\{s_6\}$	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_5\}$	$\{s_6,s_7\}$
	g_8	$\{s_4\}$	$\{s_6\}$	$\{s_5,s_6\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_6,s_7\}$	$\{s_4\}$
e_4	g_4	$\{s_5,s_6\}$	$\{s_5\}$	$\{s_4,s_5\}$	$\{s_4\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_6,s_7\}$	$\{s_4\}$	$\{s_6,s_7\}$	$\{s_5\}$
	g_5	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_7\}$	$\{s_6\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_5\}$	$\{s_5,s_6\}$
	g_6	$\{s_6,s_7\}$	$\{s_5,s_6\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_6\}$	$\{s_6,s_7\}$	$\{s_7\}$	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_4\}$
	g_7	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_6\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_6,s_7\}$	$\{s_4,s_5\}$	$\{s_6,s_7\}$	$\{s_4,s_5\}$	$\{s_6,s_7\}$
	g_8	$\{s_4,s_5\}$	$\{s_5,s_6\}$	$\{s_5,s_6\}$	$\{s_3,s_4\}$	$\{s_4,s_5\}$	$\{s_5\}$	$\{s_5,s_6\}$	$\{s_4\}$	$\{s_6,s_7\}$	$\{s_4,s_5\}$

According to the comprehensions and judgments, each expert provides his/her preferences for pairwise comparisons of projects as:

$\Omega^1 = \{<(A_3,A_5),0.9>,<(A_5,A_6),0.7>\}$,

$\Omega^2 = \{<(A_3,A_5),0.9>,<(A_5,A_6),0.7>\}$,

$\Omega^3 = \{<(A_7,A_1),0.8>,<(A_1,A_6),0.8>\}$,

$\Omega^4 = \{<(A_7,A_1),0.8>,<(A_1,A_6),0.8>\}$.

The four experts provide the same incomplete information of attribute weights, shown as: $\Lambda = \{\sum_{j=1}^{8} w_j = 1, w_4 \geq w_3, w_j \geq 0.08\}$.

Expert e_1 has an optimistic attitude with $\lambda_1 > 1$; Expert e_2 has a pessimistic attitude with $\lambda_2 \leq 0.999$; Expert e_3 is indifferent with $\lambda_3 = 0.999$ and Expert e_4 cannot provide his preference of compensation towards aggregation so that $\lambda_3 \in (0, +\infty]$ and $\lambda_3 \neq 1$.

4.2. Solution process

According to the procedure of the proposed method, Step 1 and step 2 have already been given above. We perform the computation from the Step 3.

Step 3. According to Eqs (1) and (3), we have the normalized evaluation matrix for each expert. Then, using Eq. (4), we can obtain the normalized synthesized evaluation matrix of projects in terms of the non-financial dimensions, as shown in Table 5. Here, weights of experts are considered as the same with $\varpi_q = 0.25 (q = 1,2,3,4)$.

Table 5. Normalized evaluation matrix of projects in terms of the non-financial dimensions

