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An Application of Fuzzy Analytic Hierarchy Process in Risk Evaluation of Chinese Renewable Energy Overseas Investment*

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Renewable energy sources, including wind, solar, and biofuels, are essential for promoting sustainable economic development and mitigating environmental challenges. As China's overseas investments in renewable energy expand, effective risk assessment and management have become critical. This study develops a comprehensive risk evaluation framework for China's overseas renewable energy investments using the Fuzzy Analytic Hierarchy Process (FAHP). The framework incorporates political, economic, and project-specific risks, organized through three primary criteria, nine sub-criteria, and thirty tertiary indicators. By integrating expert judgments with fuzzy set theory, the FAHP methodology assigns accurate weights to risk factors and ensures consistency in evaluation. The findings identify political risks as the most significant, emphasizing their influence on investment strategies. These insights offer valuable guidance for policymakers and investors to enhance risk management strategies and ensure the sustainability of China's renewable energy initiatives abroad.

Keywords: renewable energy, overseas investment, risk evaluation, multi-criteria decision-making (MCDM), Fuzzy Analytic Hierarchy Process (FAHP)

Introduction

The global transition to renewable energy is driven by the dual pressures of depleting fossil fuel resources and escalating environmental degradation. Renewable energy sources such as wind, solar, and biofuels are pivotal for achieving sustainable development and ensuring energy security. In recent years, China has emerged as a global leader in renewable energy production, with its photovoltaic and wind power capacities contributing significantly to the world's total output. Alongside domestic advancements, Chinese energy companies have increasingly pursued overseas investments in renewable energy projects. By 2020, China's foreign direct investment in the energy sector reached $39 billion, reflecting its strategic commitment to international energy cooperation.

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However, overseas renewable energy investments are fraught with uncertainties stemming from political instability, economic volatility, and operational challenges in host countries. Factors such as fluctuating exchange rates, policy inconsistencies, and local opposition can result in substantial financial losses. To address these issues, a systematic and scientific risk assessment framework is essential for identifying, quantifying, and mitigating these uncertainties.

Existing studies on renewable energy overseas investment risks often focus on individual risk factors, such as political or economic risks, without addressing their interdependencies. Moreover, qualitative methods dominate the field, which may limit the precision and reliability of risk evaluations. To bridge these gaps, this study employs the FAHP—a quantitative multi-criteria decision-making approach—to construct a robust risk evaluation framework. This framework accounts for the complex interactions among various risk factors and provides practical guidance for optimizing investment decisions and minimizing potential losses.

Literature Review

The risks associated with renewable energy overseas investments (REOIs) have drawn significant attention in recent years. Key risk categories include political, economic, and operational risks, with growing emphasis on their interdependencies and comprehensive management.

Political Risks

Political risks are critical in determining the success of REOIs, encompassing factors such as political stability, regulatory uncertainty, and international relations. High-impact studies, such as those by Kobrin (1987), underscore the importance of mitigating political risks through thorough risk assessments and adaptive strategies. More recent works in journals like *Energy Policy* have expanded on these themes, emphasizing the role of host-country policy frameworks in shaping renewable energy investment outcomes (Cao et al., 2020).

Economic Risks

Economic risks, including market volatility, inflation, and exchange rate fluctuations, have been extensively studied. Research by Sadorsky (2012) in *Applied Energy* highlights the dynamic interplay between renewable energy investments and macroeconomic variables, suggesting that exchange rate volatility significantly impacts investment returns. Additional insights by Zhang et al. (2018) in *Renewable and Sustainable Energy Reviews* emphasize the need for robust financial risk mitigation mechanisms in cross-border renewable energy projects.

Operational Risks

Operational risks stem from project management inefficiencies, technological limitations, and supply chain disruptions. Scholars such as Wang and Liu (2017) in *Energy Economics* discuss the role of advanced technologies and effective project governance in minimizing operational risks. Furthermore, studies in *Renewable Energy* highlight the importance of stakeholder engagement and local community integration for successful project execution (Hosseini, & Wahid, 2018).

