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A novel hybrid behavioral three-way decision-making framework for the site selection of photovoltaic hydrogen production project: A case study in Inner Mongolia

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Abstract: Selecting appropriate sites for photovoltaic hydrogen production projects (PVHPPs) is a complex multi-criteria decision-making problem involving uncertainty and different risk attitudes. This paper constructs a novel behavioral three-way decision model for the site selection of PVHPP. First of all, an evaluation system including five criteria and seventeen sub-criteria is developed. Secondly, interval 2-tuple linguistic (I2TL) variables describe experts' qualitative judgments, and a similarity measure-based power weighted average (PWA) operator aggregates individual evaluations. Thirdly, subjective SWARA II weights and objective MEREC weights are integrated using game theory. Fourthly, a relative profit function incorporating prospect and regret theories reflects the decision-makers' psychological behavior, while grey-prospect improved TOPSIS estimates conditional probabilities. Then, based on expected utility, alternatives are classified into acceptance, delay, and rejection regions and ranked. Finally, a case study of nine cities in Inner Mongolia identifies Hohhot and Ulanqab as suitable locations, with Ordos and Baotou in the delay region. Comparison and sensitivity analyses demonstrate the applicability and relative stability of the proposed framework.

1. Introduction

The development of renewable and clean energy is important for addressing climate change and reducing dependence on fossil fuels. However, the fluctuation and intermittency of photovoltaic power can result in curtailed electricity, making efficient utilization an important practical problem.

Hydrogen energy supports energy storage, transportation, fuel substitution, and carbon reduction. Photovoltaic hydrogen production may alleviate electricity costs for water electrolysis and improve the utilization of otherwise curtailed photovoltaic power [1-2].

Choosing a suitable PVHPP site is essential because light resources, hydrogen storage and transportation costs, demand, environmental effects, and investment risks differ across regions.

PVHPP site selection is a complex multi-criteria decision-making (MCDM) problem. Gao et al.

[3] proposed a framework for photovoltaic power coupled with hydrogen storage, while Wu et al. [4] applied BWM–CRITIC–MABAC to PVHPP siting. Previous studies also used hybrid AHP–TOPSIS, fuzzy VIKOR, and MARCOS approaches [6-9]. These methods mainly provide rankings, although the highest-ranked alternative may still be unsuitable. Three-way decisions (3WD) instead divide alternatives into acceptance, delay, and rejection regions [5,10].

Three limitations motivate this study: the uncertain linguistic granularities used by experts are not always adequately represented; simple aggregation of subjective and objective weights may neglect their differences; and existing 3WD models often overlook decision-makers' risk-aversion and regret-aversion behavior.

I2TL variables extend the 2-tuple linguistic model and can represent evaluations given with different linguistic term sets [11-13]. Subjective weighting reflects experts' preferences, whereas objective weighting reflects observed data; game-theoretic combination can integrate both sources [14-15]. Prospect and regret theories further account for behavioral preferences in three-way decisions [16].

The site evaluation system contains five main criteria and seventeen sub-criteria drawn from PVHPP and renewable-energy site-selection research [4,6,17-19]. The five dimensions are technical (C1), economic (C2), social (C3), environmental (C4), and risk (C5) factors. Their detailed indicators are presented in Figure 1. The system jointly considers solar resources, hydrogen demand, logistics, investment, environmental constraints, and project risks.

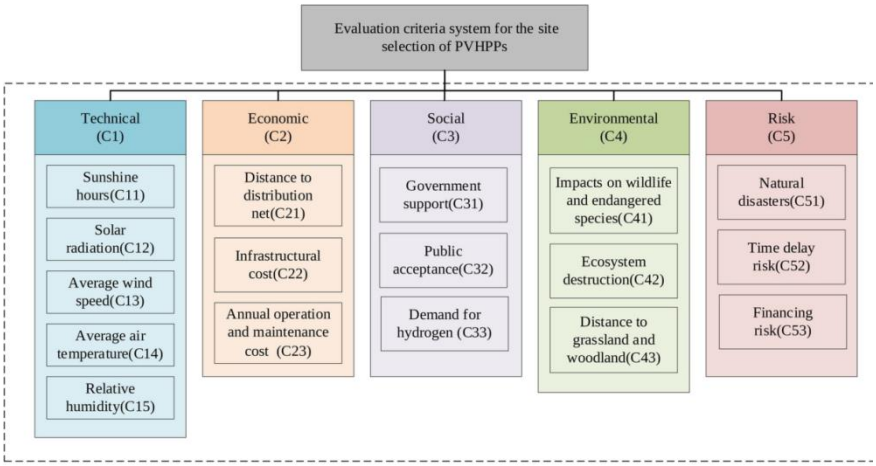


Figure 1: Criteria System for PVHPP Site Evaluation.

