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Research article

Prioritization of renewable energy for offshore ship charging stations based on intuitionistic fuzzy GLDS method: A case of China

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ABSTRACT

Offshore ship charging station (OSCS) projects can help to address the current demand for electric ships for ocean voyages to a large extent. The proper selection of the energy source for power generation is a key part of the OSCS project. To select the optimal renewable energy for OSCS with many difficulties such as the ambiguity of the decision-making environment, the differences in group assessment information, and the conflict and compensation between criteria, this paper proposed a fuzzy multi-criteria decision-making (MCDM) framework. First, a comprehensive criteria system was constructed. Second, the intuitionistic fuzzy set (IFS) was introduced to express experts' fuzzy cognition. Third, based on the quality of evaluation, a novel expert weighting method was proposed, and the generalized intuitionistic fuzzy weighted geometric interaction averaging (GIFWGIA) operator was used to aggregate the individual evaluations. Fourth, the criteria importance through intercriteria correlation (CRITIC) method, and the stepwise weight assessment ratio analysis II (SWARA II) method were introduced to determine the criteria weights. Fifth, considering criteria compensation, and individual and group ranks, the gained and lost dominance score (GLDS) method were used for ranking. Finally, to verify the applicability and reliability of the framework, a case study was conducted in Pingtan Island, Fujian Province. The results show that wind energy was the best alternative, followed by solar, wave and nuclear energy.

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1. Introduction

1.1. Background

Transportation is a major player in air pollution and ozone depletion due to high emissions of greenhouse gases such as CO, CH_4, N_2O and CO_2 [1], which lead to climate warming and the greenhouse effect. In recent years, with the intensification of the greenhouse effect and the reduction of non-renewable energy (RE), transportation is moving towards electrification, and traditional transportation has begun to make a shift towards cleaner and greener transportation, which utilizes green energy modes to improve the environment [2]. In particular, the development of land transport electrification is gradually systematic, as electric vehicles (EV) have been mass-produced and used on a large scale, and charging facilities have been gradually improved. On the other hand, the electrification of maritime transportation requires more vigorous development. Although the development of battery technology has made great progress, its efficiency is still not high enough and its weight is too heavy for long-distance sailing vessels. Therefore, the current electric ships (ES) can only travel short distances.

Most shipping involves ocean voyages, but so far, existing battery technologies have not been able to provide enough power to sustain the entire voyage [3], so how to recharge is an issue that needs to be addressed for ESs that need to make long voyages. Nowadays, the most common way of charging is to build shore-side charging stations, which are categorized into two methods: wired or wireless connection to charging outlets and replacement of battery packs [4]. For ocean-going ESs, relying entirely on shore-side power is not an optimal solution, as sometimes the shipping lanes where the ESs are located may be in far offshore areas away from land, where it is impractical to dock the ESs for charging. Therefore, it is necessary to establish charging stations for marine vessels near the shipping lanes.

OSCS project can help to address the current demand for electric ships for ocean voyages to a large extent. This project has a strong market development potential and is likely to be an extremely popular and promising project shortly after. Up to now, scholars have conducted extensive research on OSCS project from many perspectives. For example, Mutarraf et al. [4] provided a comprehensive overview of EVs and ESs and their charging equipment. Salleh et al. [5] used a simulation-based approach to assess the viability of establishing a grid-connected photovoltaic (PV) ES charging station in Tengganu, Kuala Lumpur. Temiz and Dincer [6] assessed the progression of zero-carbon bunker fuel production, stocking and bunkering for short-range ferries in terms of technology as well as economics. Sruthy et al. [7] proposed a structural scheme of charging points for a pole-based OSCS and performed a preliminary feasibility assessment. These studies mainly focused on the technical as well as feasibility aspects and lacked thinking about which RE technology to use for the OSCS. Spaniol and Hansen [8] identified and reported on six innovative concepts for ocean electrification. Yang et al. [9] compared wind, solar PV, and floating nuclear power plants from an economic perspective to demonstrate the economics of OSCS. Although they considered the selection of RE technologies for OSCS, they did not give an effective criteria system to make decisions on the selection of power generation technologies for OSCS. Therefore, the development of an effective criteria system for ranking REs for OSCS and the establishment of a reliable and comprehensive decision-making framework are the issues faced in the development of OSCS nowadays.

1.2. Motivations

Generally speaking, there are basically three types of charging stations: onboard, off-board grid-connected, and stand-alone/mobile units. Onboard chargers are installed in the vehicle with lower power. Off-board chargers are installed in public places and can be either alternating current charging units or direct current-based charging units [10]. The offshore ship charging station (OSCS) to be studied in this paper mainly provides charging services to passing ESs, which requires a great deal of power [4] and is not able to use an onboard charger. Off-board chargers are also not available due to the fact that the OSCS is located in a faraway sea, which is a remote location and requires a large amount of investment for connecting it to the main onshore power grid. Therefore, the OSCS should be a stand-alone unit by integrating RE and fixed battery packs. Thus, from the case study perspective, the choice of REs for power generation is an issue that needs to be considered at this point in time.

The selection of optimal RE is a multi-criteria decision-making (MCDM) issue involving multiple conflicting criteria including source, technical, economic, environmental and social aspects. The MCDM approach develops a system of criteria, experts evaluate all alternatives based on each criterion, and the obtain the ranking result. The fuzzy MCDM approach can be used to rank the alternatives due to the variability of the environment and the vagueness of the experts' evaluation of the alternatives. From the methodological perspective, it is necessary to construct a fuzzy MCDM framework to rank REs in OSCS project.

Therefore, this paper aims to construct a fuzzy MCDM framework for the issue of renewable energy selection in OSCS projects, to promote the sustainable development of offshore RE projects, and to provide decision-making guidance for relevant decision makers (DMs) and managers to a certain extent.

1.3. Contributions

The purpose of this study is to establish a scientific and practical framework for prioritization of REs for OSCS, which will provide some reference for related DMs and managers. The contributions of this study and the novelty of the proposed decision-making framework can be summarized as follows.

(1) A specific evaluation criteria system for ranking RE technologies for OSCS, including source, economic, technical, environmental and social criteria, had been established to enable DMs to make more effective and reliable decisions. In addition, considering the intensity of comparison and conflicts between criteria, the stepwise weight assessment ratio analysis II (SWARA II) method and the criteria importance through intercriteria correlation (CRITIC) method were used to determine the criteria weights.
(2) For the purpose to represent the fuzzy knowledge during the decision-making of RE technology selection for OSCS, intuitionistic fuzzy numbers (IFN) and linguistic variables were used to express the experts' preference for each alternative and criteria. Meanwhile, a method for calculating expert weights under intuitionistic fuzzy (IF) environment had been proposed based on the quality of expert evaluation information. Both membership and the non-membership are fuzzy based on intuitionistic fuzzy set (IFS) theory, so it's suitable for capturing uncertainty information in the prioritization of REs for OSCS.
(3) The OSCS project is still at the beginning stage and the decision-making process will inevitably face a series of uncertainties and risks. Taking into account the risk attitude of DMs, this paper introduced the generalized intuitionistic fuzzy weighted geometric interaction averaging (GIFWGIA) operator to aggregate individual expert evaluations, which can make results more realistic.
(4) To address the compensation problem that exists in the prioritization of REs for OSCS, i.e., poor performance on some criteria can be compensated by good performance on other criteria, this paper extended the gained and lost dominance score (GLDS) method to IF environment, where the "group utility" and "individual regret" values and the subordinate ranks were considered to make the final ranking of REs for OSCS more reliable.

2. Literature review

The literature review in this paper is divided into three subsections so that the topics considered can be better understood, the differences from other studies can be better revealed and the contribution can be addressed more clearly. The first subsection introduces the advantages of IFS and its applications in MCDM issues. The second subsection reviews some aggregation operators and expert weights determination methods. The third subsection discusses some criteria weights determination methods. The fourth subsection introduces the GLDS method. The fifth subsection identifies research gaps.

2.1. *Intuitionistic fuzzy set*

The prioritization of RE for OSCS is an MCDM issue, in the actual decision-making process, due to the complexity of the decision-making environment and the ambiguity of human judgment, decision makers may not be able to accurately express their preferences, in order to solve this problem, Zadeh [11] introduced the fuzzy set theory where each element is assigned a degree of membership to represent its fuzzy information. In Zadeh's fuzzy set theory, the degree of membership and non-membership add up to 1, but this is not the case in practice. So as to address this issue, Atanassov [12] proposed IFS which are more in line with the real world, the degree of membership μ and non-membership ν of each element in an IFS satisfy the equation $\mu + \nu \leq 1$, and its and its hesitancy $\pi = 1 - \mu - \nu$. Compared to Zadeh's fuzzy set which is only characterized by a membership function, IFS can depict the fuzzy character of data more detailed and comprehensively. For example, if a person wants to purchase a computer and evaluates it in six aspects, he may be satisfied with three aspects, dissatisfied with two aspects and uncertain with one aspect of the computer. In this case, the traditional fuzzy set can only reflect the satisfied aspects and lose some uncertain information, while the IFS can describe all the satisfied, dissatisfied and uncertain information, so the hesitation of DM can be well expressed by IFS during the practical decision-making. Recent years, IFS has been extensively used in MCDM issues. Bilgili et al. [13] analyzed the best RE alternatives for sustainable development in Turkey using the IF Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) approach. Dumrul et al. [14] used IF assessment based on distance to mean solution (EDAS) method to find Turkey's best RE alternative. Ren [15] combined interval hierarchical analysis with IF combinative distance-based assessment (CODAS) method to develop a novel MCDM methodology for sustainability ranking of the alternative energy storage technologies. Zhang et al. [16] extended the IF multiplicative multi-objective optimization on the basis of ratio analysis (MULTIMOORA) approach and applied it to the selection of energy storage technologies. Yener and Can [17] proposed a modified IF Multi-Attribute Border Approximation Area (MABAC) method including interactions between failure modes to determine the ranking of the failure modes by using the extended Haussdorff distance function. Ecer [18] extended IF Multi-Attribute Ideal-Real Comparative Analysis (MAIRCA) method to choose among coronavirus vaccines. Liu et al. [19] integrated the best-worst method (BWM), entropy method and VlseKriter-ijumska Optimizacija I Kompromisno Resenje (VIKOR) approach to design reverse supply chains for COVID-19 medical waste recycling channels. Ecer and Pamucar [20] proposed a Measurement of Alternatives and Ranking according to the Compromise Solution (MARCOS) technique under IF environment for determining the COVID-19 pandemic performance of insurance companies in terms of healthcare services.

2.2. *Group aggregation methods*

How to effectively aggregate decision information is one of the core issues in MCDM. As for basic operations, Xu [21] presented the intuitionistic fuzzy weighted averaging (IFWA) operator. Xu and Yager [22] proposed the intuitionistic fuzzy weighted geometric averaging (IFWGA) operator. These operators have been widely used to aggregate information in MCDM issues. However, He et al. [23] pointed out that there are actually some interactions between the membership and non-membership functions, which have not been considered in some basic operations. In fact, dealing with interaction problems is considered an effective way to improve the quality of evaluation under IF environment [24]. Therefore, He et al. [23] proposed the GIFWGIA operator to address this issue, which has been proven effective in handling interactions. In addition, since the inevitable uncertainties and risks faced by DMs when ranking RE for OSCS, it is necessary to consider the risk attitude of DMs. The GIFWGIA operator takes into account it when aggregating DMs' individual evaluations, thus providing more reasonable aggregation results.

Expert weight is a crucial factor in the aggregation process. In order to obtain more reliable results while evaluating MCDM issues by experts, it is essential to adopt the correct method to calculate the expert weights. In previous studies, the ability to objectively calculate the importance of the evaluations given by experts is one of the reasons that affects the accuracy of decision-making, since experts have different abilities and experiences [25]. Therefore, experts need to be weighted to demonstrate their respective weight in the decision. In some literature, researchers had simply assigned weights to individual experts, which seriously affected the accuracy of decision-making results. Objective methods for determining expert weights can be broadly categorized as follows: similarity-based methods [26,27], index-based methods [28,29], clustering-based methods [30], synthesis methods [31,32] and other methods [33–35]. A theory based on expert authority argues that due to experts have different knowledge and experience, they have different authority over different criteria, which implies that there may be a difference in the quality of evaluation information [36]. Therefore, this paper proposed a method for calculating the weights of experts depending on the quality of information under IF environment, which will make the decision-making results of selection of optimal RE of OSCS more accurate.