FAHP in Risk Evaluation

The Fuzzy Analytic Hierarchy Process (FAHP) has been widely applied to evaluate and prioritize risks in complex decision-making scenarios. Studies by Azadeh et al. (2011) in *International Journal of Advanced Manufacturing Technology* demonstrate the robustness of FAHP in handling uncertainty and vagueness in expert judgments. Similarly, Naghadehi et al. (2009) in *Expert Systems with Applications* applied FAHP to optimize risk evaluation in mining projects, illustrating its adaptability to diverse sectors. In the energy domain, research by Singh et al. (2019) in *International Journal of Operational Research* highlights FAHP's effectiveness in addressing multi-criteria risk evaluation for thermal power projects. These studies underscore FAHP's versatility in constructing systematic and quantifiable risk assessment frameworks.

Research Gaps

Despite these advancements, gaps remain in the quantitative modeling of interdependent risks and the integration of qualitative and quantitative methods for comprehensive risk evaluations. Existing studies often focus on isolated risk factors, overlooking systemic interactions that could compound investment risks. This study addresses these gaps by employing the FAHP method to construct an integrative risk evaluation framework, offering a nuanced understanding of REOIs.

Applied Methods

This study adopts the **Fuzzy Analytic Hierarchy Process (FAHP)** method, which integrates fuzzy set theory and the Analytic Hierarchy Process (AHP) to construct the risk evaluation framework and calculate the weights of indicators.

Overview of the FAHP Model

1. Theoretical Background

The Analytic Hierarchy Process (AHP), proposed by Saaty in the 1970s, is a multi-criteria decision-making method suitable for structuring and analyzing complex problems (Saaty, 1990).

Observed values in real-world problems are often imprecise or ambiguous. Imprecise or ambiguous data may be the result of unquantifiable, incomplete, and unavailable information. They are usually represented by bounded intervals, ordered (sorted) data, or fuzzy numbers. FAHP, developed by Van Loargoven in 1983, extends AHP by introducing triangular fuzzy numbers to handle fuzziness and uncertainty in decision-making (Van Loargoven, 1983).

Fuzzy set theory. Crisp evaluation usually leads to unreliable results, due to the expert judgement uncertainty and vagueness. Thus, the scale must be modified to meet FAHP requirements.

Triangular fuzzy number is a method of triangular fuzzy number to represent fuzzy comparative judgment. We denoted triangular fuzzy number as:

$$P = (l, \mathrm{m}, \mu,) \tag{1}$$

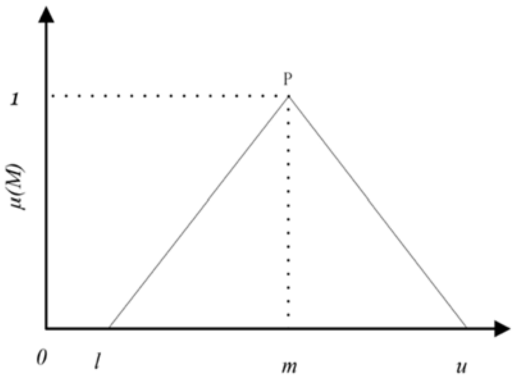

Figure 1. Triangular fuzzy number (P).

Figure 1 shows the membership function of a triangular fuzzy number. Parameter l represents the minimal value, parameter u represents the most likely value, and parameter m represents the maximum value. The membership function of M(μ) is defined as Eq. 2 (Peng et al., 2021b).

$$\mu(x|M) = \begin{cases} 0(x < l) \\ \dfrac{x-l}{m-l}(l \le x < m) \\ \dfrac{\mu-x}{\mu-m}(m \le x < \mu) \\ 0(x \ge \mu) \end{cases} \tag{2}$$

Core steps of FAHP. The following seven steps are adopted for the study by referring to ten essential steps of FAHP suggested by Long D. Nguyen and Dai Q. Tran (Nguyen et al., 2023; Singh et al., 2019b).

1) Step 1. Create the hierarchical structure of the criteria.

2) Step 2. Establish the pairwise comparisons matrix.

3) Step 3. Calculation of weight vector and check for consistency.