Projects	g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8
A_1	0.3017	0.3154	0.3297	$\{s_{5.75}, s_{6.25}\}$	$\{s_4, s_5\}$	$\{s_6, s_7\}$	$\{s_5, s_6\}$	$\{s_4, s_{4.75}\}$
A_2	0.3018	0.3154	0.2567	$\{s_5, s_{5.75}\}$	$\{s_{4.75}, s_{5.75}\}$	$\{s_5, s_{5.75}\}$	$\{s_6, s_{6.75}\}$	$\{s_{5.75}, s_6\}$
A_3	0.3101	0.3118	0.3865	$\{s_{4.75}, s_5\}$	$\{s_{6.25}, s_7\}$	$\{s_{4.75}, s_{5.25}\}$	$\{s_6, s_{6.75}\}$	$\{s_5, s_6\}$
A_4	0.3259	0.3173	0.2323	$\{s_4, s_{4.75}\}$	$\{s_6, s_{6.75}\}$	$\{s_5, s_6\}$	$\{s_{5.25}, s_6\}$	$\{s_3, s_4\}$
A_5	0.3327	0.3063	0.3104	$\{s_5, s_6\}$	$\{s_{5.25}, s_6\}$	$\{s_{5.25}, s_6\}$	$\{s_5, s_6\}$	$\{s_4, s_5\}$
A_6	0.3000	0.3099	0.2316	$\{s_4, s_5\}$	$\{s_{5.25}, s_6\}$	$\{s_{5.75}, s_{6.5}\}$	$\{s_{6.5}, s_7\}$	$\{s_{4.75}, s_{5.25}\}$
A_7	0.3253	0.3191	0.3108	$\{s_6, s_{6.5}\}$	$\{s_{5.25}, s_6\}$	$\{s_7, s_{7.25}\}$	$\{s_5, s_{5.75}\}$	$\{s_5, s_6\}$
A_8	0.3076	0.3136	0.3658	$\{s_{3.5}, s_4\}$	$\{s_6, s_7\}$	$\{s_4, s_5\}$	$\{s_6, s_7\}$	$\{s_4, s_{4.5}\}$
A_9	0.3274	0.3264	0.2664	$\{s_{5.75}, s_{6.25}\}$	$\{s_5\}$	$\{s_5, s_{5.75}\}$	$\{s_{4.5}, s_5\}$	$\{s_6, s_7\}$
A_{10}	0.3274	0.3264	0.4133	$\{s_{4.25}, s_5\}$	$\{s_{4.75}, s_{5.5}\}$	$\{s_{4.5}, s_{4.75}\}$	$\{s_{5.75}, s_{6.5}\}$	$\{s_4, s_{4.75}\}$

Step 4. Build and solve Model 2 by LINGO 18.0, we can obtain the attribute weights, compensation parameter and PIS for each expert, as shown in Table 6. Here, we set ε = 0.03.

Table 6. The derived attribute weights, compensation parameter and positive ideal solution for each expert

Experts		g_1	g_2	g_3	g_4	g_5	g_6	g_7	g_8	λ_q
e_1	v_j^{1+}	1	0.995	1	$\{s_{6.5}, s_{6.5}\}$	$\{s_7, s_7\}$	$\{s_7, s_{7.25}\}$	$\{s_{6.5}, s_7\}$	$\{s_7, s_7\}$	42.953
	w_j^1	0.08	0.39	0.10	0.10	0.08	0.08	0.08	0.08	
e_2	v_j^{2+}	1	1	1	$\{s_{6.5}, s_{6.5}\}$	$\{s_7, s_7\}$	$\{s_7, s_{7.25}\}$	$\{s_{6.56}, s_7\}$	$\{s_7, s_7\}$	0.999
	w_j^2	0.08	0.28	0.15	0.15	0.09	0.08	0.08	0.09	
e_3	v_j^{3+}	1	1	1	$\{s_8, s_8\}$	$\{s_7, s_7\}$	$\{s_7, s_{7.25}\}$	$\{s_{6.96}, s_7\}$	$\{s_7, s_7\}$	0.999
	w_j^3	0.20	0.08	0.20	0.20	0.08	0.08	0.08	0.08	
e_4	v_j^{4+}	1	1	1	$\{s_{6.5}, s_{6.5}\}$	$\{s_7, s_7\}$	$\{s_7, s_{7.25}\}$	$\{s_{6.5}, s_7\}$	$\{s_7, s_7\}$	34.205
	w_j^4	0.08	0.08	0.26	0.26	0.08	0.08	0.08	0.08	

Step 5–6. According to Eq. (7), the distances of projects from the PIS and the ranking order of projects for each expert can be obtained. Then, using Eq. (12), we have the group support degree of each project. The results are listed in Table 7.

