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Route Selection for Low-carbon Ammonia Production: A Sustainability Prioritization Framework based-on the Combined Weights and Projection Ranking by Similarity to Referencing Vector Method

Di Xu[a, d], Liping Lv[b], Xusheng Ren[a], Jingzheng Ren[c, *], Lichun Dong[a, b, e, *]

[a]School of Chemistry and Chemical Engineering, Chongqing University, Chongqing 400044, China.

[b]School of Chemistry and Chemical Engineering, Collaborative Innovation Center for Green Development in Wuling Moutain Area, Research Center for Environmental Monitoring, Hazard Prevention of Three Gorges Reservoir, Yangtze Normal University, Fuling 408100, Chongqing, China.

[c]Department of Industrial and Systems Engineering, The Hongkong Polytechnic University, Hongkong SAR, China.

[d]Centre for Sustainable Engineering Operations Management, Department of Technology and Innovation, University of Southern Denmark, Campusvej 55, 5230 Odense M, Denmark.

[e]Key Laboratory of Low-grade Energy Utilization Technologies & Systems of the Ministry of Education, Chongqing University, Chongqing 400044, PR China.

***Corresponding Authors:** Lichun Dong and Jingzheng Ren

E-mail: lcdong72@cqu.edu.cn (L Dong). Tel: +86-23-65105051.

E-mail: renjingzheng123321@163.com (J Ren). Tel: +852-27666596

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Abstract: In this study, a mathematical framework was developed for the sustainability prioritization of alternative low-carbon ammonia production routes. In the framework, a four-dimensional assessment system that can incorporate both quantitative and qualitative criteria from the environmental, economic, social-political, and technical concerns was firstly established. Subsequently, a hybrid Entropy-FANP method was employed to determine the criteria's weight by combining the objective data and subjective opinions; a novel PRSRV approach was developed to rigorously rank the alternative routes by aggregating the absolute sustainability performance and relative sustainability balance of each alternative. The proposed framework was applied to prioritize five promising low-carbon routes for ammonia production, i.e. wind turbine electrolysis (WGEA), solar photovoltaic electrolysis (PVEA), hydropower electrolysis (HPEA), biomass gasification electrolysis (BGEA), and nuclear high temperature electrolysis (NTEA), yielding the sustainability ranking of HPEA>BGEA>WGEA>PVEA>NTEA. The robustness and effectiveness of the proposed framework were verified by conducting the sensitivity analysis and comparing the results determined by the proposed framework with those determined using the previous approaches.

Keywords: Low-carbon ammonia production, sustainability prioritization, criteria system, combined weights, PRSRV method

1. Introduction

Ammonia, the second most produced chemical in the world with the capacity over 200 million tons per annum globally, was widely utilized in the fields of fertilizer, refrigerant, explosive, detergent, etc (Giddey et al., 2017). Over the past few years, it has received considerable attentions to also take ammonia as a promising fuel and energy carrier due to its characteristics of carbon free, high energy density, and convenience in transportations and storage (Bicer and Dincer, 2018). However, 96% of the global ammonia capacity is realized by using hydrogen from fossil fuels *via* three main technologies, i.e. steam reforming of nature gas, coal gasification, and partial oxidation of heavy fuel oil (Bartels., 2008), consuming nearly 2% of the total primary energy and accounting for around 1% of greenhouse gas emissions in the world (Bicer et al., 2016; Giddey et al., 2017). Therefore, a growing number of studies have recently focused on realizing more sustainable ammonia synthesis *via* different low-carbon pathways (Figure 1), especially the use of electrolysis-based hydrogen in conjunction with the low-carbon energies such as wind, solar, hydropower, and nuclear (Beerbuhl et al., 2015; Du et al., 2015; Tallaksen et al., 2015; Bicer et al., 2016; Cinti et al., 2017; Bicer and Dincer, 2017b), and the biomass gasification (Andersson and Lundgren, 2014; Arora et al., 2017). For instance, Tallaksen et al. (2015) indicated that the community-scale ammonia production system powered by wind source demands the primary energy input from 15 to 107 MJ per functional unit while only emitting 70-130 g CO_2, which has the potential to significantly reduce fossil-fuel inputs and greenhouse gas (GHG) emissions compared to the natural gas-based ammonia. Cinti et al. (2017) demonstrated that the production of ammonia using electricity from wind or solar powers *via* the solid oxide electrolysis could decrease 40% of the power input compared to the natural gas plant and realize zero emission of CO_2. Beerbuhl et al. (2015) employed the combined capacity and scheduling planning of a flexible electricity-to-hydrogen-to-ammonia plant, approving its economic potential to incoporate the renewable electricity into ammonia production. Anderson and Lundgren (2014) performed a techno-economic evaluation of ammonia production *via* the integrated biomass gasification in an existing pulp and paper mill, indicating that the overall energy efficiency of the integrated system can increase by 10% compared to a traditional stand-alone mill in parallel with the operation of ammonia production plant. Arora et al. (2017) implyed that the biomass-to-ammonia processes could gain attractive GHG emission reduction compared to the conventional fossil fuel-based systems, but the economic and environmental profiles of each process are related to the location.

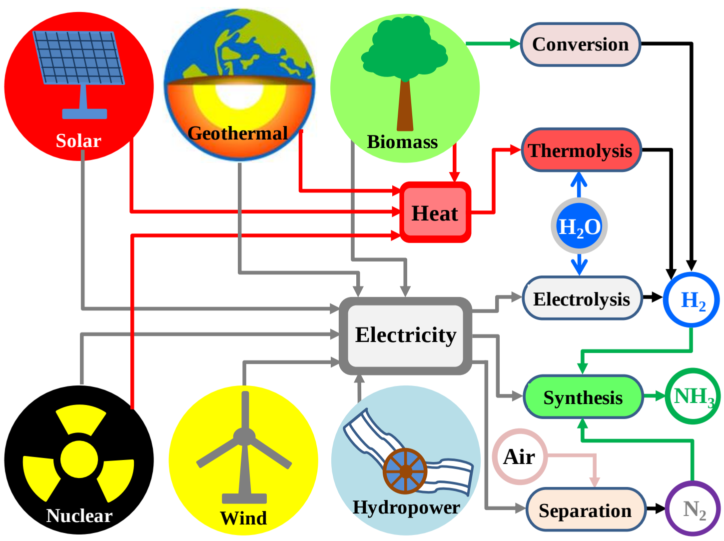

Figure 1. Several promising routes for low-carbon ammonia production.

A growing number of low-carbon ammonia generation systems have been extensively developed in the past decades, resulting in the emergence to compare the different ammonia production pathways. Frattini et al. (2016) assessed three promising ammonia generation pathways, i.e. biomass gasification, biogas reforming, and high-temperature water electrolysis by using wind or solar energy, and demonstrated that the route of water electrolysis is more preferred over the two bio-paths from the energy and environmental perspectives. A techno-economic evaluation of ammonia production using grid-based electricity produced from wind power, biogas, and woody biomass was employed by Tunå et al. (2014), demonstrating that the biomass-based technology consumes more energy while requires less costs than the other methods. Bicer et al. (2016) conducted the life cycle assessment (LCA) of four ammonia generation systems, implying that the hydropower-based process gains higher sustainability index and technical efficiency than the municipal waste-, nuclear-, and biomass-based routes. A much wider range of ammonia production routes from the conventional fossil fuels to the low-carbon sources were compared by Bicer and Dincer (2017a) using the LCA approach, offering a detailed environmental impact dataset regarding each system.

The above-mentioned studies compared the different ammonia production routes on environmental impacts or technical/economic performances individually, falling to identify the best route by using a comprehensive assessment system that consists of multiple conflicting criteria from different sustainability concerns. For tackling this issue, the Multi-Criteria Decision-Making (MCDM) methods can be adopted as feasible tools for the sustainability assessment of different options according to their performances regarding multiple criteria. Under the umbrella of MCDM, the methods of AHP (Analytic Hierarchy Process), PROMETHEE, ELECTRE, TOPSIS, and VIKOR etc., have been frequently applied for assessing energy or industrial systems like municipal solid waste management (Coban et al., 2018), polygeneration system (Wang et al., 2017), and thermal power plants (Li and Zhao, 2016), etc. Since ammonia is realized *via* the reaction of hydrogen and nitrogen, the investigation of potential pathways for green hydrogen production using the MCDM methods can offer great inspirations for the low-carbon ammonia production system. For instance, the AHP method or its fuzzy form were employed for the evaluation of hydrogen systems by considering multiple criteria from technical, environmental, economic, and other concerns (Pilavachi et al., 2009, Chung et al., 2014, Thengane et al., 2014). The Fuzzy AHP (FAHP) and data envelopment analysis (DEA) were combined to rank 13 hydrogen generation alternatives in terms of their performances regarding economic and technical criteria; in which, the criteria's weights were assigned by FAHP and the alternatives' efficiency was calculated by using the DEA method (Lee et al., 2011). Chang et al. (2011) ranked the hydrogen production technologies by using the fuzzy Delphi method to consider 14 criteria within a comprehensive sustainability assessment system. Ren et al. (2016) developed a hybrid MCDM approach for the sustainability prioritization of hydrogen generation systems, in which, the FAHP, fuzzy Analytic Network Process (FANP) and PROMETHEE methods were, respectively, used for scoring the non-quantifiable criteria, allocating the criteria's weights, and ranking the alternatives. A sustainability ranking framework based-on the life cycle thinking was proposed for the hydrogen production options by integrating the DEMATEL method for weights determination and the EDAS (evaluation based on distance from average solution) model for alternatives prioritization (Ren and Toniolo, 2018).