2.3. Criteria weights determination methods

The weighting of criteria in MCDM issues is a crucial element that influences the accuracy of results [37]. Methods for determining criteria weights are mainly divided into subjective and objective methods.

Subjective weighting methods are typically used specific rule based on the subjective experience and judgment of DMs. They are usually provided with a set of questions that allow them to directly express their opinion on the relative importance of the criteria. Some commonly used subjective methods include SWARA method [38], the Fully Consistency Method (FUCOM) [39], Level Based Weight Assignment (LBWA) [40] and Ordinal Priority Approach (OPA) [41]. The SWARA method has the advantage of fewer and simpler comparisons than other subjective weighting methods [42]. The SWARA II method proposed by Keshavarz-Ghorabaee [43] as a variant of the SWARA method, it is easier to use and more practical for DMs compared to the SWARA method, while retaining its advantages. Other subjective methods have their own advantages, but also have some limitations. For example, the computational complexity of the model increases dramatically when the number of criteria increases, and it is not applicable to group decision-making situations [44]. Therefore, the SWARA II method has several applications in group MCDM problems such as the selection offshore wind turbines [45], the evaluation of bank efficiency and productivity [46], and the assessment of distribution center locations [43].

Objective weighting methods generally obtain weights through mathematical and statistical models. There are several objective methods such as entropy method [47], Logarithmic Percentage Change-driven Objective Weighting (LOPCOW) method [48], Weights by Envelope and Slope (WENSLO) method [49] and CRITIC method [50]. The entropy method assigns weights based on the entropy value of the criterion. But there are often large differences between the criterion weights obtained through the entropy method, which is not encountered in the LOPCOW method thanks to its unique algorithm [48]. The WENSLO method combines the importance of criteria and the stability of their impact [49]. And the CRITIC method quantifies the information inherent in each assessment criterion to determine the objective weights, a process that involves calculating both the standard deviation of the criterion and the correlation between criteria [51,52]. Thus, the entropy method, the LOPCOW method and the WENSLO method just address contrast intensity, while the CRITIC method can synthesize the contrast intensity of each criterion and the conflict between criteria to obtain more reasonable objective weights for criteria [53], which is more advantageous. As a result, the CRITIC method has been widely applied. Alkan and Kahraman [54] extended the CRITIC method to figure out objective weights of criteria under IF environment for siting waste treatment stations. Ke et al. [55] used CRITIC method to calculate objective weights of criteria under IF environment to rank the integrated urban energy system. Salimian et al. [56] used IFCRITIC method to calculate objective weights for criteria to select appropriate construction projects.

Overall, both subjective and objective weighting methods have disadvantages. Subjective method ignores decision information and compromises the objectivity of the results [57], and objective method fails to reflect the opinions of relevant stakeholders [58]. Integration of subjective and objective weights provides a balance between subjective judgment and objective information and is therefore widely accepted. The linear weighted sum method is a commonly used combination approach, but its weighting coefficients rely heavily on the subjective judgment of DMs [59]. The product normalization method is another commonly used approach for obtaining the combined weights, but when the subjective and objective weights differ greatly, the method may lose some information, resulting in a mismatch between the combined weights and the objective reality [60]. Genetic algorithm can parallel search between multiple search points and effectively overcome the layout optimal solution trap, so it can quickly converge to the global optimal solution and accurately represent the subjective and objective weight information [61]. Consequently, this study proposed an integrated weighting method to obtain the combined weight of RE for OSCS. The SWARA II method and CRITIC method were used to determine subjective and objective weight, respectively. The genetic algorithm was applied to obtain the combined weights.

2.4. Ranking methods

In addition, the ranking of alternatives in MCDM problems can also affect the accuracy of decision results to a large extent. A number of ranking methods have been developed, the most commonly used of which are based on reference point types, including the TOPSIS method [62], the VIKOR method [63], the MABAC method [64], the MAIRCA method [65] and the MARCOS method [66]. The main idea of these approaches is to select a compromise solution that is close to the positive ideal solution. However, they have some limitations. For example, the ranks of individual and group are not considered, and the relative significance between positive and negative ideal points is ignored [67]. The GLDS method proposed by Wu and Liao [68] is an efficient MCDM method based on the dominance theory, which can address these limitations. The GLDS method takes into account the "group utility" value and the "individual regret" value and the subordinate ranks. Moreover, the GLDS method can solve the compensation issue well. Therefore, the selected alternative is optimal for both the overall and each criterion. Recently, the GLDS method has become popular and widely applied. Gao et al. [69] investigated the siting problem of wind-photovoltaic-shared energy storage system in a Probabilistic Linguistic Term Sets (PLTSs) environment based on the Geographic Information System (GIS) using the improved Decision-Making and Trial Evaluation Laboratory (DEMATEL) and GLDS methods. Liu et al. [70] combined Probabilistic Linguistic Preference Relationships (PLPRs) and the extended GLDS method to propose a novel Failure Mode and Effects Analysis (FMEA) methodology. Zheng et al. [71] proposed a case-driven Emergency Decision-making Model (EDM) based on bidirectional projection in PLTSs environment based on the BWM and the GLDS method. Liu et al. [72] constructed a comprehensive assessment framework to evaluate Internet hospitals in the linguistic Z-number environment based on the BWM and the GLDS method. Yao et al. [73] integrated the double hierarchy hesitant fuzzy linguistic term sets, entropy method and the GLDS method to construct a framework for anti-ship missile warhead power assessment. So far, there are very few extensions to GLDS method under IF environment. Hezam et al. [74] proposed an IFGLDS method for selecting and ranking sustainable suppliers in the case of the Indian steel industry. Hezam et al. [75] introduced an IFGLDS method for the investment firm selection problem.

2.5. Research gaps

In the past several years, the application of integrated MCDM methods for RE prioritization has increased dramatically. Table 1 summarizes some of the previously developed MCDM methods used for RE prioritization and similar issues. Even within the same country, the results of the rankings are not the same, as different MCDM methodologies are used and different aspects are taken into account. For example, Niu et al. [76] considered the objective criteria weight and found that the most suitable RE for China was hydro energy, but Pan and Wang [77] concluded that it should be solar energy when the personal weight, individual deviation and psychological characteristics were fully considered. In addition, in the three papers that studied the prioritization of RE in Turkey, the best RE were hydro energy [78], solar energy [13] and wind energy [79] because of the different aspects they focused on. As can be seen from Table 1, there is a lack of research of RE prioritization that comprehensively considers aspects including personal weight, individual deviation, psychological characteristics, subjective and objective weight of criteria, and the subordinate in the ranking. Therefore, the focus of this study is on how to integrate these aspects to prioritize RE for OSCS and obtain the reasonable results.

Based on the above conducted literature review and Table 1, this paper identified research gaps as follows: (1) The SWARA-II CRITIC and GLDS methods are very effective, but have not been used in the field of RE prioritization of OSCS. (2) The SWARA II and CRITIC methods have certain advantages over the previously used weighting approaches, but there is no study that combine them to calculate criteria weights. (3) There is limited research extending the GLDS method to the IF environment. (4) There are limited studies of RE prioritization that consider deviation among individual evaluation information in the aggregation phase. (5) Most previous studies of RE prioritization assume DMs to be fully rational and ignore their psychological characteristics. Therefore, this paper proposed a new decision-making framework for selecting optimal RE of OSCS to fill the above gaps. In this framework, individual deviation and psychological characteristics are considered, the SWARA-II and CRITIC methods are combined to calculate the weight of criteria under IF environment, and an IFGLDS method is proposed for ranking REs for OSCS.

The following is the rest of the paper: Section 3 describes the criteria system for selecting optimal RE of OSCS. The decision-making framework for selecting optimal RE for OSCS is presented in Section 4. Section 5 presents a case study. Section 6 makes both the sensitivity analysis and the comparative analysis. Finally, section 7 is the conclusion.

3. Evaluation criteria system of RE

The development of an evaluation criteria system is essential for selecting optimal RE of OSCS, and a good evaluation criteria system can increase the reliability of the ranking to a large extent. Although there is very little literature on evaluation criterion system in the field of selection of optimal RE of OSCS, there is a large amount of research on selection of optimal RE available for reference. For selection of optimal RE, the identified main criteria include but are not limited to source criteria [77,79,85], economic criteria [13,77–79,82,83,85,87,88], technical criteria [13,77–79,82,83,85,87,88], environmental criteria [2,13,77–79,82,83,87,88], and social criteria [5,13,77–79,82,83,87,88]. The above literatures have important reference value for constructing and optimizing the criterion system for evaluating the selection of optimal RE of OSCS. At the same time, as an independent unit, the offshore ship charging station should contain power generation system and energy storage system, so this paper also referred to some literature in the field of offshore RE power station and offshore RE storage system [89–94]. Based on the aforementioned literature, the system of evaluation criteria identified in this paper for selecting optimal RE for OSCS is as below.

3.1. Source criteria

The assessment of resource criteria plays an essential role for OSCS, because OSCS contains stand-alone power generation systems, and the resources of the location where the OSCS are to be built determine its actual power generation, which is critical in the ranking of RE. The sub-criteria are considered from three main aspects: resource volume, sustainability and durability.

Table 1
An overview of some MCDM methods to RE prioritization and similar issues.

Ref.	Application	Methodology	Judgment aggregation			Criteria importance		Subordination
			Personal weight	Individual deviation	Psychological characteristics	Subjective	Objective	
[80]	RE selection	TFN, SWOT and TOPSIS				✓		
[81]	RE selection	HFLTSs, EB and CRITIC	✓	✓	✓		✓	
[82]	RE selection	EWM, TOPSIS, WSM, VIKOR, and ELECTRE					✓	
[83]	RE evaluation	TNN, VIKOR, AHP and TOPSIS				✓		
[77]	RE evaluation	IT2FSs, RMM and CRM	✓	✓	✓			
[84]	RE selection	FFSs and COPRAS	✓				✓	
[78]	RE evaluation	TFN, IEWM and TOPSIS					✓	
[85]	RE prioritization	AHP and VIKOR				✓		
[86]	RE selection	MEREC and PIV					✓	
[13]	RE evaluation	IFS and TOPSIS	✓				✓	
[79]	RE prioritization	IT2FSs, HFS, AHP and TOPSIS				✓		
[76]	RE prioritization	TFN weighting, IVHFS, and ELECTRE-II					✓	
This work	RE prioritization	IFS, SWARA-II, CRITIC and GLDS	✓	✓	✓	✓	✓	✓

TFN: Triangular Fuzzy Number; SWOT: Strengths, Weaknesses, Opportunities, and Threats; HFLTSs: Hesitant fuzzy linguistic term sets; EB: Evidence-based Bayesian; EWM: Entropy weight method; TNN: Triangular neutrosophic number; IT2FSs: Interval type-2 fuzzy sets; RMM: Risk measurement model; CRM: Centroid-based ranking method; FFSs: Fermatean fuzzy sets; COPRAS: Complex proportional assessment; IEWM: Interval entropy weight method; MEREC: Method based on the removal effects of criteria; HFS: Hesitant fuzzy set; IVHFS: Interval-valued hesitant fuzzy set.

3.1.1. Resource volume (C_1) [13,77,83,89,91–93,95]

REs should be adequate at the location of OSCS, which is an important criterion for the selection of REs.

3.1.2. Sustainability (C_2) [77,79,85]

It measures the sustainability of the ability of REs to continuously provide power to storage terminals. For example, the ability of solar PV to convert to electricity is significantly reduced at night; The ability of tidal energy to convert to electricity is cyclical.

3.1.3. Durability (C_3) [77,79,85]

Durability specifies how long energy should be used. RE has varying degrees of durability. For example, bioenergy appears to be less durable than other renewable energy sources because it depends on seasons, biological processes and land use.

3.2. Economic criteria

Economic criteria can have a significant impact on OSCS project and are often used to assess whether a project is worth investing in. When selecting REs for OSCS, economic criteria must be taken into consideration, which will relate to whether OSCS project is economically profitable. The sub-criteria of the economic criteria are considered in terms of both the internal economic assessment of OSCS and the external policy subsidies.