Table 7. The ranking of projects for each expert and the group support degrees of projects

Projects	e_1		e_2		e_3		e_4		SD_i
	D_i^1	Ranking	D_i^2	Ranking	D_i^3	Ranking	D_i^4	Ranking	
A_1	0.355	5	0.261	5	0.259	4	0.292	4	0.47
A_2	0.370	8	0.268	7	0.278	7	0.341	8	0.09
A_3	0.345	2	0.244	1	0.249	2	0.259	2	0.89
A_4	0.379	9	0.290	10	0.310	10	0.367	9	0.20
A_5	0.360	7	0.263	6	0.260	5	0.299	6	0.25
A_6	0.383	10	0.282	9	0.303	9	0.367	10	0.16
A_7	0.348	3	0.247	2	0.242	1	0.293	5	0.74
A_8	0.353	4	0.270	8	0.291	8	0.285	3	0.40
A_9	0.355	6	0.261	4	0.263	6	0.327	7	0.28
A_{10}	0.331	1	0.248	3	0.254	3	0.248	1	0.83

Step 7. To establish Model 3, values of parameters listed in Table 8 are used:

Table 8. Values of parameters to build Model 3 (source: Wu et al., 2018)

Parameters	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}
AR_i (10^6.CNY)	3.01	2.33	3.7	2.11	2.9	2.19	2.78	3.36	2.37	3.68
IC_i (10^6.CNY)	12.56	9.8	14.62	8.78	11.71	8.79	11.92	13.87	10.02	15.63
AC_{it} (10^5.CNY)	7.48	5.83	6.53	4.79	4.07	2.18	7.1	6.88	3.98	6.21
CR_i (10^3. t)	2.39	1.86	2.8	1.68	2.25	1.66	2.22	2.61	1.89	2.93

The discount rate r is set to 10% and the life cycle of a solar PV project is 25 years. As projects A_2, A_4 and A_6 are geographically far apart, the enterprise plans to choose only one of them to invest in if possible. The bi-objective integer programming model (Model 3) to optimize the project investment portfolios is constructed as follows:

$$\max \sum_{i=1}^{10} \left(\sum_{t=1}^{25} [(AR_{it} - AC_{it})(1+10\%)^{-t}] - IC_i \right) X_i$$

$$\max \sum_{i=1}^{10} SD_i X_i$$

$$s.t. \begin{cases} \sum_{i=1}^{10} X_i IC_i \le 52, \\ \sum_{i=1}^{10} X_i CR_i \ge 8.5, \\ X_2 + X_4 + X_6 \le 1, \\ X_i \in \{0,1\},\ i = 1,2,\ldots,10. \end{cases}$$

The NSGA-II is run by MATLAB R2020a to solve the above model with the following parameters: a population of size 20 and a maximum of 500 generations. The non-dominated solutions and Pareto front are respectively shown in Table 9 and Figure 2.

Table 9. Non-dominated solutions of Model 3

Solutions	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	Objective 1	Objective 2
Portfolio 1	1	0	1	0	0	1	0	0	0	1	42.26	2.36
Portfolio 2	0	0	1	0	1	0	0	0	1	1	43.97	2.25
Portfolio 3	0	0	1	0	0	1	1	0	0	1	41.15	2.62
Portfolio 4	0	0	1	0	1	1	0	0	0	1	45.20	2.13
Portfolio 5	0	0	1	1	0	0	1	0	0	1	38.07	2.66

