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Risk Assessment of China's Overseas Renewable Energy Investments Based on the Fuzzy ANP Method

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Abstract

China's overseas renewable energy investments play a key role in global green development but face challenges like policy uncertainty and market volatility. This study employs the Fuzzy Analytic Network Process (FANP) method to evaluate political, economic, and project risks in the Al Dhafra photovoltaic power station project in the UAE. Results show that the FANP method effectively addresses uncertainties and interdependencies among risk factors. The AI Dhafra project demonstrates low overall risk, with political and economic risks rated as "outstanding" and project risks as "excellent." This study provides insights for optimizing investment decisions and formulating effective energy policies.

Keywords

Renewable Energy Investment, Risk Assessment, Analytic Network Process (ANP), Fuzzy Theory

1. Introduction

Against the backdrop of accelerating globalization and increasingly severe climate change challenges, renewable energy investment has become an important means for countries to achieve low-carbon economic transformation. Overseas renewable energy investment is not only an important strategic tool for China to promote global green development and energy cooperation, but also provides valuable opportunities for developing countries to build energy infrastructure and develop their economy (Zou et al., 2013).

China is the world's largest manufacturer and installer of wind power and photovoltaic equipment, with its photovoltaic production capacity accounting for 76% of the world's total and its wind power equipment output accounting for more than half of the world's total. Although the countries have abundant renewable energy resources, these investment projects also face many challenges, including policy uncertainty, market volatility, technological risks, and social and cultural conflicts (Noothout et al., 2016; Angelopoulos et al., 2017). For example, policy fluctuations often significantly affect the capital cost of investment projects, increase risk premiums, and reduce investment attractiveness (IRENA, 2016; Noothout et al., 2016). In addition, since these projects are highly capital-intensive and have long payback periods, the importance of investment risk management is particularly prominent (Ilbahar et al., 2021). Constructing a scientific risk assessment model can not only help Chinese companies better avoid risks and optimize investment decisions, but also provide data support and practical experience for the investment to formulate effective energy policies. Therefore, this study aims to comprehensively evaluate the risks of China's overseas renewable energy investment projects based on the fuzzy ANP model, to provide a reference for research and practice in related fields.

2. Literature Review

Multi-criteria decision-making (MCDM) technology is a widely used method in the field of sustainable energy risk assessment and risk management. These techniques provide solutions to problems involving multi-objective decisions and conflicting decision factors. There are many research methods for RE risk assessment, the most commonly used methods include Analytical Hierarchical Process (AHP), Analytical Network Process (ANP), Preference Techniques Ordered by Similarity to Ideal Solutions (TOPSIS), Preference Ranking Organization Method for Enriched Evaluation (PROMETHEE), Decision Experiment and Evaluation Laboratory (DEMATEL), Data Envelopment Analysis (DEA), and etc. (Kul et al., 2020)

Several methods based on weighted average, priority setting, transcendence, fuzzy principles and their combinations are used for energy planning decisions. (Strantzali & Aravossis 2016). MCDM has many applications, such as energy policy analysis, power planning, technology selection and project assessment, and environmental impact analysis (Zhou et al. 2006).

The analytic hierarchy process (AHP) is a multi-criteria analysis tool for complex decision-making problems, proposed by Saaty (1970). AHP decomposes complex problems into objectives, criteria, and sub-criteria layers by constructing a hierarchical structure, and obtains weights through pairwise comparison. However, AHP has limitations in dealing with the uncertainty of decision makers' subjective judgments. For example, Wu et al. (2021) pointed out that traditional AHP cannot fully cope with the interference of fuzzy information in complex environments, which may lead to deviations in weight allocation. To overcome this problem, the fuzzy analytic hierarchy process (FAHP) was proposed. FAHP introduces fuzzy numbers (such as triangular fuzzy numbers) into the pairwise comparison matrix to deal with the uncertainty in subjective assessment. For example, Ibhar et al. (2021) quantified the importance of each risk factor in a wind power project through fuzzy AHP, proved the effectiveness of this method in reducing cognitive bias and improving the reliability of results.

