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Prioritization of sludge-to-energy technologies under multi-data condition based on multi-criteria decision-making analysis

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Abstract

Aiming at promoting the sustainable development of sludge-to-energy and determining the decision-making process for the most sustainable option among all the scenarios, a novel multi-criteria decision-making method based on Dempster-Shafer (DS) theory and fuzzy best-worst method (FBWM) was developed. Four sludge-to-electricity technologies under uncertainty were prioritized, including incineration for electricity production, biogas from sludge digestion for electricity generation by fuel cells and gas engine, and microbial fuel cells (MFCs) for sludge treatment with electricity production. Four aspects and thirteen criteria were considered in the assessment and fuzzy BWM was employed to decide the fuzzy weights of these indicators. The uncertainty was resulted from different information forms, including crisp numbers, interval numbers and linguistic terms. Incomplete information also occurred in the data of MFCs. The results showed that incineration had the highest priority considering the overall performance on the selected indictors while MFCs had the worst performance due to the limited maturity of the technology. Biogas combustion for electricity production was also an acceptable option with stable market demand. The results also indicated the feasibility of using DS-FBWM for the multi-criteria decision-making problems of sludge-to-energy technologies with incomplete information and multi-data conditions, which can provide decision-making reference for stakeholders to make suitable choices according to the actual needs and preferences.

Keywords: sludge-to-electricity technology; Fuzzy-BWM; DS theory; DS-FBWM; sustainable development; MCDM

1 Introduction

The treatment and disposal of sewage sludge, a byproduct generated from wastewater treatment plants, has become a major issue in recent years because of the significant amount generated (Fytili and Zabaniotou, 2008; Yang et al., 2015). Harmful components such as heavy metals and pathogens contained in sludge make it necessary to process it appropriately, otherwise it will contaminate the environment and threat human health. On the other hand, valuable matters like nitrogen- and phosphorus-contained constituents and the rich-carbon content suggests that sewage sludge has high potential value for reuse and recycling (Rulkens, 2008). In the current context of sustainable development, sludge-to-energy technologies, such as anaerobic digestion (AD), composting, anaerobic fermentation, pyrolysis, gasification, incineration, and supercritical water gasification (SCWG), have been proposed and developed to address the problems caused by sewage sludge generation (Cieŝlik et al., 2015; Rulkens, 2008; Syed-Hassan et al., 2017). Various energy forms can be generated during the treatment process, such as biogas from anaerobic digestion (Mehariya et al., 2018), biohydrogen from fermentation (Yang and Wang, 2017), and waste heat and electricity from incineration. Among all these recovered energy forms, electricity is an essential form of energy which can be widely applied. Hence, sludge-to-electricity technologies are the major focus of this study.

Sludge incineration and anaerobic digestion with biogas collection are two classic approaches to produce electricity. There are two different technologies for dealing with the biogas generated from sludge digestion, i.e., electricity generation by combustion gas turbine, and biogas fuel cells for electricity generation (Su et al., 2009). Microbial fuel cells (MFCs) to treat wastewater and sewage sludge have also attracted wide attention during the decade due to the direct conversion of the biomass energy into electricity (Gude, 2016; Jiang et al., 2009; Zhang et al., 2012). Previous studies have analyzed the performances of several sludge-to-energy technologies. Rulkens (2008) reviewed and discussed the state-of-art of several typical sludge-to-energy technologies. Su et al. (2009) compared the features of incineration, biogas from sludge digestion to produce electricity by combustion and fuel cells.

Sludge-to-electricity technologies have different merits, shortcomings, and state-of-art on different aspects, which make it difficult for decision-makers to make the most suitable choice among all the options, especially when multiple criteria are taken into consideration. Multi-criteria decision-making (MCDM) methods were established and developed to help solve the problems. Meanwhile, uncertainty and vagueness are ubiquitous in the actual decision-making process, which may be the result of the indeterminate preference and descriptions from the decision-makers. Therefore, fuzzy MCDM and MCDM with incomplete information were proposed and developed to deal with this sort of problem. Fuzzy thought was introduced in the analytic hierarchy process (AHP) method and the best-worst method (BWM) to decide on the weights of the criteria according to the linguistic descriptions provided by decision-makers (Chang, 1996; Guo and Zhao, 2017). The Technique for Order Preference by Similarity to an

Ideal Solution (TOPSIS) method and the VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje [in Serbian]) method were extended to solve the decision-making problem with interval numbers to describe the information (Sayadi et al., 2009; Yue, 2011). There are also many works involving the prioritization of sludge-to-energy technologies by MCDM and fuzzy MCDM approaches. A fuzzy MCDM framework was built up to evaluate and prioritize the sustainability performances of the composting, incineration, and resource utilization of urban sludge (An et al., 2018). Fuzzy Decision-Making and Trial Evaluation Laboratory (DEMATEL) method and fuzzy TOPSIS were applied as the basis for the selection of four wastewater treatment options (Dursun, 2018). Three alternatives of the sludge treatment, including agricultural application of sludge, incineration in a waste incineration plant and incineration in a thermal power station, were investigated using the AHP method (Upka et al., 2005). These studies usually focused on some common sludge treatment technologies, such as landfilling, composting, and incineration. Few investigations made efforts to discuss and compare emerging technologies, especially biological sludge treatment techniques. In addition, the considered criteria in the assessment system mostly concentrated on economic and environmental aspects. The capital costs and operational investment from the economic perspective, and some common environmental indicators in life cycle assessment (e.g. global warming potential, eutrophication potential, and land occupied) were frequently discussed, while the involving social and technical aspects in MCDM were less focused on due to being limited by the measurement and data sources (An et al., 2018; Ren et al., 2017b, 2017a). Therefore, there is still a lot of space for improvement in both the technologies to be investigated and the indicators to be considered, especially the social and technical criteria.

On the other hand, however, traditional methods only allow the decision-makers to make the choice according to the known information without the consideration for problems with incomplete information. To solve this problem, the Dempster-Shafer (DS) theory (Dempster, 1968; Shafer, 1976) of evidence was proposed to evaluate the basic probability assignment (bpa) of a decision option with an incomplete decision matrix. A Dempster-Shafer Analytic Hierarchy Process (DS-AHP) method was proposed to solve a decision-making problem directly based on the provided incomplete decision matrix (Hua et al., 2008). Mathematical analysis of the DS-AHP approach was conducted in a previous study to investigate the appropriateness of the rating scale applied (Beynon, 2002).

Although there are many methods for solving the decision-making problems with incomplete and vague information, limited research applied these approaches to the sludge management field. A grey MCDM system was built up to help decision-makers process the decision making problems of sludge-to-electricity technologies with linguistic descriptions (Ren et al., 2017b). The researchers analyzed and ranked three sludge-to-electricity technologies and the results showed that biogas from sludge digestion to produce electricity by a gas engine was the most preferred option and incineration has the lowest priority. Nevertheless, this study only discussed the problem with linguistic preferences determined by the stakeholders, and incomplete information and multi-condition data were not included. The emerging biological technology MFCs for sewage sludge treatment and electricity production was also rarely analyzed. Hence, more efforts are still expected to analyze the emerging technology with consideration of uncertainty and assessment for sustainability performance in regard to the social and technical aspects.

In order to fill the research gaps mentioned above, this study was conducted to assess and ranking four sludge-to-electricity technologies with multi-data conditions, including crisp numbers, interval numbers, linguistic terms and incomplete information. DS theory was applied as the basis for data process and prioritization and fuzzy BWM (FBWM) was applied to determine the fuzzy weights of the selected criteria according to the preferences of decision-makers, both of which were used to construct the framework of DS-FBWM. DS theory was employed since it has the ability of dealing with incomplete information and fuzzy BWM was utilized because of the advantages in processing linguistic terms, simpler calculation process and more reliable consistency ratio. The DS-FBWM approach and Extended VIKOR method were utilized to ranking the four scenarios with incomplete information and three options with full information, respectively. As far as the authors are aware, this is the first study to apply DS theory for ranking the sludge-to-electricity technologies with multi-data conditions.

2 Methodology

To help with the decision-making process of sludge-to-energy technologies, a criteria system was first established to assess the sustainability performances of the selected alternatives given in Section 2.1. The core model for alternative prioritization and selection was described in Section 2.2. In this study, DS-FBWM was constructed based on the structure of DS-AHP and the principles of fuzzy BWM to obtain the final ranking of the assessed alternatives. The main calculation principles regarding DS theory were following the approach of Hua et al. (2008) to process the initial information and data, which is briefly introduced in Section 2.2.1. However, the weighting method applied in this paper is the fuzzy BWM method instead of the AHP approach for deciding on the weight of each criterion, which is shown in Section 2.2.2. Afterwards, DS theory utilized the weights obtained from fuzzy BWM to deal with the subsequent calculations and sorting is presented in Section 2.2.3. The Extended VIKOR method for results validation is introduced in Section 2.3.

2.1 Criteria system

A criteria system should be built up for the sustainability assessment and selection of the sludge-to-energy alternatives. Thirteen criteria belonging to four aspects, including environmental, economic, social, and technical aspects, were considered to assess the sustainability performance of the investigated alternatives. The explanation and denotation of the criteria system are listed in Table 1.