3.2.1. Investment cost (C_4) [13,77–79,82,83,85,87–89,91,93,94]

Investment cost includes the total cost of setting up an OSCS that meets all regulations, from the development phase through to the operational phase. In addition to labor costs and equipment maintenance costs, the purchase of machinery and equipment, technical installations, engineering services, drilling and other incidental construction are all investment costs, which must be taken into account by the investor.

3.2.2. Operation and maintenance cost (C_5) [13,77,78,82,83,87–89,91,93,94]

It refers to the maintenance expenditures of equipment and spare parts replaced for OSCS, and consist of both personnel wages and funds for the energy, products and services required to operate the system.

3.2.3. Payback duration (C_6) [13,77–79,83,88,89,91,93]

It refers to the time period in which an OSCS project is able to recoup its construction and operating costs, which may be longer compared to other projects due to the high construction costs of an OSCS project and the need for significant capital investment.

3.2.4. National energy policy (C_7) [13,77–79,85,87,89,91,94]

It refers to government policies that are concerned with RE and diversifying the various renewable energy sources, some of which financially subsidize the REs recommended by the government.

3.3. Technical criteria

Technical criteria are used to evaluate the fitness of REs for OSCS. The indicator is based on four main considerations: efficiency, installed capacity, technical maturity and operational life.

3.3.1. Efficiency (C_8) [13,77–79,82,83,87,93]

Efficiency refers to the potential of REs to be converted into electricity and indicates the degree to which REs are used effectively. Efficiency is calculated differently for each system, but one of the most popular methods is efficiency coefficient, which is calculated as the ratio of energy input to output.

3.3.2. Installed capacity (C_9) [13,77–79,82,83,88,89]

Installed capacity refers to the amount of electricity that can be generated by the generator set when it is operating at full load. The installed capacity of different RE generator sets varies considerably, and the larger the installed capacity, the better for OSCS because of the greater demand for electricity from the ships they serve.

3.3.3. Technical maturity (C_{10}) [79,82,83,85,87,94]

This criterion is the degree of reliability of the RE technology adopted by all sectors in the country or region and the extent to which it has been diffused nationwide. It also indicates whether there is scope for advancement or whether the technology has hit its theoretical efficiency limits. While a wide range of REs exist, some of them are technically unstable and can only be used on a small scale in actual practice or in pilot power plants.

3.3.4. Operation life (C_{11}) [13,83,85,88]

This criterion refers to life expectancy or uptime. Different RE generation systems have different life expectancies, which in the long run will affect the later operation and maintenance of OSCS.

3.4. Environmental criteria

Although OSCS uses RE technology, which significantly reduces emissions of pollutant gases, it may also have an adverse effect on the environment to a certain extent. Environmental criterion is used to assess the impacts of OSCS on the natural environment and the potential impacts on marine ecosystems during operation.

3.4.1. Greenhouse gas emission (C_{12}) [13,77–79,82,83,87–90,92,93]

This criterion relates to the pollutants, gases and wastes that may be emitted from RE systems that affect ecosystems. Although RE systems emit few pollutants compared to fossil fuel systems, they should still be taken into account.

3.4.2. Waste disposal (C_{13}) [78,79,83,88]

This criterion is used to assess the method for disposing of wastes under safe circumstances without endangering the environment around the project. Despite the fact that RE systems produce very little waste, this is a need that must be addressed in order to prevent damage to the environment. The amount of waste produced from RE systems should be considered as an important criterion in the selection of RE for OSCS.

3.4.3. Impact on the ecosystem (C_{14}) [13,77–79,83,85,87,91–94]

This criterion measures the environmental friendliness of OSCS projects, including visual impact and impact on biodiversity. For example, when solar PV power is used, large-scale arrays of PV panels can have a visual impact, and when wind power is used, a specific amount of area will be taken up by wind turbines by marine life.

3.5. Social criteria

Social criteria can influence whether or not an OSCS project can be successfully carried out. The utilization of various REs will create jobs for different groups of people and have a positive effect on the local economy. At the same time, the attitude of the public towards the RE used determine the success of the project.

3.5.1. Job creation (C_{15}) [13,77–79,82,83,85,87–89,91]

Throughout its entire life cycle, from developing to operation, an energy system will employ individuals in many related fields. Therefore, the selection of REs should take into account the enhancement of local residents' quality of life as well as the creation of jobs.

3.5.2. Social acceptance (C_{16}) [13,77–79,82,83,85,87–89,91,93,94]

Social acceptance refers to the public acceptance of the RE used. The greater the preference of the local residents for the RE project used, the faster it will develop. This criterion is important because public pressure and unacceptance may affect the time it takes to complete projects. For example, the public is generally opposed to nuclear projects in the areas where they live, even though it is safe. As you can see, there are very few nuclear projects near residential areas.

4. Research methodology

4.1. Preliminaries

This section mainly introduces some definitions and mathematical operations of IFS.

Definition 1. [12] Given a non-empty finite set X, an IFS I of X is defined as:

$$I = \{\langle x, \mu_I(x), \nu_I(x)\rangle | x \in X\} \tag{1}$$

where $\mu_I(x) : X \to [0, 1]$, $\nu_I(x) : X \to [0, 1]$ denote the membership degree and non-membership degree of $x \in X$ to the set I respectively, satisfying $0 \le \mu_I(x) + \nu_I(x) \le 1$, $\forall x \in X$.

For the IFS I of X, the parameter $\pi_I(x) = 1 - \mu_I(x) - \nu_I(x)$ is defined as the degree of indeterminacy of $x \in X$ to the set I, $\pi_I(x)$ satisfies $0 \le \pi_I(x) \le 1$, $\forall x \in X$ [22]. For clarity, $I = (\mu_I, \nu_I)$ is used to denoting the IFN in the IFS [21].

Definition 2. [12,21,22] Let $I = (\mu_I, \nu_I)$, $I_1 = (\mu_{I_1}, \nu_{I_1})$, $I_2 = (\mu_{I_2}, \nu_{I_2})$ be three IFNs, the basic mathematical operations defined on these IFNs are defined as:

$$I^C = (\nu_I, \mu_I) \tag{2}$$

$$I_1 \oplus I_2 = (\mu_{I_1} + \mu_{I_2} - \mu_{I_1}\mu_{I_2}, \nu_{I_1}\nu_{I_2}) \tag{3}$$

$$\lambda I = \left(1 - (1 - \mu_I)^\lambda, (\nu_I)^\lambda\right), \lambda > 0 \tag{4}$$

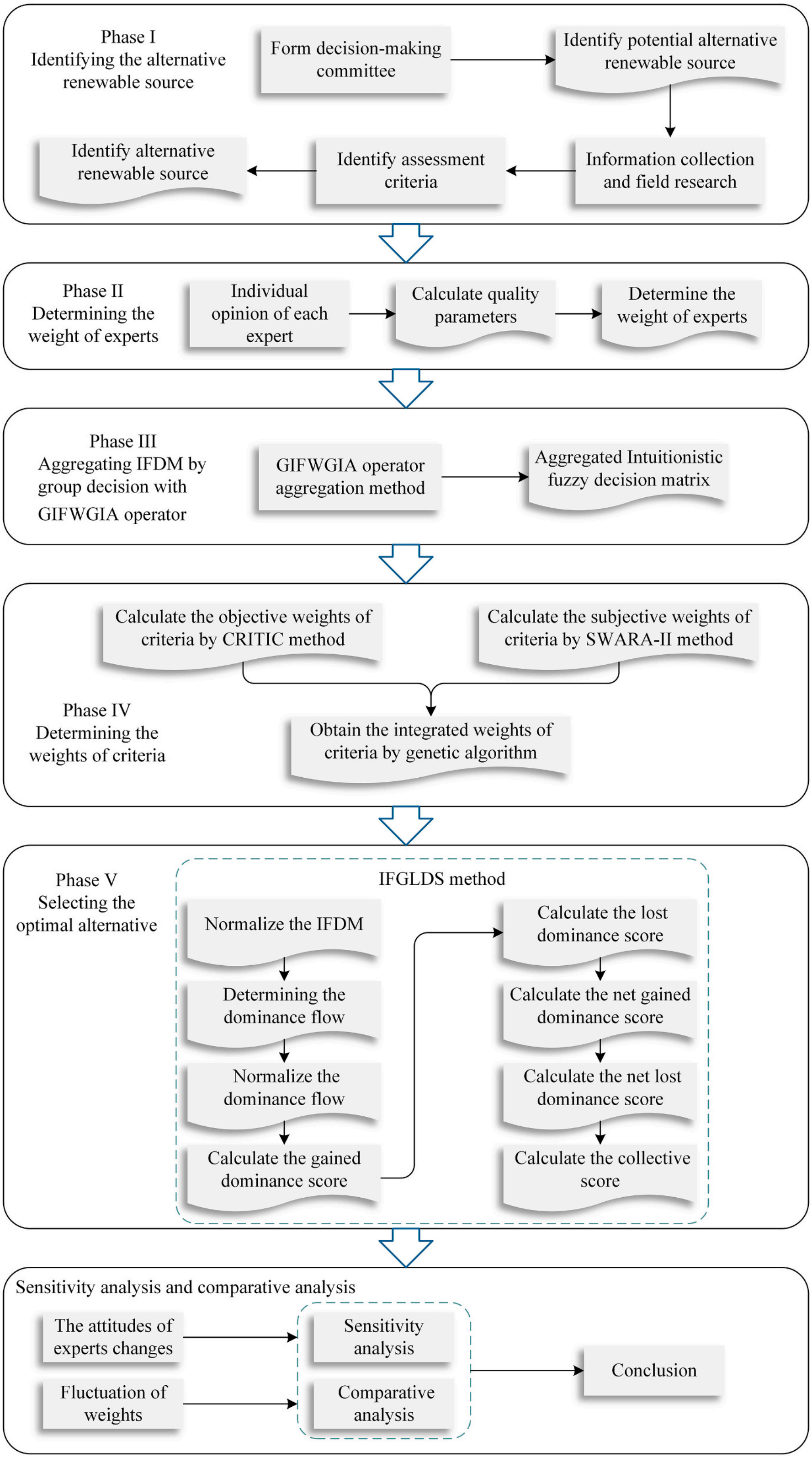

Fig. 1. Research methodology of proposed framework.

$$I_1 \otimes I_2 = \left(\mu_{I_1}\mu_{I_2}, \nu_{I_1} + \nu_{I_2} - \nu_{I_1}\nu_{I_2}\right) \tag{5}$$

$$I^{\lambda} = \left((\mu_I)^{\lambda}, 1 - (1 - \nu_I)^{\lambda}\right), \lambda > 0 \tag{6}$$

There are some interactions between membership and non-membership functions, but these interactions are not considered in the above basic operations [23,24], so the improved basic operations are presented below.

Definition 3. [23,24] Let $I = (\mu_I, \nu_I)$, $I_1 = \left(\mu_{I_1}, \nu_{I_1}\right)$, $I_2 = \left(\mu_{I_2}, \nu_{I_2}\right)$ be three IFNs, the mathematical operations are defined as:

$$I_1 \widehat{\oplus} I_2 = \left(1 - \left(1 - \mu_{I_1}\right)\left(1 - \mu_{I_2}\right)\ ,\ \left(1 - \mu_{I_1}\right)\left(1 - \mu_{I_2}\right) - \left(1 - \left(\mu_{I_1} + \nu_{I_1}\right)\right)\left(1 - \left(\mu_{I_2} + \nu_{I_2}\right)\right)\right) \tag{7}$$

$$\lambda I = \left(1\text{-}(1\text{-}\mu_I)^{\lambda}, (1\text{-}\mu_I)^{\lambda}\text{-}(1\text{-}(\mu_I + \nu_I))^{\lambda}\right), \lambda > 0 \tag{8}$$

$$I_1 \widehat{\otimes} I_2 = \left((1 - \nu_{I_1})(1 - \nu_{I_2}) - \left(1 - \left(\mu_{I_1} + \nu_{I_1}\right)\right)\left(1 - \left(\mu_{I_2} + \nu_{I_2}\right)\right), 1 - (1 - \nu_{I_1})(1 - \nu_{I_2})\right) \tag{9}$$

$$I^{\lambda} = \left((1\text{-}\nu_I)^{\lambda}\text{-}(1\text{-}(\mu_I + \nu_I))^{\lambda}\ ,\ 1\text{-}(1\text{-}\nu_I)^{\lambda}\right), \lambda > 0 \tag{10}$$

Definition 4. [22] Let $I = (\mu_I, \nu_I)$ be an IFN, then the score function $s(I)$ and accuracy function $a(I)$ of I can be defined as follows:

$$s(I) = \mu_I - \nu_I \tag{11}$$

$$a(I) = \mu_I + \nu_I \tag{12}$$

where $s(I) \in [-1, 1]$, $a(I) \in [0, 1]$.

