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Polygeneration System and Sustainability: Multi-Attribute Decision-support Framework for Comprehensive Assessment under Uncertainties

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Abstract: As an important energy-efficient production technology, polygeneration has attracted more and more attentions for its advantages of high energy efficiency, low production cost, and fewer emissions compared with the traditional industrial systems. The objective of this study is to develop a multi-attribute comprehensive assessment method for sustainability assessment of polygenerations under uncertainty conditions. Fuzzy best-worst network method which can incorporate the interdependences and interactions among the evaluation criteria has been developed for determining the weights of the criteria. Interval TOPSIS which can rank the alternative under uncertainties has been employed to rank the alternative polygeneration systems according to their sustainability performance. In order to illustrate the proposed method, an illustrative case including four industrial systems has been studied, and the results were also validated by interval grey relational analysis (GRA) method. Sensitivity analysis was also carried out to investigate the effects of the weights of the criteria on the sustainability ranking of the four polygeneration systems.

Keywords: polygeneration; multi-criteria decision making; sustainability; fuzzy; interval numbers

1. Introduction

With the rapid development of the world's economy, especially the growth in developing countries, people's living standard and consumption level have been rising significantly. Consequently, the demand of natural resources, minerals, and water increase rapidly and has excessed the renewability of the earth. Recently, humanity requires over 50% more than what the planet can regenerate, and this ratio will increase to 75% by 2020 if nothing will be done (Global Footprint Network 2016). This also leaded to severe environmental pollution and degradation problems (Serra *et al.* 2009). Therefore, polygeneration technologies which can maximize the utilization of energy and minimize the pollution have been recognized as a promising pathway for resolving these problems.

Polygeneration is an important and energy-efficient production technology, which is the combination of two or more products and/or services production processes to maximize the thermodynamic potential of the raw material resources (Serra *et al.* 2009). Adams and Ghouse (2015) accurately defined polygeneration as "*A thermochemical process which simultaneously produces at least two different products in non-trivial quantities, but is not a petroleum refining process, a co-generation process, or a tri-generation process, and at least one product is a chemical or fuel, and at least one is electricity*". It is an integrated process to co-produce chemicals, fuels and electricity with multiple production systems (see Figure 1) (Petchers 2003; Smith, 2005; Liu *et al.*, 2007). The purpose of polygeneration system is to increase the energy efficiency through making full use of natural resources, and further for decreasing the environmental burdens and production costs simultaneously.

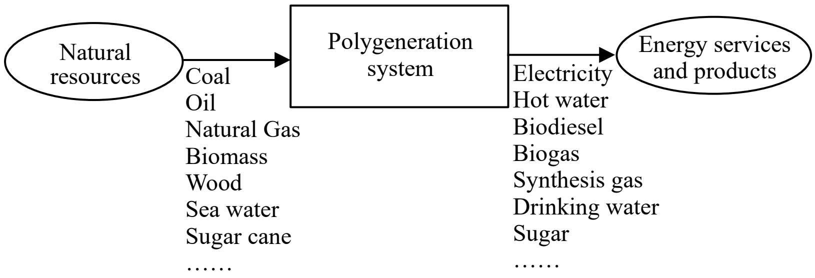

Figure 1: Multi-resource and multi-product transformation process of polygeneration systems (Serra *et al.* ,2009)

There are usually various types of polygeneration systems. For instance, they can be categorized into cogeneration system and trigeneration system according to the number of the incorporated industrial processes, and they can also be divided into different categories according to the products or the processes. The basic form of polygeneration is the combination of heat and power (CHP). Polygeneration is not a simple superposition of multiple energy systems, while it is an integrated and optimized coproduction system based on a special principle (Yi *et al.* 2017). To be specific, depending on the number of integrated production process, polygeneration can be classified as cogeneration systems, trigeneration systems (Serra *et al.*, 2009; Wang *et al*. 2009; Carvalho *et al.* 2012; Jradi and Riffat, 2014). According to the different products, or different types of production process, polygeneration can be divided into coal based polygernation system, natural gas based polygeneration system, and renewable sources based polygeneration systems and some others, i.e. drinking water or sugar as one of the products. Yi et al. (2017) presented three types of coal-based polygernation systems. For more information about some other new types of polygeneration systems, in the readers can refer to the work of Serra *et al*. (2009).

Accordingly, the decision-makers can usually have multiple choices when selecting the most suitable type of polygeneration system for achieving their targets, i.e. the production of electricity, heat, power, and drinking water, etc. The polygeneration systems usually have the advantages of high energy efficiency, low production cost and fewer emissions compared with the traditional separate production systems. Comparing with the traditional technology, the efficiency of a steam turbine for power generation is only 20-38%, while the efficiency in combined heat and power (CHP) system will be improved to 80-90% when the useful heat has also been produced (Rong and Lahdelma, 2016). However, different polygeneration systems perform different with respect to these advantages. Meanwhile, there are also some disadvantages in the polygeneration systems, i.e. high investment and complex installations architecture (Hu and Feng, 2013). Similarly, different polygeneration systems also need different capital costs and have different complexity in configurations. The disadvantage can be remedied by the more economic operation and environmental benefits in the long-term run (Heteu and Bolle, 2002). There are also some deficiencies in some specific production processes. For example, Bruno (2007) mentioned that the thermal energy storage in the polygeneration systems needs complex installations architecture, which usually loss heat and have poor performance at low temperature. Adams and Ghouse (2015) pointed out that many studies focusing on the determination of the optimum configuration of polygeneration by optimizing the best combination of the candidate routes, processes, and products. Accordingly, different combinations can form different polygeneration configurations which have different economic, environmental and technological performances.

The selection of the most suitable polygeneration system cannot merely account economic benefits, the environmental impacts and societal performances should also be incorporated in the decision-making process. Therefore, a multi-dimensional evaluation of polygeneration systems is of vital importance. Sustainability assessment as a typical multi-dimensional evaluation approach which can assess the economic, environmental and social aspects simultaneously was used as a comprehensive tool to evaluate the overall performances of the polygeneration systems.

Multi-attribute decision making (MADM), also called "multi-attribute decision analysis (MADA)" or "multi-criteria decision making (MCDM)", was widely used for technology evaluation and selection, i.e. sustainability assessment and comprehensive evaluation. Vivekh *et al*. (2006) used TOPSIS and PROMETHEE II method to have a multi-criteria evaluation of the desalination technologies by considering 11 criteria. Ren *et al*. (2015a) combined life cycle assessment, life cycle cost, and social life cycle assessment for investigating the environmental, economic, and social categories-the three pillars of sustainability, and VIKOR method was employed to rank the alternative technologies for bioethanol production. Similarly, MADM was also widely used for techno-economic evaluation or sustainability assessment of polygeneration systems. For instance, Yang *et al.* (2015) employed the House of Quality method for evaluating the polygeneration technologies based on low rank coal, in which a multi-hierarchy evaluation model including nineteen customer needs and ten technological characteristics was developed. Ng and Hernandez (2016) developed a multi-dimensional evaluation framework for decision-making on polygeneration systems by considering energetic, environmental and economic criteria simultaneously. Ganadharan *et al.* (2012) employed the embedding exergy analysis and inherent safety score for quantifying the efficiency and societal aspects to assess the sustainability of polygeneration systems. Khan *et al.* (2014) analyzed the technological and economic performances of polygeneration systems based on biogas by investigating mass flows and energy balance, levelized cost, and the payback period. Ng *et al*. (2013) investigated the techno-economic performances of polygeneration systems, and analyzed the effect of process configurations and operating conditions on the economic potential (EP) and risks. Wang *et al*. (2006) employed Analytic Hierarchy Process (AHP) to evaluate the sustainability of polygeneration systems. All these studies are significantly important for the decision-makers to select the most sustainable scenario among multiple alternative polygeneration systems; however, there are also some research gaps:

(1) The lack of the convenient methods for accurately collecting the opinions of the decision-makers, because the most commonly used method-AHP and various methods derived from AHP cannot accurately reflect the opinions of the decision-makers due to the vagueness and ambiguity existing in the opinions of the decision-makers. Moreover, all these methods determine the weights of the criteria/indicators based on the comparison matrix which has high requirement to ensure its consistency;

(2) The lack of the consideration of the independences, interdependences, and interactions among these criteria/indicators when calculating the weights of the criteria/indicators for sustainability assessment;

(3) The lack of the method for ranking the alternative polygeneration systems under uncertainty conditions. There are usually various uncertainties existing in sustainability assessment due to the lack of information/knowledge; thus, it is prerequisite to develop the multi-criteria decision making method which can address the decision-making matrix with uncertainty information.

In order to fill the above-mentioned research gaps, a novel multi-attribute decision making method was developed for sustainability assessment of the polygeneration systems. Fuzzy best-worst network method was developed for determining the weights of the criteria for sustainability assessment, and the developed weighting method can not only accurately incorporate the opinions of the decision-makers, but also consider the interdependences and interactions among the criteria/indicators for sustainability assessment of polygeneration systems. Interval TOPSIS which can handle the decision-making matrix with interval numbers and achieve decision-making under uncertainties was employed to prioritize the polygeneration systems.

Besides the introduction part, the remainder parts of this study has been organized as follows:

section 2 presented the developed multi-attribute decision making method; an illustrative case was studied in section 3; the results were discussed in section 4 through validation and sensitivity analysis; some insights and implications were presented in section 5; this study was concluded in section 6; limitations and future work was presented in section 7.

2. Methods

In this section, the basic knowledge of fuzzy number and interval number was firstly introduced; subsequently, fuzzy best-worst method was presented; then, the fuzzy best-worst network method was developed; finally, the interval TOPSIS method was presented.

2.1 Basic knowledge

Fuzzy set theory and interval number were introduced in this part.