Table 1 Criteria for sustainability assessment of sludge-to-electricity technologies

Aspect	Criteria	Description
Environmental (AS_1)[1]	Climate change (C_1)	-
	Fossil depletion (C_2)	-
	Acidification potential (C_3)	-
	Eutrophication potential (C_4)	-
	Ozone layer depletion (C_5)	-
Economic (AS_2)	Capital cost (C_6)	-
	Operation and maintenance cost (C_7)	-
Social (AS_3)	Policy support (C_8)	Policy incentives and support, cost subsides.
	Social acceptability (C_9)	Public acceptance of the technology.
Technological (AS_4)	Maturity (C_{10})	Technological maturity and application scale.
	Volume reduction (C_{11})	Degree of volume reduction.
	COD removement rate (C_{12})	Removal capacity of COD.
	Reliability (C_{13})	The degree of sludge problem solution, and the operating and maintenance ability of the technology.

Note:

1 The criteria under environmental aspect are consistent with those of Impact 2002+.

2.2 Multi-criteria decision-making model

2.2.1 DS theory

The DS theory applied in this work is based on the research of Beynon (2002) and Hua et al. (2008). Let $\Theta = \{S_1, ..., S_N\}$ denote the set of decision scenarios which is also known as the discernment frame. A basic probability assignment is defined as a mass function $m: 2^{\Theta} \rightarrow [0,1]$, which satisfies Eq. (1)

$$m(\varnothing) = 0 \quad \text{and} \quad \sum_{S \subseteq \Theta} m(S) = 1, \tag{1}$$

where $\varnothing$ represents the empty set. S is a subset of Θ, and 2^{Θ} is the set consisting of all the subsets of Θ, which can be expressed as

$$2^{\Theta}=\{\varnothing,\{S_1\},...,\{S_N\},\{S_1,S_2\},...,\{S_1,S_N\},...,\Theta\}. \quad (2)$$

Let $V=[f(S_i,C_j)]_{N\times M}=f_{ij}$ denote the decision matrix, where f_{ij} is the evaluation information of the i th $(i=1,2,...,N)$ scenario S_i under the j th criterion C_j $(j=1,2,...,M)$. If $f_{ij}=f_{kj}$ for $\forall S_i,S_k\in\Theta$ and $S_i\neq S_k$, then both S_i and S_k belong to the same focal element (Hua et al., 2008). Here the knowledgeable scale is introduced to rate the performance of each scenario under different attributes according to the preferences of decision-makers (Beynon, 2002; Hua et al., 2008). Table 2 lists the knowledgeable scale applied in this work, which is based on the 5-scale approach in the research of Beynon (2002).

Table 2 Knowledgeable scale (adapted from (Beynon, 2002))

Knowledgeable	Rating	Knowledgeable	Rating
Extremely favorable	6	Moderately to strongly	3
Strongly to extremely	5	Moderately favorable	2
Strongly favorable	4	Acceptable to favorable	1

After transforming the original evaluation information f_{ij} into the knowledgeable numerical scale $\overline{f}_{ij}$, the preference of each scenario can be decided by $p(\overline{f}_{ij})=w_j\overline{f}_{ij}$, where w_j is the weight of j th criterion. Considering Θ is the frame of discernment containing all the scenarios, the preference of Θ is supposed to be 1 (Hua et al., 2008). Suppose $A_k^j\,(j=1,2,...,M;k=1,2,...,t;t<2^N)$ is the set composed by all focal elements under the criterion C_j. When different scenarios belong to the same focal element, they share the same preference.

According to the definition proposed by Hua et al. (2008), the bpa value of each focal element can be calculated as the standard normalized preference, that is

$$m_j(A_k^j)=\frac{p(A_k^j)}{\sum_k p(A_k^j)}, \forall S_i \in \Theta, \forall A_k^j \in 2^{\Theta}, \quad S_i \in A_k^j. \tag{3}$$

To obtain the bpa of all the focal elements for all the criteria, the Dempster's rule of combination is applied (Denœux, 1999; Shafer, 1976; Smets and Kennes, 1994). For two focal elements $A_k^{j_1}$ and $A_l^{j_2}$ under two different criteria C_{j_1} and C_{j_2} (i.e., $j_1 \neq j_2$, $j_1, j_2 \in \{1,2,...,M\}$), the bpa value of $E = A_k^{j_1} \cap A_k^{j_2}$ can be obtained using Eq. (4)

$$[m_{j_1} \oplus m_{j_2}](E)=\begin{cases} 0, & E=\varnothing, \\ \dfrac{\sum\limits_{A_k^{j_1}\cap A_l^{j_2}=E} m_{j_1}(A_k^{j_1})m_{j_2}(A_l^{j_2})}{\sum\limits_{A_k^{j_1}\cap A_l^{j_2}\neq\varnothing} m_{j_1}(A_k^{j_1})m_{j_2}(A_l^{j_2})}=\dfrac{\sum\limits_{A_k^{j_1}\cap A_l^{j_2}=E} m_{j_1}(A_k^{j_1})m_{j_2}(A_l^{j_2})}{1-\sum\limits_{A_k^{j_1}\cap A_l^{j_2}=\varnothing} m_{j_1}(A_k^{j_1})m_{j_2}(A_l^{j_2})}, & E\neq\varnothing. \end{cases} \tag{4}$$

Multi-criteria decision-making problems usually have more than two criteria. Hence, this step can first be conducted between the intersections of the focal elements under two criteria, and then repeat the combination for the intersections and the focal elements of the third criterion. The process is iterated until all the criteria are combined.

The belief measure (Bel) and plausibility measure (Pls) of the focal element which have combined all criteria together are defined as follows (Hua et al., 2008):

$$Bel(A)=\sum_{B\subseteq A} m(B), \quad \forall A \in 2^{\Theta}, \tag{5}$$

$$Pls(A)=1-Bel(\bar{A})=\sum_{B\cap A\neq\varnothing} m(B), \quad \forall A \in 2^{\Theta}, \tag{6}$$

where A and B are subsets of Θ. $\bar{A}$ is the complement of A in Θ. $Bel(A)$ and $Pls(A)$ represent the exact support and possible support to A, respectively (Hua et al., 2008). According to Eq. (5) and Eq. (6), the belief interval of A, i.e. $[Bel(A), Pls(A)]$, denoting the total amount of belief of potentially placing in A, can be obtained.

In order to get the final ranking of all the alternatives, belief interval numbers should be compared. Therefore, a comparison rule is proposed to decide on the preference degree of S_i and S_k (Hua et al., 2008).

$$P(S_i > S_j) = \frac{\max[0, Pls(S_i) - Bel(S_k)] - \max[0, Bel(S_i) - Pls(S_k)]}{[Pls(S_i) - Bel(S_i)] + [Pls(S_k) - Bel(S_k)]}. \tag{7}$$

Based on the calculation result of Eq. (7), the preference situation of S_i and S_k can be defined as follows:

(1) If $P(S_i > S_k) > 0.5$, then scenario S_i is regarded as superior to S_k, which is denoted as $S_i \succ S_k$.

(2) If $P(S_i > S_k) < 0.5$, then S_i is regarded as inferior to S_k, i.e. $S_i \prec S_k$.

(3) If $P(S_i > S_k) = 0.5$, then S_i and S_k are regarded to have the same priority, denoted by $S_i \sim S_k$.

According to the calculation results of Eq. (7), and the comparison rules above, the preference ranking of all the scenarios can be finally obtained.

2.2.2 Fuzzy BWM

In the DS theory, the preference of each scenario is decided by the numerical knowledgeable scale and the weight of the corresponding criterion. Therefore, the weights of the considered criteria should be determined before conducting the following procedures. There are various weighting methods for MCDM, such as AHP method, SWING and SIMOs (Wang et al., 2009). Best-worst method was proposed to deal with MCDM problems, which requires less comparison data and can obtain more reliable consistency ratios compared with the existing MCDM approaches (Rezaei, 2015). Considering the vagueness and uncertainty frequently occurring in decision-making processes due to the lack of complete information and professional knowledge of the relevant technologies, fuzzy best-worst method was applied to deal with the linguistic description of the preference for each criterion provided by the decision-makers (Guo and Zhao, 2017). Fuzzy BWM possesses the advantages of the best-worst method and the ability of process vague information. Hence, fuzzy BWM was selected to determine the weight of each criterion. A detailed description of the calculation principles can be found in the research of Guo and Zhao (2017). The major steps of fuzzy BWM are summarized in Figure 1.