According to the literatures, a MCDM-based framework for sustainability assessment usually consists of three main steps including construction of criteria system, determination of criteria's weights, and prioritization of alternatives' sustainability sequence. However, no current research has offered a comprehensive assessment system for the low-carbon ammonia production; and the existing methods rely heavily on the subjective opinions for the weights determination, which may result in an inaccurate weighting result by ignoring the objective information. Moreover, the traditional MCDM approaches rank the sustainability sequence only based on the aggregation or multiplication of the weighted performance ratings of each alternative, failing to offer a balanced consideration among multiple sustainability criteria. Therefore, this study aims to develop a framework for the sustainability prioritization of low-carbon ammonia production routes, which compares a variety of alternative routes from multiple criteria by integrating a hybrid Entropy-FANP weighting method and a novel Projection Ranking by Similarity to Referencing Vector (PRSRV) ranking model.

Besides the introduction, the remainder of this study is organized as follows: mathematical framework was given in section 2, section 3 presented the application of the framework and the results, section 4 conducted the sensitivity analysis and results comparison, implications for the theory and practice were discussed in section 5, and finally this study was concluded in section 6.

2. Mathematical Framework

The mathematical framework of this study is summarized in Figure 2, which consists of three phases, i.e. establishment of the assessment system, determination of the criteria's weights, and prioritization of the alternatives' sequence. In this section, the three generic mathematical methodologies involved in the framework including the Logarithmic Fuzzy Preference Programming (LFPP)-FAHP method for scoring each qualitative criterion, the Entropy-FANP approach for weighting the criteria's weights, and the PRSRV methodology for ranking the alternatives were introduced.

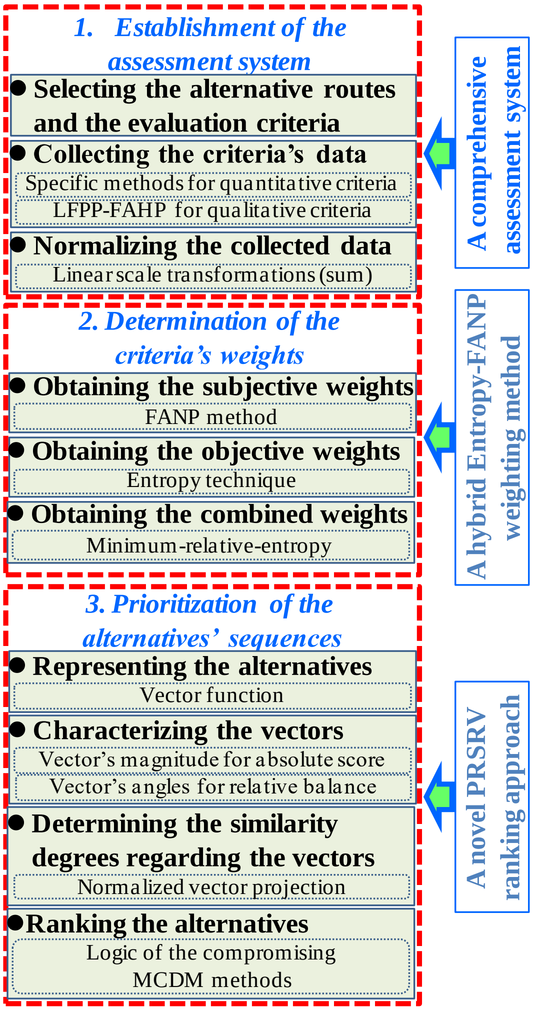

Figure 2. Framework for the sustainability prioritization of low-carbon ammonia production routes.

2.1 Overview of the mathematical framework

Phase 1: Establishment of the assessment system. The framework starts from (1). selecting the alternative routes and the evaluation criteria, in which, both qualitative and quantitative criteria from multiple concerns are considered; (2). the specific analytic tools and the LFPP-FAHP method are, respectively, utilized for collecting the alternatives' performances with respect to the quantitative criteria and the qualitative ones; (3). for the collected data have different physical units and scales, the linear scale transformations (sum) method is adopted for normalizing them into the dimensionless and unitary form for the subsquent decision-making.

Phase 2: Determination of the criteria's weights. A hybrid Entropy-FANP method is used to determine the criteria's weights by integrating both objective data and subjective opinions, which consists of (1). employing the FANP method to calculate the subjective weights, (2). using the entropy technique to determine the objective weights, and (3). obtaining the combined weights based-on the concept of minimum-relative-entropy.

Phase 3: Prioritization of the alternatives' sequence. A novel ranking method of PRSRV is developed to prioritize the alternatives by integrating the philosophy of the compromise MCDM (a preferred alternative should be close to the ideal solution while far from the nadir one) and a vector-based algorithm (a satisfactory option should simultaneously have larger absolute score and smaller relative deviation regarding the assessment system), which includes the following four procedures: (1). adopting the vector function to represent each alternative, (2). adopting the vector's absolute magnitude and relative angle to characterize the vector-presented alternative, (3). adopting the normalized vector projection to determine the similarity degree by using the vector-based algorithm, and (4). adopting the similarity coefficient to rank the alternatives by referring to the logic in the compromise MCDM methods.

2.2 Specifications of the mathematical methodologies

Three generic mathematical methodologies are adopted in the framework i.e. the LFPP-FAHP method, the Entropy-FANP approach, and the PRSRV methodology, which are introduced as follows.

Nomenclatures		P_j^*, P_j^-	Projection of the j-th vector on the ideal vector, projection of the nadir vector on the j-th vector
f_{ij}', f_{ij}	The original data and its normalized form of the j-th alternative's performance regarding the i-th criterion	NP_j^*, NP_j^-	The normalized form of P_j^* and P_j^-, respectively
u	Combined coefficient for aggregating the weights	SC	Similarity coefficient for ranking the alternative routes
w_i^O, w_i^S, w_i	Objective weight, subjective weight, combined weight of the i-th criterion, respectively	δ_i^{r-s}, $\tilde{\delta}_i^{r-s}$	The minimum change in w_i for altering the order of s-r in terms of absolute and relative form, respectively
$\vec{S}_j$, $\vec{S}^*$, $\vec{S}^-$	Vector function regarding the j-th route, the ideal vector function, the nadir vector function, respectively	CD	Criticality degree for identifying the critical criteria
M_j, M^*, M^-	Magnitude regarding the j-th vector, the ideal vector, and the nadir vector, respectively	$t_j(\alpha)$, $\tilde{t}_j(\alpha)$	Final score and its standardized form of the j-th alternative route determined by the ranking method α
A_j^*, A_j^-	Angle between the j-th vector and the ideal vector, angle between the j-th vector and the nadir vector	$\rho(\alpha)$	Spearman's rank correlation coefficient of the ranking method α

2.2.1 LFPP-FAHP method for scoring each qualitative criterion

Since the qualitative criteria that are usually involved in the assessment system rely on the qualitative evaluation derived from the decision-makers' knowledge and experiences, the AHP method is frequently adopted for converting subjective preferences into numerical scores with consistency by building pair-wise comparison matrices (Saaty, 2004). However, the conventional AHP only allows the decision-makers with crisp numbers (1-9 scale) to express their descriptions, failing to address the uncertainties, vagueness, and imprecision of human's judgments (Ren et al., 2016). In order to overcome this weakness, various extended AHP methods by incorporating the fuzzy set theory have been proposed to handle the vague and imprecise qualitative judgments (Chang, 1996; Duran and Aguilo, 2008; Wang and Chin, 2011). In this study, the LFPP-FAHP method proposed by Wang and Chin (2011) was adopted to derive crisp priorities from fuzzy comparison matrices by resorting to a logarithmic fuzzy nonlinear programming model, which not only allows the users to depict their preferences using linguistic terms instead of crisp numbers, but also avoids the non-uniqueness, invalidation, even confliction associated with the results that derived from other FAHP methods (Wang and Chin, 2011). The steps of the LFPP-FAHP for scoring a qualitative criterion are as below, while the detailed computations can be found in ***Appendix A***.

- Constructing the linguistic-based comparison matrix, and then transforming it into the form of fuzzy triangular numbers;
- Calculating the optimum solution regarding the fuzzy matrix;
- Obtaining the quantified data regarding the criterion.

2.2.2 Entropy-FANP approach for determining the criteria's weights

The weighting methods in the literatures can be categorized into three groups: subjective methods such as AHP and ANP (Saaty, 2004) that only rely on decision-makers' knowledge for assigning the relative importance to the criteria; objective methods such as the entropy and CRITIC technique (Diakoulaki et al., 1995) that allocate the criteria's weights only based on the numerical data given by the assessment system; the combined weighting approach with the consideration of both objective and subjective perspectives (Li and Zhao, 2016). In this study, a hybrid method by combining the entropy technique and FANP approach was employed for the comprehensive weighting of the criteria.