Definition 1 (Chen, 2000) A fuzzy set $\tilde{A}$ in a universe of discourse X is characterized by a membership function $\mu_{\tilde{A}}(x)$ which associates with each element x in X a real number in the interval $[0,1]$. The value of $\mu_{\tilde{A}}(x)$ denotes the level of membership of x in $\tilde{A}$,

As for the triangular fuzzy numbers which are the most commonly used for addressing the vagueness and ambiguity existing in human judgments, and they can be defined as the triplets. For example, the triangular fuzzy number $\tilde{a}$ can be defined as the triplet (a_1, a_2, a_3). The arithmetic operations among the triangular fuzzy numbers were presented in Eqs.1-4. For more details about the arithmetic operations among the triangular fuzzy numbers, the readers can refer to the works of Krohling and Campanharo (2011) and Ren *et al*. (2015).

Assuming that $\tilde{a} = (a_1, a_2, a_3)$ and $\tilde{b} = (b_1, b_2, b_3)$ are two fuzzy numbers:

$$(a_1, a_2, a_3) + (b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{1}$$

$$(a_1, a_2, a_3) - (b_1, b_2, b_3) = (a_1 - b_1, a_2 - b_2, a_3 - b_3) \tag{2}$$

$$\left(a_1, a_2, a_3\right) \times \left(b_1, b_2, b_3\right) = \left(a_1 b_1, a_2 b_2, a_3 b_3\right) \tag{3}$$

$$\left(a_1, a_2, a_3\right) / \left(b_1, b_2, b_3\right) = \left(a_1 / b_3, a_2 / b_2, a_3 / b_1\right) \tag{4}$$

The distance between two fuzzy numbers can be determined by Eq.5.

$$d\left(\tilde{a}, \tilde{b}\right) = \sqrt{\left(a_1 - b_1\right)^2 + \left(a_2 - b_2\right)^2 + \left(a_3 - b_3\right)^2} \tag{5}$$

A fuzzy number $\tilde{a} = \left(a_1, a_2, a_3\right)$ can also be defuzzied into a crisp number a by Eq.5.

$$a = \frac{a_1 + 4a_2 + a_3}{6} \tag{6}$$

Definition 2 (Yue, 2011) Let $\bar{a} = \left[a^L, a^U\right] = \left\{x \middle| 0 \le a^L \le x \le a^U\right\}$,then, $\bar{a}$ is a nonnegative interval number.

Let $\bar{a} = \left[a^L, a^U\right]$ and $\bar{b} = \left[b^L, b^U\right]$ two nonnegative interval numbers, and $\lambda > 0$ be a crisp number:

$$\bar{a} + \bar{b} = \left[a^L, a^U\right] + \left[b^L, b^U\right] = \left[a^L + b^L, a^U + b^U\right] \tag{7}$$

$$\lambda \bar{a} = \lambda \left[a^L, a^U\right] = \left[\lambda a^L, \lambda a^U\right] \tag{8}$$

The distance between two nonnegative interval numbers can be determined by Eq.9.

$$d\left(\bar{a}, \bar{b}\right) = \sqrt{\left(a^L - b^L\right)^2 + \left(a^U - b^U\right)^2} \tag{9}$$

2.2 Fuzzy Best-Worst (BW) method

The weights of the criteria in multi-criteria decision making can not only represent the relative importance of the criteria, but also the opinions/preferences of the decision-makers. Thus, the accurate determination of the weights is of vital importance for accurate and correct multi-criteria decision making. There are usually various weighting methods, i.e. the subjective weighting methods and the objective weighting methods. The subjective weighting methods can determine the weights according to the subjective judgments of the decision-makers, and the results can effectively reflect the preferences and opinions of the decision-makers. The objective weighting methods can determine the weights of the criteria by using mathematical algorithm/ model without involving the preferences of the decision-makers on multiple criteria (Zardari *et al.*, 2015). There are various subjective weighting methods, i.e. direct ranking method, point allocation, ratio method, swing method, graphical weighting method, Delphi method, simple multi-attribute ranking technique (SMART), and SIMOS method (Zardari *et al.*, 2015). Similarly, entropy method, Criteria Importance Through Inter-criteria Correlation (CRITIC), mean weight, and standard derivation methods are the most commonly used objective weighting methods. According to literature reviews (An *et al*., 2016; Ren *et al*., 2017; Ren and Lützen, 2017), there is no a unique standard for selecting the weighting methods, because each of these methods has both strengths and weak points. The users usually choose the subjective weighting methods for weights determination, because they can integrate the preferences of the users on the multiple criteria. Among these subjective weighting methods, AHP which is a typical comparison method has been widely used for determining the weights of the criteria. However, the users have to do n(n-1)/2 times of comparisons when using AHP for determining the weights of n criteria (Ren *et al*., 2014). Moreover, the overall consistency cannot be guaranteed when the number of the criteria increases. Accordingly, Rezaei (2015) developed a novel weighting method, so-called "Best-Worst (BW) method", for determining the weights of the criteria. The BW method can effectively determine the weights of the criteria based on the opinions and preferences of the decision-makers with relatively higher consistency and less times of comparisons compared with AHP and various modified AHP methods. In order to address the vagueness and ambiguity existed in human judgments when comparing each pair of criteria, Guo and Zhao (2017) extend the BW method into fuzzy environment, the fuzzy BW method can not only guarantee the consistency, but also solve the problem of the vagueness and ambiguity in human judgments successfully when doing the comparisons. The fuzzy BW method has been specified as follows based on the work of Guo and Zhao (2017):

Assuming that there are a total of n elements ($e_i\left(i=1,2,\cdots,n\right)$) to be studied, and their relative weights (relative importance) can be determined by the fuzzy best-worst method according to the following procedures:

Step 1: Building the hierarchical structure of the decision-making problem. For instance, there are a total of T categories in the second level of hierarchy ($C_t\left(t=1,2,\cdots,T\right)$) and a total of n elements (the third hierarchy) in the decision-making problem in Figure 2.

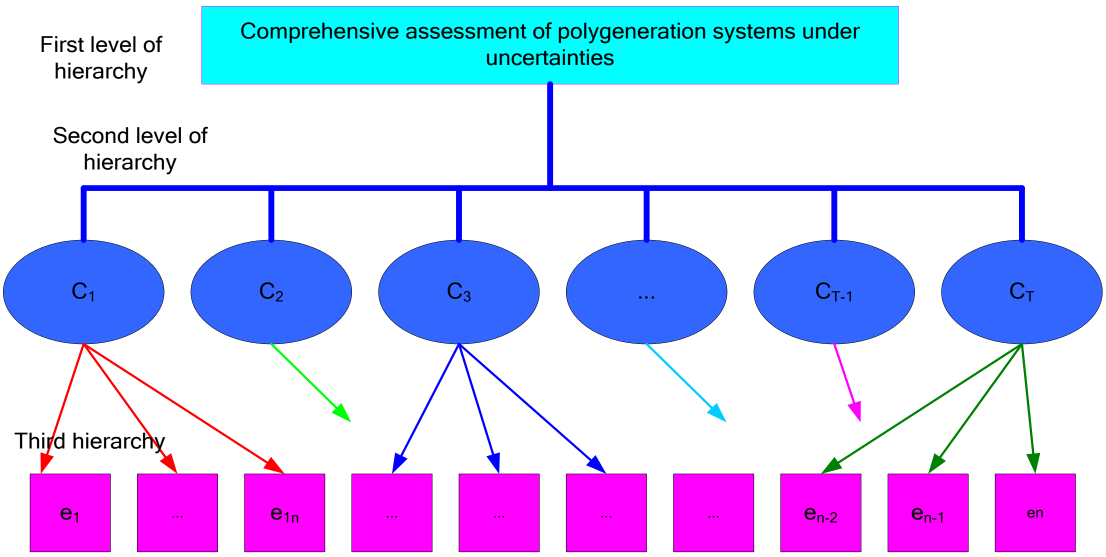

Figure 2: Hierarchical structure of the decision-making problem

Step 2: Determining the best (e.g. most preferred, most important, and most superiority) and the worst (e.g. least preferred, least important, and least superiority) decision elements among the n elements, denotes by E_B and E_W, respectively. In this step, the decision-makers will hold a meeting for discussing the relative priority of the n elements, and they will be asked to rank these n elements from the most superior to the least (or from the most important to the least important), then, E_B and E_W can be determined.

Step 3: Determining the preference comparison of E_B compared with other criteria as well as that of other criteria compared with E_W by using the linguistic terms, including "Equal importance (EI)", "Weak importance (WI)", "Fair importance (FI)", "Strong importance (SI)", and "Absolute importance (AI)". Then, the Best-to-Others (BO) vector and the Others-to-Worst (OW) vector can be determined by using the linguistic terms. Then, the linguistic terms can be transformed into triangular fuzzy numbers, EI, WI, FI, SI, and AI correspond to (1,1,1), (2/3,1,3/2),(3/2, 2, 5/2), (5/2, 3, 7/2), and (7/2, 4, 9/2), respectively (Tseng *et al.*, 2009). This fuzzy scale system for establishing the fuzzy comparison matrix has been widely used in many studies for its advantage of capturing the preference, opinions and willingness of the decision-makers/stakeholders accurately (An *et al.*, 2016; Ren *et al.*, 2016; Ren and Sovacool, 2014). After this, the BO and OW vectors composed by using the triangular fuzzy numbers, denote by $\tilde{V}_{BO}$ and $\tilde{V}_{OW}$, can be determined, as presented in Eq.10 and Eq.11, respectively.

$$\tilde{V}_{BO} = \begin{bmatrix} \tilde{a}_{B1} & \tilde{a}_{B2} & \cdots & \tilde{a}_{Bn} \end{bmatrix} \tag{10}$$

$$\tilde{V}_{OW} = \begin{bmatrix} \tilde{a}_{1W} & \tilde{a}_{2W} & \cdots & \tilde{a}_{nW} \end{bmatrix} \tag{11}$$

where $\tilde{a}_{Bj} (j = 1, 2, \cdots, n)$ and $\tilde{a}_{jW} (j = 1, 2, \cdots, n)$ represent the relative fuzzy preference of E_B comparing with the j-th criterion and that of the j-th criterion comparing with E_W.