From a methodological perspective, the I2TL model and similarity-based PWA operator aggregate uncertain expert assessments; SWARA II and MEREC are combined by game theory; and prospect-regret theory and grey-prospect improved TOPSIS establish relative profit and conditional probability. The proposed behavioral 3WD framework also permits delayed decisions rather than relying solely on the ranking of candidate sites.

2. Proposed Behavioral Three-Way Decision Framework

The proposed framework combines three stages: (i) collection and aggregation of expert information; (ii) integrated weighting of criteria; and (iii) behavioral three-way classification and ranking using relative profits and conditional probabilities (Figure 2).

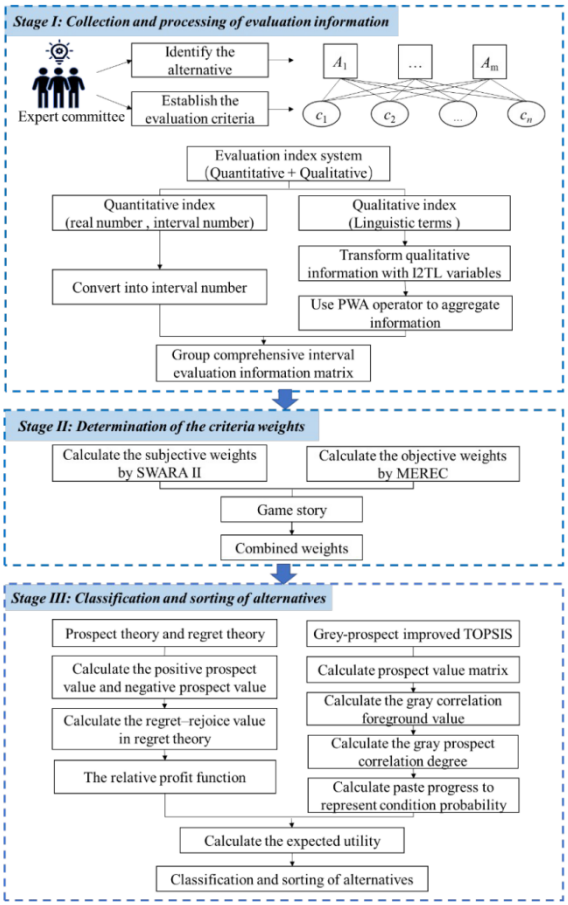


Figure 2: Process Diagram of The Proposed 3WD Framework.

2.1. Interval 2-Tuple Linguistic Model and Information Aggregation

The 2-tuple linguistic model represents linguistic evaluation information using a pair (s_i, α_i), where s_i is a term in the linguistic set S and α_i denotes a symbolic translation. The I2TL model extends a linguistic evaluation to an interval formed by two 2-tuples, [(s_i, α_i), (s_j, α_j)], and makes it possible to use linguistic term sets of different granularities [11-12]. The corresponding interval can be obtained by an inverse translation function; normalized Euclidean distances describe differences between interval 2-tuples.

$$\Delta[\beta_1,\ \beta_2]=\left[(s_i,\alpha_i),(s_j,\alpha_j)\right],\ \text{with}\ \begin{cases} s_i, & i=\text{round}(\beta_1\cdot g) \\ s_j, & \text{j}=\text{round}(\beta_2\cdot g) \\ \alpha_i=\beta_1-\dfrac{i}{g}, & \alpha_i\in\left[-\dfrac{1}{2g},\dfrac{1}{2g}\right) \\ \alpha_j=\beta_2-\dfrac{j}{g}, & \alpha_j\in\left[-\dfrac{1}{2g},\dfrac{1}{2g}\right) \end{cases} \tag{1}$$

2.2. Evaluation Information and Aggregation

An expert committee with experience in solar power generation first identifies candidate sites and evaluates them against the criteria. Quantitative indicators are measured using exact or interval numbers, whereas qualitative indicators are evaluated with linguistic term sets. An alternative A_i (i=1, …, m), a criterion C_j (j=1, …, n), and an expert E_k (k=1, …, l) are used to index the group decision matrices.