Step 1: FANP method for determining the subjective weights. ANP, as an extended version of AHP, is a well-accepted subjective weighting method that adopts a network structure instead of a hierarchic one (see Figure. 3) to deal with the interdependence among the assessment criteria, offering a more reliable weighting result than that derived from AHP (Ren et al., 2016). Therefore, this study employed the FANP method to calculate the subjective weights with the consideration of uncertainties between human's judgments and interactions among the criteria system, in which, the LFPP-FAHP was employed again to calculate the local priorities and pillar's weights for supporting the FANP computations. The FANP model can be conducted as follows (specifications are offered in ***Appendix B***):

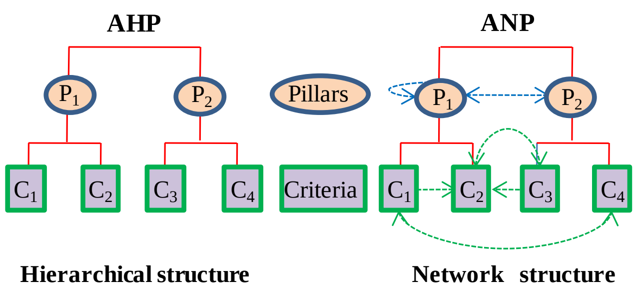

Figure 3. Structural difference between AHP and ANP.

- Establishing the network structure;
- Determining the unweighted supermatrix;

- Calculating the weighted supermatrix;
- Generating the limit supermatrix to obtain the subjective weight (w_i^S) regarding the *i*-th criterion.

Step 2: Entropy technique for determining the objective weights. Derived from thermodynamics, entropy measures the disorder degree of a system in an objective way, i.e. when the difference of the collected data of the alternatives' performance regarding a criterion is larger, this criterion would have more effect on the system, and vice versa (Li and Zhao, 2016). The entropy weighting method can be conducted as follows (computations are offered in ***Appendix C***):

- Calculating the entropy value for each criterion;
- Obtaining the objective weight (w_i^O) regard the *i*-th criterion.

Step 3: Weights combination. The objective and subjective weights are combined together to obtain a compromised relative importance regarding each criterion by using Eq. 1 (Sun et al., 2015).

$$w_i = \frac{(w_i^S)^u (w_i^O)^{(1-u)}}{\sum_{i=1}^{n} (w_i^S)^u (w_i^O)^{(1-u)}} \tag{1}$$

Here, $u \in [0,1]$ is the combined coefficient, representing the priority of the subjective weight over the objective one. If $u = 1$ or 0, the criteria's relative importance turns to be only determined by the subjective or objective weighting method; while $u = 0.5$ is the most commonly adopted value deducing by the minimum-relative-entropy, which can minimize the information losses during the weights combination (Sun et al., 2015).

2.2.3 PRSRV approach for prioritizing the alternatives' sequences

Different from the conventional MCDM methods that prioritize the alternatives only based on the absolute aggregated scores, a vector-based ranking method was recently proposed by Xu et al. (2017) to determine the sustainability sequence according to the projection of the corresponding vectors of each alternative on the ideal vector with the logic introduced by Moradi-Aliabadi and Huang (2016) that a desirable option should not only have a larger absolute score but also a smaller relative deviation from the ideal scenario as illustrated in Figure. 3(a). However, the proposed vector-based algorithm is not able to fully utilize the data regarding the alternatives' performances with respect to the weighed criteria, resulting in the difficulty to distinguish the close alternatives, especially when an alternative acts better in the magnitude while worse in the direction, e.g. $\vec{S}_1$ and $\vec{S}_2$ in Figure. 4(a). Therefore, by referring to the primary philosophy of the compromise MCDM methods, i.e. the desirable alternative should simultaneously be close to the ideal solution while far from the nadir one (Opricovic and Tzeng, 2004), this study proposes an improved vector-based MCDM method of PRSRV for the sustainability prioritization in a compromise ranking way, in which, a preferred alternative should be more similar to the ideal vector while more different from the nadir one. Figure. 4(b) illustrates the principle of the PRSRV method, while the following four steps illustrate how to use this method for the prioritization.

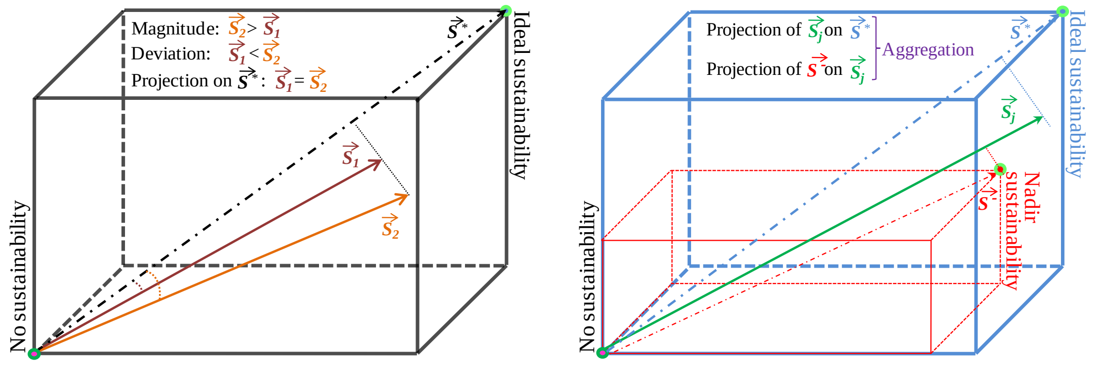

Figure 4. (a) Principle of the previous vector-based ranking method; (b) principle of the PRSRV method.

Step 1: Determining the vector function for representing the alternative. The vector function ($\vec{S}_j$) in Eq. 2 is firstly determined to represent the sustainability performance of the *j*-th alternative by modifying the procedures reported in the literatures (Moradi-Aliabadi and Huang, 2016; Xu et al., 2017); and two referencing vectors, i.e. the ideal vector ($\vec{S}^*$) in Eq. 3 and the nadir one ($\vec{S}^-$) in Eq. 4, can be deduced according to the corresponding maximal and minimal data with respect to the weighted categorized performances, implying the most desirable and undesirable alternatives, respectively.

$$\vec{S}_j = w_i f_{ij} = \left\{ w_1 f_{1j}, w_2 f_{2j}, \cdots, w_n f_{nj} \right\} \tag{2}$$

$$\vec{S}^* = w_i f_i^* = \left\{ w_1 f_1^*, w_2 f_2^*, \cdots, w_n f_n^* \right\} \tag{3}$$

$$\vec{S}^- = w_i f_i^- = \left\{ w_1 f_1^-, w_2 f_2^-, \cdots, w_n f_n^- \right\} \tag{4}$$

where $f_i^* = \max_{j=1,2,\cdots,m} \left\{ f_{ij} \right\}$, $f_i^- = \min_{j=1,2,\cdots,m} \left\{ f_{ij} \right\}$, f_{ij} represents the normalized data of the *j*-th alternative's performance regarding the *i*-th criterion, w_i is the combined weight.

Step 2: Calculating the vector's magnitude and angles for depicting the alternative. In this step, two parameters are needed, i.e. the vector's absolute magnitude and relative angle (Xu et al., 2017). In one hand, the vector's magnitude (M_j) is calculated according to Eq. 5 for representing the absolute sustainability performance of the j-th alternative with a higher value indicating a better alternative. Obviously, the ideal vector gains the largest magnitude (M^*), while the nadir vector has the smallest one (M^-) for $M^- \le M_j \le M^*$. In the other hand, the angles between the investigated vector and the referencing vectors ($\vec{S}^*$ or $\vec{S}^-$) can be calculated according to Eq. 8 or 9 to indicate the direction of the vector. Apparently, a smaller value of A_j^* is desirable for implying that the alternative is more consistent with the ideal vector's direction; in contrast, a bigger value of A_j^- would be preferred for demonstrating a larger deviation from the nadir vector.

$$M_j = \sqrt{\sum_{i=1}^{n} (w_i f_{ij})^2} \tag{5}$$

$$M^* = \sqrt{\sum_{i=1}^{n} (w_i f_i^*)^2} \tag{6}$$

$$M^- = \sqrt{\sum_{i=1}^{n} (w_i f_i^-)^2} \tag{7}$$

$$A_j^* = \arccos\left(\frac{\vec{S}_j \cdot \vec{S}^*}{M_j M^*}\right) = \arccos\left(\frac{\sum_{i=1}^{n} (w_i^2 f_{ij} f_i^*)}{\sqrt{\sum_{i=1}^{n} (w_i f_{ij})^2} \times \sqrt{\sum_{i=1}^{n} (w_i f_i^*)^2}}\right) \tag{8}$$

$$A_j^- = \arccos\left(\frac{\vec{S}_j \cdot \vec{S}^-}{M_j M^-}\right) = \arccos\left(\frac{\sum_{i=1}^{n} (w_i^2 f_{ij} f_i^-)}{\sqrt{\sum_{i=1}^{n} (w_i f_{ij})^2} \times \sqrt{\sum_{i=1}^{n} (w_i f_i^-)^2}}\right) \tag{9}$$