Unlike AHP, the Analytical Network Process (ANP) allows for interdependencies between criteria and sub-criteria and, therefore, is considered a more powerful tool for dealing with complex system decisions. Fuzzy ANP further considers fuzzy uncertainty based on traditional ANP. Wu et al. (2021) developed a multi-criteria decision-making framework based on fuzzy ANP for investment risk assessment in countries along the Belt and Road. The results show that fuzzy ANP can more accurately capture the interaction between risk factors and provide investors with more realistic decision support. Angelopoulos et al. (2017) combined policy risk, economic risk and technical risk when assessing the risk of Greek wind power projects and quantified the weights of these dynamic risks through fuzzy ANP, verifying its applicability in complex decision-making scenarios. Ilbahar et al. (2021) improved FMEA by combining fuzzy logic and prospect theory, significantly improving the model's ability to predict investor behavior. This method has been widely used in investment risk assessment in fields such as wind energy and solar energy. Peng et al. (2021) developed a combined assessment tool suitable for complex investment environments by combining fuzzy ANP and gray theory, performed well in dealing with data scarcity and decision uncertainty. Noothout et al. (2016) used machine learning to quantify policy risks in European renewable energy projects, demonstrating the critical role of policy design in reducing capital costs. Additionally, Boumella et al. (2020) conducted a systematic review of risk management in renewable energy projects, emphasizing the importance of data-driven decision-making in modern energy management. Moving forward, the integration of big data and fuzzy logic is considered a key direction for improving risk prediction capabilities.

3. Methodology

As discussed above, project investment risk typically involves multiple risk factors, each of which can significantly impact decision-making. Moreover, these risk factors are often interdependent, meaning changes in one factor may influence others, making traditional linear evaluation methods insufficient. Additionally, large-scale investment projects are characterized by high capital requirements and long investment cycles, which further increase uncertainty and complexity in risk assessment. Another key challenge is the difficulty in obtaining comprehensive and accurate project information, as investment decisions often rely on incomplete, vague, or expert-driven data. Given these complexities, the ANP-Fuzzy approach is well-suited for this study, as it allows for the systematic handling of interdependencies, the incorporation of expert judgment under uncertainty, and a more flexible and comprehensive risk assessment framework.

The reasons for choosing the ANP-Fuzzy method in investment project risk assessment are as follows:

1) Handling complex interdependencies: ANP (Analytic Network Process), as an extension of AHP, can effectively address the interdependencies and feedback relationships among various factors in decision-making problems, which is particularly important in investment project risk assessment. In the ANP structure, the control layer consists of the target layer and the criterion layer; the elements in the network layer use the elements in the control layer as criteria and influence each other.

2) Dealing with uncertainty: The introduction of Fuzzy Logic helps manage the uncertainty and vagueness in expert judgments and data, enhancing the reliability of evaluation results. Fuzzy is an assessment method that accurately defines fuzzy things. It can quantitatively evaluate qualitative indicators in complex decision-making systems through the membership theory of fuzzy mathematics(Saaty, 2004). This method goes from classification and refinement to overall comprehensive assessment. After multi-level assessment calculations, the overall assessment vector is finally obtained, and the assessment result is determined based on the maximum membership.

3) Enhancing scientific rigour and accuracy in decision-making: The ANP-Fuzzy method integrates quantitative and qualitative analysis, enabling a more comprehensive risk assessment for investment projects and providing a more scientific decision-making approach.

According to recent studies, the ANP-Fuzzy method has demonstrated effectiveness and flexibility in handling multi-criteria decision-making (MCDM) problems. This method offers distinct advantages in investment project risk assessment, providing decision-makers with a more comprehensive and reliable risk evaluation.

Therefore, the indicator weights determined by ANP can overcome the shortcomings of the traditional method that it is difficult to reflect the mutual influence between indicators, and the obtained weights will be more accurate.

Establishing a Project Risk Assessment Model for RE Overseas Investment

Step 1: According to the RE overseas investment project risk assessment indicator system, determine the mutual influence relationship between indicators and construct the ANP structure of RE overseas investment project risk assessment accordingly.

Based on relevant literature, this article divides the risk factors affecting China's foreign investment in renewable energy into three aspects: political risk, economic risk, and project risk. According to the composition of risk factors, they are divided into 26 indicators in total. The indicator system can be seen in Appendix 1.