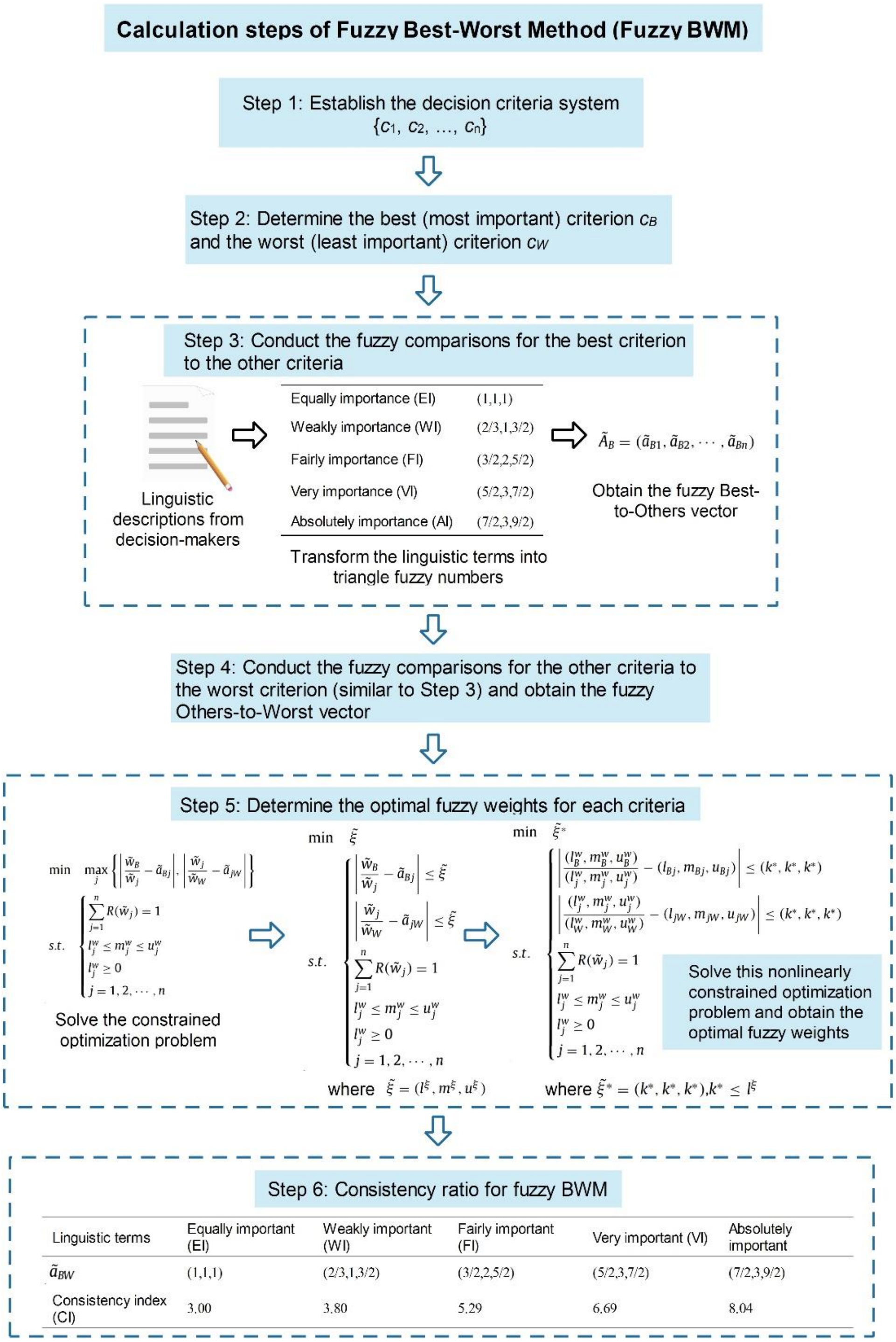


Figure 1 Major steps of fuzzy BWM (summarized from Guo and Zhao (2017))

2.2.3 DS-FBWM

Based on the all the preliminaries of DS theory and fuzzy BWM, DS-DBWM can be constructed to solve the decision-making problems with incomplete information. The major steps of DS-FBWM are summarized in Figure 2. Fuzzy BWM is applied before Step 2 to obtain the fuzzy weights of all the criteria. Subsequently, Step 2 can be conducted as well as the following procedures.

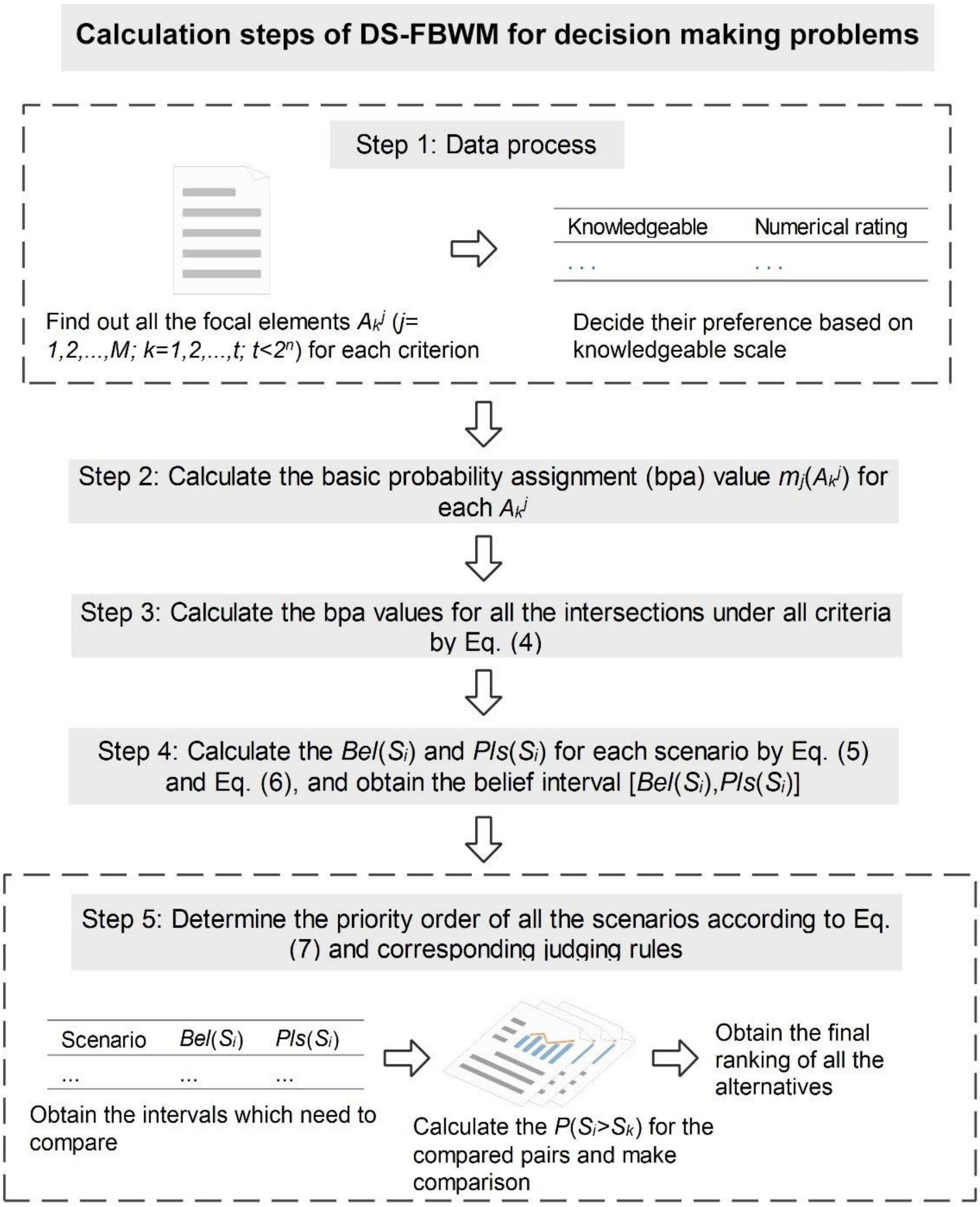


Figure 2 Major steps of DS-FBWM for incomplete information decision-making (summarized from Hua et al., (2008))

2.3 Validation method: Extended VIKOR

The Extended VIKOR method for interval numbers was applied to make comparison with the ranking result obtained based on DS-FBWM. The calculation principles applied in this work were complied with the research of Sayadi et al. (2009). Detailed computation steps can be found in their work. Figure 3 summarizes the major steps of the Extended VIKOR method for interval numbers. A transformation step was added before conducting this method to process the data forms since there are three different data forms in the case study.

Calculation steps of Extended VIKOR method

Step 1: Transform other data forms into interval forms according to Table 8 and obtain the decision matrix with interval numbers

⇩

Step 2: Determine the positive ideal solution (PIS) and the negative ideal solution (NIS)

PIS: $A^* = \{f_1^*, ..., f_n^*\} = \left\{(\max_i f_{ij}^U \mid j \in I) \text{ or } (\min_i f_{ij}^L \mid j \in J)\right\} \quad j = 1, 2, ..., n$

NIS: $A^- = \{f_1^-, ..., f_n^-\} = \left\{(\min_i f_{ij}^L \mid j \in I) \text{ or } (\max_i f_{ij}^U \mid j \in J)\right\} \quad j = 1, 2, ..., n$

⇩

Step 3: Compute the intervals $[S_i^L, S_i^U]$ and $[R_i^L, R_i^U]$

$$S_i^L = \sum_{j \in I} w_j \left(\frac{f_j^* - f_{ij}^U}{f_j^* - f_j^-}\right) + \sum_{j \in J} w_j \left(\frac{f_{ij}^L - f_j^*}{f_j^- - f_j^*}\right) \quad i = 1, ..., m$$

$$S_i^U = \sum_{j \in I} w_j \left(\frac{f_j^* - f_{ij}^L}{f_j^* - f_j^-}\right) + \sum_{j \in J} w_j \left(\frac{f_{ij}^U - f_j^*}{f_j^- - f_j^*}\right) \quad i = 1, ..., m$$

$$R_i^L = \max\left\{w_j \left(\frac{f_j^* - f_{ij}^U}{f_j^* - f_j^-}\right) \middle| j \in I, w_j \left(\frac{f_{ij}^L - f_j^*}{f_j^- - f_j^*}\right) \middle| j \in J\right\} \quad i = 1, ..., m$$

$$R_i^U = \max\left\{w_j \left(\frac{f_j^* - f_{ij}^L}{f_j^* - f_j^-}\right) \middle| j \in I, w_j \left(\frac{f_{ij}^U - f_j^*}{f_j^- - f_j^*}\right) \middle| j \in J\right\} \quad i = 1, ..., m$$