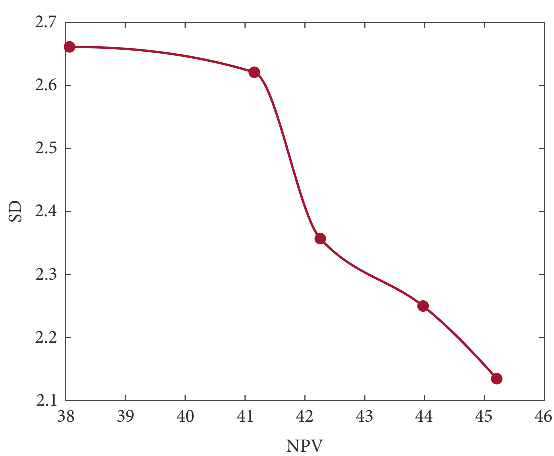

Figure 2. The pareto front of Model 3

4.3. Results and discussions

4.3.1. Result analysis

As can been seen from Table 7, when ε = 0.03, project A_3 has the highest group support degree, followed by the projects A_{10} and A_7. Observing the ranking results under individual opinions, we can find that although experts e_1 and e_2 have the same preference information on attribute weights and pairwise comparisons of projects, the ranking results of projects are different (see from Table 7 or Figure 3). The same situation exists on experts e_3 and e_4. This is because the attitudinal characters of experts towards performance aggregation, reflected in the degree of compensation, are different. In the process of deriving the project ranking, the attitudinal character of experts should be paid attention to.

As can be seen from Table 9, there are five non-dominated solutions. Portfolio 4 (A_3, A_5, A_6, A_{10}) is superior to the other portfolio under the objective of maximizing the financial return, whereas portfolio 5 (A_3, A_4, A_7, A_{10}) is the best for the group support degree maximization objective. Some information can be excavated according to the frequency of the project occurring in the non-dominated solution set. The presence of A_3 and A_{10} in all solutions means that the energy enterprise should prioritize investing in these two projects. For the geographically distant projects A_2, A_4 and A_6, A_2 should be abandoned as it does not appear in any non-dominated solutions. If the enterprise decides to invest in one of these three areas, A_6 should be given priority as it appears in solutions with a high frequency (3 of 5). For portfolios including project A_6 (portfolio 1, 3 and 4), it is difficult to compare them since the two objectives are incomparable. For example, portfolio 1 is superior to portfolio 3 under the objective of financial return maximizing strategy, but the opposite is true under the total non-financial value maximizing strategy. In order to make further decisions, it is necessary to consider the preferences of managers on these two objectives. In general, through the analysis of the non-dominated solutions, in addition to aiding decision-making of portfolio selection, managers of enterprises can obtain useful information about the time sequence for project investment.

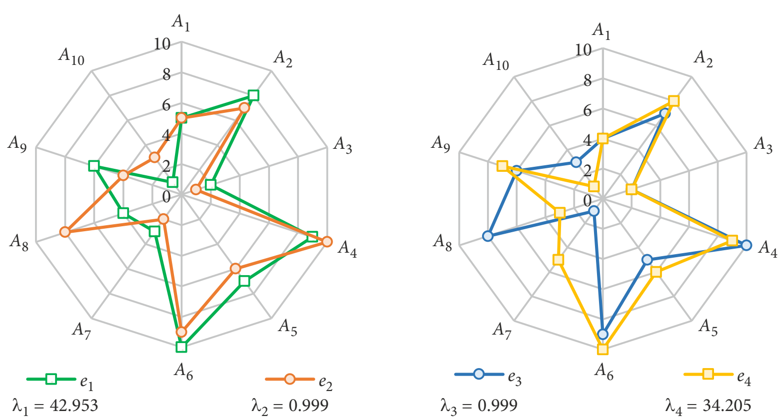

Figure 3. Rankings of projects under different experts' opinions

4.3.2. Comparative analysis

In the following, comparative analysis is conducted to see how the attitudinal character of experts affect the group support degrees of projects. We consider three scenarios. In scenario 1 ($\lambda_q > 1\,(q = 1,2,3,4)$), all experts have an optimistic attitude towards the aggregation; scenario 2 ($\lambda_q < 1\,(q = 1,2,3,4)$) supposes that all experts are pessimistic; scenario 3 ($\lambda_q = 0.999$ $(q = 1,2,3,4)$) supposes that all experts have an indifferent attitude, which is equivalent to integrating the performance of projects using the weighted averaging operator. In all scenarios, we set ε = 0.03. The results are displayed in Figure 4.