Step 3: Obtaining the normalized vector projection for determining the similarity degree. Since the investigated vectors are characterized by both the absolute magnitude and relative angles, the projection of the j-th alternative on the ideal vector (Eq. 10), and the projection of the nadir vector on the j-th alternative (Eq. 11) are correspondingly utilized to calcualte the similarity degrees between the vector-pairs: $\vec{S}_j \,\Box\, \vec{S}^*$ and $\vec{S}^- \,\Box\, \vec{S}_j$. Mathematically, the two projections can be normalized into a uniform distribution from 0 to 1 for better comparison (Xu et al., 2017) by using Eqs. 12-13, respectively. Obviously, the greater the value of NP_j^* (or NP_j^-), the higher the similarity between the pair of $\vec{S}_j \,\Box\, \vec{S}^*$ (or $\vec{S}^- \,\Box\, \vec{S}_j$).

$$P_j^* = M_j \times \cos(A_j^*) = \sqrt{\sum_{i=1}^{n}(w_i f_{ij})^2} \times \left(\frac{\sum_{i=1}^{n}(w_i^2 f_{ij} f_i^*)}{\sqrt{\sum_{i=1}^{n}(w_i f_{ij})^2} \times \sqrt{\sum_{i=1}^{n}(w_i f_j^*)^2}} \right) = \frac{\sum_{i=1}^{n}(w_i^2 f_{ij} f_i^*)}{\sqrt{\sum_{i=1}^{n}(w_i f_i^*)^2}} \tag{10}$$

$$P_j^- = M^- \times \cos(A_j^-) = \sqrt{\sum_{i=1}^{n}(w_i f_i^-)^2} \times \left(\frac{\sum_{i=1}^{n}(w_i^2 f_{ij} f_i^-)}{\sqrt{\sum_{i=1}^{n}(w_i f_{ij})^2} \times \sqrt{\sum_{i=1}^{n}(w_i f_i^-)^2}} \right) = \frac{\sum_{i=1}^{n}(w_i^2 f_{ij} f_i^-)}{\sqrt{\sum_{i=1}^{n}(w_i f_{ij})^2}} \tag{11}$$

$$NP_j^* = \frac{P_j^*}{M^*} = \frac{\sum_{i=1}^{n}(w_i^2 f_{ij} f_i^*)}{\sum_{i=1}^{n}(w_i f_i^*)^2} \tag{12}$$

$$NP_j^- = \frac{P_i^-}{M_j} = \frac{\sum_{i=1}^{n}(w_i^2 f_{ij} f_i^-)}{\sum_{i=1}^{n}(w_i f_{ij})^2} \tag{13}$$

Step 4: Calculating the similarity coefficient for ranking the alternatives. Inspirited by the philosophy of the compromise MCDM methods, it is reasonable to deem that a desirable alternative should simultaneously have higher similarity degree with the ideal vector but lower similarity degree with the nadir one, therefore, an aggregated similarity coefficient (*SC*) can be defined in Eq. 14 for ranking the alternatives. Apparently, a larger *SC* indicates a higher priority of the alternative.

$$SC_j = \frac{NP_j^*}{NP_j^* + NP_j^-} \tag{14}$$

3. Framework Application

In this section, the developed framework is illustrated by assessing and prioritizing the sustainability of five low-carbon ammonia production routes in China. This application can shed significant light not only on China's ammonia industry but also the fossil fuel-based and low-carbon energy systems in the near future since China is not only the largest ammonia producer in the world, which depends heavily on the coal gasification for more than 70% of its total capacity (Zhang et al., 2012), but also the world's largest producer and consumer of low-carbon energy products (Zhang et al., 2017), offering vast opportunities for realizing green ammonia production.

3.1 Assessment system

3.1.1 Alternative route and evaluation criteria

Alternative routes: Five low-carbon ammonia production routes using the top non-fossil energy resources espoused by the 13th five-year plan of China (CNREC, 2017), i.e. wind power, solar power, hydropower, biomass and nuclear power, were selected as the assessment alternatives. All the five routes belong to the electrolysis-based ammonia production, since the corresponding electricity-generation systems have already been commercialized, offering promising opportunities for realizing the low-carbon ammonia in the near future. Notably, the users can choose the alternative routes by themselves according to the actual assessment requirements. The simplified flowcharts regarding the five routes were presented in Figure 5 by referring to the works of Bicer et al. (2016, 2017). In four of the five routes, the electricity generated from the corresponding wind power, solar power, hydropower, and biomass-gasification plant is used in the electrolyzer to obtain hydrogen from water, the cryogenic air separation (CAS) is used to produce nitrogen from air, and the Haber-Bosch (HB) process is used to synthesize ammonia; and the corresponding route is denoted as WGEA, PVEA, HPEA, and BGEA. Being slightly different from the four alternatives, the waste heat from the nuclear power plant is used to reduce the required amount of electricity for water electrolysis in the route of NTEA, while the nuclear-based electricity is employed for driving the same three units.

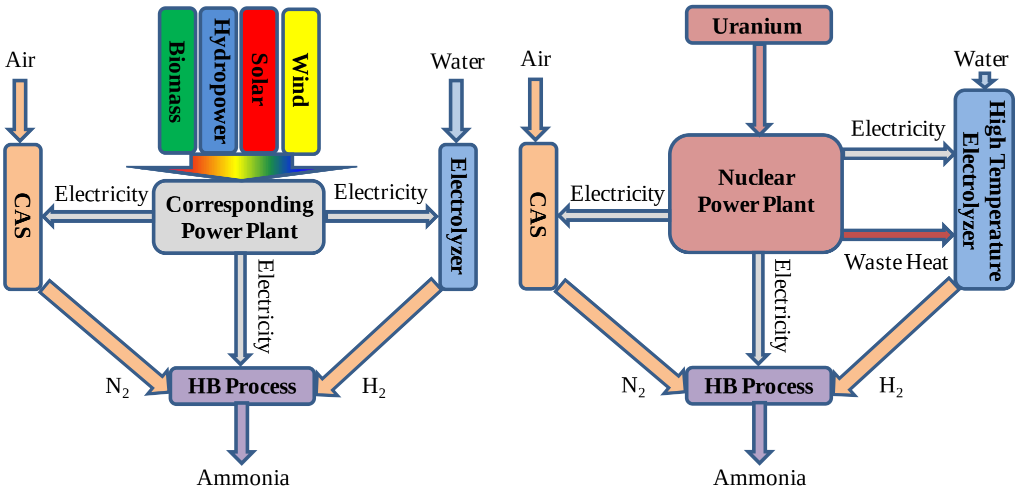

Figure 5. (a) Low-carbon ammonia production routes powered by wind/solar/hydropower/biomass;
(b) low-carbon ammonia production route *via* nuclear powered high-temperature electrolysis.

Evaluation criteria: Typically, a comprehensive criteria system for the assessment of complex energy routes is the integration of the classic three pillars, i.e. the economic prosperity, environmental impacts, and social responsibility. However, various criteria from the technical and politic concerns are increasingly suggested to be incorporated into the sustainability assessment, because these criteria could affect the criteria from the environmental, economic, and social pillars (Ren et al., 2016). Therefore, in this study, a criteria system (Table 1) consisting of twelve criteria from the environmental, economic, social-political, and technical pillars was established based-on literature reviews and a focus group meeting. For more detailed descriptions regarding each criterion, the literatures listed in the last column of Table 1 can be referred. Notably, the users can add or delete criteria according to the actual conditions and their preferences.

Table 1. Overview of the criteria system

Pillar	Criterion	Type	Collection method	Reference
(P_1) Environmental	Human toxicity(C_{11})	Quantitative(Negative)	CML 2001	Bicer et al., 2016
	Global warming(C_{12})	Quantitative (Negative)	CML 2001	Bicer et al., 2016
	Abiotic depletion(C_{13})	Quantitative (Negative)	CML 2001	Bicer et al., 2016
(P_2) Economic	Life cycle costs(C_{21})	Quantitative (Negative)	Life cycle costing	Li et al., 2017
	Economic contribution(C_{22})	Qualitative (Positive)	LFPP-FAHP	Troldborg et al., 2014
	Market potential(C_{23})	Quantitative (Positive)	Statistical data	Zubaryeva and Thiel, 2013
(P_3) Social-political	Inherent safety(C_{31})	Quantitative (Negative)	Inherent safety analysis	Heikkilä, 1999
	Social acceptance(C_{32})	Qualitative (Positive)	LFPP-FAHP	Troldborg et al., 2014
	Policy applicability(C_{33})	Qualitative (Positive)	LFPP-FAHP	Ren et al., 2016
(P_4) Technical	Energy efficiency(C_{41})	Quantitative (Positive)	Thermodynamic analyses	Bicer et al., 2016
	Technology maturity(C_{42})	Qualitative (Positive)	LFPP-FAHP	Troldborg et al., 2014
	Resource reliability(C_{43})	Qualitative (Positive)	LFPP-FAHP	Ren et al., 2016

3.1.2 Data Collection

In Table 1, the involved twelve criteria can be classified into the quantitative type or qualitative type (the 3rd column in Table 1). Accordingly, various specific analytic tools (the 4th column of Table 1) were used for collecting the data of each quantitative criterion, while the LFPP-FAHP approach was used for scoring the performances regarding qualitative criteria based-on literature reviews and experts judgments. Table 2 summarizes the collected data regarding each criterion, while their detailed computations are offered in the ***Supplementary data***.