For any two IFNs $I_1 = \left(\mu_{I_1}, \nu_{I_1}\right)$, $I_2 = \left(\mu_{I_2}, \nu_{I_2}\right)$,

(1) if $s(I_1) > s(I_2)$, then $I_1 > I_2$;
(2) if $s(I_1) = s(I_2)$,then
(i) if $a(I_1) > a(I_2)$, the $I_1 > I_2$;
(ii) if $a(I_1) = a(I_2)$, the $I_1 \sim I_2$.

Considering that the result of the above score function may contain negative numbers and does not take into account the degree of hesitation, Alkan and Kahraman [54] defined the following defuzzification function.

Definition 5. [54]. Let $I = (\mu_I, \nu_I)$ be an IFN, then the defuzzification function $D(I)$ of I can be defined as follows:

$$D(I) = \mu_I + \left(\frac{\mu_I \nu_I e^{\pi_I}}{2}\right)^2 \tag{13}$$

Where $D(I) \in [0, 1]$. The larger $D(I)$ is, the larger I is.

Definition 6. [96] Let $I_1 = \left(\mu_{I_1}, \nu_{I_1}\right)$, $I_2 = \left(\mu_{I_2}, \nu_{I_2}\right)$ be two IFNs, the Hamming distance between them is as follows:

$$d(I_1, I_2) = \frac{1}{2}\left(\left|\mu_{I_1} - \mu_{I_2}\right| + \left|\nu_{I_1} - \nu_{I_2}\right| + \left|\pi_{I_1} - \pi_{I_2}\right|\right) \tag{14}$$

4.2. Methods and decision-making framework

This paper proposes a five-phase decision-making framework for selecting an optimal RE, as shown in Fig. 1. In this section, the five phases of the research methodology are described in detail.

4.2.1. Phase I – identifying the alternative renewable source

Step 1. First of all, a committee of experts is established, consisting of professionals in the field of RE and in the field of OSCS. Subsequently, potential alternative REs are identified through field studies, exploration of REs in areas determined for the installation of OSCS, including through the use of satellite remote sensing technology.

4.2.2. Phase II – determining the weight of experts

Experts have different authorities for various criteria because of their varied knowledge and experience, which implies that there may be a difference in the quality of evaluation information [36]. This paper introduces the concept of quality of information in IF environment.

Step 2. Calculate the quality of information. The quality parameter presents the degree of authority of an expert on a certain criterion.

Definition 7. Suppose $R^l_{ij} = \left(\mu^l_{ij}, \nu^l_{ij}\right)$ $(i = 1, 2, \ldots, n)$ $(j = 1, 2, \ldots, m)$ $(l = 1, 2, \ldots, k)$ is the evaluation given by l-th expert to criterion C_j in alternative A_i, and q^l_{ij} represents the quality of R^l_{ij} as shown below:

$$q^l_{ij} = 1 - d\left(R^l_{ij}, \overline{R_{ij}}\right) \tag{15}$$

where $q^l_{ij} \in [0, 1]$, $\overline{R_{ij}} = \frac{1}{k}\left(R^1_{ij} \hat{\oplus} R^2_{ij} \hat{\oplus} \ldots \hat{\oplus} R^k_{ij}\right)$, the closer R^l_{ij} is to $\overline{R_{ij}}$, the higher its quality.

Step 3. Calculate the weight of experts. The quality parameter can present the degree of authority of an expert on a certain criterion, which facilitates better decision-making results. Then the weight of experts can be determined by following equation:

$$\omega^l_{ij} = \frac{q^l_{ij}}{\sum\limits_{l=1}^{k} q^l_{ij}} \tag{16}$$

Where ω^l_{ij} denotes the weight of the l-th expert on the criterion C_j in alternative A_i, satisfying $\omega^l_{ij} \geq 0$, and $\sum_{l=1}^{k} \omega^l_{ij} = 1$.

4.2.3. Phase III – aggregating IFDM by group decision with GIFWGIA operator

Considering the interactions between non-membership and membership functions of different IFSs as well as the experts' attitudes, the GIFWGIA operator is used in this phase to aggregate the experts' individual evaluations.

Step 4. Aggregating the decision matrix. Using the GIFWGIA operator to obtain the aggregated IF-decision matrix (IFDM) $\Re_{ij} = \left[R_{ij}\right]_{n\times m}$.

Definition 8. [23] Let $\Re^l_{ij} = \left[R^l_{ij}\right]_{n\times m}$ $(i = 1, 2, \ldots, n)$ $(j = 1, 2, \ldots, m)$ $(l = 1, 2, \ldots, k)$ be an IFDM of k DMs, the GIFWGIA operator is defined as below:

$$GIFWGIA_\lambda\left(R^1_{ij}, R^2_{ij}, \ldots R^k_{ij}\right) = \frac{1}{\lambda}\left(\hat{\bigotimes}_{l=1}^{k}\left(\lambda R^l_{ij}\right)^{\omega^l_{ij}}\right) = \begin{Bmatrix} 1 - \left(1 - \prod\limits_{l=1}^{k}\left(1 - \left(1 - \mu^l_{ij}\right)^\lambda + \left(1 - \left(\mu^l_{ij} + \nu^l_{ij}\right)\right)^\lambda\right)^{\omega^l_{ij}} \right. \\ \left. + \prod\limits_{l=1}^{k}\left(1 - \left(\mu^l_{ij} + \nu^l_{ij}\right)\right)^{\lambda\omega^l_{ij}}\right)^{1/\lambda}, \left(1 - \prod\limits_{l=1}^{k}\left(1 - \left(1 - \nu^l_{ij}\right)^\lambda \right.\right. \\ \left.\left. + \left(1 - \left(\mu^l_{ij} + \nu^l_{ij}\right)\right)^\lambda\right)^{\omega^l_{ij}} + \prod\limits_{l=1}^{k}\left(1 - \left(\mu^l_{ij} + \nu^l_{ij}\right)\right)^{\lambda\omega^l_{ij}}\right)^{1/\lambda} \\ - \prod\limits_{l=1}^{k}\left(1 - \left(\mu^l_{ij} + \nu^l_{ij}\right)\right)^{\omega^l_{ij}} \end{Bmatrix} \tag{17}$$

where Î» > 0, which represents preference of the DMs. When Î» $= 1$, the attitude of DMs is considered neutral. And Ï‰$^l_{ij}$ denotes the weight of the l-th expert on the criterion C_j in alternative A_i. For example, let Î» $= 2$, $R^1_{11} = (0.8, 0.1)$, $R^2_{11} = (0.6, 0.2)$, the weight vector is Ï‰$^l_{ij} = (0.3, 0.7)$, then the calculation is shown below:

$$\begin{aligned} R_{11} &= \frac{1}{2}\left(\left(2R^1_{11}\right)^{0.3} \hat{\otimes} \left(2R^2_{11}\right)^{0.7}\right) \\ &= \left\{1 - \left(1 - \left(1 - \left(1 - (1-0.8)^2 + (1-(0.8+0.1))^2\right)^{0.3} \times \left(1 - (1-0.6)^2 + (1-(0.6+0.2))^2\right)^{0.7}\right) + (1-(0.8+0.1))^{2\times0.3} \times (1-(0.6+0.2))^{2\times0.3}\right)^{1/2}, \right. \\ &\quad \left. \left(1 - \left(1 - (1-0.1)^2 + (1-(0.8+0.1))^2\right)^{0.3} \times \left(1 - (1-0.2)^2 + (1-(0.6+0.2))^2\right)^{0.7} + (1-(0.8+0.1))^{2\times0.3} \times (1-(0.6+0.2))^{2\times0.7}\right)^{1/2} - (1-(0.8+0.1))^{0.3} \times (1-(0.6+0.2))^{0.7}\right\} \\ &= (0.6531, 0.1843) \end{aligned}$$

4.2.4. Phase IV – determining the weights of criteria

Since there are multiple criteria in selection of optimal RE of OSCS, and different criteria have different impacts on the results of ranking, it is important to calculate the weight of each criterion in a rational way. In this paper, a comprehensive weighting method is used. On the basis of the aggregated decision matrix, the objective and subjective weights of the criteria was determined using the CRITIC method [54] and SWARA-II method [43], respectively, and then a genetic algorithm is used to calculate the combined weights.

Determining the objective weights of criteria by CRITIC method

Step 5. Determine the degree of correlation between criteria. First, the IFDM $\Re_{ij} = [R_{ij}]_{n\times m}$ is fuzzified according to Eq. (18). Then the standard deviation of each criterion is calculated by Eq. (19) and the correlation between each criterion and other criteria is determined by Eq. (20).

$$\widetilde{R}_{ij} = \begin{cases} \dfrac{1-\dfrac{\mu_{ij}\times\mu_- + \nu_{ij}\times\nu_- + \pi_{ij}\times\pi_-}{\mu_{ij}^2\vee\mu_-^2 + \nu_{ij}^2\vee\nu_-^2 + \pi_{ij}^2\vee\pi_-^2}}{1-\dfrac{\mu_-\times\mu_+ + \nu_-\times\nu_+ + \pi_-\times\pi_+}{\mu_-^2\vee\mu_+^2 + \nu_-^2\vee\nu_+^2 + \pi_-^2\vee\pi_+^2}} & \text{if } C_j\in C^B \\ \dfrac{1-\dfrac{\mu_{ij}\times\mu_+ + \nu_{ij}\times\nu_+ + \pi_{ij}\times\pi_+}{\mu_{ij}^2\vee\mu_+^2 + \nu_{ij}^2\vee\nu_+^2 + \pi_{ij}^2\vee\pi_+^2}}{1-\dfrac{\mu_-\times\mu_+ + \nu_-\times\nu_+ + \pi_-\times\pi_+}{\mu_-^2\vee\mu_+^2 + \nu_-^2\vee\nu_+^2 + \pi_-^2\vee\pi_+^2}} & \text{if } C_j\in C^S \end{cases} \tag{18}$$

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{n}\left(\widetilde{R}_{ij}-\overline{\widetilde{R}}_j\right)^2}{n}} \tag{19}$$

$$r_{jj'} = \frac{\sum_{i=1}^{n}\left(\widetilde{R}_{ij}-\overline{\widetilde{R}}_j\right)\left(\widetilde{R}_{ij'}-\overline{\widetilde{R}}_{j'}\right)}{\sqrt{\sum_{i=1}^{n}\left(\widetilde{R}_{ij}-\overline{\widetilde{R}}_j\right)^2\sum_{i=1}^{n}\left(\widetilde{R}_{ij'}-\overline{\widetilde{R}}_{j'}\right)^2}} \tag{20}$$

Where $\widetilde{R}_{ij}$ denotes the defuzzied score of criterion C_j in alternative A_i. $\vee$ represents the maximization operation. C^B denotes a set of benefit criteria, and C^S denotes a set of cost criteria. μ_- and μ_+ represent the minimum and maximum membership degrees respectively, ν_- and ν_+ represent the minimum and maximum non-membership degrees respectively, π_- and π_+ represent the minimum and maximum indeterminacy degrees respectively. $\overline{\widetilde{R}}_j$ and $\overline{\widetilde{R}}_{j'}$ respectively represent the average of the defuzzied score of criteria C_j and $C_{j'}$. σ_j denotes the standard deviation of criterion C_j. $r_{jj'}$ represents the correlation between criterion C_j and criterion $C_{j'}$.