The quantitative assessments are converted into interval numbers and normalized to eliminate

differences in physical magnitudes. Benefit and cost criteria are normalized separately. For qualitative criteria, the experts select linguistic term sets according to their preferences; their judgments are then transformed into I2TL values. This transformation permits experts to use different linguistic granularities while obtaining comparable assessment information.

Expert weights are determined from four factors: professional position, years of work experience, education level, and age. The score qk of each expert is converted into a normalized expert weight ωk. A similarity measure-based PWA operator then fuses experts' I2TL judgments, taking both expert importance and the support between judgments into account.

The PWA aggregation operator is expressed as follows:

$$\tilde{r}_{ij} = PWA(\tilde{r}_{ij}^{(1)}, \tilde{r}_{ij}^{(2)}, \cdots, \tilde{r}_{ij}^{(l)}) = \sum_{k=1}^{l} \frac{\omega_k (1 + T(\tilde{r}_{ij}^{(k)}))}{\sum_{k=1}^{l} \omega_k (1 + T(\tilde{r}_{ij}^{(k)}))} \cdot \tilde{r}_{ij}^{(k)} \tag{2}$$

The similarity measure between I2TL judgments provides the support values used by the PWA operator. After aggregating individual assessments and applying the inverse linguistic translation, the quantitative and qualitative criteria are represented as a comprehensive interval group evaluation matrix.

2.3. Combined Criteria Weighting

Subjective SWARA II and objective MEREC weights are integrated through game theory to account for both expert preferences and the removal effects of criteria.

2.3.1. Subjective Weights: SWARA II

SWARA II is a modified version of SWARA characterized by a relatively simple calculation procedure. First, the committee ranks the criteria in descending order of importance. The preference of each criterion over the next is expressed by the linguistic preference scale. The preference degree and relative weight coefficients are then calculated and normalized to obtain the subjective criteria weights. The nonlinear utility function follows the SWARA II procedure described in the original methodology [15].

$$w_j^s = \frac{K_{[P_j]}}{\sum_{P_j=1}^{n} K_{[P_j]}} \tag{3}$$

2.3.2. Objective Weight by MEREC

MEREC determines objective weights from the removal effects of criteria. First, the evaluation matrix is normalized and an overall performance value is calculated for each alternative. Then the performance is recalculated after removing each criterion in turn. The absolute changes in alternative performance measure the removal effect of each criterion; larger effects correspond to greater objective weights.

$$w_j^o = \frac{E_j}{\sum_j E_j} \tag{4}$$

2.3.3. Combined Weights Based on Game Theory

The combined weight method seeks consistency or a trade-off between weight vectors. Based on the idea of equilibrium in game theory, the coefficients of subjective and objective weighting methods are optimized by minimizing their deviation from the combined weight. The resulting coefficients are

normalized and the final combined criterion weight vector is computed as their weighted combination.

$$w_i^* = \sum_{l=1}^{L} a_l^* w_{il} \tag{5}$$

2.4. Behavioral Three-Way Decisions

The proposed 3WD model considers two elements: relative profit and conditional probability. The first is constructed using prospect theory and regret theory to reflect risk-aversion and regret-aversion behavior. The second is estimated by grey-prospect improved TOPSIS. The Bayesian decision procedure and the principle of maximum expected utility are then applied to classify and rank alternatives.

2.4.1. Prospect-Regret Profit

The perspective of loss and utility reflects two attitudes of DMs when selecting actions under uncertainty. Profit describes more directly the consequences of each decision; therefore, this study combines relative costs and revenues into a relative profit function [20]. Prospect theory describes the different attitudes toward gains and losses, while regret theory captures the psychological response to foregone alternatives [16].

First, the positive and negative ideal alternatives are selected as reference points for each attribute. The gain and loss of each alternative are calculated from its interval-valued score relative to the corresponding ideal values. Then the positive and negative prospect values are obtained by applying the prospect value function and the decision weight function.