Table 2. Collected data of the alternative's performance regarding each criterion

f'_{ij}	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
	kg 1,4-DB eq	kg CO_2 eq	10^{-2}kg Sb eq	M$/(t/day)	-	%	scores	-	-	%	-	-
WGEA	0.82	0.47	0.35	3.318	0.231	27.3	16	0.267	0.247	16.4	0.204	0.179
PVEA	0.87	0.86	0.63	4.549	0.279	14.0	16	0.267	0.211	9.4	0.179	0.179
HPEA	0.13	0.38	0.29	3.615	0.165	47.9	16	0.234	0.289	42.7	0.234	0.330
BGEA	0.08	0.85	0.28	1.341	0.173	1.9	33	0.149	0.126	15.4	0.179	0.202
NTEA	0.95	0.84	0.64	2.230	0.151	9.0	49	0.084	0.126	23.8	0.204	0.110

3.1.3 Data normalization

In order to eliminate the effect of different physical units and scales existing in the decision-making, the linear scale transformations (sum) (Celen, 2014) as one of the most practiced normalization method was adopted in this framework for the data normalization according to the positive or negative nature of each criterion (the 3rd column in Table 1) depending whether a higher criterion value is desirable or not. For instance, a larger market potential or a higher energy efficiency is desirable for a better sustainability, so the positive criteria of C_{23} and C_{41} should be normalized by using $f_{ij} = f' / \sum_{j=1}^{5} f'_{ij}$. In contrast, the data with respect to C_{11}, C_{12}, C_{13}, C_{21}, and C_{31} were normalized by using $f_{ij} = (1/f'_{ij}) / \sum_{j=1}^{5} (1/f'_{ij})$ for a lower value regarding these criteria is more desirable (negative). The normalized data are given in Table 3; notably, there is no change of the data with respect to the qualitative criteria because they have already been normalized in the final step of LFPP-FAHP.

Table 3. Normalized data of the alternative's performance regarding each criterion

f_{ij}	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
WGEA	0.052	0.257	0.219	0.151	0.231	0.273	0.262	0.267	0.247	0.152	0.204	0.179
PVEA	0.049	0.140	0.122	0.110	0.279	0.140	0.262	0.267	0.211	0.087	0.179	0.179
HPEA	0.326	0.317	0.265	0.139	0.165	0.479	0.262	0.234	0.289	0.396	0.234	0.330
BGEA	0.529	0.142	0.274	0.374	0.173	0.019	0.127	0.149	0.126	0.143	0.179	0.202
NTEA	0.045	0.144	0.120	0.225	0.151	0.090	0.086	0.084	0.126	0.221	0.204	0.110

3.2 Weight determination

3.2.1 Subjective weights

Based-on the constructed network structure for the criteria system (Figure 6), the FANP method yielded the criteria's subjective weights (the 1st row in Table 4), indicating that the top four importance criteria are technology maturity (C_{42}), energy efficiency (C_{41}), life cycle costs (C_{21}), and political acceptability (C_{33}), which, in turn, approves the necessity of integrating the technical and political criteria into the assessment system. The detailed calculations of FANP were specified in ***Supplementary data***.

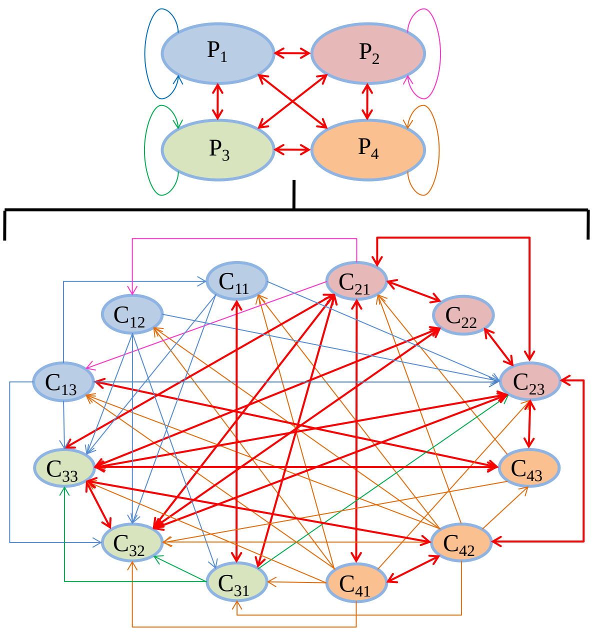

Figure 6. Network structure of the FANP method regarding the criteria system.

3.2.2 Objective weights

Based-on the dataset in Table 3, the entropy technique generated the criteria's objetive weights (the 2nd row in Table 4), implying that human toxicity (C_{11}) is the most important criterion for the final ranking for the significant differences between the alternatives' performances are involved in this criterion; in contrast, technology maturity (C_{42}), which is regarded as the least important one in the objective weights, almost has no effect on the ranking from the objective perspective, since the five routes have quite similar performance ratings regarding this criterion.

Table 4. Subjective, objective, and combined weights with respect to the criteria

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
w_i^S	0.061	0.022	0.029	0.133	0.058	0.098	0.061	0.050	0.116	0.164	0.192	0.017
w_i^O	0.304	0.047	0.041	0.071	0.019	0.233	0.058	0.051	0.038	0.091	0.004	0.043
w_i	0.163	0.039	0.041	0.116	0.040	0.181	0.071	0.060	0.079	0.146	0.031	0.032

3.2.3 Combined weights

A more comprehensive weighting result can be offered as given in the 3rd row of Table 4 by considering both the objective data and the subjective opinions using Eq. 1. In the process, the combined coefficient was set as u=0.5 to minimize the information losses; however, the users can set the coefficient by themselves according to the actual assessment requirements.

3.3 Prioritization of sustainability sequence

Based-on the database in Tables 3-4, the PRSRV method was utilized to prioritize the sustainability sequence of the five alternatives.

3.3.1 Vector function

The performances of each alternative as well as the ideal and nadir ones were depicted as the vector functions in Table 5 according to Eqs. 2-4.

Table 5. Vector functions regarding the five alternatives, and the ideal and nadir ones

$$\vec{S}_{WGEA} = \{0.89, 0.98, 0.90, 1.76, 0.92, 4.92, 1.86, 1.61, 1.96, 2.23, 0.64, 0.58\} \times 10^{-2}$$

$$\vec{S}_{PVEA} = \{0.84, 0.54, 0.50, 1.28, 1.12, 2.52, 1.86, 1.61, 1.67, 1.28, 0.56, 0.58\} \times 10^{-2}$$

$$\vec{S}_{HPEA} = \{5.64, 1.25, 1.09, 1.62, 0.66, 8.64, 1.86, 1.41, 2.29, 5.80, 0.74, 1.06\} \times 10^{-2}$$

$$\vec{S}_{BGEA} = \{8.14, 0.54, 1.13, 4.36, 0.69, 0.34, 0.90, 0.90, 1.00, 2.09, 0.56, 0.65\} \times 10^{-2}$$

$$\vec{S}_{NTEA} = \{0.77, 0.55, 0.49, 2.62, 0.60, 1.62, 0.61, 0.50, 1.00, 3.23, 0.64, 0.35\} \times 10^{-2}$$

$$\vec{S}^{*} = \{8.14, 1.25, 1.13, 4.36, 1.12, 8.64, 1.86, 1.61, 2.29, 5.80, 0.74, 1.06\} \times 10^{-2}$$

$$\vec{S}^{-} = \{0.77, 0.54, 0.49, 1.28, 0.60, 0.34, 0.61, 0.50, 1.00, 1.28, 0.56, 0.35\} \times 10^{-2}$$

3.3.2 Vector's magnitude and angles

Eqs. 5-7 and Eqs. 8-9 were used to obtain the vectors' magnitudes and angles, respectively (columns 2-4 in Table 6). Here, the sequence of HPEA>BGEA>WGEA>PVEA>NTEA was determined according to the absolute aggregated sustainability scores (M); while A^{*} and A^{-} imply that HPEA has the smallest deviation from the ideal scenario, while BGEA has the biggest deviation from the nadir scenario, respectively.

3.3.3 Vector's normalized projection

The normalized projection of the vector functions with respect to the alternative on the ideal vector (NP^*), and that of the nadir vector on the alternative (NP^-) can be correspondingly obtained (columns 5-6 in Table 6) by using Eq. 12 and Eq. 13, two sequences with a slight difference were obtained, i.e. NTEA acts better than PVEA by referring to the ideal scenario (higher value of NP^* is desirable), while PVEA is better than NTEA by referring to the nadir scenario (lower value of NP^- is desirable).

3.3.4 Sustainability ranking

According to the similarity coefficients (the 7th column in Table 6) calcualted by running Eq. 14, HPEA is regarded as the best route for realizing the low-carbon ammonia production in China, followed by BGEA,WGEA, PVEA, and NTEA in a descending order. This result is reasonable since among the twelve criteria in the assessment system, HPEA owns the best performances regarding seven criteria (C_{21}, C_{23}, C_{31}, C_{33}, C_{41}, C_{42}, and C_{43}), and two of which belong to the top three important criteria (see w_{23}, w_{11}, and w_{42}), resulting in that the vector corresponding to the HPEA is more similar to the ideal vector while more different from the nadir, simultaneously.