Step 6. Determining the objective weight of criteria. First, Eq. (21) is used to calculate the information content of each criterion is calculated from the standard deviation of each criterion and its correlation with each other criterion, and then Eq. (22) is used to determine the objective weights of the criteria.

$$IC_j = \sigma_j\sum_{j'=1}^{m}\left(1-r_{jj'}\right) \tag{21}$$

$$\omega_j^o = \frac{IC_j}{\sum_{j=1}^{m} IC_j} \tag{22}$$

Where IC_j represents the information content of criterion C_j. ω_j^o denotes the objective weight of criterion C_j, satisfying $\omega_j^o \geq 0$, and $\sum_{j=1}^{m}\omega_j^o = 1$.

Determining the subjective weights of criteria by SWARA-II method

Table 2
Linguistic variables and corresponding preference values.

Linguistic variable	Preference values
Extreme low (EL)	1
Very low (VL)	2
Low (L)	3
Medium low (ML)	4
Medium (M)	5
Medium high (MH)	6
High (H)	7
Very high (VH)	8
Extreme high (EH)	9

Step 7. Rank the criteria in descending order of importance. The most important criterion ranks at the top of the ranked list, and the subsequent criteria have decreasing importance. p_j ($j = 1, 2, \ldots, m$) presents the position of the j-th criterion in the ranked list.
Step 8. Experts express their preference for the criterion in the ranked list over the next criterion using the linguistic variables in Table 2. In this paper, $h_{[p_j]}$ is used to represent the preference value of the $\left[p_j\right]$ th criterion.

Step 9. Calculate relative weighting coefficients. The preference degree (PD) for criteria is computed using the nonlinear utility function in Eq. (23), which is defined by Keshavarz-Ghorabaee [43]. Then calculate the relative weighting coefficient $T_{[p_j]}$ of each criterion based on its position in the ordered list and value of $PD_{[p_j]}$ by Eq. (24).

$$PD_{[p_j]} = \left(\frac{h_{[p_j]}}{10}\right)^2 \tag{23}$$

$$T_{[p_j-1]} = \left(1 + PD_{[p_j-1]}\right) \times T_{[p_j]} \tag{24}$$

Where $PD_{[p_j]} \in [0,1]$, $T_m = 1$ and $T_{[p_j]} \in [1,2]$.

Step 10. Based on the relative weighting coefficient $T_{[p_j]}$, using Eq. (25) to determine the subjective weight.

$$\omega_j^s = \frac{T_{[p_j]}}{\sum\limits_{p_j=1}^{m} T_{[p_j]}} \tag{25}$$

Where ω_j^s denotes the subjective weight of criterion C_j, satisfying $\omega_j^s \geq 0$, and $\sum_{j=1}^{m} \omega_j^s = 1$.

Determining the comprehensive weight of criteria by genetic algorithm.

Step 11. Determine the comprehensive weights of criteria using following equation:

$$\min \chi = \sum_{j=1}^{m} \left(\omega_j^o - \omega_j\right)^2 + \sum_{j=1}^{m} \left(\omega_j^s - \omega_j\right)^2$$
$$s.t. \begin{cases} \sum\limits_{j=1}^{m} \omega_j = 1 \\ \omega_j > 0 \end{cases} \tag{26}$$

Where ω_j denotes the comprehensive weights of criterion C_j, ω_j^o and ω_j^s represents the objective and subjective weight of criterion C_j, respectively.

4.2.5. Phase V – selecting the optimal alternative

At this stage, this paper extends the GLDS method under IF environment and uses the IFGLDS method to rank the alternatives. The computational procedure of the extended GLDS method under IF environment is as follows.

Step 12. Normalize the given IFDM $\Re_{ij} = \left[R_{ij}\right]_{n\times m}$ into the normalized IFDM $\Re_{ij}^N = \left[R_{ij}^N\right]_{n\times m}$ according to the type of criteria by Eq. (27).

$$R_{ij}^N = \begin{cases} R_{ij}, \text{if } C_j \in C^B \\ R_{ij}^C, \text{if } C_j \in C^S \end{cases} \tag{27}$$

Where C^B denotes a set of benefit criteria, and C^S denotes a set of cost criteria.

Step 13. Determine the dominance flow $DF_j(A_\alpha, A_\beta)$ between alternative A_α ($\alpha = 1, 2, \ldots, n$) and alternative A_β ($\beta = 1, 2, \ldots, n$) over criterion C_j by Eq. (28).

$$DF_j(A_\alpha, A_\beta) = \begin{cases} D\left(R_{\alpha j}^N\right) - D\left(R_{\beta j}^N\right), \text{if } D\left(R_{\alpha j}^N\right) \geq D\left(R_{\beta j}^N\right) \\ 0, \text{if } D\left(R_{\alpha j}^N\right) < D\left(R_{\beta j}^N\right) \end{cases} \tag{28}$$

Where $D\left(R_{\alpha j}^N\right)$ and $D\left(R_{\beta j}^N\right)$ represent the defuzzied values of $R_{\alpha j}^N$ and $R_{\beta j}^N$ by using Eq. (13), respectively. $DF_j(A_\alpha, A_\beta) \in [0,1]$.

Step 14. Normalize $DF_j(A_\alpha, A_\beta)$ into $DF_j^N(A_\alpha, A_\beta)$ using by Eq. (29).

$$DF_j^N(A_\alpha, A_\beta) = \frac{DF_j(A_\alpha, A_\beta)}{\sqrt{\sum_{\alpha=1}^{n}\sum_{\beta=1}^{n}\left[DF_j(A_\alpha, A_\beta)\right]^2}} \tag{29}$$

Step 15. Calculate the gained dominance score $GDS_j(A_\alpha)$ of A_α under criterion C_j by Eq. (30).

$$GDS_j(A_\alpha) = \sum_{\beta=1}^{n} DF_j^N(A_\alpha, A_\beta) \tag{30}$$

Step 16. Calculate the lost dominance score $LDS_j(A_\alpha)$ of A_α under criterion C_j by Eq. (31).

$$LDS_j(A_\alpha) = \max_{\beta} DF_j^N(A_\beta, A_\alpha) \tag{31}$$

Step 17. Determine the net gained dominance score $NGDS(A_\alpha)$ of A_α by Eq. (32).

$$NGDS(A_\alpha) = \sum_{j=1}^{m} \omega_j GDS_j(A_\alpha) \tag{32}$$

The net gained dominance score denotes the "group utility" value of each alternative. Arrange $NGDS(A_\alpha)$ in descending order to obtain a ranking set $\rho_1 = \{r_1(A_1), r_1(A_2), \ldots, r_1(A_n)\}$.

Step 18. Calculate the net lost dominance score $NLDS(A_\alpha)$ of A_α by Eq. (33).

$$NLDS(A_\alpha) = \max_{j} \omega_j LDS_j(A_\alpha) \tag{33}$$

The net lost dominance score represents the maximum "individual regret" value of each alternative. Arrange $NLDS(A_\alpha)$ in ascending order to obtain a ranking set $\rho_2 = \{r_2(A_1), r_2(A_2), \ldots, r_2(A_n)\}$.

Step 19. Based on the dominance score and the ranking of the subordination, the collective score CS_α of each alternative is determined by Eq. (34).

$$CS_\alpha = \frac{NGDS(A_\alpha)}{\sqrt{\sum_{\alpha=1}^{n} NGDS(A_\alpha)^2}} \cdot \frac{n - r_1(A_\alpha) + 1}{n(n+1)/2} - \frac{LGDS(A_\alpha)}{\sqrt{\sum_{\alpha=1}^{n} LGDS(A_\alpha)^2}} \cdot \frac{r_2(A_\alpha)}{n(n+1)/2} \tag{34}$$

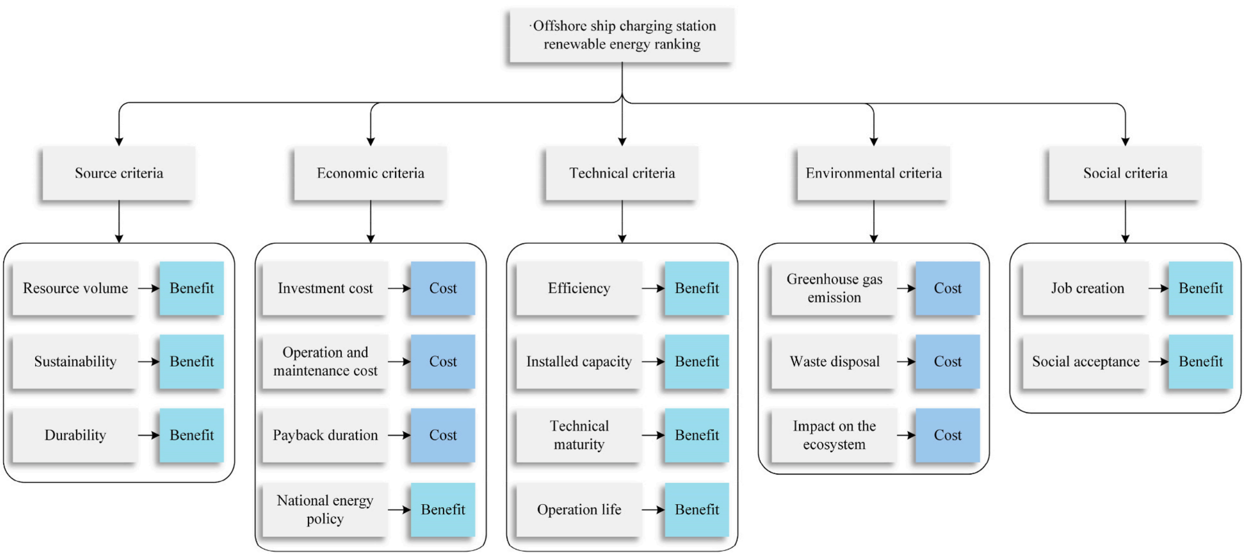

Fig. 2. Selection of optimal RE criteria system for OSCS.

The ranking of A_α increases with the value of the collective score CS_α.

5. Case study

This section presents a case study from China to demonstrate the effectiveness and practicality of the proposed decision-making framework for ranking RE for OSCS. In response to a circular issued by ten departments, including the Department of Industry and Information Technology of Fujian Province, on the issuance of the Implementation Opinions on Comprehensively Promoting the Construction of "Electric Fujian" (2023–2025), a company wants to invest in an OSCS project in the sea area of Pingtan Island, Fujian Province.

5.1. Phase-I identifying the alternative renewable source

In the first phase, five experts in the field of RE and OSCS formed a decision-making committee. After field research, visits to local authorities and review of literature, the decision-making committee learned that Pingtan Island has sufficient irradiation and long sunshine hours. The average annual total solar radiation is 451×10^4kJ/m_2, the average annual sunshine hours amount to 1869.5h, and the average annual temperature is 19.8 °C. Meanwhile, Pingtan, as one of the three major wind breaks in the global sea, is rich in wind resources. The average annual wind speed in the coastal area of Pingtan Island reaches 8.9 m/s, and the number of days of high winds (level 7 or above) in the bay area is 125 days in a year. The average annual impact of typhoons ranges from 3 to 5 times, with a maximum of 11 times, and the intensity is greater than that of the inland, and the wind speed often reaches more than 40 m/s. Therefore, the wind energy in Pingtan Island is very rich in wind resources. Thus, the expert committee identified four potential offshore power technologies: offshore wind power, offshore solar PV, offshore wave energy and offshore floating nuclear power plant. They were identified as A_1, A_2, A_3 and A_4 respectively.

Fig. 2 illustrates the selection of optimal RE criteria system for OSCS.

5.2. Phase II – determining the weight of experts

In the second stage, the experts used the linguistic variables in Table 3 to evaluate each alternative according to the criteria in Fig. 1, and established the evaluation matrix, as shown in Table 4. In order to ensure the independence of the experts' ratings, the experts were asked to evaluate them individually without communication and discussion. After the evaluation, the evaluation information quality of each expert was calculated using Eq. (15), as shown in Table 5. Then the weight of each expert was determined using Eq. (16), as shown in Table 6.