⇩

Step 4: Compute the intervals $[Q_i^L, Q_i^U]$, i=1, 2, ...,m.

$$Q_i^L = v\frac{(S_i^L - S^*)}{(S^- - S^*)} + (1 - v)\frac{(R_i^L - R^*)}{(R^- - R^*)}$$

$$Q_i^U = v\frac{(S_i^U - S^*)}{(S^- - S^*)} + (1 - v)\frac{(R_i^U - R^*)}{(R^- - R^*)}$$

where

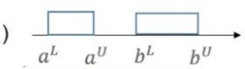
$$S^* = \min_i S_i^L, \quad S^- = \max_i S_i^U, \quad R^* = \min_i R_i^L, \quad R^- = \max_i R_i^U.$$

v represents the weight of the strategy of the "majority of criteria"

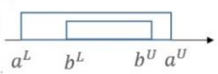
⇩

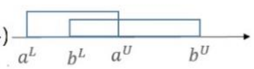
Step 5: Compare the interval numbers $Q_i=[Q_i^L, Q_i^U]$ (i=1, 2, ...,m) based on the judging rules and obtain the final ranking

Judging rules: assume that compare $[a^L, a^U]$ and $[b^L, b^U]$

(1)  $a^U \le b^L \rightarrow [a^L, a^U]$ is the minimum interval number

(2)  $a^L = b^L, a^U = b^U \rightarrow [a^L, a^U], [b^L, b^U]$ share the same priority

(3)  $a^L \le b^L \le b^U \le a^U \rightarrow$ If $\alpha(b^L - a^L) \ge (1 - \alpha)(a^U - b^U)$
Then $[a^L, a^U]$ is the minimum interval number, else $[b^L, b^U]$ is the minimum interval number

(4)  $a^L < b^L < a^U < b^U \rightarrow$ If $\alpha(b^L - a^L) \ge (1 - \alpha)(b^U - a^U)$
Then $[a^L, a^U]$ is the minimum interval number, else $[b^L, b^U]$ is the minimum interval number

α is the optimism level of the decision maker ($0 < \alpha \le 1$), which means that the optimist decision-maker has a higher α value than the pessimist decision maker

The interval number Q_i which is closer to 0 is regarded as a better option.

Figure 3 Basic steps of Extended VIKOR method for decision-making problems with interval numbers (Sayadi et al., 2009)

3 Case study

In this study, the proposed DS-FBWM approach was applied to evaluate four sludge-to-electricity technologies under uncertainty for decision-making, which are listed as follows:

(1) Sludge incineration for electricity generation (denoted by S1) (Xu et al., 2014);

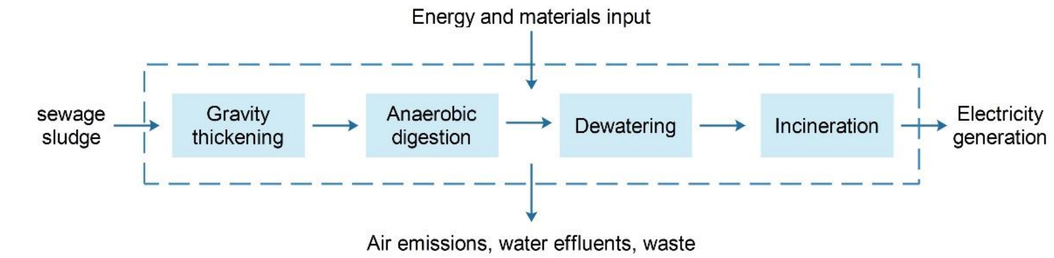
(2) Biogas generated from the anaerobic digestion process of sludge for electricity production by fuel cells (SOFC, denoted by S2) (Strazza et al., 2015);

(3) Biogas generated from the anaerobic digestion process of sludge for electricity generation by combustion gas engine (denoted by S3) (Xu et al., 2014);

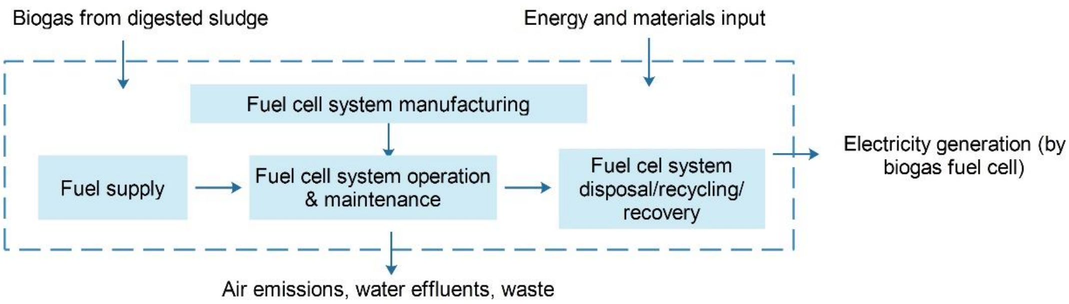
(4) Pretreated sludge for electricity generation by MFCs (denoted by S4).

As for S4, there are scarce data on the sustainability performances of MFCs for sludge treatment and electricity production. Nevertheless, there have been a few studies regarding MFCs for wastewater treatment with electricity generation. The characteristics of sewage sludge, a byproduct generated from wastewater treatment process, have a close relationship with wastewater. Therefore, the data for S4 in this work were based on the related data of MFCs for wastewater treatment and electricity generation (Foley et al., 2010; Gude, 2016) in order to roughly estimate the performance of S4 under the current development status. The flowcharts of the four scenarios are shown in Figure 4. The reasons for selecting these four technologies are as follows: i) incineration is widely accepted worldwide and is regarded as one of the most thorough processes for sludge, but its application is still limited in China and the high cost and secondary pollution still hinder the generalization of sludge incineration for electricity production; ii) biogas fuel cells, regarded as a potential sludge-to-energy method, are actively tested, supported, and promoted for commercial application by developed countries such as Japan and America, but there are few cases in China (Su et al., 2009); iii) biogas combustion for electricity is a relatively mature approach compared with other scenarios and is widely used in rural areas; iv) MFCs for sludge treatment and electricity production is an emerging technology with many features which can promote sustainable development in the future (Gude, 2016). These four technologies have different advantages and shortcomings on different aspects. Some are rarely discussed regarding the evaluation of sustainability performance and decision-making. Hence, these four scenarios are investigated in this work to provide decision-making reference for the sludge-to-electricity technologies especially when the information is incomplete and vague.

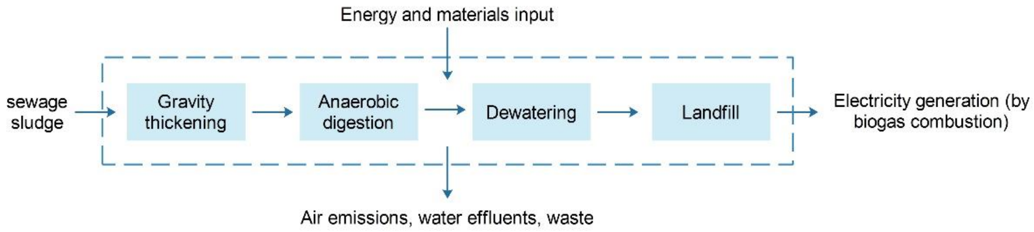
The performance data of the four alternatives were collected through literature review on the life cycle assessment of the related technologies (Foley et al., 2010; Strazza et al., 2015; Xu et al., 2014). In this work, the functional unit was 1 kWh of net electricity generation and the lifespan was supposed to be 30 years.



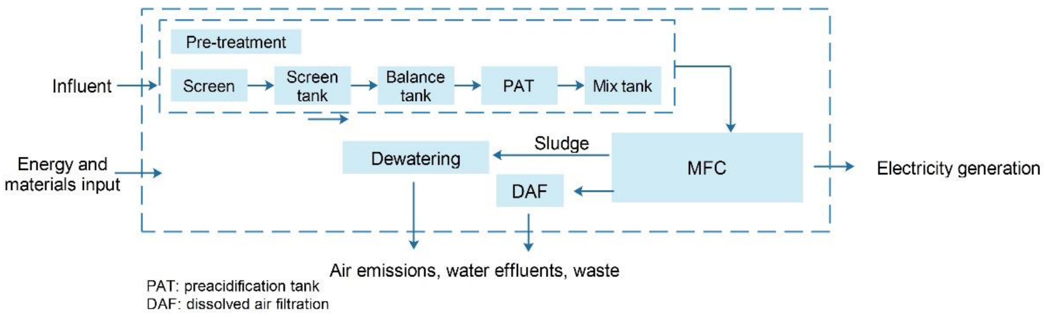
(a) S1



(b) S2



(c) S3



(d) S4

Figure 4 Life cycle boundaries of the four scenarios (Foley et al., 2010; Strazza et al., 2015; Xu et al., 2014)

4 Results

4.1 Criteria weighted by Fuzzy best-worst method

Since there are four aspects and thirteen criteria in the indices system as shown in Section 2.1, the calculation of fuzzy BWM was conducted hierarchically, i.e. the weight of each aspect w_{AS_j} $(j=1,2,3,4)$ was first computed, then the local fuzzy weight of each criterion under each aspect w'_i $(i=1,2,...,13)$ was obtained. The global fuzzy weight of each criterion w_i $(i=1,2,...,13)$ was determined by: $w_i = w_{AS_j} \cdot w'_i$, ($j=1,2,3,4$; $i=1,2,...,13$). The calculation process can be carried out step by step according to the principles, as shown in the Supplementary Information. The fuzzy weight of each aspect and the global weight of all the criteria can be obtained and listed in Table 3 and Table 4, respectively.