In this case when $j = B$, then $\tilde{a}_{Bj} == (1,1,1)$, and when $j = W$, then $\tilde{a}_{jW} = (1,1,1)$.

Step 4: Determining the fuzzy optimum weights of the n elements $\begin{bmatrix} \tilde{\omega}_1 & \tilde{\omega}_2 & \cdots & \tilde{\omega}_n \end{bmatrix}$.

The optimum weight of each criterion is the one for each pair $\frac{\tilde{\omega}_B}{\tilde{\omega}_j}$ and $\frac{\tilde{\omega}_j}{\tilde{\omega}_W}$ should satisfy:

$$\frac{\tilde{\omega}_B}{\tilde{\omega}_j} = \tilde{a}_{Bj} (j = 1, 2, \cdots, n) \tag{12}$$

$$\frac{\tilde{\omega}_j}{\tilde{\omega}_W} = \tilde{a}_{jW} \,(j = 1, 2, \cdots, n) \tag{13}$$

where $\tilde{\omega}_B$ represents the weight of the best criterion, $\tilde{\omega}_W$ represent the weight of the worst criterion, and $\tilde{\omega}_j$ denotes the weight of the j-th criterion.

The objective of this step is to determine the optimum weights by making all the maximum absolute gaps $\left|\frac{\tilde{\omega}_B}{\tilde{\omega}_j} - \tilde{a}_{Bj}\right|$ and $\left|\frac{\tilde{\omega}_j}{\tilde{\omega}_W} - \tilde{a}_{jW}\right|$ for all j are the minimum. Then, the constrained optimization programming for determining the optimum fuzzy weights can be obtained:

$$\begin{aligned}
&\min \max_j \left\{ \left|\frac{\tilde{\omega}_B}{\tilde{\omega}_j} - \tilde{a}_{Bj}\right|, \left|\frac{\tilde{\omega}_j}{\tilde{\omega}_W} - \tilde{a}_{jW}\right| \right\} \\
&s.t. \\
&\sum_{j=1}^{n} R\left(\tilde{\omega}_j\right) = 1 \\
&\tilde{\omega}_j = \left(\omega_j^L, \omega_j^M, \omega_j^U\right) \\
&\omega_j^L \le \omega_j^M \le \omega_j^U \\
&\omega_j^L \ge 0 \\
&j = 1, 2, \cdots, n
\end{aligned} \tag{14}$$

where $\tilde{\omega}_B = \left(\omega_B^L, \omega_B^M, \omega_B^U\right)$, $\tilde{\omega}_j = \left(\omega_j^L, \omega_j^M, \omega_j^U\right)$, $\tilde{\omega}_W = \left(\omega_W^L, \omega_W^M, \omega_W^U\right)$, $\tilde{a}_{Bj} = \left(a_{Bj}^L, a_{Bj}^M, a_{Bj}^U\right)$, and $\tilde{a}_{jW} = \left(a_{jW}^L, a_{jW}^M, a_{jW}^U\right)$

$R\left(\tilde{\omega}_j\right)$ is the graded mean integration representation of $\tilde{\omega}_j$, it can be determined by Eq.15.

$$R\left(\tilde{\omega}_j\right) = \frac{\omega_j^L + 4\omega_j^M + \omega_j^U}{6} \tag{15}$$

Accordingly, programming (15) can be transferred into (16):

$$
\begin{aligned}
&\min \tilde{\xi} \\
&s.t. \\
&\left| \frac{\tilde{\omega}_B}{\tilde{\omega}_j} - \tilde{a}_{Bj} \right| \le \tilde{\xi},\ j = 1, 2, \cdots, n \\
&\left| \frac{\tilde{\omega}_j}{\tilde{\omega}_W} - \tilde{a}_{jW} \right| \le \tilde{\xi},\ j = 1, 2, \cdots, n \\
&\sum_{j=1}^{n} R\left(\tilde{\omega}_j\right) = 1 \\
&\tilde{\omega}_j = \left(\omega_j^L, \omega_j^M, \omega_j^U\right) \\
&\omega_j^L \le \omega_j^M \le \omega_j^U \\
&\omega_j^L \ge 0 \\
&j = 1, 2, \cdots, n
\end{aligned}
\tag{16}
$$

where $\tilde{\xi} = \left(\xi^L, \xi^M, \xi^U\right)$

With the consideration that $\xi^L \le \xi^M \le \xi^U$, it is supposed that $\tilde{\xi} = \left(k^*, k^*, k^*\right), k^* \le \xi^L$, thus, programming (15) can be transformed into:

$$
\begin{aligned}
&\min k^* \\
&s.t. \\
&\left| \frac{\left(\omega_B^L, \omega_B^M, \omega_B^U\right)}{\left(\omega_j^L, \omega_j^M, \omega_j^U\right)} - \left(a_{Bj}^L, a_{Bj}^M, a_{Bj}^U\right) \right| \le k^*,\ j = 1, 2, \cdots, n \\
&\left| \frac{\left(\omega_j^L, \omega_j^M, \omega_j^U\right)}{\left(\omega_W^L, \omega_W^M, \omega_W^U\right)} - \left(a_{jW}^L, a_{jW}^M, a_{jW}^U\right) \right| \le k^*,\ j = 1, 2, \cdots, n \\
&\sum_{j=1}^{n} R\left(\tilde{\omega}_j\right) = 1 \\
&\tilde{\omega}_j = \left(\omega_j^L, \omega_j^M, \omega_j^U\right) \\
&\omega_j^L \le \omega_j^M \le \omega_j^U \\
&\omega_j^L \ge 0 \\
&j = 1, 2, \cdots, n
\end{aligned}
\tag{17}
$$

According to the arithmetic operations between the fuzzy numbers, programming (17) can be transformed into (18). After solving programming (18), the fuzzy optimum weights of the n elements $\left[\tilde{\omega}_1 \quad \tilde{\omega}_2 \quad \cdots \quad \tilde{\omega}_n\right]$ can be obtained.

$$
\begin{aligned}
&\min k^* \\
&s.t. \\
&\left|\frac{\omega_B^L}{\omega_j^U} - a_{Bj}^L\right| \le k^* \\
&\left|\frac{\omega_B^M}{\omega_j^M} - a_{Bj}^M\right| \le k^* \\
&\left|\frac{\omega_B^U}{\omega_j^L} - a_{Bj}^U\right| \le k^* \\
&\left|\frac{\omega_j^L}{\omega_W^U} - a_{Bj}^L\right| \le k^* \\
&\left|\frac{\omega_j^M}{\omega_W^M} - a_{jW}^M\right| \le k^* \\
&\left|\frac{\omega_j^U}{\omega_W^L} - a_{jW}^U\right| \le k \\
&\sum_{j=1}^{n} R\left(\tilde{\omega}_j\right) = 1 \\
&\tilde{\omega}_j = \left(\omega_j^L, \omega_j^M, \omega_j^U\right) \\
&\omega_j^L \le \omega_j^M \le \omega_j^U \\
&\omega_j^L \ge 0 \\
&j = 1, 2, \cdots, n
\end{aligned}
\tag{18}
$$

Step 5: Defuzzy the fuzzy optimum weights of the n elements $\left[\tilde{\omega}_1 \quad \tilde{\omega}_2 \quad \cdots \quad \tilde{\omega}_n\right]$ into crisp numbers $\left[\omega_1 \quad \omega_2 \quad \cdots \quad \omega_n\right]$ according to Eq.19.

$$
\omega_j = \frac{\omega_j^L + 4\omega_j^M + \omega_j^U}{6} \tag{19}
$$

Step 6: Consistency check. The purpose of consistency check is to measure the whole consistency level of the BO and OW vectors. According to the work of Guo and Zhao (2017), the consistency ratio (CR) can be calculated by Eq.20.

$$CR = \frac{k^*}{CI} \qquad (20)$$

The value of the consistency index (CI) can be determined according to $\tilde{a}_{BW}$, as presented in Table 1.

Table 1: CI with respect to $\tilde{a}_{BW}$ used in the fuzzy best-worst method

$\tilde{a}_{BW}$	(1,1,1)	(2/3,1,3/2)	(3/2,2,5/2)	(5/2,3,7/2)	(7/2,4,9/2)
CI	3.00	3.80	5.29	6.69	8.04

Reference: adapted from Guo and Zhao (2017)

The more close the value of CR to zero, the more consistent the BO and OW vectors are. However, there is no a unique standard to judge whether the BO and OW vectors are consistent or not. In this study, 0.10 was set as the threshold value. In other words, when $CR \le 0.10$, the BO and OW vectors can be recognized as consistent, or the users need to modify the BO or the OW vector to make it consistent.

2.3 FBW network method

The fuzzy best-worst method can determine the relative priority (weight) of each element with a better consistency and less times of comparisons compared with AHP and various methods derived from AHP. However, all these methods cannot effectively consider the independence, interdependence, and interactions among the elements to be studied, thus, these weights of the elements cannot be determined accurately without considering the interactions and interdependence among these elements. Therefore, the fuzzy best-worst network has been developed in this study, and it consists of four steps:

Step 1: Using FBW method to determine the global weights of the n elements. The global weight of each element can be derived from the local weight of the element (the third hierarchy) in each category (the second hierarchy) multiplied with the weight of the corresponding category $W_1 = [\omega_1 \quad \omega_2 \quad \cdots \quad \omega_n]$.

Step 2: Determining the inner dependency matrix (D) of the elements with respect to each element. $d_{kj}(k = 1, 2, \cdots, n)$ in the *j*-th column vector of the matrix D which is the relative independence (interdependence or interaction) of all the elements on the *j*-th element, can also be determined by FBW method. In a similar way, all the other column vectors in matrix D can also be determined, as presented in Eq.20.

$$D = \begin{vmatrix} 1 & d_{12} & \cdots & d_{n1} \\ d_{21} & 1 & \cdots & d_{n2} \\ \vdots & \cdots & \ddots & \vdots \\ d_{n1} & d_{n2} & \cdots & 1 \end{vmatrix} \tag{20}$$

where D is the inner dependency matrix, and d_{kj} represent the relative independence (interdependence or interaction) of the *k*-th element on the *j*-th element.