Step 2: Calculate the supermatrix and weighted supermatrix of the ANP structure. the judgment matrices of first-level indicators, second-level indicators and third-level indicators are constructed respectively, and the characteristic vectors of the second-level indicators $\left(w_{1k}, w_{2k}, \cdots, w_{mk}\right)$ and the characteristic vectors of the third-level indicators are formed.

When the eigenvector of the secondary index u_{ij} passes the consistency test, it is expressed in matrix form to generate a local weight vector matrix W_{ij}. Under the influence of the first-level index $u_{i,m}$ super matrices $\boldsymbol{W}$, and $\boldsymbol{W}$ is not a normalized matrix. In the matrix, each element represents a matrix, and the column sum is I, as shown in formula (1). The supermatrix $\boldsymbol{W}$ column is normalized to obtain the weighted ultra-short matrix $\overline{\boldsymbol{W}} = \left(\boldsymbol{W}\right)_{m\times m}$, where $\overline{\boldsymbol{W}} = \alpha_{ij} \times W_{ij}$, α_{ij} is the weighted factor.

$$\overline{\boldsymbol{W}} = \begin{bmatrix} w_{11} & w_{12} & \cdots & w_{1k} \\ w_{21} & w_{22} & \cdots & w_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mk} \end{bmatrix} \tag{1}$$

When the eigenvector of the third-level indicator passes the consistency test, a local weight vector, i.e., a matrix, is generated. K super matrices are formed under the influence of the second-level indicator, and the super matrix columns are normalized to obtain a reinforcement matrix, as shown in Formula (2).

$$\boldsymbol{W} = \begin{bmatrix} w_{111} & w_{112} & \cdots & w_{11n} \\ w_{211} & w_{212} & \cdots & w_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ w_{m1} & w_{m2} & \cdots & w_{mk} \end{bmatrix} \tag{2}$$

Step 3: Calculate the limit permutation sorting vector of the third level indicator weighted supermatrix $\overline{w'}$, as shown in formula (3), and stabilize the weighted supermatrix. When i tends to infinity and the limit convergence is unique, the limit matrix $W^{\infty\prime}$ of the indicators will be generated. The column vectors in the limit matrix $W^{\infty\prime}$ are the weights of each indicator.

$$\boldsymbol{W}^{\infty\prime} = \lim_{j\to\infty}\left(\frac{1}{k}\right)\sum_{j=1}^{k}\overline{\boldsymbol{W}}_j \tag{3}$$

The column vectors in the limit matrix $\boldsymbol{W}^{\infty}$ are the weights of each second-level indicator.

$$\boldsymbol{W}^{\infty} = \lim_{i\to\infty}\left(\frac{1}{m}\right)\sum_{i=1}^{m}\overline{\boldsymbol{W}}_i \tag{4}$$

Step 4: Let the assessment set be $\left(l_1, l_2, \cdots, l_v\right)$, The evaluator evaluates and scores each of the thrird-level indicators based on the assessment set. According to the assessment level of the third-level indicators, the assessment set of this paper $\left(l_1, l_2, \cdots, l_5\right) = \left(\text{outstanding, exerllent, good, common, bad}\right)$.

Evaluation grades and standards of indicators can be seen in the appendix. Summarize third-level indicator assessment vector $\left(b_{ijh1}, b_{ijh2}, \cdots, b_{ijhv}\right)$. f_{ijhl}, is the total number of times the third-level indicator u_{ijh} is evaluated as level l_v, and b_{ijhl} is the membership degree of the third-level indicator classified to the assessment level

$$b_{ijhl} = \frac{f_{ijhl}}{\sum_{l=1}^{v} f_{ijhl}} \tag{5}$$

The assessment matrix of the second-level indicators is constructed based on the assessment vector of the third-level indicators, as shown in formula 6.

$$\boldsymbol{B}_{ij} = \begin{bmatrix} \boldsymbol{B}_{ij1} \\ \boldsymbol{B}_{ij2} \\ \vdots \\ \boldsymbol{B}_{ijh} \end{bmatrix} = \begin{bmatrix} b_{ij11} & b_{ij12} & \cdots & b_{ij1v} \\ b_{ij21} & b_{ij22} & \cdots & b_{ij2v} \\ \vdots & \vdots & & \vdots \\ b_{ijk1} & b_{ijh2} & \cdots & b_{ijhv} \end{bmatrix} \tag{6}$$