Prospect theory uses value functions for gains and losses. Five common parameters are set following Tversky and Kahneman [16]: $\varphi = 0.88$, $\phi = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, and $\delta = 0.69$. Positive and negative prospect values are aggregated across the criteria with corresponding prospect weights.

$$\upsilon_{ij}^{+} = \left(\triangle S_{ij}^{+}\right)^{\phi} \left(\triangle S_{ij}^{+} \geq 0\right) \tag{6}$$

$$\upsilon_{ij}^{-} = -\lambda\left(-\triangle S_{ij}^{-}\right)^{\varphi} \left(\triangle S_{ij}^{-} \leq 0\right) \tag{7}$$

The prospect values of each alternative measure gains and losses relative to the reference points. To describe regret avoidance, the regret–rejoice functions compare an alternative with other available alternatives, and then aggregate the comparisons to obtain total regret and total rejoice values. Regret-rejoice values between alternatives Ai and At are calculated as follows:

$$r_{it} = \begin{cases} 1 - e^{-\sigma(V(A_i) - V(A_t))}, & V(A_i) < V(A_t) \\ 0, & V(A_i) \geq V(A_t) \end{cases} \tag{8}$$

$$g_{it} = \begin{cases} 1 - e^{-\sigma(V(A_i) - V(A_t))}, & V(A_i) \geq V(A_t) \\ 0, & V(A_i) < V(A_t) \end{cases} \tag{9}$$

The overall psychological perception value combines total regret and total rejoice and is normalized. The resulting value is used with the positive and negative prospect values when constructing the relative cost and revenue functions.

$$rg_i = tr_i + tg_i, \quad i = 1, 2, \ldots, n \tag{10}$$

Relative costs and revenues are defined for three actions (accept, delay, reject) under two opposite states (good and bad). The risk-aversion coefficient $\varepsilon \in$ controls the balance between avoiding loss and pursuing utility. The relative profit function is obtained from the difference between the

corresponding relative revenue and cost, as summarized in Table 1.

Table 1: Relative profit functions of three actions under two states.

	Γ (P)	$\neg\Gamma$ (N)
ζ_A	$p_{AP}^i = r_{AP}^i - c_{AP}^i = \overline{rg_i} - \min$	$p_{AN}^i = r_{AN}^i - c_{AN}^i = \left(\overline{rg_i} - \max\right)$
ζ_D	$p_{DP}^i = r_{DP}^i - c_{DP}^i = (1-2\varepsilon)\left(\overline{rg_i} - \min\right)$	$p_{DN}^i = r_{DN}^i - c_{DN}^i = (1-2\varepsilon)\left(\max - \overline{rg_i}\right)$
ζ_R	$p_{RP}^i = r_{RP}^i - c_{RP}^i = \min - \overline{rg_i}$	$p_{RN}^i = r_{RN}^i - c_{RN}^i = \max - \overline{rg_i}$

2.4.2. Conditional Probability by Gray-Prospect TOPSIS

The TOPSIS method measures the proximity of alternatives to the positive and negative ideal solutions, while grey relational analysis emphasizes similarity in the shape of indicator sequences. Grey-prospect improved TOPSIS combines these two types of information and incorporates the limited rationality and risk preferences of DMs in the evaluation procedure.

Grey relational coefficients are calculated for each alternative with respect to the positive and negative ideal solutions:

$$\begin{cases} gr_{ij}^{+} = \dfrac{\min\limits_i \min\limits_j \left|d_{oj}^{+} - d_{ij}\right| + \rho \max\limits_i \max\limits_j \left|d_{oj}^{+} - d_{ij}\right|}{\left|d_{oj}^{+} - d_{ij}\right| + \rho \max\limits_i \max\limits_j \left|d_{oj}^{+} - d_{ij}\right|} \\ gr_{ij}^{-} = \dfrac{\min\limits_i \min\limits_j \left|d_{oj}^{-} - d_{ij}\right| + \rho \max\limits_i \max\limits_j \left|d_{oj}^{-} - d_{ij}\right|}{\left|d_{oj}^{-} - d_{ij}\right| + \rho \max\limits_i \max\limits_j \left|d_{oj}^{-} - d_{ij}\right|} \end{cases} \tag{11}$$