Accordingly, $d_{kj} = 0$ if there is not any independence (interdependence or interaction) of the *k*-th element on the *j*-th element, and the diagonal elements in matrix D equal 1.

Step 3: Calculating the inter-dependent weights of the n elements by Eq.21, then normalizing the inter-dependent priorities of the n factors by Eq. 22.

$$\mathrm{W}^{'} = D \times \mathrm{W}_1 = [\omega_1', \omega_2', \cdots, \omega_n'] \tag{21}$$

$$\mathrm{W} = \left[\omega_1' \Big/ \sum_{i=1}^{n} \omega_i', \omega_2' \Big/ \sum_{i=1}^{n} \omega_i', \cdots, \omega_n' \Big/ \sum_{i=1}^{n} \omega_i' \right] = \left[\omega_1^*, \omega_2^*, \cdots, \omega_n^* \right] \tag{22}$$

where W represents the normalized weight vector of the inter-dependent weight of the n elements, and $\omega_j^*(j = 1, 2, \cdots, n)$ represents the normalized weights of the *j*-th element.

2.4 Interval TOPSIS

An interval TOPSIS method was developed based on the previous work (Torfi *et al.*, 2010; Wang *et al.*, 2009;Yue, 2011; Yue, 2012), in which the elements in the decision-making matrix are all interval numbers, and the weights of the decision criteria were determined by the fuzzy best-worst network method. The interval TOPSIS consists of four steps:

Step 1: Establishing the interval decision-making matrix. This step is to determine the weights of the decision criteria by using the fuzzy best-worst network method and to collect the data of the alternatives with respect to the decision criteria.

Assuming that there are a total of n decision attributes $C_1, C_2, \cdots, C_n$ to assess the n alternatives, namely $A_1, A_2, \cdots, A_m$, then, the interval decision-making matrix can be determined, as presented in Eq.23.

$$X = \left| x_{ij}^{\pm} \right|_{m \times n} = \begin{vmatrix} & C_1 & C_2 & \cdots & C_n \\ A_1 & x_{11}^{\pm} & x_{12}^{\pm} & \cdots & x_{1n}^{\pm} \\ A_2 & x_{21}^{\pm} & x_{22}^{\pm} & \vdots & x_{2n}^{\pm} \\ \vdots & \vdots & \cdots & \ddots & \vdots \\ A_m & x_{m1}^{\pm} & x_{m2}^{\pm} & \cdots & x_{mn}^{\pm} \end{vmatrix} \tag{23}$$

where $x_{ij}^{\pm} = \left[x_{ij}^{-} \; x_{ij}^{+} \right]$ represents the value of the *i*-th alternative with respect to the *j*-th attribute.

Step 2: Normalizing the decision-making matrix. In order to avoid the effects caused by the unit gaps existing in the data of the interval decision-making matrix, all the data determined by step 1 can be normalized according to Eqs. 24-25.

As for the benefit-type criteria,

$$r_{ij}^{\pm} = \left[r_{ij}^{-}\ r_{ij}^{+} \right] = \begin{cases} \dfrac{x_{ij}^{-}}{\sqrt{\dfrac{1}{n}\sum_{j=1}^{m} x_{ij}^{+2}}} \\ \dfrac{x_{ij}^{+}}{\sqrt{\dfrac{1}{n}\sum_{j=1}^{m} x_{ij}^{+2}}} \end{cases} \tag{24}$$

As for the cost-type criteria,

$$r_{ij}^{\pm} = \left[r_{ij}^{-}\ r_{ij}^{+} \right] = \begin{cases} \dfrac{1/x_{ij}^{+}}{\sqrt{\sum_{j=1}^{m} \dfrac{1}{n}\left(1/x_{ij}^{-}\right)^{2}}} \\ \dfrac{1/x_{ij}^{-}}{\sqrt{\sum_{j=1}^{m} \dfrac{1}{n}\left(1/x_{ij}^{-}\right)^{2}}} \end{cases} \tag{25}$$

Step 3: Determining the weighted normalized decision-making matrix. After determining the normalized decision-making matrix, the weighted normalized decision-making matrix, Eq.26, can be obtained by incorporating the criterion weights. .

$$V = \left| v_{ij}^{\pm} \right|_{m \times n} = \begin{vmatrix} & C_1 & C_2 & \cdots & C_n \\ A_1 & \omega_1^{*} r_{11}^{\pm} & \omega_2^{*} r_{12}^{\pm} & \cdots & \omega_n^{*} r_{1n}^{\pm} \\ A_2 & \omega_1^{*} r_{21}^{\pm} & \omega_2^{*} r_{22}^{\pm} & \vdots & \omega_n^{*} r_{2n}^{\pm} \\ \vdots & \vdots & \cdots & \ddots & \vdots \\ A_m & \omega_1^{*} r_{m1}^{\pm} & \omega_2^{*} r_{m2}^{\pm} & \cdots & \omega_n^{*} r_{mn}^{\pm} \end{vmatrix} \tag{26}$$

where ω_j^{*} represents the interval weight of the j-th criterion determined by the fuzzy best-worst network method. According to Eq. 26, the positive ideal solutions (PIS), a series of real numbers representing the best ideal aspirations of the decision-makers /stakeholders, can be obtained by Eq.27 and Eq. 28, while the negative ideal solutions (NIS), a series of real numbers representing the constructed worst state of the alternatives, can be obtained by Eq.29 and Eq. 30, respectively.

$$PIS = \left(v_1^{+}, v_2^{+}, \cdots, v_n^{+} \right) \tag{27}$$

$$v_j^+ = \max_{i=1,2,\cdots,m} v_{ij}^+ , j = 1, 2, \cdots, n \tag{28}$$

$$NIS = \left(v_1^-, v_2^-, \cdots, v_n^-\right) \tag{29}$$

$$v_j^- = \min_{i=1,2,\cdots,m} v_{ij}^- , j = 1, 2, \cdots, n \tag{30}$$

Then, the distance between each alternative to the PIS (the positive ideal solutions) and that to the NIS (the negative ideal solutions) could be determined by Eq.31 and Eq.32, respectively. For PIS and NIS are two series of real numbers, they have to be converted into interval numbers before calculating the distance between each alternative and the positive ideal solutions, and that between each alternative and the negative ideal solutions.

$$d_i^+ = \sum_{j=1}^{n} d(v_{ij}^\pm, v_j^+) = \sum_{j=1}^{n} \sqrt{\left(v_{ij}^- - v_j^+\right)^2 + \left(v_{ij}^+ - v_j^+\right)^2} , i = 1, 2, \cdots, m \tag{31}$$

$$d_i^- = \sum_{j=1}^{n} d(v_{ij}^\pm, v_j^-) = \sum_{j=1}^{n} \sqrt{\left(v_{ij}^- - v_j^-\right)^2 + \left(v_{ij}^+ - v_j^-\right)^2} , i = 1, 2, \cdots, m \tag{32}$$

where d_i^+ represents the distance between the *i*-th alternative and the positive ideal solutions, and d_i^- represents the distance between the *i*-th alternative and the negative ideal solutions. Afterwards, the relative closeness coefficient of each alternative could be determined by Eq.33.

$$CC_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{33}$$

where CC_i is the closeness coefficient of the *i*-th alternative.

The closeness coefficient can reflect of the priority of the corresponding alternative, and it approaches to 1 as an alternative is closer to the positive ideal solutions and farther to the negative ideal solution. The closeness coefficient can characterize the closeness of the alternative to the ideal value and the farness to the anti-ideal value. Accordingly, the larger the closeness coefficient is, the better the alternative is. As for sustainability assessment of polygeneration systems in this study, the closeness coefficient can be recognized as the integrated sustainability of a polygeneration system which is similar to ecological footprint (Ren *et al.*, 2013) and emergy index of sustainability (Ren *et al.*, 2015b).

3. Case study

Four industrial systems for 200,000 tones methanol production and 300 MW electricity generation were assessed by the proposed multi-attribute sustainability assessment framework in this study, and they include the individual system for methanol production and electricity generation, two parallel polygeneration systems, and one series polygeneration system, and they can be illustrated by Figure 3 based on the work of Yi *et al.* (2017).

A_1(Individual system for methanol production using the gas-phase method, and chilled type IGCC (Integrated Gasification Combined Cycle) system): this system was composed by one individual system for methanol production by using the low pressure gas-phase method, and another individual system the chilled type two-stage IGCC technology for electricity generation;

A_2 (Parallel polygeneration, methanol production based on low pressure gas-phase method, and circle ratio is 4.5:1): the sub-systems for methanol and electricity production are parallel, and syngas was used for methanol production by the low pressure gas-phase technology and electricity generation parallel;

A_3 (Parallel polygeneration, liquid-phase CO-rich cycle, and circle ratio is 1:1): the sub-systems for methanol and electricity production are also parallel, and syngas was used for methanol production by the liquid-phase CO-rich cycle technology and electricity generation parallel;

A_4 (Series polygeneration, CO-rich once through methanol method): the sub-systems for methanol and electricity production are in series, and CO-rich once through methanol technology was used for methanol production.