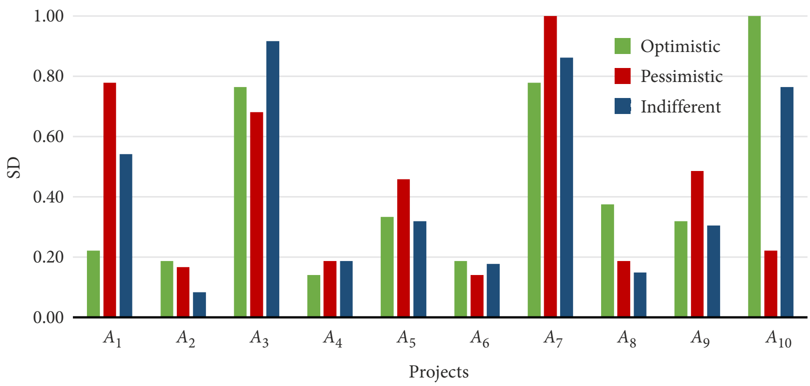

Figure 4. Rankings of projects under experts' different attitudes

As can be seen from Figure 4, whether the experts are pessimistic, optimistic, or indifferent, the group support degrees of projects A_3 and A_7 are high. However, with experts being pessimistic, there is a substantial decline in the support degree of project A_{10}. The reason can be found by analyzing the data listed in Table 5. Project A_{10} has an absolute high score on attribute g_3 and a high score on g_2, but underperforms on attributes g_4 to g_8; while the scores of project A_3 and A_7 are relatively balanced on all attributes. Therefore, when experts are pessimistic, the support degree of project A_{10} declines significantly, as in this situation, the poor performances on attributes cannot be adequately compensated by the good performances; whereas that of project A_3 and A_7 remain stable. Based on the above discussion, we suggest that when the cash flow of an enterprise is sufficient, project A_{10} can be selected as the enterprise usually has enough ability to take risks in such situation. However, when the enterprise's cash flow is tight, a prudent investment strategy is important. Thus, priority should be given to projects A_3 and A_7.

4.3.3. Sensitivity analysis

In the above analysis, the value of ε was set to 0.03. ε is greater than 0 since the consistency index CI^q is required to be not less than the inconsistency index CI^q, and the value of ε is larger when the expert is stricter. In the following, a sensitivity analysis is conducted to see the impact of ε on the group support degree of projects. The value of ε increases from 0.005 to 0.05 with a step of 0.005. The results are displayed in Figure 5.

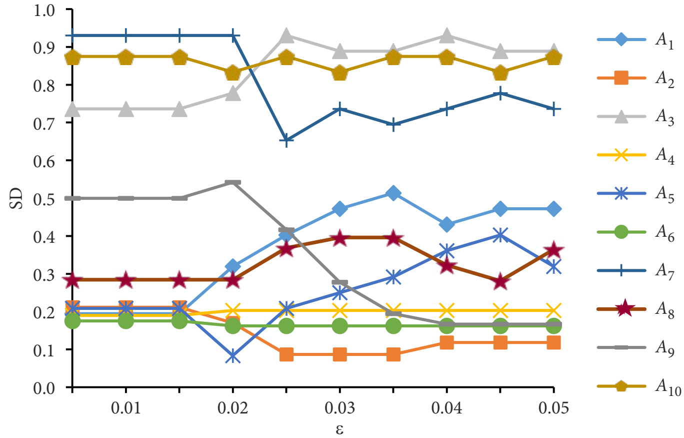

Figure 5. Impact of ε on the support degree of projects

As can be seen from Figure 5, when $\varepsilon \leq 0.02$, project A_7 is the optimal choice. When $\varepsilon > 0.02$, the group support degree of A_3 gradually exceeds that of A_7 and finally became the best choice. In general, the support degree of projects A_3, A_{10} and A_7 are in the high level. The robustness and stability of the proposed method are demonstrated.