Table 3 Fuzzy weights of the four aspects

	AS_1	AS_2	AS_3	AS_4	CR
Weight	0.3206	0.3601	0.1152	0.2042	0.031

Table 4 Global fuzzy weight of the thirteen criteria

Environmental	$\mathbf{C_1}$	$\mathbf{C_2}$	$\mathbf{C_3}$	$\mathbf{C_4}$	$\mathbf{C_5}$
Weight	0.0922	0.0435	0.0745	0.0767	0.0337
Economic	$\mathbf{C_6}$	$\mathbf{C_7}$	**Social**	$\mathbf{C_8}$	$\mathbf{C_9}$
Weight	0.1824	0.1777		0.0766	0.0386
Technical	$\mathbf{C_{10}}$	$\mathbf{C_{11}}$	$\mathbf{C_{12}}$	$\mathbf{C_{13}}$	**Total CR**
Weight	0.0831	0.0261	0.0475	0.0475	0.0245

4.2 Ranking result based on DS-FBWM

According to the principle description in the Methodology section, DS-FBWM was conducted to obtain the priority order of the four alternatives. The detailed process was presented in the following.

Step 1: In the initial known information for the four scenarios, there are four different types of data. Crisp numbers mostly occur in the environmental and economic aspects. Two interval numbers also exist in the description of economic indicators for S2. Linguistic descriptions were used for social and technical aspects. Incomplete information appears in the data list of S4 due to the limited data sources (in C_3, C_4, C_5). The detailed information for the four sludge-to-electricity options is shown in Table 5. In this step, the focal elements for each criterion were found according to the known information. The corresponding focal elements, preference and final priority under each attribute were also obtained, and are shown in Table S.17, and Tables S.18 and S.19, respectively.

Table 5 Initial known information of the four scenarios (data are presented per functional unit)

		Unit	S1	S2	S3	[1]S4
AS_1	C_1	kg CO_2 eq	3.60	0.2	9.96	0.195
	C_2	MJ	-18.8	0.06	-41.6	-0.876
	C_3	kg SO_2 eq	-0.0190	5.07E-04	0.0040	NA
	C_4	kg PO_4^{3-} eq	-8.4271E-04	6.96E-05	-6.493E-04	NA
	C_5	kg CFC-11 eq	9.91E-08	2.18E-08	-1.059E-10	NA
AS_2	C_6	USD/kWh	0.0824	[0.1295, 0.1665]	0.1644	0.0467
	C_7	USD/kWh	0.0045	[0.017, 0.019]	0.0085	3.3592
AS_3	C_8	-	(Poor, good, poor)	(Medium, good, medium)	(Good, very good, good)	Poor
	C_9	-	[2]Medium	[3]Low	[4]High	Low
AS_4	C_{10}	-	(Good, medium, poor)	(Very poor, poor, very poor)	(Very good, very good, very good)	Very Poor

C_{11}	-	[5]High	[6]Medium	[5]Medium	Low
C_{12}	-	[5]High	[3]Low	[5]Low	90%
C_{13}	-	[5,7]High	[3]Low	[5]Medium	Low

Note:

Data sources: For the criteria $C_1 - C_7$ of S1 and S3: (Xu et al., 2014); for the criteria $C_1 - C_7$ of S2: (Strazza et al., 2015); for the criteria C_1, C_2 and C_{12} of S4: (Foley et al., 2010); for the criteria C_6 and C_7 of S4: estimated from (Gude, 2016); for C_8 and C_{10} of S1 -S3: (Ren et al., 2017b).

1€=1.12USD.

[1] The performances of $C_8 - C_{11}$ and C_{13} of S4 were estimated according to the development status of MFCs and related literature review.

[2] Medium was judged based on the situation of incineration applied in China. It was reported that incineration occupied 18.3% of the total sludge disposal. Incineration was widely recognized by the developed countries (western countries), but the application and information transparency in China is still limited (Asian Development Bank, 2012).

[3] Estimated based on the development status of biogas fuel cells. Currently biogas from digested sludge for electricity generation by fuel cell is still not practiced (Su et al., 2009).

[4] High was judged according to the reference (Tarpani and Azapagic, 2018). The electricity generated from biogas has a prepared market. Biogas combustion for electricity production is widely applied in rural area.

[5] (Asian Development Bank, 2012).

[6] The only difference between S2 and S3 is the electricity production way from biogas. The volume reduction degree should be similar.

[7] (Qin et al., 2011).

Step 2: Based on the result in **Step 1**, the fuzzy weights determined by fuzzy BWM, and Eq. (3), the bpa values of each focal element under each criterion was calculated, as presented in Table 6. Taking the bpa value of the focal element {S1} for criterion C_1 as an example, the preference of {S1} in C_1 determined by decision-makers was $3w_1$. The weight of criterion C_1 has been decided by fuzzy BWM in the last section as 0.0922. Hence, the preference of {S1} can be obtained by $p(\{S1\}^1) = 3w_1 = 0.2766$, where the superscript 1 refers to the investigated focal element in criterion C_1. Similarly, the preferences of the other four focal elements can be calculated. Then, the bpa value of the focal element {S1} towards criterion C_1 can be determined by

$$m_1(\{S1\}^1) = p(\{S1\}^1) / (p(\{S2\}^1) + p(\{S3\}^1) + p(\{S4\}^1) + p(\Theta^1)) = 0.1161.$$

Through similar calculations, the bpa values for all the focal elements can be correspondingly obtained.

Table 6 The basic probability assignment value of each focal element

C_1	**Priority**	**C_2**	**Priority**	**C_3**	**Priority**	**C_4**	**Priority**	**C5**	**Priority**
{S1}	0.1161	{S1}	0.1580	{S1}	0.2134	{S1}	0.2170	{S1}	0.0259
{S2}	0.1935	{S2}	0.0790	{S2}	0.1280	{S2}	0.0868	{S2}	0.0777
{S3}	0.0387	{S3}	0.1316	{S3}	0.0854	{S3}	0.1302	{S3}	0.1294
{S4}	0.2322	{S4}	0.0263	Θ	0.5732	Θ	0.5660	Θ	0.7670
Θ	0.4196	Θ	0.6051						
C_6	**Priority**	**C_7**	**Priority**	**C_8**	**Priority**	**C_9**	**Priority**	**C_{10}**	**Priority**
{S1}	0.2053	{S1}	0.2836	{S1, S2}	0.1350	{S1}	0.0836	{S1}	0.1361
{S2}	0.1540	{S2}	0.1135	{S3}	0.2266	{S3}	0.1393	{S3}	0.2723
{S3}	0.1027	{S3}	0.2269	{S4}	0.0453	{S2, S4}	0.0557	{S2, S4}	0.0454
{S4}	0.2566	{S4}	0.0567	Θ	0.5921	Θ	0.7215	Θ	0.5462
Θ	0.2814	Θ	0.3193						
C_{11}	**Priority**	**C_{12}**	**Priority**	**C_{13}**	**Priority**				
{S1}	0.1033	{S1}	0.1664	{S1}	0.1611				
{S2,S3}	0.0620	{S2,S3}	0.0666	{S3}	0.0966				
{S4}	0.0413	{S4}	0.0666	{S2, S4}	0.0644				
Θ	0.7933	Θ	0.7005	Θ	0.6779				

Step 3: With Dempster's rule of combination, the bpa values of all the intersections under all criteria can be obtained, and are shown in Table 7.

Table 7 The bpa values of all the intersections by using Dempster's rule of combination

m_{combined}	Value
S1	0.4794
S2	0.1666
S3	0.1913
S4	0.1062
S1, S2	0.0037
S2, S3	0.0029
S2, S4	0.0044

Θ	0.0160

Step 4: The belief measure and the plausibility measure of each scenario can be calculated based on the results of **Step 3**. Subsequently, the belief intervals were obtained, as listed in Table 8.

Table 8 The belief intervals of evaluated scenarios

Scenario	*Bel*	*Pls*
S1	0.4794	0.4991
S2	0.1666	0.1937
S3	0.1913	0.2102
S4	0.1062	0.1267

Step 5: Determine the final priority order of the four alternatives by applying Eq. (7). According to the results in Table 8, the belief intervals of S2 and S3 have an intersection. Hence, S2 and S3 need to be compared. Substituting the corresponding values into Eq. (7), gave $P(\text{S3} > \text{S2}) = 0.9487 > 0.5$, which indicates that S3 is superior to S2. Therefore, the final preference order of the four scenarios determined by DS-FBWM is: $\text{S1} \succ \text{S3} \succ \text{S2} \succ \text{S4}$.

4.3 Ranking result based on the Extended VIKOR method

The ranking for the former three alternatives, i.e. S1, S2, and S3 with full information was also obtained based on the Extended VIKOR method for interval numbers, aiming to compare with the ranking results generated from DS-FBWM. The detailed steps are described as follows:

Step 1: Transform other data forms into interval form. The transferring of crisp numbers follows this rule: $a \to [a, a]$. The linguistic description is transformed into interval numbers according to Table 9.