In this article we use the square root method to calculate the eigenvalues and eigenvectors of each judgment matrix. And still use factor B (economic risk) as an example to illustrate every step and how to calculate.

Calculate the sum of elements in each row of the fuzzy judgment matrix:

$$\mathrm{M_I} = \sum_{\mathrm{J}=1} \mathrm{A_{Ij}}, \mathrm{i} = 1,2,\cdots \tag{3}$$

Calculate the square of M_i, where “n” represents the rank of matrix:

$$\mathrm{W_I} = \sqrt[n]{\mathrm{M_I}} \tag{4}$$

The eigenvectors are expressed as:

$$\mathrm{W_1} = \frac{\mathrm{W_1}}{\sum_{\mathrm{J}=1}^{\mathrm{N}} \mathrm{W_J}} \tag{5}$$

Calculate the greatest eigenvalue of the judgment matrix:

$$Aw = \lambda_{max}\mathrm{W} \tag{6}$$

A is the priority judgment matrix, and W_i represents the corresponding eigenvector. $A = [\ a_{ij}\ ]_{n\times n}$, a_{ij} is represented by elements in the “i” row and “j” column of the judgment matrix. $1 \le I \le n$, $1 \le j \le n$. The greatest eigenvalue λ_{max}

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_i} \tag{7}$$

To evaluate the consistency of experts’ judgments on the relative importance of each indicator, it is necessary to test the consistency of the judgment matrix. The basis for judgment is to calculate the consistency index CI and consistency ratio CR of each layer. Saaty (1980) suggested that CR ≤ 0.1 is the acceptable range, otherwise the judgment matrix must be adjusted until it meets the consistency standard.

The consistency ratio means that the size of the consistency index will be affected by the order of the matrix and the number of evaluation scales.

The consistency of the obtained pairwise comparison matrix will be checked using Eq. 8:

$$\mathrm{CR}=\frac{\mathrm{CI}}{\mathrm{RI}} \tag{8}$$

where

$$CI=\frac{\lambda_{max}-n}{n-1} \tag{9}$$

$$\mathrm{CR}=\frac{\mathrm{CI}}{\mathrm{RI}}<0.1$$

when value of CR is less than 0.1, we can confirm that the judgement matrix is acceptable, the local weights for indicators can be approved.

4) Step 4. Convert experts' judgment into fuzzy numbers by using the triangular fuzzy number.

In this study, triangular fuzzy numbers are used to represent subjective pair-wise comparisons. The α -cut value of 1 is considered for converting the crisp inputs into fuzzy inputs. The α -cut values of zero are considered for upper and lower bound numbers (Singh et al., 2019a). The scale of the relative importance to measure comparison and the corresponding triangular fuzzy numbers are given in Table 1.

Table 1

The Scale of the Relative Importance and the Corresponding Triangular Fuzzy Numbers

Scale of relative importance (crisp number)	Triangular fuzzy number	Linguistic variable	Membership function $(l, \mathrm{m}, \mu,)$
1	$\tilde{1}$	Equally important/preferred	(1, 1, 2)
3	$\tilde{3}$	Weakly more important/preferred	(2, 3, 4)
5	$\tilde{5}$	Strongly more important/preferred	(4, 5, 6)
7	$\tilde{7}$	Very strongly more important/preferred	(6, 7, 8)
9	$\tilde{9}$	Extremely more important/preferred	(8, 9, 9)

Note: X = 2, 4, 6, 8 are scales in the middle.

Value is automatically assigned to the reverse comparison within the matrix. That is, if $\tilde{a}_{ij}$ Is a matrix value assigned to the relationship of component i to component j, then $\tilde{a}_{ji}$ Is equal to $1/\tilde{a}_{ij}$.

$$\tilde{A}=\begin{pmatrix} 1 & \tilde{a}_{12}\dots\dots\tilde{a}_{1n} & \\ \tilde{a}_{21} & \cdots & \tilde{a}_{2n} \\ & & \\ \tilde{a}_{n1}\tilde{a}_{n2}\ \dots\dots & & 1 \end{pmatrix} \tag{10}$$

5) Step 5. Aggregate experts' judgments into fuzzy judgment matrices.