Conclusions

This study presented a two-stage hybrid approach to evaluate and select the optimal portfolio of distributed PV projects under the condition of incomplete preference information and limited resources. First, the extended LINMAP was used to rank the projects according to their performance in the non-financial dimension. This method allowed incomplete preference information of attribute weights and took into account the compensation effect between attributes. According to the derived multiple ranking results, a rank acceptability index was used to obtain the group support degree of each project. Based on the obtained support degrees, a bi-objective integer programming model was formulated in the second stage to optimize the project investment portfolio. The NSGA-II was adopted to solve the model such that the uniformly distributed Pareto-optimal solutions are found. A case study of distributed PV project portfolio selection with comparative and sensitivity analyses was carried out to demonstrate applicability and rationality of the proposed approach.

The merits of the proposed approach can be summarized as follows: 1) it can process uncertainties and fuzziness in project evaluations. Using hesitant fuzzy linguistic term sets to score qualitative attributes aligns well with people's habits and cognition. 2) It can deal with complex problems containing hybrid evaluation information. 3) It is capable of considering the attitudinal character of an expert. The degree of compensation between attributes in the aggregation process is adjustable according to the pessimistic, optimistic and indifferent attitudes of an expert. 4) It allows incomplete preference information and reduces the cognitive burden of experts. Experts just need to provide partial weight preference information and roughly give some pairwise comparisons of projects with hesitancy degrees. 5) It takes into account the financial value and non-financial value of the project when optimizing the project investment portfolio, and such a comprehensive evaluation can help reduce the investment risk of an energy enterprise.

According to the result analysis, some managerial implications of PV project portfolio selection practice can be obtained: 1) Even though experts have the same preference information for attribute weights and pairwise judgments, different compensation parameters can lead to significant changes in project ranking and group support degree. We suggest that, when the cash flow of an energy enterprise is sufficient, managers can consider a large degree of compensation such that projects with large fluctuations in attribute values can also be considered; while when the enterprise's cash flow is tight, setting a small degree of compensation is recommended as it could help to make a prudent investment decision. 2) In order to achieve enterprise strategic objectives and reduce investment risk, decision makers and project managers should make a project portfolio considering both the financial and non-financial values. 3) Although it is difficult to compare non-dominated solutions obtained from the project portfolio optimization model when managers cannot provide their preferences for objectives, the solutions could provide theoretical guidance for project managers in the practice of project portfolio management. For example, the frequency of the project occurring in the non-dominated solution set could guide the formulation of the time sequence of project investment.

The paper at hand also has limitations. We have considered the different degrees of compensation in the aggregation process. However, the positive and negative interactions between attributes are not taken into account. In the future, interactions between attributes modelled by the attitudinal Choquet integral (Aggarwal & Fallah Tehrani, 2019) will be an interesting topic. In addition, when calculating the portfolio financial returns, we did not consider the uncertain factors, such as the electricity price and investment cost. Future works could integrate the real options method in building a portfolio optimization model so as to further reduce the investment risk.

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Author contributions

Zhiying Zhang and Huchang Liao conceived the study and were responsible for the design and development of the data analysis. Zhiying Zhang was responsible for data collection and interpretation. Zhiying Zhang wrote the first draft of the article. Huchang Liao checked and revise the draft.

Disclosure statement

The authors have no competing financial, professional, or personal interests from other parties that are related to this paper.