Table 9 The scale of interval number transformed from linguistic description (Ren et al., 2017b)

Description	Abbreviation	Interval number
Very Poor	VP	(1.5, 3.0)
Poor/Low	P/L	(3.0, 4.5)
Medium	M	(4.5, 6.0)
Good/High	G/H	(6.0, 7.5)
Very Good	VG	(7.5, 9.0)

If the performance evaluation data come from several different experts, then the final interval number can be obtained by the following equation:

$$\otimes f_{ij} = \sum_{k=1}^{L} \otimes f_{ij}^{k} / L = [\sum_{k=1}^{L} f_{ij}^{k,-} / L, \sum_{k=1}^{L} f_{ij}^{k,+} / L], i = 1, 2, ..., N; j = 1, 2, ..., M, \qquad (8)$$

where $\otimes f_{ij}$ represents the interval number of i th scenario at j th criterion. L is the total number of participating experts and $\otimes f_{ij}^{k}$ is the opinion of the k th expert. $\otimes f_{ij}^{k,-}$ and $\otimes f_{ij}^{k,+}$ mean the lower bound and upper bound of $\otimes f_{ij}^{k}$, respectively.

Afterwards, a decision matrix with interval numbers was obtained according to the transferring principles and initial information in Table 5, as listed in Table 10.

Table 10 The decision matrix with interval numbers

Aspect	Criterion	S1		S2		S3	
		Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound
AS_1	C_1	3.60	3.60	0.2	0.2	9.96	9.96
	C_2	-18.8	-18.8	0.06	0.06	-41.6	-41.6
	C_3	-0.0190	-0.0190	5.07E-04	5.07E-04	4.0255E-03	4.0255E-03
	C_4	-8.4271E-04	-8.4271E-04	6.96E-05	6.96E-05	-6.493E-04	-6.493E-04
	C_5	9.91E-08	9.91E-08	2.18E-08	2.18E-08	-1.06E-10	-1.06E-10

AS_2	C_6	0.8243	0.8243	0.1295	0.1665	0.16441026	0.1644103
	C_7	0.0045	0.0045	0.017	0.019	0.0085	0.0085
AS_3	C_8	4	5.5	5	6.5	6	8
	C_9	4.5	6	4.5	6	6	7.5
AS_4	C_{10}	4.5	6	3	4.5	6	7.5
	C_{11}	4.5	6	2	3.5	7.5	9
	C_{12}	4.5	6	1.5	3	7.5	9
	C_{13}	6	7.5	4.5	6	4.5	6

Step 2: Determine the positive ideal solution (PIS) f_j^* and the negative ideal solution (NIS) f_j^-, which are given in Table 11.

Table 11 The PIS and NIS of each criterion

	C_1	**C_2**	**C_3**	**C_4**	**C_5**
f_j^*	0.20	-41.6	-0.0190	-8.4271E-04	-1.06E-10
f_j^-	9.96	0.06	4.0255E-03	6.96E-05	9.91E-08
	C_6	**C_7**	**C_8**	**C_9**	**C_{10}**
f_j^*	0.1295	0.0045	8	7.5	9
f_j^-	0.8243	0.019	4	3	2
	C_{11}	**C_{12}**	**C_{13}**		
f_j^*	7.5	7.5	7.5		
f_j^-	4.5	3	3		

Step 3: Compute the intervals $[S_i^L, S_i^U]$ and $[R_i^L, R_i^U]$. The related results are given in Table 12.

Table 12 The intervals $[S_i^L, S_i^U]$ and $[R_i^L, R_i^U]$ of each scenario

	S_i^L	S_i^U	R_i^L	R_i^U
S1	3.68E-01	4.72E-01	1.82E-01	1.82E-01
S2	5.40E-01	6.78E-01	1.53E-01	1.78E-01

S3	3.01E-01	4.15E-01	9.22E-02	9.22E-02

Step 4: Calculate the intervals $Q_i = [Q_i^L, Q_i^U], i = 1, 2, 3$. The calculation results are presented in Table 13. According to the core principle of the Extended VIKOR method, the alternative with minimum interval number Q_i is the best choice (Sayadi et al., 2009). Detailed comparison of the interval numbers is conducted in **Step 5**.

Table 13 The interval Q_i of each scenario

Scenarios	Q_i^L	Q_i^U
S1	0.589011719	0.727054018
S2	0.654517155	0.973863563
S3	0	0.150733475

$v = 0.5$

Step 5: Obtain the ranking based on the judging rules. According to the results in **Step 4**, the interval Q_1 and Q_2 have an intersection. Therefore, these two interval numbers need to be compared by the judging rule. Considering the length of these two intervals, α was assumed to be 0.8. Then, the following results were obtained: $\alpha(Q_2^L - Q_1^L) = 0.0524$, $(1-\alpha)(Q_2^U - Q_1^U)$=0.0494. Since the former one is larger than the latter one, S1 is considered to be better than S2. Hence, the final ranking of the three scenarios is: $S3 \succ S1 \succ S2$.

5 Discussion

5.1 Comparison of the ranking results between DS-FBWM method and Extended VIKOR method

According to the calculation results, the ranking obtained by DS-FBWM and Extended VIKOR method are $S1 \succ S3 \succ S2 \succ S4$ and $S3 \succ S1 \succ S2$, respectively. Both methods assessed and ranked the former three scenarios, i.e. S1, S2, and S3. Scenario 2 is in the last place in the ranking results of the two methods. Based on the performance data and calculation process, this result may be caused by the immaturity of the biogas fuel cell technology. The application of biogas from digested sludge for electricity production by fuel cells in China is not widespread with a lack of experience in this domain (Su et al., 2009). Although some of the environmental aspects of S2 are acceptable and even impressive, the imbalance in other aspects makes it less prefer than the other two scenarios. Considering the potential in environmental indicators and current development tendency, biogas fuel cells for electricity generation still has potential and would benefit further research (Rillo et al., 2017). Promoting the related research and practice can be helpful to improve the maturity, reduce the total costs and make it more acceptable to the public in the future.

On the other hand, there are three major differences in the ranking results of these two methods. Analysis for the three differences are listed as follows:

- The first difference lying in the number of assessed scenarios. Four scenarios were evaluated by DS-FBWM method including Scenario 4 with incomplete information. The Extended VIKOR method only ranked the former three scenarios with complete information.

- The second difference is the core thought of processing data. Although the DS-FBWM method can deal with the situation when information is missing, it cannot make the full use of exact information. To process the option with missing information, knowledgeable scale was applied to transfer the specific values into preference ranking, which may result in the loss of generality due to subjectivity. On the contrary, the Extended VIKOR method preserves the accuracy of the known data and makes use of information as much as possible. It can process the data and rank the scenarios without the loss of generality.
- The ranking of S1 and S3 is the third difference between the results of the two methods. Besides the additional S4 in the ranking result of DS-FBWM, the priority orders of S1 and S3 are also different. In DS-FBWM, S1 is superior to S3. However, S1 is inferior to S3 in the ranking result obtained by Extended VIKOR. Except for the difference in the core thought of processing data and calculation, the preference of the stakeholders, and the selection of indices may also lead to the occurrence of the difference. Some indices which can reflect the influence of dust and incinerated ash from incineration were not selected and investigated because of lack of data. If those indictors are considered, the priority order of S1 is worth discussion. Nevertheless, incineration in take the first place still indicates that it can be competitive with biogas from digested sludge for

electricity production by combustion under certain situation, especially when policy support and ash handling are satisfactory. More efforts are expected to examine the preference order of S1 and S3 when more complete indicators are considered.

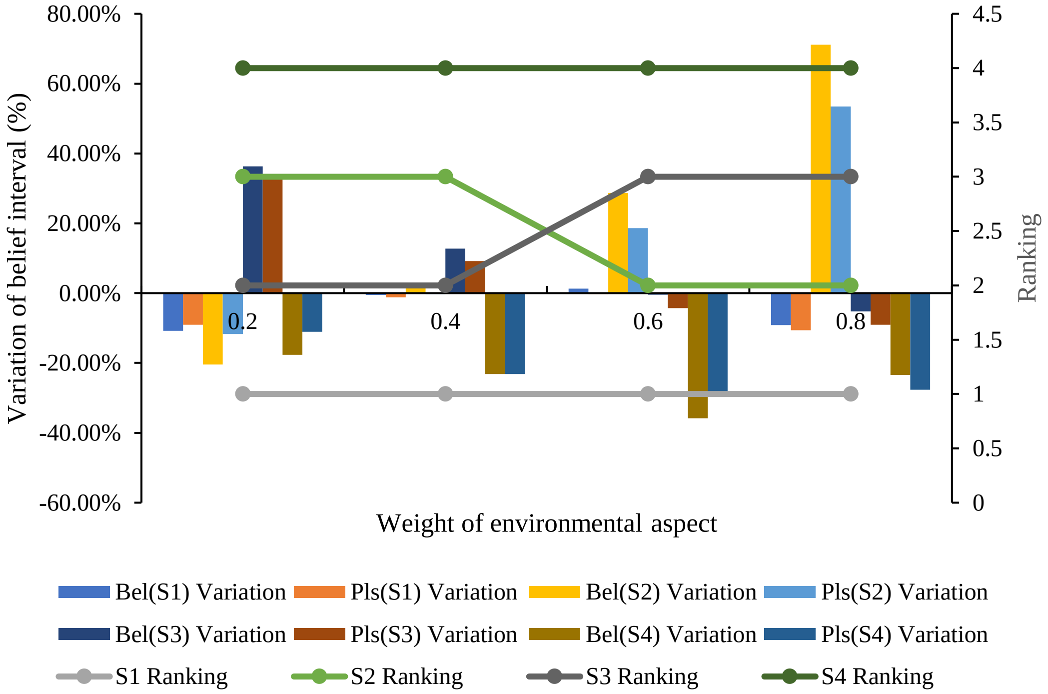
It should be noted that the ranking result of the Extended VIKOR method is also influenced by the value assignment of α. According to the calculation results, if $\alpha < 0.78$, then S2 is superior to S1. The interval length of S1 is shorter than that of S2, leading to the assignment of α as 0.8, which means a higher level of optimism. The optimism degree cannot be reflected by DS-FBWM. If the variation of α is taken into consideration, the ranking results of Extended VIKOR may have more differences compared with those of DS-FBWM, which also indicates stronger subjectivity and fuzziness in the calculation principles of DS-FBWM.