The positive and negative grey prospect values are obtained from the correlation coefficients and weighted by the prospect weighting functions. These values are combined with the prospect distances to form the positive and negative ideal correlations used for the final relative closeness measure.

$$vg_i^{+} = \sum_{j=1}^{n} \pi^{+}\left(\omega_j\right) vp_{ij}^{+}\left(gr_{ij}^{+}\right) \tag{12}$$

$$vd_{ij} = \begin{cases} \left(d_{rp} - d_{ij}\right)^{\phi}, & d_{rp} \geq d_{ij} \\ -\lambda\left(d_{rp} - d_{ij}\right)^{\varphi}, & d_{rp} < d_{ij} \end{cases} \tag{13}$$

The resulting prospect distances and grey correlations form the positive and negative ideal correlation degrees:

$$\begin{cases} vd_i^{+} = \sqrt{\sum_{j=1}^{n} \omega_j \left(vd^{+} - vd_{ij}\right)^2} \\ vd_i^{-} = \sqrt{\sum_{j=1}^{n} \omega_j \left(vd^{-} - vd_{ij}\right)^2} \end{cases} \tag{14}$$

$$d_i = \frac{C_i^{-}}{C_i^{+} + C_i^{-}} \tag{15}$$

The relative closeness represents an alternative's proximity to the positive ideal solution. A higher closeness indicates better overall suitability. The normalized grey-prospect TOPSIS result is used as the conditional probability of the good state in the subsequent three-way decision.

2.4.3. Three-Way Classification and Ranking

Given relative profits and the conditional probability $Pr(\Gamma|[A_i])$, the expected profit of each decision action is calculated. Based on Bayesian decision theory, each alternative is assigned to the action with maximum expected utility. Acceptance corresponds to the POS region, non-commitment

to the BND region, and rejection to the NEG region.

$$EP(\zeta_A|[A]) = (\overline{rg_i} - \min) Pr(\Gamma|[A]) + (\overline{rg_i} - \max) Pr(\neg\Gamma|[A])$$
$$EP(\zeta_D|[A]) = (1-2\varepsilon)(\overline{rg_i} - \min) Pr(\Gamma|[A]) + (1-2\varepsilon)(\max - \overline{rg_i}) Pr(\neg\Gamma|[A]) \quad (16)$$
$$EP(\zeta_R|[A]) = (\min - \overline{rg_i}) Pr(\Gamma|[A]) + (\max - \overline{rg_i}) Pr(\neg\Gamma|[A])$$

The three decision actions are compared using their expected profits. The action that offers the largest expected profit is selected; when a boundary equality occurs, the rule for the boundary region is applied to prevent inconsistent decisions. Alternatives within each region are then ranked according to their expected utility, while alternatives in POS are preferred to those in BND and NEG.

$$\alpha_i = \frac{(p^i_{AN} - p^i_{DN})}{(p^i_{AN} - p^i_{DN}) + (p^i_{DP} - p^i_{AP})} = \frac{(1-\varepsilon)(\max - \overline{rg_i})}{(1-\varepsilon)(\max - \overline{rg_i}) + \varepsilon(\overline{rg_i} - \min)} \quad (17)$$

The overall order gives priority to the acceptance region, followed by the boundary and rejection regions; expected utility distinguishes alternatives within each region.

$$\text{Utility} = \begin{cases} EP(\zeta_A|[A_i]) & if \quad A_i \in POS(\Gamma) \\ EP(\zeta_D|[A_i]) & if \quad A_i \in BND(\Gamma) \\ EP(\zeta_R|[A_i]) & if \quad A_i \in NEG(\Gamma) \end{cases} \quad (18)$$

3. Case Study in Inner Mongolia

3.1. Candidate Sites and Expert Assessments

Nine Inner Mongolian cities were considered: Chifeng (A1), Tongliao (A2), Hulunbuir (A3), Hohhot (A4), Ulanqab (A5), Ordos (A6), Bayannur (A7), Baotou (A8), and Wuhai (A9). These candidates were assessed on five criteria and seventeen sub-criteria.

Five experienced professionals and scholars evaluated the alternatives. For qualitative criteria, E1 and E2 used five linguistic labels, E3 and E4 used seven labels, and E5 used nine labels. The different linguistic assessments were transformed into I2TL information and aggregated using the PWA operator. Quantitative data were converted into normalized intervals. The expert weights obtained from the original scoring procedure were incorporated into the aggregation.