Table 6. Parameters and results calculated by using the PRSRV method

	M	A^*	A^-	NP^*	NP^-	SC	Rank
WGEA	0.068	0.863	0.751	0.405	0.291	0.582	3
PVEA	0.047	0.815	0.826	0.261	0.468	0.358	4
HPEA	0.126	0.972	0.703	0.842	0.147	0.851	1
BGEA	0.098	0.774	0.718	0.521	0.194	0.728	2
NTEA	0.049	0.815	0.910	0.273	0.494	0.356	5
Ideal	0.145	1.000	-	1.000	-	-	-
Nadia	0.026	-	1.000	-	1.000	-	-

4. Sensitivity analysis and results comparison

To test the robustness of the assessment result, as well as to demonstrate the effectiveness and advantages of the developed framework, three analysis items were conducted in this section, i.e. (1). sensitivity analysis by varying the combined coefficient regarding criteria's weights, (2). sensitivity analysis by identifying the critical criteria, and (3). results comparison with the conventional MCDM methods.

4.1 Sensitivity analysis by varying the combined coefficient

In this study, the combined weights were employed with the consideration of both objective data and subjective judgments. In order to test the effect of the criteria's weights on the prioritization results, the sensitivity analysis has been conducted by varying the combined coefficient in Eq. 1 from 1 to 0. The results illustrated in Figure. 7 verified that, on the one hand, the overall ranking regarding the five alternatives is relatively robust with the route of HPEA being always the best choice followed by BGEA and WGEA in a descending order, demonstrating that the proposed weighting method is relatively reliable for the sustainability prioritization of the low-carbon ammonia production routes. On the other hand, NTEA is preferred over PVEA when the subjective weights are regarded as more important ($u = 1 \sim 0.6$); otherwise, NTEA is the most undesirable one ($u = 0.5 \sim 0$), implying that both the objective data and subjective opinions can affect the final ranking.

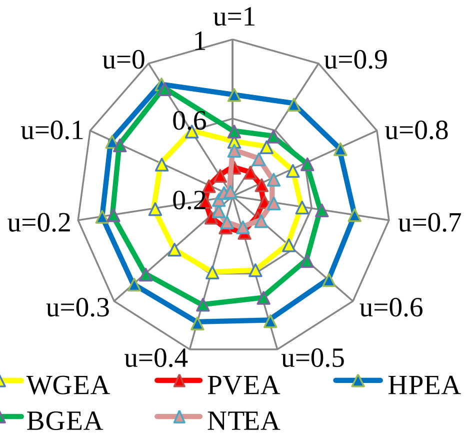

Figure 7. Results of the sensitivity analysis by varying the combined coefficient.

4.2 Sensitivity analysis by identifying the critical criteria

According to Triantaphyllou and Sanchez (1997), the most critical criterion is the one for which the minimum change in its current weight could reverse the original sequence of alternatives. Accordingly, the critical criterion is identified by altering the current weight of an investigated criterion while keeping the weights regarding the other criteria invariant (Triantaphyllou and Sanchez, 1997). Here, this study develops a programming for calculating the criticality degree (*CD*) of each criterion (specifications can be found in ***Appendix D***); while the obtained result is given in Table 7. On the one hand, according to the *CD* values (the smaller the *CD* value is, the more critical the criterion will be), the top three critical criteria for preserving the original sequence are C_{41} (*CD*=1.4), C_{23} (*CD*=1.7), and C_{21} (*CD*=2.7) in a descending order; in particularly, the ranking between PVEA-NTEA is usually reversed by the minimum change in each criterion's weight, agreeing well with the findings of subsection 4.1. On the other hand, according to the bold element in Table 7, for preserving HPEA as the best choice, the criteria of C_{23} (*CD*=55.0) and C_{11} (*CD*=81.0) are more critical than others. It is worthy pointing out that the four critical criteria of C_{11}, C_{21}, C_{23}, and C_{41} identifyed in this subsection are the same criteria being assinged with higher weights in subsection 3.2 (see w_i in Table 4). Consequently, the effectiveness of the Entropy-FANP method for the weights determination can be verified.

Table 7. Results of the sensitivity analysis for identifying the critical criteria

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{31}	C_{32}	C_{33}	C_{41}	C_{42}	C_{43}
HPEA-WGEA	N/F	N/F	N/F	-1582.8	-2011.8	N/F	N/F	**-1597.3**	N/F	N/F	N/F	N/F
HPEA-PVEA	N/F	N/F	N/F	N/F	**-1648.3**	N/F	N/F	-1793.7	N/F	N/F	N/F	N/F
HPEA-BGEA	**-81.0**	N/F	**-3631.2**	**-206.4**	-4826.5	**55.0**	N/F	N/F	N/F	N/F	N/F	N/F
HPEA-NTEA	N/F	N/F	N/F	-579.5	N/F	N/F	N/F	N/F	N/F	N/F	N/F	N/F
BGEA-WGEA	33.1	-943.0	N/F	N/F	-1267.3	-39.4	-405.8	-503.0	-423.5	-828.1	-2567.0	N/F
BGEA-PVEA	N/F	N/F	N/F	N/F	-1154.3	-148.4	-538.1	-668.4	-680.4	N/F	N/F	N/F
BGEA-NTEA	89.3	-11048.4	N/F	N/F	N/F	-268.5	N/F	N/F	N/F	-287.5	-3286.0	N/F
WGEA-PVEA	N/F	N/F	N/F	N/F	-1015.8	N/F	N/F	N/F	N/F	N/F	N/F	N/F
WGEA-NTEA	N/F	N/F	N/F	-229.5	N/F	87.9	N/F	N/F	N/F	-166.9	N/F	N/F
PVEA-NTEA	70.4	-144.3	-202.91	-2.7	34.8	1.7	4.8	6.3	14.7	-1.4	-95.6	N/F
CD	33.1	-144.3	-202.91	2.7	34.8	1.7	4.8	6.3	14.7	1.4	95.6	-

Notes: N/F (nonfeasible) due to the corresponding model is infeasible according to Lingo 11.0; bold element means that the best choice HPEA is replaced by another route; "-" refers to non-critical.

4.3 Results comparison with the conventional MCDM methods

To validate the proposed PRSRV method, three conventional MCDM methods, i.e. the most straightforward method-WSM (Triantaphyllou and Sanchez, 1997), the most practiced outranking technique-PROMETHEE (Ren et al., 2016), and the most popular compromise ranking approach-TOPSIS (Opricovic and Tzeng, 2004), were employed to rank the five alternatives by using the same data (Tables 3-4). The final scores (Figure 8) demonstrated that the PRSRV-sequence is consistent to that determined by the conventional MCDM methods, i.e. HPEA>BGEA>WGEA>PVEA> NTEA. Taking one step forward, the Spearman's rank correlation coefficient (ρ) was calculated according to the work of Kou et al. (2012) for comparing the final scores resulting from different ranking methods (computations are offered in ***Appendix E***), and the obtained values were also given in Figure 8.

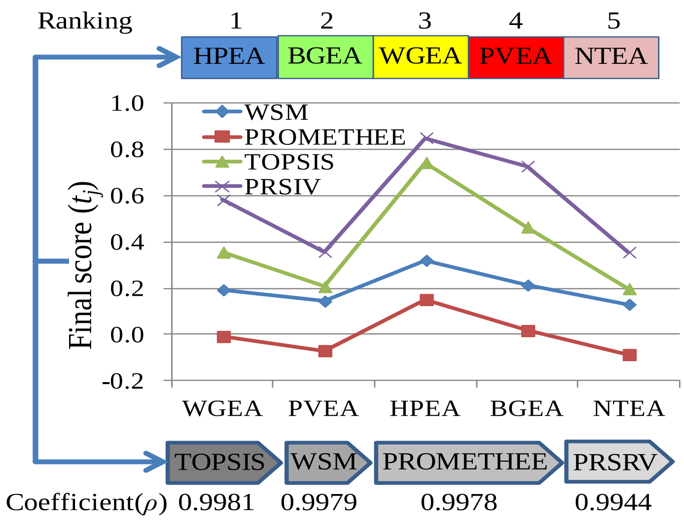

Figure 8. Final scores, ranking results, and Spearman's rank correlation coefficients of different ranking methods.

The obtained PRSRV coefficient implies that there is a very strong correlation between the outputs of the PRSRV with the conventional MCDM methods ($\rho = 1$ means a complete agreement), approving the feasibility of the proposed PRSRV. However, the PRSRV is also identified as the method that has the largest deviation from the other ranking methods (ρ = 0.9944). This difference could be attributed to the fact that the relative balance among the criteria system is innovatively incorporated into the aggregated scores in the PRSRV method. More important, it is pretty favored by the nature of the sustainability to balance the performances among multiple criteria (Moradi-Aliabadi and Huang, 2016; Xu et al., 2017), making it reasonable to draw the conclusion that the sustainability of the low-carbon ammonia production routes in particular, but not exclusively, can be more comprehensively and reliably prioritized by using the PRVIS method instead of the conventional MCDM.