According to the above analysis, the application of these two methods can be found and related suggestions can be provided for decision-makers. When the known information is complete, both methods can be considered to help with the decision-making process. Compared with DS-FBWM, the Extended VIKOR approach can provide more exact and objective data results because there is less human intervention in the calculation process than in DS-FBWM. Therefore, it could be more reliable than DS-FBWM under the situation with complete information. However, DS-FBWM can is more flexible to deal with different types of situations especially when the information is incomplete. DS-FBWM is recommended in that case since the Extended

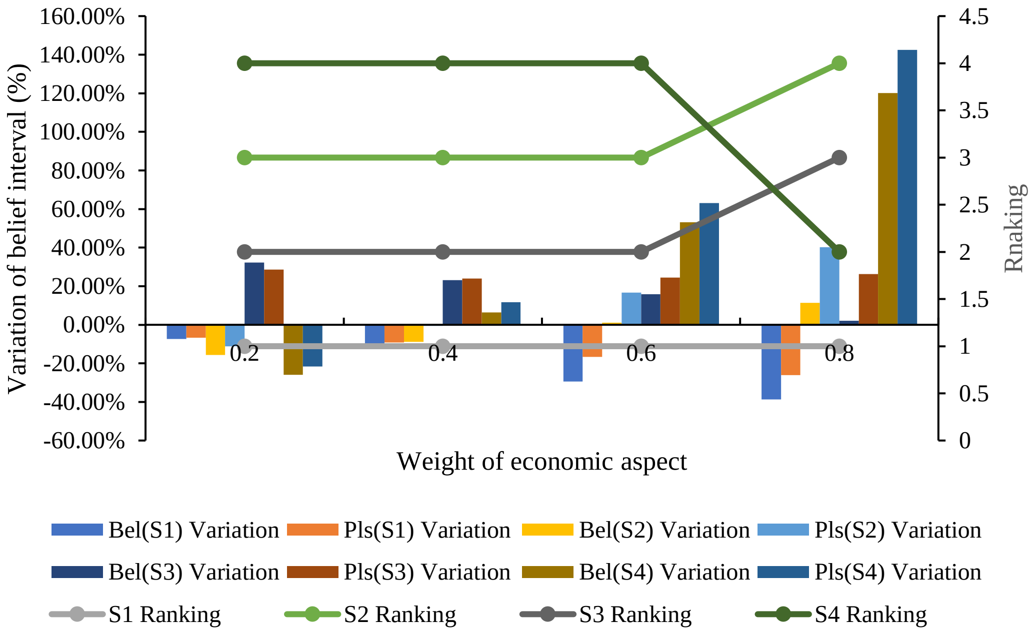
VIKOR method does not possess the ability for processing the missing information.

5.2 Sensitivity analysis

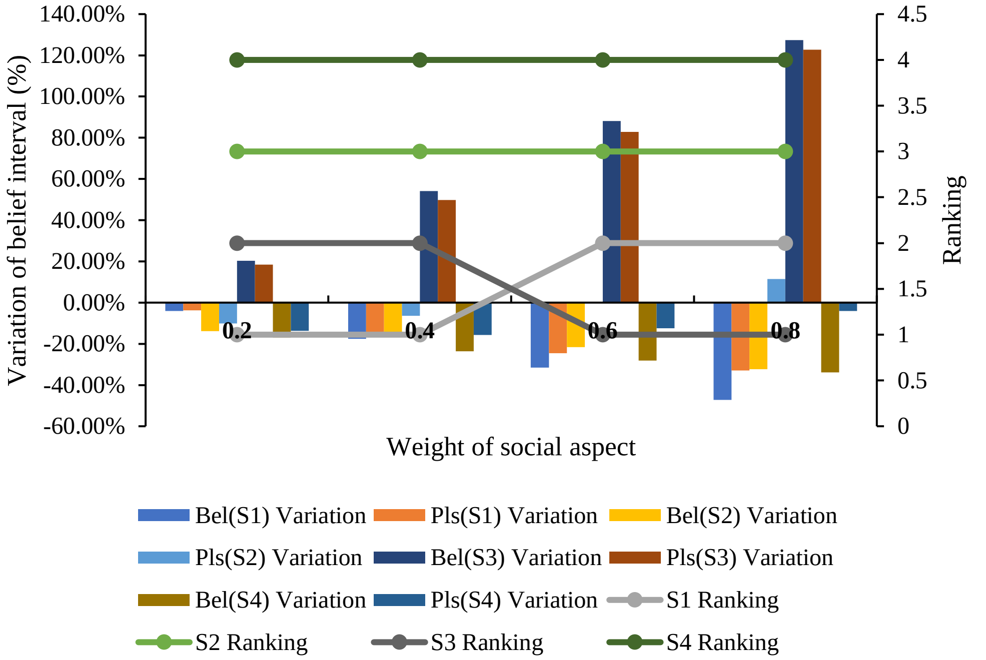
Sensitivity analysis was conducted to investigate the influence of the weight variations of different aspects and criteria on the decision-making process. To study the effect of the weight change of each aspect, the local weights of all the indicators were fixed. Then the weight of the investigated aspect is set to be 0.2, 0.4, 0.6, and 0.8, respectively. Meanwhile, the weights of the other three aspects were set to be the same. Hence, four groups of weighting assignments can be obtained and each group contains 4 pieces of data records, which are shown in Figure 5. The ranking "1" represents the top place and "4" means the last place. The variation of the belief interval is calculated by $\frac{Bel'(S_i) - Bel(S_i)}{Bel(S_i)}$, where $Bel(S_i)$ is the lower bound of the belief interval of i th scenario in the original calculation results, $Bel'(S_i)$ is the value of sensitivity analysis. The variation of $Pls(S_i)$ can be similarly calculated.


80.00%
60.00%
40.00%
20.00%
0.00%
-20.00%
-40.00%
-60.00%
Variation of belief interval (%)
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Ranking
0.2
0.4
0.6
0.8
Weight of environmental aspect
Bel(S1) Variation
Pls(S1) Variation
Bel(S2) Variation
Pls(S2) Variation
Bel(S3) Variation
Pls(S3) Variation
Bel(S4) Variation
Pls(S4) Variation
S1 Ranking
S2 Ranking
S3 Ranking
S4 Ranking

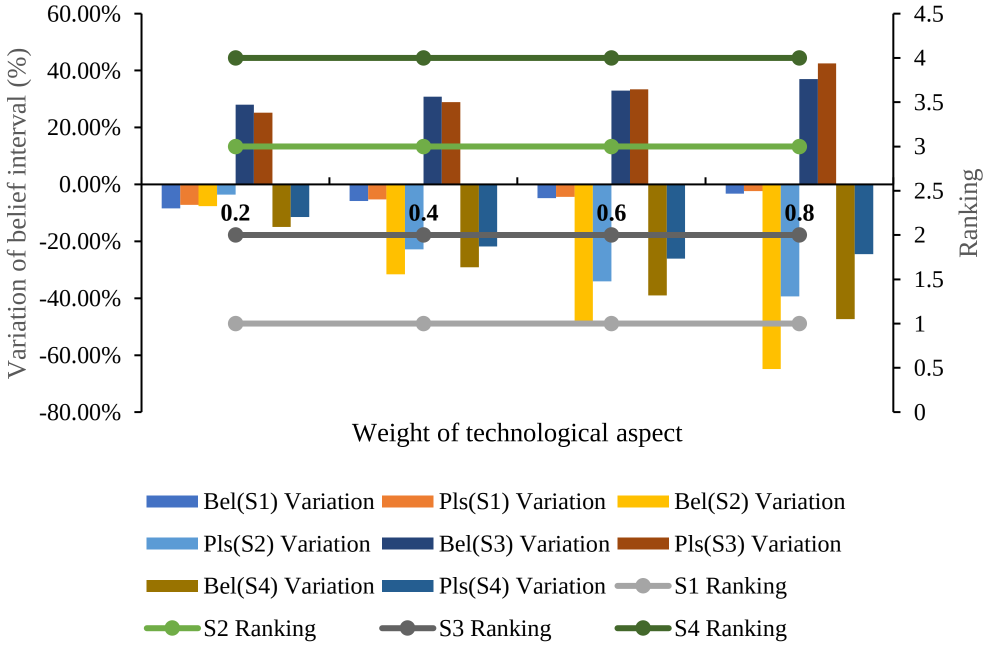
(a)


160.00%
140.00%
120.00%
100.00%
80.00%
60.00%
40.00%
20.00%
0.00%
-20.00%
-40.00%
-60.00%
Variation of belief interval (%)
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Rnaking
0.2
0.4
0.6
0.8
Weight of economic aspect
Bel(S1) Variation
Pls(S1) Variation
Bel(S2) Variation
Pls(S2) Variation
Bel(S3) Variation
Pls(S3) Variation
Bel(S4) Variation
Pls(S4) Variation
S1 Ranking
S2 Ranking
S3 Ranking
S4 Ranking

(b)



(c)



(d)

Figure 5 Variations of the belief intervals when the weight of major aspect changes and corresponding ranking of the four scenarios. Sub-figures (a), (b), (c), and (d) present the situation of environmental, economic, social and technological aspect, respectively.