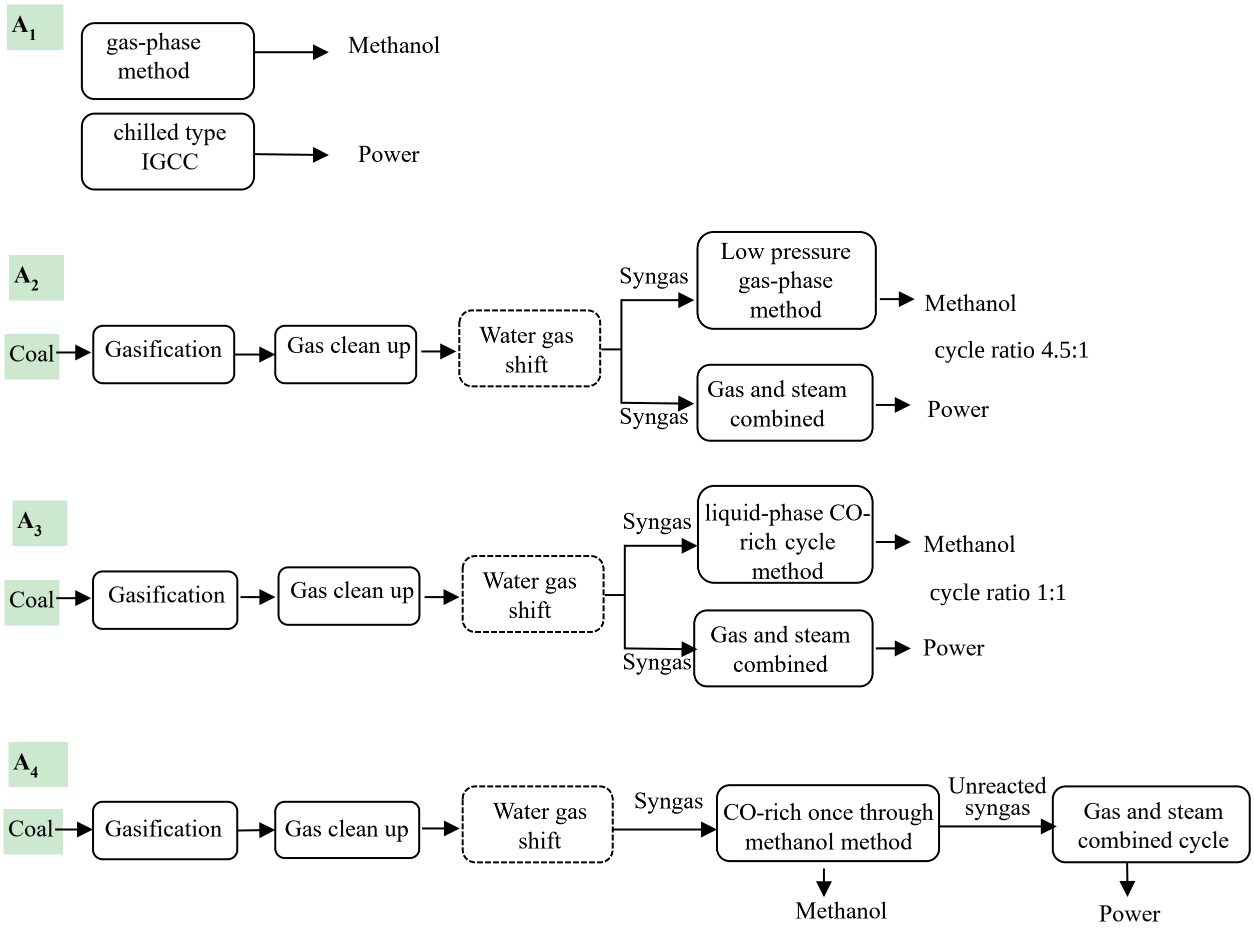

Figure 3: The illustrations of the four systems

For more details about the four systems, the readers can refer to the works of Wang *et al.* (2006). A total of eleven criteria four categories including economic performance, environmental impact, social effect, and technological characteristic were employed to assess the sustainability of these four alternative systems for methanol production and electricity generation, as presented in Figure 4.

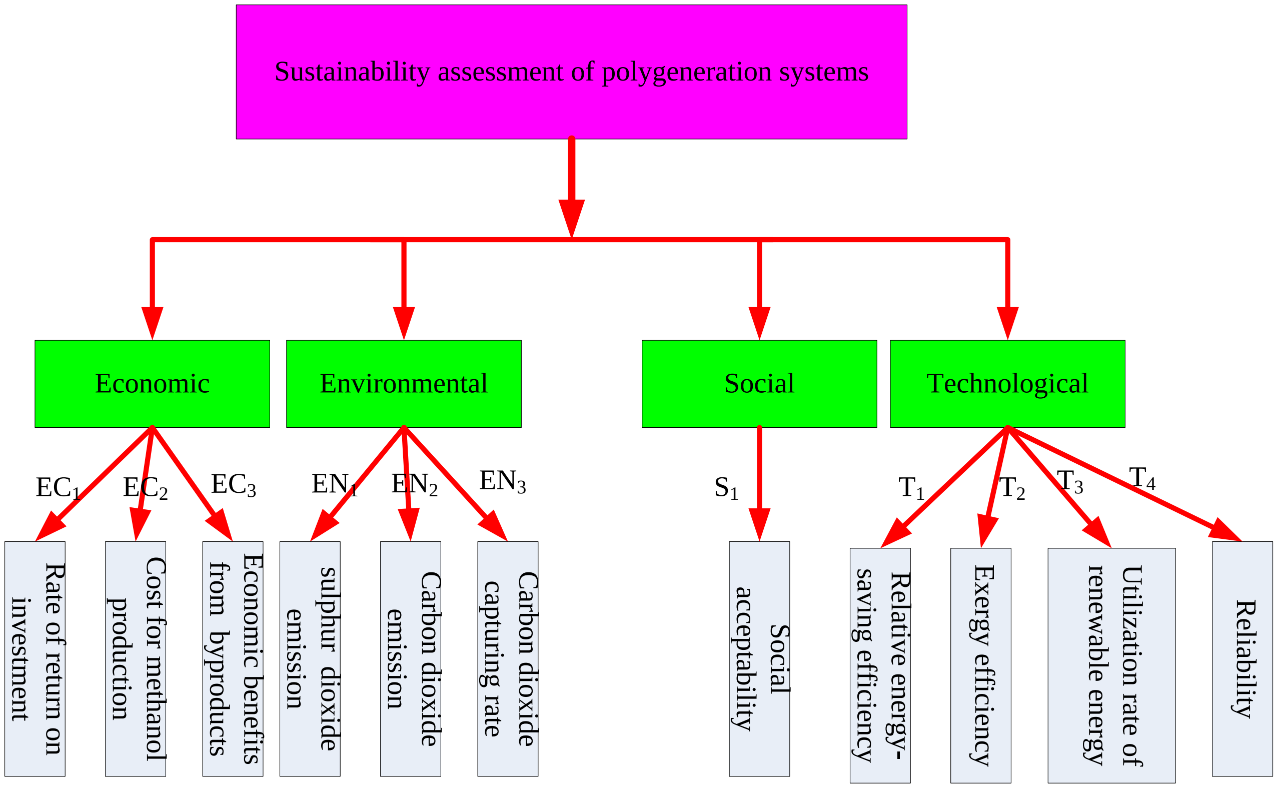

Figure 4: Sustainability assessment framework for polygeneration systems

The best-worst network method was firstly used to determine the weights of the eleven criteria. For instance, the weights of the four categories can be de by the following procedures:

Among these four categories, the 'Economic' and 'Social' categories have been recognized as the most important and the least important, respectively. The BO and OW vectors using linguistic terms were presented in Table 2.

Table 2: The BO and OW vectors using linguistic terms

Linguistic terms	**Best:** Economic		**Worst:** Social	
	Economic	Environmental	Social	Technological
BO	EI	FI	AI	SI
OW	AI	FI	EI	WI

Then, the BO and OW vectors can be obtained by transforming the linguistic terms into triangular fuzzy numbers, as presented in Eq.34.

$$\begin{array}{lcccc} & \textit{Economic} & \textit{Environmental} & \textit{Social} & \textit{Technological} \\ BO & (1,1,1) & (3/2,\ 2,\ 5/2) & (7/2,\ 4,\ 9/2) & (5/2,\ 3,\ 7/2) \\ OW & (7/2,\ 4,\ 9/2) & (3/2,\ 2,\ 5/2) & (1,1,1) & (2/3,1,3/2) \end{array} \tag{34}$$

According to programming (18), the model for determining the fuzzy optimum weights of the four categories can be obtained, as presented in (35). After solving this programming, the minimum value of k^* is 0.2167, and the results were presented in Table 3.

Table 3: The results of programming (35)

Category	Economic	Environmental	Social	Technological
Weights	(0.4877,0.4877,0.4877)	(0.2136,0.2246,0.2841)	(0.1139,0.1246,0.1485)	(0.1312,0.1516,0.1795)

According to the fuzzy weights, the crisp weight of each can be determined by Eq.19. For instance, the crisp weight of 'economic' can be determined by Eq.35.

$$\frac{0.2136+4\times 0.2246+0.2841}{6}=0.2327 \tag{35}$$

The crisp weights of the four categories are 0.4877, 0.2327, 0.1268, and 0.1529, respectively. In a similar way, the local crisp weights of the criteria in each category can also be obtained by the best-worst method, and they results were presented in Tables 4-6.