5. Theoretical and Practical Implications

The results of this study could have some implication for theory and practice. For the theoretical part, (1). it contributes to the literature on the comparison of ammonia production routes by proving insight into the application and importance of a comprehensive four-dimensional evaluation criteria system, which not only extends the existing evaluation system but also approves the importance for incorporating the technical and political criteria. (2). The hybrid weighting method by combining the objective data and subjective opinions is supported by this study; in particularly, the Entropy-FANP method used in this study can offer a flexible way to adjust the priority of the subjective weight over the objective one. (3). A novel ranking approach of PRSRV is developed in this work by integrating the vector-based algorithm with the philosophy of the compromise MCDM methods, which overcomes the limitation of the conventional MCDM methods in respect of ignoring the relative sustainability balance. Moreover, the PRSRV method can be taken as a generic approach for ranking other energy or industrial-related technologies or systems due to its rigorous logic but simple procedures.

In practice, (1). the selected evaluation criteria with detailed computations provide the decision-makers with a comprehensive criterial system on assessing the sustainability of low-carbon ammonia production. (2). The weighting result reveals that the most effective way to enhance the sustainability of an alternative route is to improve its technical performances including energy efficiency and technology maturity; consequently, more efforts are needed in the future to create a more efficient and reliable way for converting input power to green ammonia. (3). This work prioritized the sustainability of five promising low-carbon ammonia production routes, and showed that the hydropower-based pathway might be the best option under current conditions. This finding is in line with the result reported by Bicer et al. (2016), which provides useful information to the decision-makers who seeking to realize the sustainable ammonia product in the near future.

6. Conclusion

In this contribution, a novel mathematical framework was developed for the sustainability prioritization of low-carbon ammonia production routes, in which, a comprehensive evaluation system that consists of twelve criteria from four categorized pillars was established to assess the ammonia production alternatives using the top five espoused low-carbon energy in China. For offering the best evaluation regarding the alternatives' performances with respect to each criterion, several specific analytic tools were suggested to collect the quantitative data, while the LFPP-FAHP method was adopted to score the qualitative ones. Subsequently, the Entropy-based objective weights and the FANP-derived subjective weights were combined for comprehensively representing the relative importance of each criterion; consequently, the disorder degrees and mutual relationships among the criteria, as well as the uncertainties in human's judgments can be properly addressed. Finally, a novel and rigorous PRSRV ranking method was developed to prioritize the alternatives' sustainability sequence by deeming that the desirable route should simultaneously be more similar to the ideal scenario and more different from the nadir one.

By using the developed framework, the sustainability sequence of the five low-carbon ammonia production routes was prioritized to be HPEA>BGEA>WGEA>PVEA>NTEA. Two sensitivity analysis approaches, i.e. varying the combined coefficient and identifying the critical criteria, were employed to investigate the robustness of the ranking result, and the effectiveness of the PRSRV method was confirmed by comparing with three well-practiced MCDM approaches.

The proposed framework provides a novel and rigorous methodology for the sustainability prioritization of low-carbon ammonal production routes with the advantages: (1). considering both the quantitative and qualitative criteria for offering a comprehensive assessment system; (2). combining the objective and subjective weights for assigning accurate weights to the criteria; (3). integrating the logic of a vector-based algorithm with the philosophy of the compromise MCDM ranking for providing a rigorous prioritization result. However, this framework can not able to address the uncertainties associated with the collected quantitative data. Consequently, a further work should focus on adapting this framework for dealing with the input numerical data with certain ranges or distributions rather than fixed numbers.

Acknowledgements

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Appendix A. Steps for the LFPP-FAHP method (Wang and Chin, 2011)

Step.1: Assuming there are *m* alternatives; the performances between each pair of alternatives regarding a criterion are compared by using the linguistic terms (Table A1). After transferring the linguistic judgments into fuzzy triangular numbers according to Table A1, a fuzzy comparison matrix can be established (Eq. A1).

Table A1. Linguistic variables and corresponding fuzzy scales for the pair-wise comparison (Tseng et al., 2009)

Linguistics variable	Abbreviation	Fuzzy triangular number
Equally priority	E	(1,1,1)
Weak priority	W	(2/3,1,3/2)
Moderate priority	M	(1,3/2,2)
Fairly strong priority	FS	(3/2,2,5/2)
Very strong priority	VS	(2,5/2,3)
Absolute priority	A	(5/2,3,7/2)
Reciprocals of these	RW, RM, RFS, RVS, RA	The reciprocals of the fuzzy numbers

$$\tilde{X} = [\tilde{x}_{ij}]_{m\times m} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1m} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mm} \end{bmatrix} \quad \text{(A1)}$$

where $\tilde{x}_{ij} = (x_{ij}^L, x_{ij}^M, x_{ij}^U)$ is a triangular fuzzy number that represents the performance of the *i*-th alternative compared to the *j*-th alternative regarding the criterion.

Step.2: Eq. A2 is used to obtain the optimal solution $X = \left[x_1, x_2, ..., x_m\right]$ regarding the fuzzy matrix (Eq. A1):

$$\begin{aligned}
& Minimize\ \ J = (1-\lambda)^2 + N\sum_{t=1}^{m-1}\sum_{k=t+1}^{m}\left(\delta_{ij}^2 + \eta_{ij}^2\right) \\
& x_i + x_j - \lambda \ln(x_{ij}^M / x_{ij}^L) + \delta_{ij} \geq \ln x_{ij}^L, i = 1,2,...,m-1;\ j = 1,2,...,m \\
& -x_i + x_j - \lambda \ln(x_{ij}^U / x_{ij}^M) + \eta_{ij} \geq -\ln x_{ij}^U, i = 1,2,...,m-1;\ j = 1,2,...,m \\
& \lambda, x_i \geq 0, i = 1,2,...,m \\
& \delta_{ij}, \eta_{ij} \geq 0, i = 1,2,...,m-1;\ j = i+1,2,...,m
\end{aligned} \tag{A2}$$

where *N* is a specified sufficiently large constant set by the user (e.g. N=10^7), λ is the minimum membership degree to the logarithm of a triangular fuzzy judgment, and $\delta_{ij}, \eta_{ij} \geq 0, i = 1,2,...,m-1;\ j = i+1,2,...,m$ are the assumed nonnegative deviation variables to avoid λ from taking a negative value.

Step.3: Eq. A3 is utilized to obtain the relative priorities of the involved elements.

$$p_i = \frac{\exp(x_i)}{\sum_{i=1}^{m}\exp(x_i)} \tag{A3}$$

where $x_i (i = 1, 2, \cdots, m)$ is the optimal solution of Eq. A2, $\left[p_1, p_2, ..., p_m\right]$ denotes the quantified scores of the alternatives' performances with respect to the investigated criterion.

Appendix B. Steps for the FANP method (Govindan et al., 2016; Ren et al., 2016)

Step 1: The network structure including the interactions among the criteria and the interdependencies between the pillars is established by the decision-makers.

Step 2: The unweighted supermatrix is created directly from the local priorities derived from the pair-wise comparison matrix regarding the criteria' relationships by using the LFPP-FAHP, while the comparison matrix is constructed by pair-wisely comparing the criteria in each pillar with respect to their impacts on an investigated criterion.

Step 3: The pillars' weights are generated according to the pair-wise comparison matrix regarding the pillars relationships also by using the LFPP-FAHP, during which, the matrix is constructed by pair-wisely comparing the pillars in terms of their influences on the investigated one. Subsequently, by multiplying the criterion's local priority with the corresponding pillar's weight, the weighted supermatrix can be obtained, where the global priorities regarding the criteria need to be normalized to make the sum of each column of the weighted supermatrix to be equal to 1.

Step 4: In this step, the weighted supermatrix is converted into the limit one by raising itself to multiple powers; then, the final subjective weight of each criterion can be obtained.

Appendix C. Steps for the Entropy technique (Li and Zhao, 2016).

Step 1: Assuming there are *m* alternatives and *n* criteria; the entropy value of the *i*-th criterion (E_i) is determined by using Eq. C1:

$$E_i = \frac{-\sum_{j=1}^{m}\left[f_{ij} \ln(f_{ij})\right]}{\ln(m)} \tag{C1}$$

Step 2: The objective weight is obtained by using Eq. C2:

$$w_i^O = \frac{1-E_i}{\sum_{i=1}^{n}(1-E_i)} \tag{C2}$$

Appendix D. Computations for identifying the critical criteria.