The following equations are used to integrate experts' judgments

$$\bar{I}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \text{ such that } l_{ij} \leq m_{ij} \leq u_{ij} \text{ and } l_{ij}, m_{ij}, u_{ij} \in [\tfrac{1}{9}, 9]$$
$$l_{ij} = min(l_{ijk}) \tag{11}$$

$$m_{ij} = \sqrt[K]{\prod_{k=1}^{K} m_{ijk}} \tag{12}$$

$$u_{ij} = max(u_{ijk}) \tag{13}$$

where (l_{ijk}, m_{ijk}, u_{ijk}) is the pairwise comparison between criteria i and j evaluated by the kth expert and K is the number of experts. Alternatively, geometric means can also be used to determine l_{ij} and u_{ij}.

6) Step 6. Find the relative weights by defuzzify judgment matrices.

The defuzzification process is to convert the fuzzy numbers in pair- wise comparison matrixes into crisp numbers. The degree of confidence (α-cut) and attitude toward risk (λ) of the decision maker are used. Both α-cut and λ are from 0 to 1. A greater α-cut or λ shows more confidence or a more optimistic view of the decision maker respectively. In this study, the defuzzification process is carried out based on the following equations (Liou, & Wang, 1992):

$$z_{ijl}^{\alpha} = (m_{ij} - l_{ij})\alpha + l_{ij} \tag{14}$$

$$z_{ijr}^{\alpha} = u_{ij} - (u_{ij} - m_{ij})\alpha \tag{15}$$

$$z_{ij,\alpha}^{\lambda} = \lambda z_{ijr}^{\alpha} + (1 - \lambda) z_{ijl}^{\alpha} \tag{16}$$

Using the equation below, we can get the local weights of matrix F

$$w_i = \frac{1}{n} \sum_{j=1}^{n} \frac{z_{ij}}{\sum_{k=1}^{n} z_{kj}} \tag{17}$$

7) Step 7. Calculate the global weights of all criteria, sub-criteria and indicators.

Using the above steps, we can get the weights for all criteria and sub-criteria. The higher weight the criteria get, the more important role it plays in the evaluation system. The judgement matrix for each layer of the criteria system can be seen in the appendix.

Results

This article invited 7 experts who have worked in the field of renewable energy investment for many years to conduct a pairwise comparison of the relative importance between secondary indicators and third-level indicators.

Weights of the Assessment System Using Fuzzy Analytic Hierarchy Process (FAHP)

In order to illustrate how to determine the triangular fuzzy numbers and judgment matrices based on the new questionnaire, the author uses the expert responses to the first-level factors A-C to establish the judgment matrix as an example; for specific language variables and corresponding fuzzy numbers, please refer to relevant publications.

Seven experts rated the relative importance of factors A to B, A to C and B to C.

Expert	Triangular Fuzzy Judgment Numbers									Experts' Judgment		
	AB			AC			BC			AB	AC	BC
	L	M	U	L	M	U	L	M	U			
1	1	2	3	2	3	4	1	1	1	2'	3'	1'
2	1	1	1	1	2	3	1/3	1/2	1	1'	2'	1/2'
3	1	2	3	1/3	1/2	1	1/3	1/2	1	2'	1/2'	1/2'
4	1	1	1	1	1	1	1	1	1	1'	1'	1'
5	1	2	3	1	1	1	1/4	1/3	1/2	2'	1'	1/3'
6	1	2	3	1	2	3	1	2	3	2'	2'	2'
7	2	3	4	1	1	1	1	1	1	3'	1'	1'

For example, the pairwise comparisons matrix of criteria F from the first expert can be expressed as follows:

$$F_B{}' = \begin{pmatrix} 1 & 2' & 3' \\ 1/2' & 1 & 1' \\ 1/3' & 1' & 1 \end{pmatrix} \tag{18}$$