$$
\begin{aligned}
&\min k^* \\
&s.t. \\
&\left|\frac{\omega_1^L}{\omega_2^U}-\frac{3}{2}\right| \le k^*, \left|\frac{\omega_1^M}{\omega_2^M}-2\right| \le k^*, \left|\frac{\omega_1^U}{\omega_2^L}-\frac{5}{2}\right| \le k^* \\
&\left|\frac{\omega_1^L}{\omega_3^U}-\frac{7}{2}\right| \le k^*, \left|\frac{\omega_1^M}{\omega_3^M}-4\right| \le k^*, \left|\frac{\omega_1^U}{\omega_3^L}-\frac{9}{2}\right| \le k^* \\
&\left|\frac{\omega_1^L}{\omega_4^U}-\frac{5}{2}\right| \le k^*, \left|\frac{\omega_1^M}{\omega_4^M}-3\right| \le k^*, \left|\frac{\omega_1^U}{\omega_3^L}-\frac{7}{2}\right| \le k^* \\
&\left|\frac{\omega_2^L}{\omega_3^U}-\frac{3}{2}\right| \le k^*, \left|\frac{\omega_2^M}{\omega_3^M}-2\right| \le k^*, \left|\frac{\omega_2^U}{\omega_3^L}-\frac{5}{2}\right| \le k \\
&\left|\frac{\omega_4^L}{\omega_3^U}-\frac{2}{3}\right| \le k^*, \left|\frac{\omega_4^M}{\omega_3^M}-1\right| \le k^*, \left|\frac{\omega_4^U}{\omega_3^L}-\frac{3}{2}\right| \le k \\
&\frac{\omega_1^L+4\omega_1^M+\omega_1^U}{6}=1, \frac{\omega_2^L+4\omega_2^M+\omega_2^U}{6}=1, \frac{\omega_3^L+4\omega_3^M+\omega_3^U}{6}=1, \frac{\omega_4^L+4\omega_4^M+\omega_4^U}{6}=1 \\
&\omega_1^L \le \omega_1^M \le \omega_1^U \\
&\omega_2^L \le \omega_2^M \le \omega_2^U \\
&\omega_3^L \le \omega_3^M \le \omega_3^U \\
&\omega_4^L \le \omega_4^M \le \omega_4^U \\
&\omega_1^L \ge 0, \omega_2^L \ge 0, \omega_3^L \ge 0, \omega_4^L \ge 0
\end{aligned} \tag{36}
$$

According to $a_{BW}=\left(7/2,\ 4,\ 9/2\right)$, it could obtain that CI=8.04, $CR=\frac{\min k^*}{8.08}=\frac{0.2167}{8.04}=0.0270\le 0.10$, and the value of CR is very close to zero, thus, the BO and OW vectors can be recognized as consistent.

Table 4: The fuzzy BW method for determining the local weights of the criteria in economic category

Economic	Best: EC_1		Worst: EC_3	
	EC_1	EC_2	EC_3	
BO	(1,1,1)	(3/2, 2, 5/2)	(7/2, 4, 9/2)	$k^* = 0.3542$
OW	(7/2, 4, 9/2)	(5/2, 3, 7/2)	(1,1,1)	CI=8.04
Fuzzy weights	(0.4851, 0.5400, 0.6020)	(0.2806, 0.3281, 0.4130)	(0.1240,0.1240,0.1264)	$CR = 0.0441$ $CR \leq 0.10$
Crisp weights	0.5401	0.3337	0.1262	

Table 5: The fuzzy BW method for determining the local weights of the criteria in environmental category

Environmental	Best: EN_2		Worst: EN_3	
	EN_1	EN_2	EN_3	
BO	(2/3, 1, 3/2)	(1,1,1)	(5/2, 3, 7/2)	$k^* = 0.2361$
OW	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(1,1,1)	CI=6.69
Fuzzy weights	(0.2960, 0.3777, 0.4276)	(0.3860, 0.4668, 0.5101)	(0.1563,0.1689,0.1705)	$CR = 0.0353$ $CR \leq 0.10$
Crisp weights	0.3724	0.4606	0.1671	

Table 6: The fuzzy BW method for determining the local weights of the criteria in technological category

Technological	Best: T_4			Worst: T_3	
	T_1	T_2	T_3	T_4	
BO	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(7/2, 4, 9/2)	(1,1,1)	$k^* = 0.2167$
OW	(2/3,1,3/2)	(3/2, 2, 5/2)	(1,1,1)	(7/2, 4, 9/2)	CI=8.04
Fuzzy weights	(0.1308,0.1511, 0.1789)	(0.2027,0.2292,0.2832)	(0.1042,0.1285,0.1481)	(0.4862,0.4862,0.4862)	$CR = 0.0270$ $CR \leq 0.10$
Crisp weights	0.1524	0.2337	0.1277	0.4862	

Then, the global weights of the eleven criteria without considering the interdependences among these criteria can be determined by using the local weight of the criterion in each category multiplied the weight of the corresponding category. For instance, the global weight of EC_1 without the consideration of the interdependences among these criteria can be calculated by: the local weight of EC_1 in economic category × the weight of 'economic' category =0.4877×0.5401=0.2634. In a similar approach, the weights of the other ten criteria can also be calculated, and the results were summarized in Table 7.

Table 7: The global weights of the eleven criteria without considering the interdependences among these criteria

Category	Weights	Criteria	Local weights	Global weights
		EC_1	0.5401	0.2634
Economic	0.4877	EC_2	0.3337	0.1627
		EC_3	0.1262	0.0615
		EN_1	0.3724	0.0867
Environmental	0.2327	EN_2	0.4606	0.1072
		EN_3	0.1671	0.0389
Social	0.1268	S_1	1	0.1268
		T_1	0.1524	0.0233
		T_2	0.2337	0.0357
Technological	0.1529	T_3	0.1277	0.0195
		T_4	0.4862	0.0743

After determining the global weights of the eleven criteria without considering the interdependences among them, the inner dependency matrix (D) of the eleven criteria with respect to each criterion can also be obtained. The interdependent and interacted relationships among these eleven criteria should be incorporate in the weights determination, and parts of the interdependent and interacted relationships among these eleven criteria were presented in Figure 5.

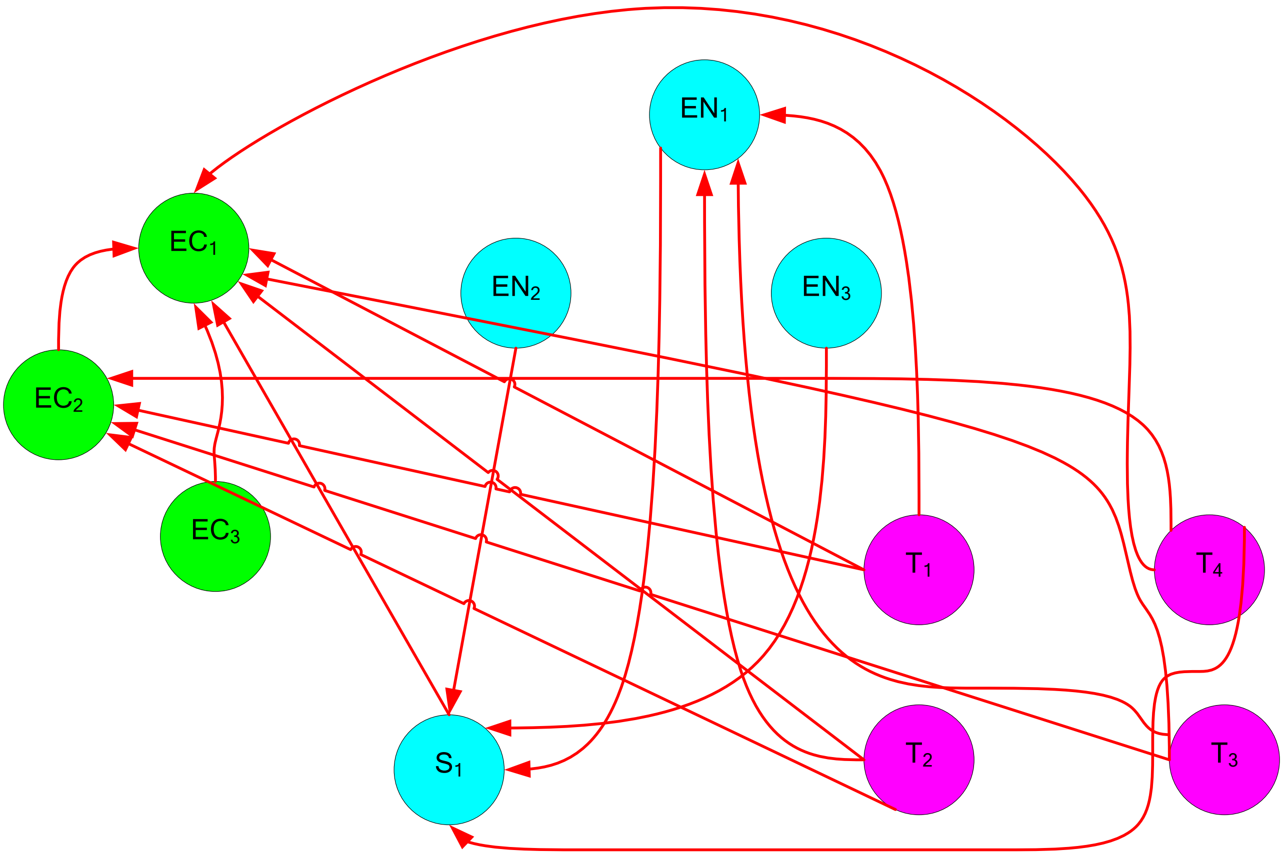

Figure 5: Parts of the interdependent and interacted relationships among these eleven criteria

Taking the relative effects of cost for methanol production (EC_2), economic benefits from byproducts (EC_3), relative energy-saving efficiency (T_1), exergy efficiency (T_2), utilization rate of renewable energy (T_3), and reliability (T_4) on rate of return on investment (EC_1) as an example. The related BO and OW vectors can be firstly determined, as presented in Table 8. Accordingly, 0.1900, 0.1900, 0.1201, 0.3093, 0.0703, and 0.1203 can be put in the corresponding positions of the first column in the inner dependency matrix (see Table 12). However, all the other elements in the first column equal zero if the corresponding criteria do not have any effects on EC_1. In a similar way, the relative effects of all the criteria on each criterion can be determined (see Tables 9-11).