3.2. Combined Criteria Weights

The technical and economic quantitative indicators and the distance to grassland and woodland were normalized as interval numbers. The remaining eight qualitative criteria (C31, C32, C33, C41, C42, C51, C52, and C53) were evaluated by five experts and converted into a comprehensive interval group evaluation matrix. Benefit and cost attributes were treated separately in the normalization step. The expert opinions were fused by the similarity-based PWA operator before the criteria weights were computed.

The game-theoretic coefficients are 0.65 for subjective weights and 0.35 for objective weights. Table 2 reports the final weights of all seventeen criteria.

Table 2: Integrated subjective, objective, and combined criteria weights.

Main-criteria	Sub-criteria	*wsj*	*woj*	*wj*
C1	C11	0.044	0.054	0.048
	C12	0.042	0.054	0.046
	C13	0.028	0.057	0.038

	C14	0.024	0.066	0.039
	C15	0.019	0.055	0.032
	C21	0.047	0.059	0.051
C2	C22	0.050	0.054	0.051
	C23	0.048	0.059	0.052
	C31	0.059	0.06	0.059
C3	C32	0.054	0.058	0.055
	C33	0.097	0.062	0.085
	C41	0.153	0.057	0.119
C4	C42	0.178	0.059	0.136
	C43	0.113	0.053	0.092
	C51	0.016	0.064	0.033
C5	C52	0.014	0.073	0.035
	C53	0.014	0.06	0.030

3.3. Three-Way Classification Results

Relative profits and grey-prospect improved TOPSIS probabilities (Tables 3 and 4) were used to calculate expected profits and classify the candidate sites.

Table 3: Relative profit function values for candidate sites.

	p^i_{AP}	p^i_{DP}	p^i_{RP}	p^i_{AN}	p^i_{DN}	p^i_{RN}	α_S	β_S
A_1	0.359	0.144	-0.359	-1.034	0.414	1.034	0.870	0.552
A_2	0.107	0.043	-0.107	-1.286	0.514	1.286	0.965	0.837
A_3	0.034	0.014	-0.034	-1.359	0.544	1.359	0.989	0.945
A_4	1.393	0.557	-1.393	0.000	0.000	0.000	0.000	0.000
A_5	1.109	0.444	-1.109	-0.284	0.114	0.284	0.374	0.099
A_6	0.875	0.350	-0.875	-0.519	0.207	0.519	0.580	0.203
A_7	0.000	0.000	0.000	-1.393	0.557	1.393	1.000	1.000
A_8	0.711	0.284	-0.711	-0.682	0.273	0.682	0.691	0.291
A_9	0.354	0.141	-0.354	-1.040	0.416	1.040	0.873	0.558

Table 4: Conditional probabilities obtained from grey-prospect improved TOPSIS.

	VG_i^+	VG_i^-	VD_i^+	VD_i^-	d_i
A_1	0.797	0.832	0.575	0.630	0.516
A_2	0.679	0.941	0.546	0.666	0.568
A_3	0.708	0.986	0.553	0.682	0.569
A_4	0.978	0.550	0.753	0.704	0.420
A_5	0.881	0.847	1.000	1.000	0.495
A_6	1.000	0.731	0.601	0.609	0.456
A_7	0.784	1.000	0.474	0.641	0.566
A_8	0.931	0.829	0.575	0.623	0.491
A_9	0.757	0.855	0.621	0.709	0.532

Hohhot (A4) and Ulanqab (A5) belong to the acceptance region; Ordos (A6) and Baotou (A8) fall in the delay region; the other five cities are rejected. The final ranking is A5 > A4 > A8 > A6 > A7 > A3 > A1 > A2 > A9, demonstrating that three-way decisions provide classification as well as prioritization.

4. Further Analysis and Discussion

4.1. Comparative Analysis

The proposed grey-prospect improved TOPSIS approach was compared with TOPSIS, grey relational analysis, and grey improved TOPSIS (Table 5).