The third-level indicator weights and the second-level indicator assessment matrix determined by the ANP method $\boldsymbol{B}_{ij}$, Calculate the assessment vector $\boldsymbol{P}_{ij}$ of the secondary index u_{ij}. Since the number of indicators is big, weighted average operator is used M in the fuzzy calculation, see formular (7). According to the membership principle of fuzzy mathematics, the maximum membership b_{ijv} corresponding assessment level is the assessment result of the indicator.

$$\boldsymbol{P}_{ij} = \boldsymbol{W}_{ij} \otimes \boldsymbol{B}_{ij} = \left(w_{ij1}, w_{ij2}, \cdots, w_{ijh}\right) \otimes \begin{bmatrix} b_{ij11} & b_{ij12} & \cdots & b_{ij1v} \\ b_{ij21} & b_{ij22} & \cdots & b_{ij2v} \\ \vdots & \vdots & & \vdots \\ b_{ijh1} & b_{ijh2} & \cdots & b_{ijhv} \end{bmatrix} \\ = \left(b_{ij1}, b_{ij2}, \cdots, b_{ijv}\right) \tag{7}$$

Based on the assessment vector $\boldsymbol{P}_{ij}$ of the secondary index, the assessment matrix Bi of the primary index is constructed, as shown in formula (8).

$$\boldsymbol{B}_{i} = \begin{bmatrix} \boldsymbol{P}_{i1} \\ \boldsymbol{P}_{i2} \\ \vdots \\ \boldsymbol{P}_{ij} \end{bmatrix} = \begin{bmatrix} b_{i11} & b_{i12} & \cdots & b_{i1v} \\ b_{i21} & b_{i22} & \cdots & b_{i2v} \\ \vdots & \vdots & & \vdots \\ b_{ij1} & b_{ij2} & \cdots & b_{ijv} \end{bmatrix} \tag{8}$$

The second-level indicator weights and the first-level indicator assessment matrix Bi can be determined according to the ANP method,

Calculate assessment vector $\boldsymbol{P}_{i}$ see formula (9).

$$\boldsymbol{P}_{i} = \boldsymbol{W}_{i} \otimes \boldsymbol{B}_{i} = \left(w_{i1}, w_{i2}, \cdots, w_{ij}\right) \otimes \begin{bmatrix} b_{i11} & b_{i12} & \cdots & b_{i1v} \\ b_{i21} & b_{i22} & \cdots & b_{i2v} \\ \vdots & \vdots & & \vdots \\ b_{ij1} & b_{ij2} & \cdots & b_{ijv} \end{bmatrix} = \left(b_{i1}, b_{i2}, \cdots, b_{iv}\right) \tag{9}$$

Based on the assessment vector $\boldsymbol{P}_{i}$ of the first-level indicators, the overall assessment matrix $\boldsymbol{B}$ is constructed, as shown in formula (10).

$$\boldsymbol{B} = \begin{bmatrix} \boldsymbol{P}_{1} \\ \boldsymbol{P}_{2} \\ \vdots \\ \boldsymbol{P}_{i} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1v} \\ b_{21} & b_{22} & \cdots & b_{2v} \\ \vdots & \vdots & & \vdots \\ b_{i1} & b_{i2} & \cdots & b_{iv} \end{bmatrix} \tag{10}$$

According to the first-level indicator weights determined by the ANP method and the overall assessment matrix $\boldsymbol{B}$, Overall assessment vector $\boldsymbol{P}$ of REOIR is calculated, see formula (11). Here the assessment level lv corresponding to the maximum membership degree bv is the REOIR comprehensive score.

$$\boldsymbol{P} = \boldsymbol{W}_i \otimes \boldsymbol{B}_i = \left(w_1, w_2, \cdots, w_i\right) \otimes \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1v} \\ b_{21} & b_{22} & \cdots & b_{2v} \\ \vdots & \vdots & & \vdots \\ b_{i1} & b_{i2} & \cdots & b_{iv} \end{bmatrix} \tag{11}$$