5.3. Phase III - aggregating IFDM by group decision with GIFWGIA operator

In the third stage, after determining the weights of the experts, the individual opinions were summarized according to the importance of each expert by Eq. (17) ($\lambda = 1$), as shown in Table 7, where it can be seen that wind energy (A_1) and solar PV (A_2) have higher ratings for technical maturity (C_{10}) and job creation (C_{15}), while wave energy (A_3) and nuclear energy (A_4) have lower ratings. This may be due to the fact that the research related to A_3 and A_4 is still in its infancy, and there is a greater need for people with relevant experience and knowledge to participate in the development and operation and maintenance of the facilities, and therefore fewer jobs are available. It should also be noted that the social acceptance (C_{16}) scores for A_1, A_2, and A_3 show a neutral attitude towards these three REs, while the score for A_4 shows an unacceptable attitude towards nuclear energy, which may be due to the fear of local residents that accidents, such as nuclear leakage, may cause serious harm to the local community.

5.4. Phase IV – determination of the weights of criteria

In the fourth stage, Firstly, the correlation degree between the criteria was determined by Eqs. (18)–(20), and then determining the objective weights of the criteria using Eqs. (21) and (22). Next, the experts rated each criterion based on their preferences as shown in Table 8. Then the relative weight coefficients of each criterion were calculated by Eqs. (23) and (24). After that, the subjective weights

Table 3
Linguistic variables for the rating of alternatives [97].

Linguistic variables	Intuitionistic fuzzy numbers
Extremely high (EH)	(0.80,0.10)
Very high (VH)	(0.80,0.20)
High (H)	(0.60,0.20)
Medium high (MH)	(0.60,0.30)
Medium (M)	(0.40,0.30)
Medium low (ML)	(0.40,0.40)
Low (L)	(0.20,0.40)
Very low (VL)	(0.20,0.55)
Extremely low (EL)	(0.10,0.80)

Table 4
Evaluation rating matrixes of alternatives on sub-criteria

		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
A_1	E_1	EH	H	H	H	MH	M	VH	MH	H	VH	MH	ML	ML	H	H	M
	E_2	VH	H	H	MH	MH	MH	EH	MH	H	VH	H	ML	M	VH	VH	MH
	E_3	VH	VH	MH	MH	MH	MH	EH	M	VH	VH	MH	L	ML	H	VH	M
	E_4	EH	MH	H	H	H	M	VH	MH	VH	H	H	ML	M	H	H	M
	E_5	VH	MH	H	H	H	MH	VH	H	H	VH	MH	L	M	VH	H	M
A_2	E_1	H	M	H	H	H	MH	VH	M	MH	H	MH	L	L	VH	H	M
	E_2	H	MH	VH	H	MH	M	VH	M	MH	VH	MH	ML	M	VH	MH	MH
	E_3	MH	M	H	MH	H	MH	H	ML	H	VH	MH	L	ML	H	MH	M
	E_4	VH	ML	VH	MH	MH	M	VH	ML	H	H	H	L	ML	H	H	ML
	E_5	MH	ML	VH	H	H	MH	VH	M	MH	VH	MH	ML	M	VH	H	M
A_3	E_1	VH	MH	MH	VH	VH	H	H	M	MH	H	MH	ML	M	ML	M	MH
	E_2	VH	H	MH	VH	H	VH	H	ML	M	H	M	ML	ML	M	MH	H
	E_3	H	M	M	H	VH	H	MH	ML	MH	MH	M	L	L	ML	MH	M
	E_4	VH	MH	H	H	H	H	H	ML	MH	H	M	L	M	L	H	M
	E_5	H	H	MH	VH	VH	H	H	M	M	MH	MH	ML	ML	L	MH	M
A_4	E_1	M	EH	EH	EH	H	VH	M	H	M	MH	H	VL	VL	M	M	VL
	E_2	M	VH	VH	EH	MH	VH	MH	H	ML	M	VH	L	L	M	ML	VL
	E_3	MH	VH	VH	VH	MH	H	M	MH	ML	MH	H	L	VL	ML	M	EL
	E_4	M	H	EH	VH	MH	H	M	H	M	H	VH	VL	VL	M	ML	EL
	E_5	MH	VH	VH	EH	H	H	MH	H	ML	M	VH	VL	L	M	L	VL

of each criterion were calculated by Eq. (25). Finally, the combination weights were calculated using Eq. (26) as shown in Table 9.

5.5. *Phase V – selecting the optimal alternative*

In the fifth stage, a GLDS method under IF environment is proposed. Firstly, the IFDM was normalized using Eq. (27), and then calculating the dominance flow $DF_j(A_\alpha, A_\beta)$ between the two alternatives under each criterion by Eq. (28), then it was normalized by using Eq. (29), and then the gained dominance score $GDS_j(A_\alpha)$ and the lost dominance score $LDS_j(A_\alpha)$ of A_α under criterion C_j were computed using Eqs. (30) and (31) respectively, then the net gained dominance score $NGDS(A_\alpha)$ and the net lost dominance score $NLDS(A_\alpha)$ of A_α under criterion C_j were calculated by Eqs. (32) and (33) respectively. Finally, the collective score CS_α of each alternative was obtained by Eq. (34). The result of ranking is as shown in Table 10, from which it is known that the final result of the ranking is $A_1>A_2>A_3>A_4$.

6. Discussion

6.1. *Sensitivity analysis*

Sensitivity analysis is a key part of applying the MCDM method to practical problems, which measures the changes in the output data caused by changes in the input data in the decision framework to verify the applicability and robustness of the decision framework. In this sub-section, two sensitivity analysis methods were used: (1) Analyzing the impact of changes in the weights of sub-criteria on the final ranking. (2) Analyzing the impact of changes in attitudes of DMs on the final ranking.

6.1.1. *Analysis of the impact of changes in criteria weights*

On the basis of the original weights, the sixteen sub-criteria's weights were increased or decreased by 10 %, 20 %, and 30 %, respectively, and it is observed whether the changes in the weights of the sub-criteria will lead to qualitative changes in the ranking results. After calculation, it is found that after increasing or decreasing the weights of each criterion, the most result of the ranking is still $A_1>A_2>A_3>A_4$ which is the same as the ranking of the original alternatives, the analysis results are show in Fig. 3.

As it can be seen from Fig. 3, the fluctuation of the weights of most of the criteria, including Resource volume (C_1), Sustainability (C_2), Durability (C_3), National energy policy (C_7), Efficiency (C_8), Installed capacity (C_9), Technical maturity (C_{10}), Operation life (C_{11}), Greenhouse gas emissions (C_{12}), Waste disposal (C_{13}), Job creation (C_{15}), and Social acceptance (C_{16}), do not have a significant effect on the ranking results. The fluctuations in the weights of other criteria including Investment cost (C_4), Operation and maintenance cost (C_5), Payback duration (C_6), Impact on the ecosystem (C_{14}) have significant impacts on the ranking results.

For Investment cost (C_4), when the weight of C_4 decreases by 10 %, the collective score of nuclear energy (A_4) increases significantly, overtaking solar energy (A_2) and wave energy (A_3), while the score of wind energy (A_1) decreases slightly, at this time, the ranking is $A_1>A_4>A_3>A_2$; when the weight of C_4 decreases by 20 %, the score of A_4 increases again, overtaking A_1 to become the first ranked alternative, while the scores of the other alternatives remain basically unchanged, at this time, the ranking is $A_4>A_1>A_3>A_2$. When the weight of C_4 continues to decrease, the ranking remains unchanged. When the weight of C_4 increases, the score of alternatives decreases slightly, the ranking results remain $A_1>A_2>A_3>A_4$.

For Operation and maintenance cost (C_5), when the weight of C_5 decreases by 10 %, the collective scores of alternatives change slightly, but the ranking results change to $A_1>A_3>A_2>A_4$. When the weight of C_5 continues to decrease, the ranking remains

Table 5
Expert evaluation quality parameter matrixes of alternatives.

		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
A_1	E_1	0.90	0.79	0.97	0.93	0.91	0.94	1.00	0.94	0.80	0.97	0.91	0.93	0.94	0.80	0.80	0.98
	E_2	0.20	0.30	0.70	0.80	0.80	0.84	0.20	0.82	0.30	0.20	0.70	0.83	0.86	0.30	0.20	0.88
	E_3	1.00	0.79	0.83	0.87	0.91	0.96	0.90	0.92	0.90	0.97	0.91	0.86	0.94	0.80	0.90	0.98
	E_4	0.90	0.80	0.97	0.93	0.89	0.94	1.00	0.94	0.90	0.80	0.89	0.93	0.96	0.80	0.80	0.98
	E_5	1.00	0.80	0.97	0.93	0.89	0.96	1.00	0.85	0.80	0.97	0.91	0.86	0.96	0.90	0.80	0.98
A_2	E_1	0.79	0.94	0.80	0.93	0.93	0.96	0.97	0.96	0.91	0.80	0.95	0.90	0.84	0.94	0.93	0.96
	E_2	0.50	0.84	0.30	0.70	0.70	0.84	0.30	0.86	0.70	0.20	0.80	0.79	0.87	0.30	0.80	0.86
	E_3	0.80	0.94	0.80	0.87	0.93	0.96	0.80	0.94	0.89	0.94	0.95	0.90	0.93	0.80	0.87	0.96
	E_4	0.79	0.96	0.94	0.87	0.87	0.94	0.97	0.94	0.89	0.80	0.85	0.90	0.93	0.80	0.93	0.94
	E_5	0.80	0.96	0.94	0.93	0.93	0.96	0.97	0.96	0.91	0.94	0.95	0.89	0.93	0.94	0.93	0.96
A_3	E_1	0.94	0.89	0.94	0.94	0.94	0.80	0.97	0.94	0.96	0.93	0.94	0.93	0.93	0.91	0.92	0.90
	E_2	0.30	0.72	0.82	0.30	0.30	0.30	0.70	0.84	0.84	0.70	0.86	0.83	0.86	0.89	0.82	0.76
	E_3	0.80	0.91	0.92	0.80	0.94	0.80	0.83	0.96	0.96	0.87	0.96	0.86	0.84	0.91	0.94	0.95
	E_4	0.94	0.89	0.85	0.80	0.80	0.80	0.97	0.96	0.96	0.93	0.96	0.86	0.93	0.87	0.85	0.95
	E_5	0.80	0.89	0.94	0.94	0.94	0.80	0.97	0.94	0.94	0.87	0.94	0.93	0.93	0.87	0.94	0.95
A_4	E_1	0.89	0.87	0.90	0.90	0.89	0.90	0.96	0.97	0.94	0.92	0.80	0.95	0.95	0.98	0.93	0.88
	E_2	0.69	0.20	0.20	0.20	0.80	0.30	0.86	0.70	0.84	0.84	0.30	0.80	0.80	0.88	0.83	0.56
	E_3	0.89	0.97	1.00	1.00	0.91	0.80	0.96	0.83	0.96	0.92	0.80	0.90	0.95	0.92	0.93	0.87
	E_4	0.89	0.80	0.90	1.00	0.91	0.80	0.96	0.97	0.94	0.85	0.94	0.95	0.95	0.98	0.93	0.87
	E_5	0.89	0.97	1.00	0.90	0.89	0.80	0.94	0.97	0.96	0.94	0.94	0.95	0.90	0.98	0.84	0.88