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APPENDIX

Table A.1. Abbreviations and explanations

Abbreviations	Explanations
AHP	Analytic Hierarchy Process
ANP	Analytic Network Process
DEMATEL	Decision Making Trial and Evaluation Laboratory
PROMETHEE	Preference Ranking Organization METHod for Enrichment of Evaluations
TODIM	TOmada de Decisao Interativa e Multi-critevio in French (An acronym in Portuguese of interactive and multi-criteria decision making in English)
TOPSIS	Technique for Order Performance by Similarity to Ideal Solution
VIKOR	VIse Kriterijumska Optimizacija kompromisno Resenje, in Serbian (Multiple criteria optimization compromise solution in English)
SMAA	Stochastic Multicriteria Acceptability Analysis
MADM	Multiple Attribute Decision Making
GRA	Grey Relational Analysis
BWM	Best Worst Method
OWA	Ordered Weighted Averaging
CWA	Compensative Weighted Averaging
HFLTS	Hesitant Fuzzy Linguistic Term Set
HFLE	Hesitant Fuzzy Linguistic Element
LINMAP	Linear Programming Technique for Multidimensional Analysis of Preference
PV	Photovoltaic
PIS	Positive Ideal Solution
NPV	Net Present Value

Table A.2. Notations and explanations

Notations	Explanations
$A=\{A_i \mid i=1,2,\ldots,m\}$	set of m PV projects
$E=\{e_q \mid q=1,2,\ldots,Q\}$	set of Q experts
$G_N=\{g_j \mid j=1,2,\ldots,n\}$	set of n attributes, satisfying $G_N=G_C\cup G_H$ and $G_C\cap G_H=\varnothing$
G_C	quantitative attributes scored in crisp numbers
G_H	qualitative attributes represented by HFLTSs
I_A, I_E, I_C, I_H	index sets of alternatives, experts, quantitative attributes and qualitative attributes, respectively
$\overline{v}_{ij}$	evaluation value of the ith project on the jth attribute
$\overline{v}_{ij}=\overline{r}_{ij}$	evaluation value denoted by crisp numbers
$\overline{v}_{ij}^{q}=\overline{h}_{Sij}^{q}=\{\overline{s}_{Lij}^{q(k)} \mid \overline{s}_{Lij}^{q(k)}\in S;$ $q(k)=1,2,\ldots,K^q\}$	evaluation value denoted by HFLTS provided by the qth expert, where S is the linguistic term set and K^q is the number of linguistic terms in $\overline{h}_{Sij}^{q}$
$v_{ij}=r_{ij}$	normalized value of crisp numbers
$v_{ij}=h_{Sij}=\{s_{L_{ij}}^{(k)} \mid k=1,2,\ldots,K\}$	synthesized evaluation value of the group of experts
λ_q	compensation parameter
$w^q=(w_1^q,w_2^q,\ldots,w_n^q)$	weight vector of attributes
Λ^q	incomplete information set of attribute weights
$\Omega^q=\{<(A_l,A_z),t^q(l,z)> \mid l,z\in I_A, l\neq z\}$	partial pairwise comparisons between projects, where $t\ (l,z)\in[0,1]$ is the truth degree to which A_l is better than A_z
IC^q	inconsistency index between the lth and zth project
CI^q	consistency index between the lth and zth project
ε	threshold to ensure that the consistency index is not less than the inconsistency index
v^{q+}	positive ideal solution
D_i^q	distance between evaluation vector v_i and the PIS v^{q+}
R_q	ranking of projects under the opinions of the qth expert
SD_i	support degree of the ith project
$\varpi=(\varpi_1,\varpi_2,\ldots,\varpi_Q)$	weight vector of experts
AR_{it}	annual capital income of the ith project at the tth year
AC_{it}	annual operation and maintenance cost of the ith project at the tth year
IC_i	initial investment cost of the ith project
L	life cycle of the PV project
r	discount rate
CR_i	carbon emission reduction of the ith project
$X=\{X_i \mid i=1,2,\ldots,m\}$	decision variables for project investment portfolio optimization

Note: The superscript or subscript q that does not descript in explanations denotes the qth expert.