4. Case Study: Assessment of Investment Al Dhafra

This article selected the investment of AI Dhafra photovoltaic power station as the case study for empirical analysis. AI Dhafra is located in the Al Dhafra area, United Arab Emirates (UAE), covering an area of more than 20 square kilometres, with a total installed capacity of 2.1 GW. total investment of US$1051 million, of which the Chinese investment is US$210.2 million. It has been selected as the case study for empirical analysis for the following key reasons:

1) Photovoltaic power is the most significant category within renewable energy investments, accounting for more than half of China's overseas RE investments. Given its dominant share, evaluating a major photovoltaic project provides critical insights into China's RE investment strategy and associated risks.

2) Asia, particularly Southeast Asia and the Middle East, is a key focus area for China's overseas RE investments. The Middle East, with its abundant solar resources and strategic economic importance, has emerged as a crucial destination for large-scale renewable energy projects, making this case highly relevant.

3) The AI Dhafra project represents one of the largest Chinese overseas renewable energy investments in the past decade, both in terms of capital investment and production capacity. The project's extended timeline, complex information landscape, and high decision-making difficulty introduce significant risks, making it an ideal case for applying the ANP-Fuzzy method in investment risk evaluation.

By analyzing this project, the study aims to provide a comprehensive risk assessment framework that can be extended to other large-scale overseas RE investments, contributing valuable insights for both academia and industry.

4.1. Data Collection

This paper uses the expert scoring method to determine the score of each indicator. The experts are composed of 1) invest managers of the National Development Bank, who are responsible for approving foreign investment loans. 2) Project manager and of Jinko Power. They have been directly involved in and followed up the project investment process, have the most comprehensive project knowledge, and are experts in the investment field. A total of 20 questionnaires were distributed, and 17 valid questionnaires were collected. Considering that the questionnaire survey method has a certain degree of subjectivity, this paper combines the practical data of the Global Corruption Index Report, CEIC's economic databases, and the exchange rate, interest rate, and inflation index of the host country UAE in the past five years to test the objectivity of the questionnaire data.

4.2. Determine the Index Weights Based on ANP

According to the indicators system above-mentioned, combined with the relationship between each assessment index, this paper uses Excel software to calculate the weight of each level of indicators.

In the structural model of REOI assessment, experts in the industry are invited to judge and score in the order of criteria, sub-criteria, and indicators. In the software, the nine-point method is used to judge the relationship between two indicators, from 1 to 9, indicating that a certain indicator's influence or relative importance on another indicator gradually increases. The score value of the judgment matrix is the average of the expert score value. The overseas investment risk level is used as the assessment criterion in the control layer. The judgment matrix is shown in the figure. The criteria weights are 0.433, 0.329 and 0.238, and the consistency test results are all passed. The sub-criteria weights under the A standard are 0.144 and 0.289, the sub-criteria weights under the B standard are 0.209, 0.085, and 0.034, and the weights under the C standard are 0.022, 0.062, 0.117, and 0.038, and the consistency test is passed. The weight results of each indicator are shown in **Table 1** and **Figure 1**.

Table 1. Weights of indicators.

Indic	Aa1	Aa2	Aa3	Aa4	Ab1	Ab2	Ab3	Ba1	Ba2	Bb1	Bb2	Bb3	Bb4
weights	0.019761	0.019761	0.039522	0.065250	0.180372	0.068825	0.0393	0.052369	0.157108	0.028333	0.015592	0.008580	0.032433
Indic	Bc1	Bc2	Ca1	Ca2	Ca3	Cb1	Cb2	Cb3	Cc1	Cc2	Cc3	Cd1	Cd2
weights	0.022960	0.011480	0.002440	0.009762	0.009762	0.035436	0.008	0.017718	0.083838	0.012059	0.020815	0.012520	0.025041

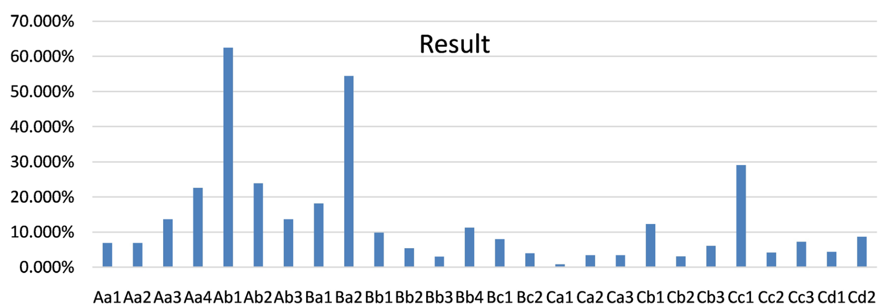

Figure 1. Result of weights of indicators.