Table 6
The expert weight of alternatives

		C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	C_{14}	C_{15}	C_{16}
A_1	E_1	0.23	0.23	0.22	0.21	0.21	0.20	0.24	0.21	0.22	0.25	0.21	0.21	0.20	0.22	0.23	0.20
	E_2	0.05	0.09	0.16	0.18	0.18	0.18	0.05	0.18	0.08	0.05	0.16	0.19	0.18	0.08	0.06	0.18
	E_3	0.25	0.23	0.19	0.20	0.21	0.21	0.22	0.21	0.24	0.25	0.21	0.20	0.20	0.22	0.26	0.20
	E_4	0.23	0.23	0.22	0.21	0.20	0.20	0.24	0.21	0.24	0.20	0.21	0.21	0.21	0.22	0.23	0.20
	E_5	0.25	0.23	0.22	0.21	0.20	0.21	0.24	0.19	0.22	0.25	0.21	0.20	0.21	0.25	0.23	0.20
A_2	E_1	0.21	0.20	0.21	0.22	0.21	0.21	0.24	0.21	0.21	0.22	0.21	0.21	0.19	0.25	0.21	0.20
	E_2	0.14	0.18	0.08	0.16	0.16	0.18	0.07	0.18	0.16	0.05	0.18	0.18	0.19	0.08	0.18	0.18
	E_3	0.22	0.20	0.21	0.20	0.21	0.21	0.20	0.20	0.21	0.25	0.21	0.21	0.21	0.21	0.20	0.20
	E_4	0.21	0.21	0.25	0.20	0.20	0.20	0.24	0.20	0.21	0.22	0.19	0.21	0.21	0.21	0.21	0.20
	E_5	0.22	0.21	0.25	0.22	0.21	0.21	0.24	0.21	0.21	0.25	0.21	0.20	0.21	0.25	0.21	0.20
A_3	E_1	0.25	0.21	0.21	0.25	0.24	0.23	0.22	0.20	0.21	0.22	0.20	0.21	0.21	0.20	0.21	0.20
	E_2	0.08	0.17	0.18	0.08	0.08	0.09	0.16	0.18	0.18	0.16	0.18	0.19	0.19	0.20	0.18	0.17
	E_3	0.21	0.21	0.21	0.21	0.24	0.23	0.19	0.21	0.21	0.20	0.21	0.20	0.19	0.20	0.21	0.21
	E_4	0.25	0.21	0.19	0.21	0.20	0.23	0.22	0.21	0.21	0.22	0.21	0.20	0.21	0.20	0.19	0.21
	E_5	0.21	0.21	0.21	0.25	0.24	0.23	0.22	0.20	0.20	0.20	0.20	0.21	0.21	0.20	0.21	0.21
A_4	E_1	0.21	0.23	0.23	0.23	0.20	0.25	0.20	0.22	0.20	0.21	0.21	0.21	0.21	0.21	0.21	0.22
	E_2	0.16	0.05	0.05	0.05	0.18	0.08	0.18	0.16	0.18	0.19	0.08	0.18	0.18	0.19	0.19	0.14
	E_3	0.21	0.25	0.25	0.25	0.21	0.22	0.20	0.19	0.21	0.21	0.21	0.20	0.21	0.20	0.21	0.21
	E_4	0.21	0.21	0.23	0.25	0.21	0.22	0.20	0.22	0.20	0.19	0.25	0.21	0.21	0.21	0.21	0.21
	E_5	0.21	0.25	0.25	0.23	0.20	0.22	0.20	0.22	0.21	0.21	0.25	0.21	0.20	0.21	0.19	0.22

Table 7
Aggregate evaluation ratings of the experts group

Sub-criteria	A_1	A_2	A_3	A_4
C_1	(0.8435,0.1564)	(0.7059,0.2940)	(0.8000,0.2000)	(0.5104,0.3000)
C_2	(0.7009,0.2990)	(0.4029,0.3614)	(0.4722,0.3098)	(0.8218,0.1781)
C_3	(0.5578,0.2421)	(0.8000,0.2000)	(0.4367,0.3458)	(0.8435,0.1564)
C_4	(0.5182,0.2817)	(0.5120,0.2879)	(0.8000,0.2000)	(0.8485,0.1514)
C_5	(0.4740,0.3259)	(0.5212,0.2787)	(0.8000,0.2000)	(0.4740,0.3259)
C_6	(0.4029,0.3614)	(0.4028,0.3638)	(0.8000,0.2000)	(0.8000,0.2000)
C_7	(0.8256,0.1743)	(0.8000,0.2000)	(0.5578,0.2421)	(0.4030,0.3404)
C_8	(0.4367,0.3458)	(0.4030,0.3424)	(0.4029,0.3614)	(0.5578,0.2421)
C_9	(0.8000,0.2000)	(0.4758,0.3241)	(0.4028,0.3638)	(0.4029,0.3614)
C_{10}	(0.8000,0.2000)	(0.8000,0.2000)	(0.5120,0.2879)	(0.4388,0.3262)
C_{11}	(0.4670,0.3329)	(0.4333,0.3666)	(0.4030,0.3424)	(0.8000,0.2000)
C_{12}	(0.3375,0.4000)	(0.2930,0.4000)	(0.3375,0.4000)	(0.2030,0.4988)
C_{13}	(0.4030,0.3424)	(0.3706,0.3617)	(0.3704,0.3603)	(0.2030,0.4988)
C_{14}	(0.8000,0.2000)	(0.8000,0.2000)	(0.3342,0.3813)	(0.4020,0.3207)
C_{15}	(0.8000,0.2000)	(0.5182,0.2817)	(0.4367,0.3458)	(0.3702,0.3600)
C_{16}	(0.4019,0.3194)	(0.4030,0.3404)	(0.4355,0.3058)	(0.1493,0.6814)

Table 8
The results using the SWARA-II method

	p_j	Preference	$PD_{[p_j]}$	$h_{[p_j]}$	$T_{[p_j]}$	ω_j^s
C_4	1	VL	2	0.04	6.883	0.115
C_6	2	L	3	0.09	6.618	0.110
C_5	3	VL	2	0.04	6.072	0.101
C_1	4	EL	1	0.01	5.838	0.097
C_{14}	5	M	5	0.25	5.781	0.097
C_8	6	L	3	0.09	4.624	0.077
C_7	7	L	3	0.09	4.243	0.071
C_9	8	M	5	0.25	3.892	0.065
C_3	9	VL	2	0.04	3.114	0.052
C_{10}	10	L	3	0.09	2.994	0.050
C_{11}	11	M	5	0.25	2.747	0.046
C_2	12	MH	6	0.36	2.198	0.037
C_{16}	13	MH	6	0.36	1.616	0.027
C_{15}	14	L	3	0.09	1.188	0.020
C_{12}	15	L	3	0.09	1.090	0.018
C_{13}	16	–	–	–	1.000	0.017

Table 9
The weights of criteria

Main-criterion	Sub-criterion	Objective weight	Subjective weight	Integrated weight
Source	C_1	0.076	0.097	0.0865
	C_2	0.050	0.037	0.0435
	C_3	0.069	0.052	0.0605
Economic	C_4	0.104	0.115	0.1095
	C_5	0.083	0.101	0.0920
	C_6	0.091	0.110	0.1005
	C_7	0.046	0.071	0.0585
Technical	C_8	0.051	0.077	0.0640
	C_9	0.048	0.065	0.0565
	C_{10}	0.062	0.050	0.0560
	C_{11}	0.066	0.046	0.0560
Environment	C_{12}	0.031	0.018	0.0245
	C_{13}	0.013	0.017	0.0150
	C_{14}	0.129	0.097	0.1130
Social	C_{15}	0.041	0.020	0.0305
	C_{16}	0.040	0.027	0.0335

unchanged. When the weight of C_5 increases by 10 %, the score of A_3 decreases slightly while the score of A_4 increases slightly, but it has no effect on the ranking. When the weight of C_5 rises by 20 %, the score of A_3 plummets, while the scores of the other alternatives rise slightly, at which time the ranking is A_1>A_2>A_4>A_3. When the weight of C_5 continues to increase, the ranking remains unchanged, although the scores of the alternatives minor change.

Table 10
The result of the ranking

Alternative	$NGDS(A_\alpha)$	$NLDS(A_\alpha)$	CS_α
A_1	0.715	0.0652	0.163
A_2	0.490	0.0652	−0.012
A_3	0.294	0.0563	−0.017
A_4	0.559	0.0654	−0.051

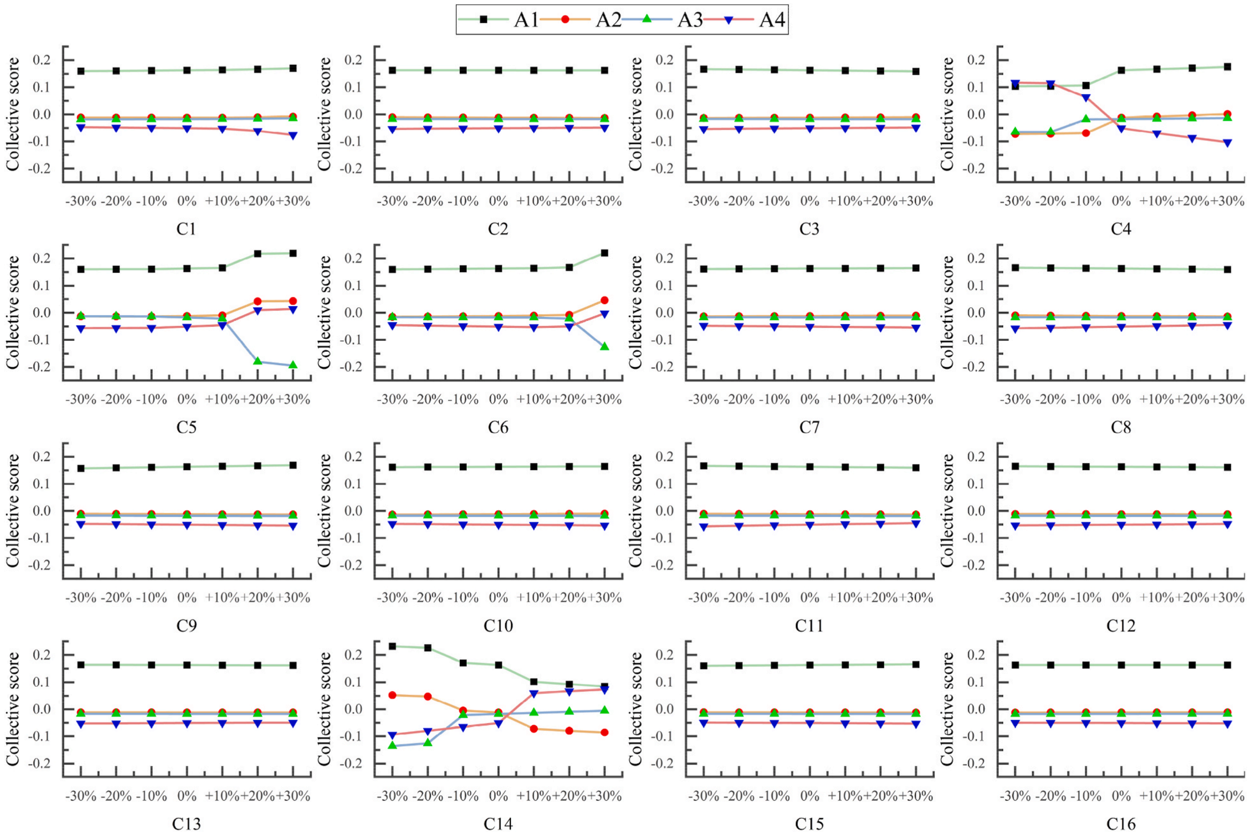

Fig. 3. Sensitivity analysis results of the sub-criteria.

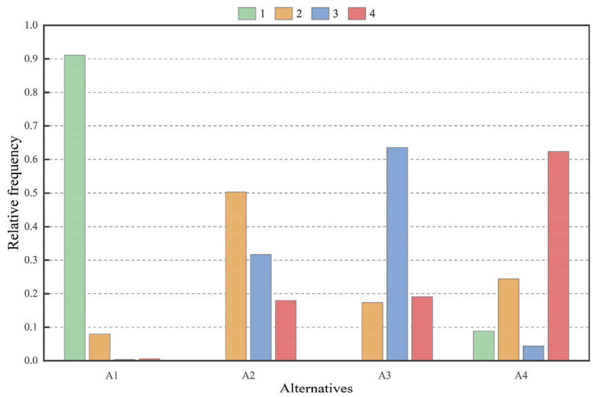

Fig. 4. Relative frequency of alternative rankings under Monte Carlo simulation (N = 5000).

For Payback duration (C_6), when the weight of C_6 decreases, the ranking of the alternatives remains unchanged. When the weight of C_6 increase by 20 %, the collective score of A_3 decreases slightly and the score of A_4 increases slightly, but there is no effect on the ranking. When the weight of C_6 increases by 30 %, the score of A_3 decreases significantly and the scores of the other alternatives increase significantly, and the ranking is $A_1 > A_2 > A_4 > A_3$.