The four methods produce consistent decision classifications but not identical ranking orders. Grey relational analysis ranks A4 first, whereas the other methods rank A5 first. The differences mainly appear in the ordering of alternatives within the negative region. Conventional TOPSIS and grey relational analysis do not explicitly describe the DMs' risk preferences; grey-prospect improved TOPSIS incorporates prospect-based valuations and grey correlation information. The comparison indicates that the proposed method preserves the three-way decision classes while allowing behavioral preferences to influence the ranking.

Table 5: Comparison of classification and ranking results.

	Classification	Ranking order
Grey correlation analysis	$POS(\Gamma) = \{A_4, A_5\}$ $BND(\Gamma) = \{A_6, A_8\}$ $NEG(\Gamma) = \{A_1, A_2, A_3, A_7, A_9\}$	$A_4>A_5>A_8>A_6>A_7>A_1>A_3>A_2>A_9$
TOPSIS	$POS(\Gamma) = \{A_4, A_5\}$ $BND(\Gamma) = \{A_6, A_8\}$ $NEG(\Gamma) = \{A_1, A_2, A_3, A_7, A_9\}$	$A_5>A_4>A_8>A_6>A_7>A_3>A_1>A_9>A_2$
Grey improved TOPSIS	$POS(\Gamma) = \{A_4, A_5\}$ $BND(\Gamma) = \{A_6, A_8\}$ $NEG(\Gamma) = \{A_1, A_2, A_3, A_7, A_9\}$	$A_5>A_4>A_8>A_6>A_7>A_1>A_3>A_2>A_9$
The proposed method	$POS(\Gamma) = \{A_4, A_5\}$ $BND(\Gamma) = \{A_6, A_8\}$ $NEG(\Gamma) = \{A_1, A_2, A_3, A_7, A_9\}$	$A_5>A_4>A_8>A_6>A_7>A_3>A_1>A_2>A_9$

4.2. Sensitivity Analysis

The risk-aversion coefficient ε and regret-preference parameter σ were varied independently while other case-study parameters were held fixed.

When ε varies from 0 to 0.50 in steps of 0.05, the boundary region decreases as the risk-aversion coefficient increases. At ε approaching zero, all alternatives fall into the boundary region; when ε approaches 0.50, the boundary becomes empty and the model reduces to a two-way decision. For intermediate values, the alternatives are divided among acceptance, delay, and rejection regions.

With ε = 0.3, the parameter σ is varied from 0.1 to 2.0 in steps of 0.1. As σ increases, the number of alternatives in the boundary region decreases and the number in the negative region increases. This shows that different risk and regret attitudes can affect the classification results. Nevertheless, Hohhot (A4) and Ulanqab (A5) remain among the leading alternatives over the tested parameter settings, supporting the relative stability of the preferred sites.

5. Conclusions and Outlook

This paper proposes a behavioral three-way decision framework for PVHPP site selection. An evaluation system is developed with five criteria and seventeen sub-criteria. I2TL variables and the similarity-based PWA operator aggregate evaluations expressed by different experts, and the combination of SWARA II, MEREC, and game theory determines criterion weights. Prospect and

regret theories are incorporated into the relative profit function, while grey-prospect improved TOPSIS provides conditional probabilities. The case study of nine cities in Inner Mongolia shows that Hohhot and Ulanqab are suitable locations for PVHPP development, while Ordos and Baotou warrant delayed decisions. Comparative and sensitivity analyses show broadly consistent classification results and relatively stable preferred alternatives.

The proposed framework contributes a behavioral classification perspective to renewable-energy site selection and reduces dependence on a ranking alone. Nevertheless, the evaluation involves five DMs and a limited number of candidate cities; future research may expand the decision-making group, investigate large-scale group decision-making, and test the framework in other regions and renewable-energy applications.

References

[1] Sako, N., Koyama, M., Okubo, T., Kikuchi, Y., 2021. Techno-economic and life cycle analyses of battery-assisted hydrogen production systems from photovoltaic power. J. Clean. Prod. 298, 126809.

[2] L. Kong, L. Li, G. Cai, C. Liu, P. Ma, Y. Bian, T. Ma, Techno-economic analysis of hydrogen energy for renewable energy power smoothing, Int. J. Hydrogen Energy 46 (03) (2021) 2847–2861.

[3] Gao Jianwei, Men Huijuan, Guo Fengjia, Liang Pengcheng, Fan Yuejin. A multi-criteria decision-making framework for the location of photovoltaic power coupling hydrogen storage projects[J]. Journal of Energy Storage,2021,44(PB).