4.3. Evaluating REOIR Based on Fuzzy Method

To ensure that the assessment results can more effectively reflect the level of REOIR, experts and scholars in the industry are invited to evaluate and score the specific indicators (third-level indicators) of the investment risk of this project. Based on the three main risk sources, political risk, economic risk, and project risk, the evaluator ticks the corresponding level of the indicator in the assessment form according to the third-level indicator assessment level and standards. Each indicator can only correspond to one assessment level, and multiple selections or no selections are considered invalid. This assessment form was distributed via e-mail. A total of 7 assessment forms were distributed, 7 were collected within the specified time, and all were valid, with a successful rate of 100%. Among the experts and scholars participating in the assessment, 86% have the title of professor or professor-level senior engineer, and 70% are engaged in research in the field of smart grids. The corresponding number of times the third-level indicators were rated at each level was summarized and counted. The statistical results are shown in Table 2.

Table 2. Weights of risk assessment indicators and the assessment numbers of the indicators.

Criteria	Weights	Sub-criteria	Weights	Indicators	Weights	Outstanding	Excellent	Good	Common	Bad
A	0.4328853	(Aa)	0.1442951	(Aa1)	0.019761	7	0	0	0	0
				(Aa2)	0.019761	5	2	0	0	0
				(Aa3)	0.03952	2	4	1	0	0
				(Aa4)	0.065250	0	1	4	2	0
		(Ab)	0.2885902	(Ab1)	0.180372	5	2	0	0	0
				(Ab2)	0.068825	5	1	1	0	0
				(Ab3)	0.039392	5	2	0	0	0
B	0.3288585	(Ba)	0.2094781	(Ba1)	0.052369	1	5	1	0	0
				(Ba2)	0.157108	6	1	0	0	0
		(Bb)	0.0849392	(Bb1)	0.028333	0	6	1	0	0
				(Bb2)	0.015592	1	5	1	0	0
				(Bb3)	0.008580	6	1	0	0	0
				(Bb4)	0.032433	6	1	0	0	0
		(Bc)	0.0344412	(Bc1)	0.022960	4	3	0	0	0
				(Bc2)	0.011480	5	2	0	0	0
C	0.2382547	(Ca)	0.0219663	(Ca1)	0.002440	0	3	3	1	0
				(Ca2)	0.009762	1	4	2	0	0
				(Ca3)	0.009762	0	2	4	1	0
		(Cb)	0.0620132	(Cb1)	0.035436	5	2	0	0	0
				(Cb2)	0.008859	7	0	0	0	0
				(Cb3)	0.017718	2	4	1	0	0
		(Cc)	0.1167133	(Cc1)	0.083838	0	3	3	1	0
				(Cc2)	0.012059	0	3	2	2	0
				(Cc3)	0.020815	1	4	2	0	0
		(Cd)	0.0375618	(Cd1)	0.012520	5	2	0	0	0
				(Cd2)	0.025041	6	1	0	0	0

According to Table 2, the assessment results and grade times of each indicator are counted, and MATLAB software is used to perform a fuzzy linear transformation on the above data to form the assessment vector of each indicator, and the assessment matrix F_{ij}, of the indicator is constructed based on this. Here I = 1, 2, 3, 4; j = 1, 2, 3, 4, 5. Thus we can get the assessment matrix for Risks.

5. Assessment Results

Based on the overall assessment vector P and the assessment vectors of each level of criteria, the risk assessment results of overseas investment of Chinese renewable energy enterprises are determined according to the maximum fuzzy mathematics membership principle, as shown in Table 3 and Figure 2.