Assuming that the r-th route is prior to the s-th route in the original sequence ($SC_r > SC_s$), the decision-makers want to alter the $r-s$ order by modifying the original weight (w_1) regarding the criterion C_1. If δ_1^{s-r} denotes the minimum change in w_1 for converting $SC_r > SC_s$ into $SC_s' \geq SC_r'$, the renormalized weights of the varied criterion C_1 and the other invariant criteria can be determined by using Eqs. D1-D2 (Triantaphyllou and Sanchez, 1997).

$$w_1' = \frac{w_1 - \delta_1^{s-r}}{1-\delta_1^{s-r}} \tag{D1}$$

$$w_i' = \frac{w_i}{1-\delta_1^{s-r}};\ i=2,3,\cdots,\mathrm{n} \tag{D2}$$

According to Eq. 14, $SC_s' - SC_r' \geq 0$ can be expressed in Eq. D3.

$$\begin{aligned} &SC_s' - SC_r' \overset{\text{Eq.14}}{=} \frac{NP_s^{*\prime}}{NP_s^{-\prime} + NP_s^{*\prime}} - \frac{NP_r^{*\prime}}{NP_r^{-\prime} + NP_r^{*\prime}} \overset{\because NP^{*\prime}>0}{=} \frac{1}{NP_s^{-\prime} / NP_s^{*\prime} + 1} - \frac{1}{NP_r^{-\prime} / NP_r^{*\prime} + 1} \geq 0 \\ &\Rightarrow NP_r^{-\prime} NP_s^{*\prime} - NP_s^{-\prime} NP_r^{*\prime} \geq 0 \end{aligned} \tag{D3}$$

By integrating Eqs.D1-D2 with Eq. D3, Eq. D4 is deduced.

$$
\begin{aligned}
NP_r^{-\prime} NP_s^{*\prime} - NP_s^{-\prime} NP_r^{*\prime} &= \frac{\sum_{i=1}^{n}(w_i'^2 f_{ir} f_i^-)}{\sum_{i=1}^{n}(w_i' f_{ir})^2} \times \frac{\sum_{i=1}^{n}(w_i'^2 f_{is} f_i^*)}{\sum_{i=1}^{n}(w_i' f_i^*)^2} - \frac{\sum_{i=1}^{n}(w_i'^2 f_{is} f_i^-)}{\sum_{i=1}^{n}(w_i' f_{is})^2} \times \frac{\sum_{i=1}^{n}(w_i'^2 f_{ir} f_i^*)}{\sum_{i=1}^{n}(w_i' f_i^*)^2} \\
&= \frac{[(\frac{w_1-\delta_1^{s-r}}{1-\delta_1^{s-r}})^2 f_{1r} f_1^- + \sum_{i=2}^{n}(\frac{w_i}{1-\delta_1^{s-r}})^2 f_{ir} f_i^-]}{[(\frac{w_1-\delta_1^{s-r}}{1-\delta_1^{s-r}}) f_{1r}]^2 + \sum_{i=2}^{n}[(\frac{w_i}{1-\delta_1^{s-r}}) f_{ir}]^2} \times \frac{[(\frac{w_1-\delta_1^{s-r}}{1-\delta_1^{s-r}})^2 f_{1s} f_1^* + \sum_{i=2}^{n}(\frac{w_i}{1-\delta_1^{s-r}})^2 f_{is} f_i^*]}{1} \\
&- \frac{[(\frac{w_1-\delta_1^{s-r}}{1-\delta_1^{s-r}})^2 f_{1s} f_1^- + \sum_{i=2}^{n}(\frac{w_i}{1-\delta_1^{s-r}})^2 f_{is} f_i^-]}{[(\frac{w_1-\delta_1^{s-r}}{1-\delta_1^{s-r}}) f_{1s}]^2 + \sum_{i=2}^{n}[(\frac{w_i}{1-\delta_1^{s-r}}) f_{is}]^2} \times \frac{[(\frac{w_1-\delta_1^{s-r}}{1-\delta_1^{s-r}})^2 f_{1r} f_1^* + \sum_{i=2}^{n}(\frac{w_i}{1-\delta_1^{s-r}})^2 f_{ir} f_i^*]}{1} \\
&= \frac{[(w_1-\delta_1^{s-r})^2 f_{1r} f_1^- + \sum_{i=2}^{n}(w_i)^2 f_{ir} f_i^-] \times [(w_1-\delta_1^{s-r})^2 f_{1s} f_1^* + \sum_{i=2}^{n}(w_i)^2 f_{is} f_i^*]}{[(w_1-\delta_1^{s-r}) f_{1r}]^2 + \sum_{i=2}^{n}(w_i f_{ir})^2} \\
&- \frac{[(w_1-\delta_1^{s-r})^2 f_{1s} f_1^- + \sum_{i=2}^{n}(w_i)^2 f_{is} f_i^-] \times [(w_1-\delta_1^{s-r})^2 f_{1r} f_1^* + \sum_{i=2}^{n}(w_i)^2 f_{ir} f_i^*]}{[(w_1-\delta_1^{s-r}) f_{1s}]^2 + \sum_{i=2}^{n}(w_i f_{is})^2} \geq 0
\end{aligned}
\tag{D4}
$$

Since

$$
\begin{aligned}
&(w_1-\delta_1^{s-r})^2 f_{1s(1r)} f_1^- + \sum_{i=2}^{n}(w_i)^2 f_{is(ir)} f_i^- = (\delta_1^{s-r})^2 f_{1s(1r)} f_1^- - 2w_1\delta_1^{s-r} f_{1s(1r)} f_1^- + \sum_{i=1}^{n}(w_i)^2 f_{is(ir)} f_i^- = (\delta_1^{s-r})^2 f_{1s(1r)} f_1^- - 2w_1\delta_1^{s-r} f_{1s(1r)} f_1^- + P^-(M_{s(r)})^2 \\
&(w_1-\delta_1^{s-r})^2 f_{1s(1r)} f_1^* + \sum_{i=2}^{n}(w_i)^2 f_{is(ir)} f_i^* = (\delta_1^{s-r})^2 f_{1s(1r)} f_1^* - 2w_1\delta_1^{s-r} f_{1s(1r)} f_1^* + \sum_{i=1}^{n}(w_i)^2 f_{is(ir)} f_i^* = (\delta_1^{s-r})^2 f_{is(ir)} f_1^* - 2w_1\delta_1^{s-r} f_{1s(1r)} f_1^* + P^*(M^*)^2 \\
&[(w_1-\delta_1^{s-r}) f_{1s(1r)}]^2 + \sum_{i=2}^{n}(w_i f_{is(ir)})^2 = (\delta_1^{s-r} f_{1s(1r)})^2 - 2w_1\delta_1^{s-r}(f_{1s(1r)})^2 + \sum_{i=1}^{n}(w_i f_{1s(1r)})^2 = (\delta_1^{s-r} f_{1s(1r)})^2 - 2w_1\delta_1^{s-r}(f_{1s(1r)})^2 + (M_{s(r)})^2
\end{aligned}
\tag{D5}
$$

From Eqs. D3-D5, Eq. D5 can be obtained to calculate the minimum change (δ_1^{s-r}) in w_1 for realizing the reversion. Here, except δ_1^{s-r}, the values of the other parameters in Eq. D6 can all be found in the Tables 3, 4 and 6; while Eq. D6 can be easily solved by Lingo 11.0- a popular software to solve linear and nonlinear optimization models.

$$
\begin{aligned}
SC_s' - SC_r' &= \frac{[(\delta_1^{s-r})^2 f_{r1} f_1^- - 2w_1\delta_1^{s-r} f_{r1} f_1^- + P^-(M_r)^2] \times [(\delta_1^{s-r})^2 f_{s1} f_1^* - 2w_1\delta_1^{s-r} f_{s1} f_1^* + P^*(M^*)^2]}{[(\delta_1^{s-r} f_{r1})^2 - 2w_1\delta_1^{s-r}(f_{r1})^2 + (M_r)^2]} \\
&- \frac{[(\delta_1^{s-r})^2 f_{s1} f_1^- - 2w_1\delta_1^{s-r} f_{s1} f_1^- + P^-(M_s)^2] \times [(\delta_1^{s-r})^2 f_{r1} f_1^* - 2w_1\delta_1^{s-r} f_{r1} f_1^* + P^*(M^*)^2]}{[(\delta_1^{s-r} f_{s1})^2 - 2w_1\delta_1^{s-r}(f_{s1})^2 + (M_s)^2]} \geq 0
\end{aligned}
\tag{D6}
$$

Similarly, all the possible reversion caused by the minimum weight change regarding each pair of alternatives can be calculated by conducting the above-mentioned programming. After converting the absolute change (δ_i^{r-s}) into the relative version ($\tilde{\delta}_i^{r-s}$)

for better comparison (Eq. D7), the criticality degree (CD, Eq. D8) regarding each criterion can be obtained as given in Table 7.

$$\tilde{\delta}_i^{r-s} = \frac{\delta_i^{r-s} \times 100\%}{w_i} \tag{D7}$$

$$CD_i = \min(\left|\tilde{\delta}_i^{r-s}\right|) \tag{D8}$$

Appendix E. Computations for the Spearman's rank correlation coefficient (Kou et al., 2012).

By running Eqs. E1-E3, the coefficient of each ranking method canbe obtained.

$$\bar{t}_j(\alpha) = [t_j(\alpha) - t_{\underset{j=1,2\cdots,n}{\min}}(\alpha)] / [t_{\underset{j=1,2\cdots,n}{\max}}(\alpha) - t_{\underset{j=1,2\cdots,n}{\min}}(\alpha)] \tag{E1}$$

$$\rho(\alpha|\beta) = 1 - \frac{6\sum_{j=1}^{n}(\bar{t}_j(\alpha) - \bar{t}_j(\beta))^2}{n(n^2-1)} \tag{E2}$$

$$\rho(\alpha) = \frac{\sum_{\beta}\rho(\alpha|\beta)}{R-1} \tag{E3}$$

where n(=5) and R(=4) is the number of alternative routes and ranking methods, respectively; Eq. E1 is to standardize the scores; $\rho(\alpha|\beta)$ in Eq. E2 is the similarity between two ranking methods (α and β); Eq. E3 offers the result of the coefficient regarding each method.

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