Aggregate Experts' Judgments into Fuzzy Judgment Matrices. The following equations are used to integrate experts' judgments

$$\bar{I}_{ij} = (l_{ij}, m_{ij}, u_{ij}) \text{ such that } l_{ij} \le m_{ij} \le u_{ij} \text{ and } l_{ij}, m_{ij}, u_{ij} \in [\tfrac{1}{9}, 9]$$
$$l_{ij} = min(l_{ijk}) \tag{19}$$

$$m_{ij} = \sqrt[K]{\prod_{k=1}^{K} m_{ijk}} \tag{20}$$

$$u_{ij} = max(u_{ijk}) \tag{21}$$

where (l_{ijk} , m_{ijk} , u_{ijk}) is the pairwise comparison between criteria i and j evaluated by the kth expert and K is the number of experts. Alternatively, geometric means can also be used to determine l_{ij} and u_{ij}.

Accordingly, we can get that

For comparison of criteria A to criteria B, $l = 1, m = 1.74, u = 4$

For comparison of criteria A to criteria C, $l = 0.33, m = 1.29, u = 4$

For comparison of criteria B to criteria C, $l = 0.25, m = 0.77, u = 3$

Fuzzy pair-wise judgment matrix can be drawn in table:

$$F' = \begin{pmatrix} 1,1,1 & 1,1.74,4 & 0.33,1.29,4 \\ 0.25,0.57,1 & 1,1,1 & 0.25,0.77,3 \\ 0.25,0.78,3 & 0.33,1.30,4 & 1,1,1 \end{pmatrix}$$

Find the relative weights by Defuzzify Judgment Matrices. The defuzzification process is to convert the fuzzy numbers in pair- wise comparison matrixes into crisp numbers. The degree of confidence (α-cut) and attitude toward risk (λ) of the decision maker are used. Both α-cut and λ are from 0 to 1. A greater α-cut or λ shows more confidence or a more optimistic view of the decision maker, respectively. In this study, the defuzzification process is carried out based on the following equations (Liou, & Wang, 1992):

$$z_{ijl}^{\alpha} = \left(m_{ij} - l_{ij}\right)\alpha + l_{ij} \tag{22}$$

$$z_{ijr}^{\alpha} = u_{ij} - \left(u_{ij} - m_{ij}\right)\alpha \tag{23}$$

$$z_{ij,\alpha}^{\lambda} = \lambda z_{ijr}^{\alpha} + (1-\lambda) z_{ijl}^{\alpha} \tag{24}$$

With α-cut = 0.5 (moderate confidence) and λ = 0.5 (moderate risk attitude), we can get the crisp numbers of pair-wise judgment. For example, the value of crisp number of criteria A to B is calculated as below:

$$z_{ABl}^{\alpha=0.5} = (1.74-1)\times 0.5 + 1 = 1.37$$

$$z_{ABr}^{\alpha=0.5} = 4-(4-1.74)\times 0.5 = 2.87$$

$$z_{AB,\alpha}^{\lambda} = 0.5\times 2.87 + (1-0.5)\times 1.37 = 2.12$$

Using the same method, we can get the crisp numbers for criteria A to C and B to C, the whole matrix as table

$$\mathrm{F}= \begin{pmatrix} 1 & 2.12 & 1.78 \\ 0.47 & 1 & 1.17 \\ 0.56 & 0.85 & 1 \end{pmatrix}$$

Using the equation below, we can get the local weights of matrix F

$$w_i = \frac{1}{n}\sum_{j=1}^{n} \frac{z_{ij}}{\sum_{k=1}^{n} z_{kj}} \tag{25}$$

The weights were calcluted as:

Wa = 0.38, wb = 0.33, wc = 0.29.

Calculate the global weights of all criteria, sub-criteria and indicators. Using the above steps, we can get the weights for all criteria and sub-criteria. The higher weight the criteria get, the more important role it plays in the evaluation system. The judgement matrix for each layer of the criteria system can be seen in the appendix.

The relative weights and global weights of the evaluation indicators were calculated, the value can be seen in Table 2.