Table 3. Results of fuzzy assessment.

criteria	Assessment vector					Maximum membership	Assessment results
	outstanding	excellent	good	common	bad		
A	0.06711	0.0270	0.0065	0.0016	0	0.06711	outstanding
Aa	0.066368	0.041227	0.025407	0.011292	0	0.066368	outstanding
Ab	0.206136	0.072622	0.009832	0	0	0.206136	outstanding
B	0.0370	0.0165	0.002	0	0	0.0370	outstanding
Ba	0.142146	0.059851	0.007481	0	0	0.142146	outstanding
Bb	0.037382	0.041282	0.006275	0	0	0.041282	excellent
Bc	0.021321	0.01312	0	0	0	0.021321	outstanding
C	0.0040	0.0072	0.0021	0.0004	0	0.0072	excellent
Ca	0.001395	0.009413	0.009414	0.001743	0	0.009414	good
Cb	0.039233	0.020249	0.002531	0	0	0.039233	outstanding
Cc	0.002974	0.052994	0.045324	0.015422	0	0.052994	excellent
Cd	0.030407	0.007155	0	0	0	0.030407	outstanding

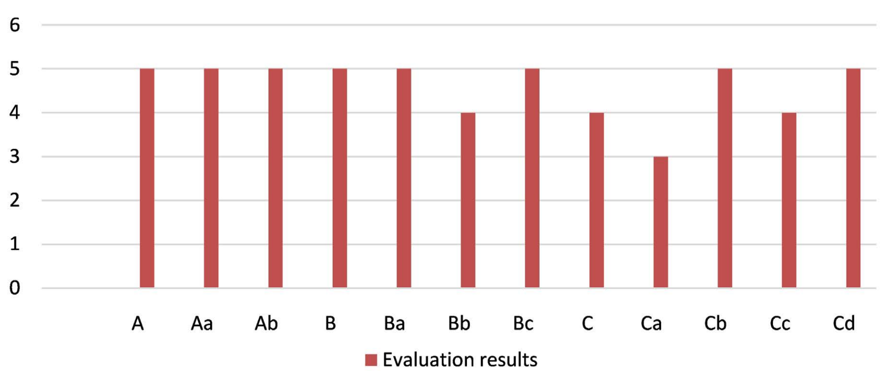

Figure 2. Results of fuzzy assessment.

From the results in Table 3 and Figure 2, Al Dhafra 2100 is a very good investment project with low overall investment risk. Among the three main sources of risk, political risk, economic risk and project risk, the assessment results of economic risk and political risk are both outstanding, and the assessment result of project risk is excellent, which is slightly worse than the other two indicators.

6. Conclusion

This study systematically assessed the risks associated with China's overseas renewable energy investment projects using the fuzzy analytic network process (FANP) method. By establishing a multi-level risk assessment framework and applying it to the Al Dhafra photovoltaic power station project in the UAE, several key findings have been obtained.

The FANP method proved to be highly effective in capturing the interdependencies between risk factors and addressing uncertainties inherent in subjective assessments. Compared to traditional methods, FANP provided more robust and realistic risk evaluation results; The comprehensive risk level of the Al Dhafra project was found to be low, with political risk and economic risk assessed as "outstanding" and project risk as "excellent." This demonstrates that the investment environment in the UAE, particularly for renewable energy projects, is favorable due to stable political conditions and sound economic policies.

The findings provide valuable insights for Chinese enterprises seeking to expand renewable energy investments overseas. By focusing on risk mitigation strategies tailored to political and economic stability, investors can optimize their decision-making processes and enhance project success rates.

7. Future Research Directions

To further enhance the reliability and applicability of this framework, future research could explore:

1) The integration of big data analytics with FANP for real-time risk monitoring.

2) Expanding the case studies to include multiple projects across diverse geographic regions.

3) Investigating the long-term impacts of renewable energy investments on local economic and environmental sustainability.