Figure 5 (a) indicates the effect of changing the weight of the environmental aspect.

According to the figure, the rankings of S1 and S4 remain the same as the original ranking result. The ranking of S2 increases to second place when the weight of environmental aspect is or is above 0.6, while the ranking of S3 correspondingly decreases. The variation bars illustrate that although the rankings of S1 and S4 remain stable, the belief intervals actually change to different extents. The belief interval of S4 clearly decreases when the weight of the environmental aspect increases, while the values of S1 are not sensitive to the change. This figure also reveals that biogas from sludge digestion for fuel cells to produce electricity can be competitive in the environmental perspective.

The ranking results have a big shift when the weight of the economic aspect increases from 0.6 to 0.8 (see Figure 5 (b)). Scenario 1 is still in the first place, though the belief interval keeps reducing as the weight of economic aspect rises. Instead of S3, S4 comes in second place when the weight of the economic aspect is 0.8, and the rankings of S3 and S2 correspondingly reduce. Considering the efficiency of electricity production, S4 is a promising option and S2 and S3 are not so preferred. However, the ranking result of the fourth situation may not be so reliable due to the missing information and the wide range of the belief intervals of the four scenarios. This fact reflects that DS-FBWM may not be suitable to a situation with extreme preferences which may lead to unreliable ranking results.

If the importance of the social aspect is or higher than 0.6, S3 is more preferrable than S1, while the rankings of S2 and S4 remain in the initial places (see Figure 5 (c)).

Hence, the obvious increase of belief intervals for S3 occurs with the weight of social aspect rising. Incineration is investment-intensive which usually requires for complete policy support and subsidies from the government. It is also less accepted by the public due to the limited apparent information and potential secondary air pollution. These barriers may impede the further promotion of wide application of incineration if there are not effective measures to deal with them.

The weight variation of the technological aspect does not have influence on the ranking result according to Figure 5 (d), especially the belief interval of S1 which always remains at a similar value to original result. The value of $Bel(S_2)$ continuously reduces as the weight of technological aspect increases and reaches a peak value at about 65% when the weight is 0.8. Compared to $Bel(S_2)$, the reduction of $Pls(S_2)$ is not so obvious (at most around 40%). The variation of the belief interval of S3 is relatively stable which remains at approximate 30%. Similar to the belief interval of S2, the lower and upper bounds of S4 also decrease with the increasing weight of the technological aspect. According to the data reflected from Figure 5 (d), both biogas fuel cells and MFCs for electricity production are weak in technological indicators due to the limited maturity, while incineration and biogas combustion for electricity generation have a longer development history and higher maturity.

To investigate the influence of the weight variations of each criterion, the weight of the major criterion is fixed at 0.25 and the weights of the other 12 criteria are assumed to be equal, i.e. 0.75/12=0.0625. The variations of the belief intervals of the four scenarios under the 13 weighting assignments are listed in Table 14.

Table 14 Variations of the belief intervals and corresponding ranking when the weight of major criterion changes

Denotation	S1		S2		S3		S4		Priority order
	Bel(S1) Variation	Pls(S1) Variation	Bel(S1) Variation	Pls(S2) Variation	Bel(S3) Variation	Pls(S3) Variation	Bel(S4) Variation	Pls(S4) Variation	
C_1	-7.03%	-8.75%	31.12%	20.72%	-22.74%	-24.48%	18.05%	7.68%	S1>S2>S3>S4
C_2	0.79%	-1.49%	-17.31%	-21.93%	49.18%	40.32%	-62.03%	-60.55%	S1>S3>S2>S4
C_3	6.15%	5.00%	-4.64%	-5.63%	15.71%	13.42%	-55.61%	-49.22%	S1>S3>S2>S4
C_4	5.33%	4.19%	-15.74%	-15.27%	27.83%	24.39%	-55.95%	-49.61%	S1>S3>S2>S4
C_5	-20.26%	-20.03%	5.83%	4.73%	67.92%	61.82%	-50.74%	-43.65%	S1>S3>S2>S4
C_6	3.80%	2.51%	-11.83%	-12.75%	6.98%	4.86%	-18.96%	-19.52%	S1>S3>S2>S4
C_7	-0.57%	-0.09%	-12.88%	-7.18%	22.55%	23.29%	-35.66%	-26.40%	S1>S3>S2>S4
C_8	-11.26%	-10.31%	-9.53%	-6.23%	50.36%	44.90%	-45.27%	-40.64%	S1>S3>S2>S4
C_9	-9.22%	-9.77%	-18.55%	-14.65%	51.26%	45.77%	-40.83%	-32.32%	S1>S3>S2>S4
C_{10}	-8.82%	-9.37%	-29.45%	-25.36%	63.97%	57.37%	-48.57%	-40.86%	S1>S3>S2>S4
C_{11}	0.79%	-0.31%	-13.88%	-10.24%	14.58%	15.63%	-38.57%	-35.62%	S1>S3>S2>S4
C_{12}	3.74%	2.62%	-21.42%	-17.48%	7.48%	8.38%	-37.81%	-34.61%	S1>S3>S2>S4
C_{13}	0.20%	-0.89%	-23.09%	-19.40%	14.97%	12.29%	-44.13%	-36.09%	S1>S3>S2>S4

In the 13 assigned situations, all the rankings are the same as the original ranking result, i.e., $S1 \succ S3 \succ S2 \succ S4$. According to the presented data in Table 14, S1 is insensitive to almost all the criteria except for C_5, which decreases about 20%. S2 has advantages in C_1 and C_5 and the former one is more obvious. Improving the importance on other criteria makes S2 less preferred. As for S3, the only weakness is C_1 which can cause around 20% reduction of the belief interval of S2. Attaching more importance on the other 12 criterion makes S2 have higher priority to different extents, especially on C_2, C_5, C_8, C_9, and C_{10} (increase above 40%). Similar to S2, S4 also performs well when the weight of C_1 is increased but is disadvantaged on the other criteria. However, S4 has much wider variation than S2. The variation range of S2 is about 5%-30%, while that of S4 is 8%-60% (absolute values). Hence, from the perspective of ranking, the method is not sensitive to the weight changing of each criterion. Nevertheless, with respect to the belief intervals, i.e., the preferred extent, S2, S3 and S4 are all sensitive to the weight changing of the criteria, especially for the four criteria in environmental aspect (C_2-C_5), and the criteria in social and technical aspect.

6 Conclusions

This article developed a new method based on DS theory and fuzzy BWM, called the DS-FBWM framework, and applied it to assess and rank the sustainability performances of four sludge-to-electricity technologies: incineration, biogas from digested sludge for electricity production by fuel cells, biogas from digested sludge to generate electricity by combustion, and MFCs, where part of the information of MFCs is missing. DS-FBWM can deal with the decision-making problem with incomplete information. Four aspects and thirteen criteria were selected to form a criteria system and fuzzy BWM was used to decide the weight of each criterion. The ranking results of DS-FBWM indicated that sewage sludge incineration for electricity production has relatively high priority and MFCs is at the inferior place under the current development status. The Extended VIKOR method was utilized to rank the former three scenarios with complete performance information and compared with the ranking result of DS-FBWM. Biogas combustion for electricity generation is preferable than incineration in the ranking result of the Extended VIKOR method. The difference may be resulted from the diversity of the core computing thought. DS-FBWM is a relatively subjective method which transfers the exact information into knowledgeable scale according to the preferences of the decision-makers, leading to the underutilization of the known information. However, it can provide necessary reference for the decision-making process with incomplete information. In future work, a new method can be developed to solve the decision-making problem with missing information which can make full use of the known data.

Sensitivity analysis revealed that improving the weight of the environmental aspect can increase the priority of S2. MFCs (i.e., S4) would become more preferred if the economic aspect is attached to higher importance. S3 can be more competitive when the weights of the social and technological aspects improve. These results also indicated the strengths and weaknesses of these technologies. Incineration performs acceptably in the set situation of this work, but it is not widely accepted by the public due to the possible secondary pollution which is not fully reflected by the selected indicators, and still requires more government support. Considering the social acceptance and technological conditions, digested biogas combustion for electricity generation may be a more suitable choice with prepared markets and wide demanding. Biogas fuel cells and MFCs are both environmental-friendly especially on the climate change and they may become cost-effective if they can be fully developed in the future. All in all, related research and effective measures are still expected to improve current management for sludge-to-energy technologies. More reports and data from practical application are needed to study the performance of the technologies so that more reliable ranking results can be provided as a decision-making reference.

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