Table 8: The relative effects of all the criteria on each criterion in economic category

EC_1	Best: T_2					Worst: T_3	
	EC_2	EC_3	T_1	T_2	T_3	T_4	$k^* = 0.4074$
BO	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(1,1,1)	(7/2, 4, 9/2)	(5/2, 3, 7/2)	CI=8.04
OW	(5/2, 3, 7/2)	(5/2, 3, 7/2)	(3/2, 2, 5/2)	(7/2, 4, 9/2)	(1,1,1)	(3/2, 2, 5/2)	$CR = 0.0507$ $CR \leq 0.10$
Crisp weights	0.1900	0.1900	0.1201	0.3093	0.0703	0.1203	
EC_2	Best: T_2					Worst: T_3	
	T_1	T_2	T_3	T_4			$k^* = 0.3182$
BO	(2/3,1,3/2)	(1,1,1)	(7/2, 4, 9/2)	(7/2, 4, 9/2)			CI=8.04
OW	(5/2, 3, 7/2)	(7/2, 4, 9/2)	(1,1,1)	(2/3,1,3/2)			$CR = 0.0396$ $CR \leq 0.10$
Crisp weights	0.3360	0.4390	0.1055	0.1194			

Table 9: The relative effects of all the criteria on each criterion in environmental category

EN_1	Best: T_2			Worst: T_3	
	T_1	T_2	T_3		$k^* = 0.2167$
BO	(2/3,1,3/2)	(1,1,1)	(7/2, 4, 9/2)		CI=8.04
OW	(5/2, 3, 7/2)	(7/2, 4, 9/2)	(1,1,1)		$CR = 0.0270$ $CR \leq 0.10$
Crisp weights	0.3964	0.4774	0.1262		
EN_2	Best: T_2			Worst: T_3	
	T_1	T_2	T_3		$k^* = 0.2167$
BO	(2/3,1,3/2)	(1,1,1)	(7/2, 4, 9/2)		CI=8.04
OW	(5/2, 3, 7/2)	(7/2, 4, 9/2)	(1,1,1)		$CR = 0.0270$ $CR \leq 0.10$
Crisp weights	0.3964	0.4774	0.1262		

Table 10: The relative effects of all the criteria on each criterion in social category

S_1	Best: EN_2									Worst: EC_3
	EC_1	EC_2	EC_3	EN_1	EN_2	EN_3	T_1	T_2	T_3	T_4
BO	(2/3, 1,3/2)	(5/2, 3, 7/2)	(7/2, 4, 9/2)	(2/3,1,3/2)	(1,1,1)	(5/2, 3, 7/2)	(3/2,2,5/2)	(3/2,2,5/2)	(3/2,2,5/2)	(7/2, 4, 9/2)
OW	(7/2, 4, 9/2)	(3/2,2,5/2)	(1,1,1)	(7/2, 4, 9/2)	(7/2, 4, 9/2)	(3/2,2,5/2)	(5/2, 3, 7/2)	(5/2, 3, 7/2)	(5/2, 3, 7/2)	(2/3,1,3/2)
Weights	0.0921	0.0483	0.0383	0.1081	0.1948	0.1081	0.1211	0.1466	0.0795	0.0632
	$k^* = 1.1716$， CI=8.04， $CR = 0.1457$， $CR \le 0.15$									

Table 11: The relative effects of all the criteria on each criterion in technological category

T_1	Best: T_2	Worst: T_4	
	T_2	T_4	
BO	(1,1,1)	(3/2,2,5/2)	
OW	(3/2,2,5/2)	(1,1,1)	$CR = 0$ $CR \leq 0.10$
Crisp weights	0.6632	0.3368	
T_2	Best: T_1	Worst: T_4	
	T_2	T_4	
BO	(1,1,1)	(5/2,3,7/2)	
OW	(5/2,3,7/2)	(1,1,1)	$CR = 0$ $CR \leq 0.10$
Crisp weights	0.7496	0.2504	

Table 12: The inner dependency matrix

	EC_1	EC_2	EC_3	EN_1	EN_2	EN_3	S_1	T_1	T_2	T_3	T_4
EC_1	0	0	0	0	0	0	0.0921	0	0	0	0
EC_2	0.1900	0	0	0	0	0	0.0483	0	0	0	0
EC_3	0.1900	0	0	0	0	0	0.0383	0	0	0	0
EN_1	0	0	0	0	0	0	0.1081	0	0	0	0
EN_2	0	0	0	0	0	0	0.1948	0	0	0	0
EN_3	0	0	0	0	0	0	0.1081	0	0	0	0
S_1	0	0	0	0	0	0	0	0	0	0	0
T_1	0.1201	0.3360	0	0.3964	0.3964	0	0.1211	0	0.7496	0	0
T_2	0.3093	0.4390	0	0.4774	0.4774	0	0.1466	0.6633	0	0	0
T_3	0.0703	0.1055	0	0.1262	0.1262	0	0.0795	0	0	0	0
T_4	0.1202	0.1194	0	0	0	0	0.0632	0.3367	0.2504	0	0

According to Eq.21, the weights of the eleven criteria with the considerations of the interactions and interdependences among them can be determined, and the results were presented in Eq.37.

$$\begin{pmatrix} 0.2634 \\ 0.1627 \\ 0.0615 \\ 0.0867 \\ 0.1072 \\ 0.0389 \\ 0.1268 \\ 0.0233 \\ 0.0357 \\ 0.0195 \\ 0.0743 \end{pmatrix}^T \times \begin{vmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0.0921 & 0 & 0 & 0 & 0 \\ 0.1900 & 1 & 0 & 0 & 0 & 0 & 0.0483 & 0 & 0 & 0 & 0 \\ 0.1900 & 0 & 1 & 0 & 0 & 0 & 0.0383 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0.1081 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0.1948 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0.1081 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0.1201 & 0.3360 & 0 & 0.3964 & 0.3964 & 0 & 0.1211 & 1 & 0.7496 & 0 & 0 \\ 0.3093 & 0.4390 & 0 & 0.4774 & 0.4774 & 0 & 0.1466 & 0.6633 & 1 & 0 & 0 \\ 0.0703 & 0.1055 & 0 & 0.1262 & 0.1262 & 0 & 0.0795 & 0 & 0 & 1 & 0 \\ 0.1202 & 0.1194 & 0 & 0 & 0 & 0 & 0.0632 & 0.3367 & 0.2504 & 0 & 1 \end{vmatrix} = \begin{pmatrix} 0.3301 \\ 0.1971 \\ 0.0615 \\ 0.1154 \\ 0.1359 \\ 0.0389 \\ 0.2100 \\ 0.0720 \\ 0.0718 \\ 0.0195 \\ 0.0743 \end{pmatrix}^T$$

(37)

Finally, the normalized weights of the eleven criteria can be determined by Eq.22., and the results were presented in Table 13.

Table 13: The normalized weights of the eleven criteria with the considerations of the interactions and interdependences among them

Criteria	EC_1	EC_2	EC_3	EN_1	EN_2	EN_3	S_1	T_1	T_2	T_3	T_4
Weights	0.2488	0.1486	0.0464	0.0870	0.1024	0.0293	0.1583	0.0543	0.0541	0.0147	0.0560

Among these eleven criteria for sustainability assessment of polygeneration systems, all the data with respect to the criteria about the four alternative polygeneration systems can be quantified directly except social acceptability (S_1), because this criterion belongs to the soft-type criteria the data with respect to which cannot be obtained from literatures or filed investigation. The fuzzy best-worst method was employed to determine the relative performances of the four polygeneration systems with respect to S_1. Six experts including two professor whose research focused on polyeneration, two senior researchers of combined cooling, heating and power systems, and two engineers of power engineering were invited to participate in the determination of the BO and OW vectors for determining the relative performances of the four polygeneration systems with respect to social acceptability. The social acceptability of these four systems were firstly depicted by using linguistic terms, and they recognized as “low”, “medium”, “high”, and “medium”, respectively. Based on these, the BO and OW vectors can be determined, and the results were presented in Table 14.

Table 14: The fuzzy BW method for determining the relative performances of S_1 about the four polygeneration systems

Technological	Best: A_3			Worst: A_1	
	A_1	A_2	A_3	A_4	
BO	(5/2, 3, 7/2)	(2/3,1,3/2)	(1,1,1)	(2/3,1,3/2)	$k^* = 0.0505$
OW	(1,1,1)	(5/2, 3, 7/2)	(5/2, 3, 7/2)	(5/2, 3, 7/2)	CI=6.69
Fuzzy weights	(0.1014,0.1014, 0.1014)	(0.2483,0.2990,0.3497)	(0.2483,0.2990,0.3599)	(0.2483,0.2990,0.3497)	$CR = 0.0075$ $CR \le 0.10$
Crisp weights	0.1014	0.2990	0.3007	0.2990	

Besides the data with respect to social acceptability, some other data were modified from Wang et al. (2006) by changing the data with 10% positive/negative derivations, and the decision-making can be obtained, as presented in Table 15.

Table 15: The interval decision-making matrix

		A_1	A_2	A_3	A_4
EC_1	/	[0.4896 0.5984]	[0.7128 0.8712]	[0.7614 0.9306]	[0.7812 0.9548]
EC_2	USD.t^{-1}	[166.32 203.28]	[167.40 204.60]	[155.25 189.75]	[150.93 184.47]
EC_3	/	[0.0243 0.0297]	[0.0558 0.0682]	[0.0648 0.0792]	[0.1233 0.1507]
EN_1	t.Year^{-1}	[37.1520 45.4080]	[36.1710 44.2090]	[18.3780 22.4620]	[0.4230 0.5280]
EN_2	kg.s^{-1}	[63.2340 77.2860]	[60.4980 73.9420]	[60.3630 73.7770]	[60.0390 73.3810]
EN_3	%	[13.1760 16.1040]	[12.7440 15.5760]	[9.1530 11.1870]	[12.1410 14.8390]
S_1	/	[0.1014 0.1014]	[0.2990 0.2990]	[0.3007 0.3007]	[0.2990 0.2990]
T_1	%	[0 0]	[3.42 4.18]	[6.23 7.61]	[6.96 8.50]
T_2	%	[39.97 48.85]	[41.55 50.79]	[42.94 52.48]	[43.32 52.94]
T_3	%	[0 0]	[0 0]	[0 0]	[0 0]
T_4	/	[0.2403 0.2937]	[0.0522 0.0638]	[0.0522 0.0638]	[0.0153 0.0187]

After determining the interval decision-making matrix, the data presented in Table 14 can be standardized by Eqs.24-25. As for the benefit-type criteria, including EC_1, EC_3, EN_3, S_1, T_1, T_2, and T_4, they can be normalized by Eq.24. As for the cost-type criteria, including EC_2, EN_1 and EN_2, they can be normalized by Eq.25. It is worth pointing out that there is not any renewable energy sources used in these four polygeneration systems, thus, all the data with respect to T_3 are zero. The normalized interval decision-making matrix was presented in Table 16.