For Impact on the ecosystem (C_{14}), When the weight of C_{14} decreases by 10 %, the collective scores of A_1 and A_2 increase slightly and the scores of A_3 and A_4 decrease slightly, but the ranking results remain $A_1 > A_2 > A_3 > A_4$. When the weight of C_{14} drops by 20 %, the scores of A_1 and A_2 increase greatly, and the score of A_3 decreases greatly, at which time the ranking is $A_1 > A_2 > A_4 > A_3$. When the weight of C_{14} continues to decrease, the scores of the alternatives do not change in the ranking, although there are slight changes in the scores. When the weight of C_{14} rises by 10 %, the scores of A_1 and A_2 fall slightly, while the collective score of A_4 rises sharply, at which time the ranking is $A_1 > A_4 > A_3 > A_2$.When the weight of C_{14} continues to rise to 30 %, although the score of A_1 continues to fall, and the score of A_4 continues to rise, the ranking result does not change.

Next, this paper further used Monte Carlo simulation [98,99] to fully test the stability of the proposed methodology against changes in the weights of other criteria. Assuming that these criteria weights are perturbed, random numbers are drawn independently for each criterion from a uniform distribution. The pseudo-random uniform distribution numbers were generated using the RAND(.) function in Microsoft Excel. The generated weights were then normalized with the sum of the individual weights. This process was repeated 5000 times, note that this number considered as sufficiently large given the number of criteria and alternatives considered in this study. The result is shown in Fig. 4. A_1 has the maximum probability for the first ranking (0.911); A_2 then has the maximum probability for the second ranking (0.503); A_3 is ranked third with a maximum probability of 0.636, and A_4 is ranked last with a maximum probability of 0.624. This is consistent with the rankings in this paper. Therefore, the proposed framework is highly stable and adaptable.

Overall, in the majority of cases, the optimal alternative is A_1, so the ranking results are relatively stable. And Monte Carlo simulation also justified the stability of the framework. In addition, it is important to note that A_4 is sensitive to fluctuations in the weights of C_4 and C_{14}; as the weight of C_4 gradually decreases, A_4 will overtake A_1 as the best alternative; as the weight of C_{14} gradually increases, A_4 may replace A_1 as the optimal alternative.

6.1.2. *Analysis of the impact of changes in the attitudes of DMs*

In decision analysis, since various attitudes of DMs bring about various ranking results, sensitivity analysis of parameter λ based on the preference of DMs was conducted to test the degree of influence of attitude changes on ranking. In order to understand the change in the final ranking when the attitude of the expert changes from neutral to pessimistic or optimistic, we let $\lambda = 0.5, 0.6, 0.7, \ldots, 5$ denote the different preferences of the expert and accordingly obtained the ranking results. A total of 10 scenarios were generated, the results were shown in Table 11, and the ranking changes were shown in Fig. 5. The results of the analysis indicate that the ranking of the alternatives is $A_1 > A_4 > A_2 > A_3$ when $\lambda = 0.5, 0.3, 0.4, \ldots, 0.9$ as the change of expert attitude. When $\lambda = 1$, the ranking of A_4 becomes the last, and the ranking of A_2 and A_3 increase, the ranking is $A_1 > A_2 > A_3 > A_4$. When $\lambda = 2$, the optimal alternative remains unchanged, but the worse alternative changes slightly, and A_2 and A_4 swap rankings, the ranking is $A_1 > A_4 > A_3 > A_2$. When $\lambda = 3, 4, 5$, the best alternative remains unchanged, but A_3 and A_4 swap rankings, the ranking is $A_1 > A_3 > A_4 > A_2$. Although the ranking of the alternative changes with attitude of experts, the best alternatives is always A_1. In addition, it is important to note that the managerial significance of parameter λ is the impact on the scoring values of the alternatives through the different preferences of DMs [23]. From the results we can see that when the manager becomes pessimistic, the ranking of A_1 remains unchanged, the rankings of A_2 and A_3 fall, and the ranking of A_4 rises. When the manager becomes relatively optimistic, the rankings of A_1 and A_3 remain the same, while A_4 swaps places with A_2 to become the second-ranked alternative. When managers become very optimistic, the rankings of A_1 and A_2 remain unchanged, while A_3 overtakes A_4 as the second-ranked alternative. In order to investigate the reasons for such changes, we analyzed the original evaluations of the experts. It can be seen that A_2 and A_3 have low Sustainability and Operational life ratings compared to A_4, when managers are conservative, they are more expectant from being able to the project to be able to run stably for a long period of time, so when managers' attitudes become pessimistic, A_4 will be ranked higher. Compared to A_2, A_3 has high ratings on Impact on the ecosystem and A_4 has high ratings on Sustainability and Operational life, but A_2 and A_4 have low ratings on National energy policy and Technical maturity, which suggests that A_3 and A_4 have some potential to be ranked higher when managers become optimistic.

6.2. *Comparative analysis*

For the purpose to study the impact of various ranking methods on selecting optimal RE of OSCS, this paper compared the proposed method with IFTOPSIS [13] , IFEDAS [14] and IFCODAS [15]. Since the methods proposed in this paper take into account individuals

Table 11
The results of changes in the attitudes of decision makers

Scenario	Attitude change	A_1	A_2	A_3	A_4	Scenario	Attitude change	A_1	A_2	A_3	A_4
S_1	$\lambda = 0.5$	0.033	0.005	−0.022	0.008	S_6	$\lambda = 1$	0.163	−0.012	−0.017	−0.051
S_2	$\lambda = 0.6$	0.037	0.002	−0.021	0.008	S_7	$\lambda = 2$	0.227	−0.158	−0.052	−0.006
S_3	$\lambda = 0.7$	0.042	−0.001	−0.020	0.006	S_8	$\lambda = 3$	0.222	−0.142	0.006	−0.081
S_4	$\lambda = 0.8$	0.048	−0.004	−0.019	0.005	S_9	$\lambda = 4$	0.150	−0.127	0.062	−0.071
S_5	$\lambda = 0.9$	0.054	−0.008	−0.018	0.003	S_{10}	$\lambda = 5$	0.087	−0.073	0.063	−0.067

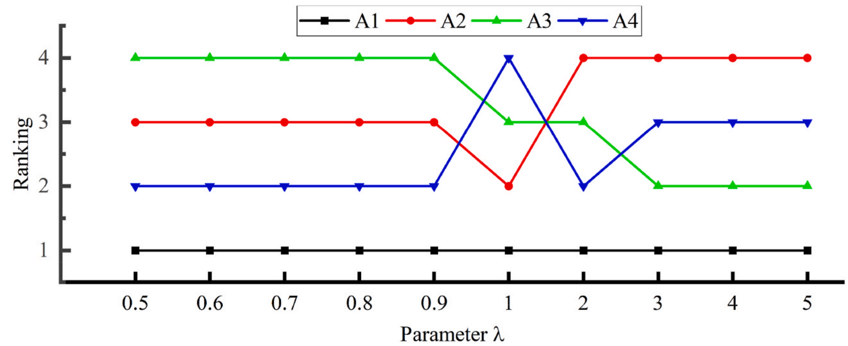

Fig. 5. Rankings of changes in the attitudes of DMs.

Table 12
The results of different MCDM methods

	A_1	A_2	A_3	A_4	Ranking
Proposed method	0.163	−0.012	−0.017	−0.051	$A_1>A_2>A_3>A_4$
IFTPOSIS	0.695	0.540	0.287	0.439	$A_1>A_2>A_4>A_3$
IFEDAS	0.838	0.566	0.207	0.352	$A_1>A_2>A_4>A_3$
IFCODAS	0.802	0.141	−0.854	−0.088	$A_1>A_2>A_4>A_3$

and groups as well as subordinate hierarchies, corresponding differences may be obtained when conducting comparative analyses. The results of the four methods were shown in Table 12, where it can be observed that by using different MCDM methods, the best and the second alternatives are always the same, while the remaining alternatives are ranked slightly differently. Among the other three methods, nuclear power plant (A_4) is ranked third, and wave energy (A_3) is ranked the last, which is the reverse of the ranking order that the methods proposed in this paper obtained. Therefore, as to verify the reliability of the proposed method, this paper tested the results using the Spearman rank correlation coefficient method, and the results were all 0.8, which means that the results obtained by the proposed method are strongly correlated with the results obtained by the other methods, which proves the reliability of the proposed method.

Furthermore, by observing the results in Tables 12 and it can be found that the scores of A_2 and A_3 in the proposed method are very close to each other, while in the rankings of the other methods, the scores of A_2 and A_3 are so large that it produces the phenomenon that the ranking of A_4 exceeds that of A_3. The reason for this phenomenon is the difference in the calculation rules of different decision-making methods, as follows.

(1) The GLDS method ranks the alternatives based on their dominance scores, taking into account individual, group, and subordinate ranking factors.
(2) Ref. [13] determines and ranks the relative closeness coefficients based on the Hamming distance between the alternatives and the positive and negative ideal solutions.
(3) Ref. [14] calculates and ranks the assessment scores based on the positive and negative distances between the alternatives and the average solution
(4) Ref. [15] constructs the relative assessment matrix based on the Euclidean distance and Hamming distance between the alternatives and the negative ideal solution and ranks them based on the final assessment scores.

Therefore, we can summarize the advantage and limitation of the proposed method as follows:

Advantage: The proposed method takes into account both individual and group as well as subordinate rank factors, which consider more criteria compensation rules than other methods and thus can simulate more practical decision-making conditions.

Limitation: The computing process of the proposed method is complicated, which may reduce the efficiency of decision-making.

7. Conclusions

In this paper, the selection of optimal RE of OSCS based on MCDM is studied. Due to the increase of greenhouse effect and the decrease of non-renewable energy, marine transportation is moving towards electrification. The establishment of OSCS using RE for power generation is an important part of the development process of marine electrification, and the selection of appropriate RE according to local conditions is crucial for the development and operation of OSCS project. Previous studies on the ranking of RE for OSCS have been limited and have been conducted only from the economic point of view, which does not take into account the uncertainty of the environment and the ambiguity of human cognition, and the criteria for the evaluation are difficult to reflect the actual situation. In order to more effectively solve these issues and encourage the healthful development of marine electrification, this paper proposed a hybrid fuzzy MCDM framework, which had the following main advantages.

(1) An evaluation system consisting 16 criteria has been constructed in five aspects, which can better reflect the actual situation.
(2) The use of IFS to express the uncertainty of perceptions of experts provides them with a more humanized way of expressing their opinions as well as making their evaluations more realistic.
(3) The method of calculating expert weights based on information quality under IF environment can calculate the weights of each expert under various criterion in various alternative, and the expert weights obtained by this method are more reasonable, taking into account the differences in the knowledge and experience of experts.
(4) Combining subjective judgment and objective information of experts, the comprehensive weighting method combining SWARA-II and CRITIC methods is used to obtain the weight of criteria, so as to make the allocation of weights of criteria more credible.
(5) Aggregation using the GIFWGIA operator takes into account expert attitudes to make the obtained aggregation results more realistic.
(6) Utilizing the IFGLDS method, which considers both the ambiguity of the environment in the real world, as well as individuals and groups and subordinate rank, and finally using aggregation equation to obtain decision-making results.

In this paper, the proposed framework was applied to study the case of ranking REs for OSCS in Pingtan Island, Fujian Province, and the results showed that the best RE was wind energy. The reliability and practicality of the framework were verified by sensitivity and comparative analyses, and several sensitive criteria were also checked, such as investment cost, operation and maintenance cost, payback duration, and impact on the ecosystem. These criteria help to improve the potential alternatives by optimizing the corresponding ratings. In conclusion, the decision-making framework proposed in this paper can overcome the shortcomings of previous studies, improve the accuracy and efficiency of decision-making, and provide a theoretical reference for researches on selection of optimal RE of OSCS.

Statements and declarations

Competing interests

The authors declare no conflicts of interest.

Data availability

Data will be made available on request.

Consent to participate

Not applicable.

Consent for publication

Not applicable.

Ethical approval

This article does not contain any studies with human participants or animals performed by any of the authors.

CRediT authorship contribution statement

Qinghua Mao: Supervision, Project administration, Investigation, Conceptualization. **Jiacheng Fan:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Formal analysis, Data curation. **Saqif Imtiaz:** Validation, Supervision, Funding acquisition. **Hafiz Mudassir Munir:** Validation, Supervision, Writing – review & editing. **Theyab R. Alsenani:** Validation, Supervision, Conceptualization, Writing – review & editing. **Mohammed Alharbi:** Validation, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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