[4] Wu Yunna, Deng Zhongqing, Tao Yao, Wang Linwei, Liu Fangtong, Zhou Jianli. Site selection decision framework for photovoltaic hydrogen production project using BWM-CRITIC-MABAC: A case study in Zhangjiakou[J]. Journal of Cleaner Production,2021,324.

[5] Y. Yao, Three-way decisions with probabilistic rough sets, Inform. Sci. 180 (2010) 341–353.

[6] Sonal Sindhu, Vijay Nehra, Sunil Luthra. Investigation of feasibility study of solar farms deployment using hybrid AHP-TOPSIS analysis: Case study of India[J]. Renewable and Sustainable Energy Reviews,2017,73.

[7] Ao Xuan Hoa, Vu Trinh Vuong, Techato Kuaanan, Phoungthong Khamphe. Use of hybrid MCDM methods for site location of solar-powered hydrogen production plants in Uzbekistan[J]. Sustainable Energy Technologies and Assessments,2022,52(PA).

[8] Rezaei Mostafa, Khalilpour Kaveh R.,Jahangiri Mehdi. Multi-criteria location identification for wind/solar based hydrogen generation: The case of capital cities of a developing country[J]. International Journal of Hydrogen Energy, 2020,45(58).

[9] Hosseini Dehshiri Seyyed Shahabaddin, Firoozabadi Bahar. A new application of measurement of alternatives and ranking according to compromise solution (MARCOS) in solar site location for electricity and hydrogen production: A case study in the southern climate of Iran[J]. Energy,2022,261(PB).

[10] He ShiFan, Wang YingMing, Pan XiaoHong, Chin KwaiSang. A novel behavioral three-way decision model with application to the treatment of mild symptoms of COVID-19. [J]. Applied soft computing,2022,124.

[11] Herrera F, Martinez L. A 2-tuple fuzzy linguistic representation model for computing with words. IEEE Trans Fuzzy Syst 2000;8: 746–52. https://doi.org/10.1109/91.890332.

[12] Zhang H. The multi attribute group decision making method based on aggregation operators with interval-valued 2-tuple linguistic information. Math Comput Modell 2012;56: 27–35. https://doi.org/10.1016/j.mcm.2012.01.001.

[13] Liu H-C, Lin Q-L, Wu J. Dependent Interval 2-Tuple Linguistic Aggregation Operators and Their Application to Multiple Attribute Group Decision Making. Int J Uncertainty Fuzziness Knowledge Based Syst 2014;22: 717–35. https://doi.org/10.1142/S0218488514500366.

[14] Tao Yao, Luo Xu, Zhou Jianli, Wu Yunna, Zhang Lihui, Liu Yuanxin. Site selection for underground pumped storage plant using abandoned coal mine through a hybrid multi-criteria decision-making framework under the fuzzy environment: A case in China[J]. Journal of Energy Storage,2022,56(PA).

[15] Keshavarz-Ghorabaee M. Assessment of distribution center locations using a multiexpert subjective–objective decision-making approach. Sci Rep 2021;11: 19461. https://doi.org/10.1038/s41598-021-98698-y.

[16] Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263–291.

[17] Mostafaeipour A, Sedaghat A, Qolipour M, Rezaei M, Arabnia H, SaidiMehrabad M, et al. Localization of solar-hydrogen power plants in the province ofKerman, Iran. Adv Energy Res 2017;5: 179–205. https://doi.org/10.12989/eri.2017.5.2.179.

[18] Kannan D, Moazzeni S, Darmian S mostafayi, Afrasiabi A. A hybrid approach based on MCDM methods and Monte Carlo simulation for sustainable evaluation of potential solar sites in east of Iran. J Clean Prod 2021;279:122368. https://doi.org/10.1016/j.jclepro.2020.122368.

[19] Messaoudi, D., Settou, N., Negrou, B., Settou, B., 2019. GIS based multi-criteria decision making for solar hydrogen production sites selection in Algeria. Int. J. Hydrogen Energy 44 (60), 31808–31831.
[20] Jia, F., & Liu, P. D. (2019). A novel three-way decision model under multiple-criteria environment. Information Sciences, 471, 29–51.