Table 2

Relative Weights

A = 0.38		B = 0.33			C = 0.29			
Aa = 0.62	Ab = 0.38	Ba = 0.36	Bb = 0.31	Bc = 0.33	Ca = 0.41	Cb = 0.32	Cc = 0.15	Cd = 0.12
Aa1 = 0.22	Ab1 = 0.54	Ba1 = 0.38	Bb1 = 0.29	Bc1 = 0.36	Ca1 = 0.64	Cb1 = 0.18	Cc1 = 0.47	Cd1 = 0.4
Aa2 = 0.22	Ab2 = 0.23	Ba2 = 0.38	Bb2 = 0.07	Bc2 = 0.64	Ca2 = 0.18	Cb2 = 0.64	Cc2 = 0.31	Cd2 = 0.6
Aa3 = 0.19	Ab3 = 0.23	Ba3 = 0.32	Bb3 = 0.32		Ca3 = 0.18	Cb3 = 0.18	Cc3 = 0.15	
Aa4 = 0.15			Bb4 = 0.32				Cc4 = 0.07	
Aa5 = 0.11								
Aa6 = 0.11								

This article divides the risk factors affecting China's foreign investment in renewable energy into three aspects: political risk, economic risk, and project risk. The global weights of each layer of criteria and indicators are shown in Table.

Table 3

Global Weights

	Criteria	Sub-criteria	Indicators
Renewable energy invest risk F	Political Risks A = 0.38	Country Risks (Aa) 0.2356	Political stability (Aa1) 0.052
			Law and order (Aa2) 0.052
			Internal conflict (Aa3) 0.045
			National default risk (Aa4) 0.035
			Bilateral relations (Aa5) 0.026
			Political corruption (Aa6) 0.026
		Political and Regulatory Risks (Ab) 0.1444	Energy policy (Ab1) 0.078
			Environmental policy, (Ab2) 0.033
			Policy guarantee (Ab3) 0.033
	Economic Risks B = 0.33	Market Risks (Ba) 0.1188	Market analysis risks (Ba1) 0.045
			Supply and demand structure risks (Ba2) 0.045
			Industry competition (Ba3) 0.038
		Macro-economic risks (Bb) 0.1023	Economic level (Bb1) 0.030
			Economic growth (Bb2) 0.007
			Inflation (Bb3) 0.033
			Exchange rate fluctuations (Bb4) 0.033
		Financial risks (Bc) 0.1089	Interest rate fluctuations (Bc1) 0.039
			Foreign exchange restrictions (Bc2) 0.070
	Project Risks C = 0.29	Management risks (Ca) 0.1189	Project management risks (Ca1) 0.076
			Organizational structure risks (Ca2) 0.021
			HR risks (Ca3) 0.021
		Partner Risks (Cb) 0.0928	Supplier reliability (Cb1) 0.017
			Raw material reliability (Cb2) 0.059
			Pay back reliability (Cb3) 0.017
		Social Risks (Cc) 0.0435	Environmental and social risks (Cc1) 0.020
			Climate Impact (Cc2) 0.013
			Environmental Impact (Cc3) 0.007
			Public Will (Cc4) 0.003
		Technology Risks (Cd) 0.0348	Technology maturity level (Cd1) 0.014
			Core technology ownership (Cd2) 0.021

Conclusion and Future Research

Based on the research literature on overseas investment risks of Chinese enterprises and renewable energy investment risks, this article constructs an indicator system for risk evaluation of overseas investment in Chinese renewable energy. The indicator system includes 3 first-level criteria, 9 sub-criteria indicators and 30 third-level indicators, which are used to identify the comprehensively and scientifically various risks existing in investment activities.

The second part of the article uses the fuzzy Delphi method to invite industry experts to rate the relative importance of the evaluation indicators, uses the fuzzy analytic hierarchy process to calculate the weights of indicators at all levels in the indicator system. Through the consistency test, the conclusion is that all the weights data meet the requirements and can effectively reflect the importance of indicators at all levels.

For future research, this article will apply the fuzzy comprehensive evaluation method to evaluate the main destination countries of China's renewable energy overseas investment activities, specifically analyze the risk levels and risk structures of investment activities in each region, provide more information for subsequent overseas investment activities of enterprises. It is a scientific basis to effectively avoid and respond to risks and improve investment efficiency and investment reliability.

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