In conclusion, this research underscores the importance of systematic risk assessment in promoting the sustainable development of China's overseas renewable energy investments. By leveraging advanced decision-making models like FANP, stakeholders can better navigate the challenges of globalization and contribute to the global transition toward a low-carbon economy.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix 1. AI Dhafra Project Invest Risk Evaluation Indicator System

Criteria	Sub-Criteria	Indicators
Political Risk A	Country Risks (Aa)	Political stability, (Aa1)
		Law and order, (Aa2)
		Bilateral relations, (Aa3)
		Political corruption, (Aa4)
	Political and Regulatory Risks (Ab)	Energy policy, (Ab1)
		Environmental policy, (Ab2)
		Policy guarantees (Ab3)
Economic Risk B	Market Risks (Ba)	Supply and demand structure risks (Ba1)
		Industry competition (Ba2)
	Macro Economic Risks (Bb)	Economic level (Bb1)
		Economic growth (Bb2)
		Inflation (Bb3)
		Exchange rate fluctuations (Bb4)
	Financial Risks (Bc)	Interest rate fluctuations (Bc1)
		Foreign exchange restrictions (Bc2)
Operation Risk C	Management Risks (Ca)	Project management risks (Ca1)
		Organizational structure risks (Ca2)
		HR risks (Ca3)
	Partner Risks (Cb)	Supplier reliability (Cb1)
		Raw material reliability (Cb2)
		Pay back reliability (Cb3)
	Social Risks (Cc)	Environmental and social risks (Cc1)
		Climate Impact (Cc2)
		Public Will (Cc3)
	Technology Risks (Cd)	Technology maturity level (Cd1)
		Core technology ownership (Cd2)

Appendix 2. Evaluation Grades and Standards of Indicators

Indicators	Evaluation grades and standards				
	outstanding	excellent	good	common	bad
(Aa1)	Fifth area	Forth area	Third area	Second area	First area
(Aa2)	Fully support	Almost fully support	Some degree support	Insufficient support	Barely sopport
(Aa3)	Very close and friendly	Close and friendly	Friendly not too related	A bit hostile	Hostile

Continued

(Aa4)	CPI > 80	80 > CPI > 70	70 > CPI > 60	60 > CPI > 40	CPI < 40
(Ab1)	Very strong support RE	Strong support RE	A bit support	Supportive but no policy	No relative policy
(Ab2)	Very high dimand	High demand	A bit high demand	Less dimand	No demand
(Ab3)	Strongly reliable	Very reliable	Reliable but has risk	Higher risk	Not reliable
(Ba1)	Demand far more than supply	Demand more than supply	balanced	Supply more demand	Supply far more demand
(Ba2)	Monopoly or exclusive	More adtantage or leading	A bit leading	Many competitors	No advantage
(Bb1)	GDP Top 10 countries	GDP 11th-30th countries	GDP 31-50th countries	GDP 51-100th countries	Worse than 100th countries
(Bb2)	>6%	4% - 6%	2% - 4%	0 - 2%	<0
(Bb3)	<4%	4% - 6%	6% - 8%	8% - 10%	>10%
(Bb4)	Average < 5%	5% - 8%	8% - 12%	12% - 20%	>20%
(Bc1)	Average < 6%	6% - 15%	15% - 20%	20% - 30%	>30%
(Bc2)	Complete free	Free but with a bit restriction	Possible but with some restriction	Many restriction	Not possible
(Ca1)	Highly efficient management	Efficient management	Moderate management	Some inefficiencies	Poor management
(Ca2)	Well-structured and flexible	Structured and moderately flexible	Acceptable structure	Weak structure	Chaotic structure
(Ca3)	Highly skilled and motivated	Skilled and moderately motivated	Average skills and motivation	Low skills or motivation	Unskilled and unmotivated
(Cb1)	Very high reliability	High reliability	Moderate reliability	Low reliability	Unreliable
(Cb2)	Very high reliability	High reliability	Moderate reliability	Low reliability	Unreliable
(Cb3)	Almost guaranteed	Highly likely	Likely	Somewhat unlikely	Highly unlikely
(Cc1)	Very low risk	Low risk	Moderate risk	High risk	Very high risk
(Cc2)	Minimal impact	Low impact	Moderate impact	Significant impact	Severe impact
(Cc3)	Strongly supportive	Supportive	Moderately supportive	Barely supportive	Opposed
(Cd1)	Highly advanced and proven	Advanced and reliable	Reliable with minor issues	Emerging with moderate issues	Unproven and problematic
(Cd2)	Full ownership	High ownership	Partial ownership	Limited ownership	No ownership