Table 16: The normalized interval decision-making matrix

	A_1	A_2	A_3	A_4
EC_1	[0.5755 0.7034]	[0.8379 1.0241]	[0.8950 1.0939]	[0.9183 1.1224]
EC_2	[0.7847 0.9590]	[0.7796 0.9528]	[0.8406 1.0274]	[0.8647 1.0568]
EC_3	[0.2616 0.3197]	[0.6007 0.7342]	[0.6976 0.8526]	[1.3273 1.6223]
EN_1	[0.0186 0.0228]	[0.0191 0.0234]	[0.0376 0.0460]	[1.6016 1.9992]
EN_2	[0.7892 0.9646]	[0.8249 1.0082]	[0.8267 1.0105]	[0.8312 1.0159]
EN_3	[0.9053 1.1065]	[0.8756 1.0702]	[0.6289 0.7686]	[0.8342 1.0196]
S_1	[0.3836 0.3836]	[1.1311 1.1311]	[1.1375 1.1375]	[1.1311 1.1311]
T_1	[0 0]	[0.5629 0.6880]	[1.0255 1.2526]	[1.1456 1.3991]
T_2	[0.7793 0.9524]	[0.8101 0.9902]	[0.8372 1.0232]	[0.8446 1.0322]
T_3	[0 0]	[0 0]	[0 0]	[0 0]
T_4	[1.5613 1.9083]	[0.3392 0.4145]	[0.3392 0.4145]	[0.0994 0.1215]

According to Eq.26, the weighted normalized decision-making matrix can be determined, as presented in Table 17. Each element in the weighted normalized decision-making matrix can be derived from the product of the corresponding element in the normalized decision-making matrix and the corresponding weight of the criterion. For instance, the element of cell (1,1) in the weighted normalized decision-making matrix can be determined by: the element of cell (1,1) in the normalized decision-making matrix × the weight of EC_1=[0.5755 0.7034] ×0.2488=[0.1432 0.1750]. In a similar way, all the other elements in the weighted normalized decision-making matrix can also be determined.

Table 17: The weighted normalized interval decision-making matrix

	A_1	A_2	A_3	A_4
EC_1	[0.1432 0.1750]	[0.2085 0.2548]	[0.2227 0.2722]	[0.2285 0.2793]
EC_2	[0.1166 0.1425]	[0.1158 0.1416]	[0.1249 0.1527]	[0.1285 0.1570]
EC_3	[0.0121 0.0148]	[0.0279 0.0341]	[0.0324 0.0396]	[0.0616 0.0753]
EN_1	[0.0016 0.0020]	[0.0017 0.0020]	[0.0033 0.0040]	[0.1393 0.1739]
EN_2	[0.0808 0.0988]	[0.0845 0.1032]	[0.0847 0.1035]	[0.0851 0.1040]
EN_3	[0.0265 0.0324]	[0.0257 0.0314]	[0.0184 0.0225]	[0.0244 0.0299]
S_1	[0.0607 0.0607]	[0.1791 0.1791]	[0.1801 0.1801]	[0.1791 0.1791]
T_1	[0 0]	[0.0306 0.0374]	[0.0557 0.0680]	[0.0622 0.0760]
T_2	[0.0422 0.0515]	[0.0438 0.0536]	[0.0453 0.0554]	[0.0457 0.0558]
T_3	[0 0]	[0 0]	[0 0]	[0 0]
T_4	[0.0874 0.1069]	[0.0190 0.0232]	[0.0190 0.0232]	[0.0056 0.0068]

The positive and negative ideal solutions can be determined by Eq.27-30, and the results were presented in Table 18. The positive and negative ideal solutions represent the ideal best polygeneration system and the ideal worst polygeneration system, respectively.

Table 18: The positive and negative ideal solutions

	EC_1	EC_2	EC_3	EN_1	EN_2	EN_3	S_1	T_1	T_2	T_3	T_3
PIS	0.2793	0.1570	0.0753	0.1739	0.1040	0.0324	0.1801	0.0760	0.0558	0	0.1069
NIS	0.1432	0.1158	0.0121	0.0016	0.0808	0.0184	0.0607	0	0.0422	0	0.0056

The distance between each alternative polygeneration system to the ideal best polygeneration system and the ideal worst polygeneration system can be determined by Eq.31 and Eq.32, respectively. Then, the closeness coefficients of each alternative polygeneration can also be calculated by Eq.33. The results were summarized in Table 19. Therefore, A_4 (series polygeneration, CO-rich once through methanol method) was recognized as the most sustainable polygeneration system among these four alternatives, follows by A_3 (parallel polygeneration, liquid-phase CO-rich cycle, and circle ratio is 1:1), A_2 (parallel polygeneration, methanol production based on low pressure gas-phase method, and circle ratio is 4.5:1), and A_1(individual system for methanol production using the gas-phase method, and chilled type IGCC (Integrated Gasification Combined Cycle) system) in the descending order.

Table 19: The distance between each alternative to the ideal best and the ideal worst polygeneration system, and the relative closeness coefficient of each alternative

	A_1	A_2	A_3	A_4
Distance to PIS	0.3733	0.2993	0.2853	0.1605
Distance to NIS	0.1392	0.2232	0.2501	0.3483
Closeness coefficient	0.2716	0.4272	0.4680	0.6845
Sustainability ranking	4	3	2	1

The results are reasonable for ranking A_4 as the most sustainable, because this polygeneration system has very good performances on economic and technological aspects, and the sulphur dioxide emission from this system is the lowest among these four alternative polygeneration systems. Meanwhile, the polygeneration configuration A_4 is the series structure is relative easier compared with A_2 and A_3. Accordingly, the energy utilization efficiency of this scenario is high. A_1 was recognized as the worst according to its integrated sustainability performances compared with these other three polygeneration systems. To some extent, it could be concluded that the polygeneration systems have better sustainability performances than the individual industrial systems.

4. Validation and sensitivity analysis

In order to validate the developed multi-attribute sustainability assessment method based on interval TOPSIS for assessing the sustainability of the polygeneration system, the interval grey relational analysis (GRA) method based on the work of Zhang (2005) and Manzardo *et al*. (2012). After determining the weighted normalized decision-making matrix (see Eq.38), the sustainability sequence of the four polygeneration systems can be determined according to the following steps:

$$V=\left|v_{ij}^{\pm}\right|_{m\times n}=\begin{vmatrix} & C_1 & C_2 & \cdots & C_n \\ A_1 & v_{11}^{\pm} & v_{12}^{\pm} & \cdots & v_{1n}^{\pm} \\ A_2 & v_{21}^{\pm} & v_{22}^{\pm} & \vdots & v_{2n}^{\pm} \\ \vdots & \vdots & \cdots & \ddots & \vdots \\ A_m & v_{m1}^{\pm} & v_{m2}^{\pm} & \cdots & v_{mn}^{\pm} \end{vmatrix} \tag{38}$$

Step 1: Determining the reference series. The reference series (RS) $v_j^{RS\pm}=\left[v_j^{RS-}\ v_j^{RS+}\right], j=1,2,\cdots,n$ can be determined by Eqs.39-41.

$$RS=\left(v_1^{RS\pm},v_2^{RS\pm},\cdots,v_n^{RS\pm}\right) \tag{39}$$

$$v_j^{RS+}=\max_{i=1,2,\cdots,m} v_{ij}^{+}, j=1,2,\cdots,n \tag{40}$$

$$v_j^{RS-}=\max_{i=1,2,\cdots,m} v_{ij}^{-}, j=1,2,\cdots,n \tag{41}$$

Step 2: Calculating the correlation coefficients of the series of each alternative to the reference series with respect to each criterion. ρ takes the value of 0.5 in this study.

$$\xi_i(j)=\frac{\min\limits_i\min\limits_j d\left(v_{ij}^{\pm},v_j^{RS\pm}\right)+\rho\max\limits_i\max\limits_j d\left(v_{ij}^{\pm},v_j^{RS\pm}\right)}{d\left(v_{ij}^{\pm},v_j^{RS\pm}\right)+\rho\max\limits_i\max\limits_j d\left(v_{ij}^{\pm},v_j^{RS\pm}\right)} \tag{42}$$

Step 3: Determining the correlation degree of the series of each alternative to the reference series.

$$r_i = \sum_{j=1}^{n} \omega_j \xi_i j, i = 1, 2, \cdots, m \tag{43}$$

After determining the correlation degree of the series of each alternative to the reference series, the priority sequence of the alternatives can be determined according to the rule that the greater the value of r_i, the more superior the alternative will be. Accordingly, the greater the value of r_i, the more sustainable the polygeneration will be. The results based on interval GRA were presented in Table 20.

Table 20: Sustainability assessment results by interval GRA

	A_1	A_2	A_3	A_4
Correlation degree	1.5459	1.5393	2.1066	2.1725
Sustainability ranking	3	4	2	1

The results determined by interval GRA are consistent with that determined by the developed multi-attribute decision analysis method, both A_4 (Series polygeneration, CO-rich once through methanol method) and A_3 (Parallel polygeneration, liquid-phase CO-rich cycle, and circle ratio is 1:1) were recognized as the most sustainable polygeneration systems; however, the sustainability assessment results of A_1 and A_2 by these two methods are different.

Sensitivity analysis was carried out by studying the following cases:

Base case 1: weights determined by the fuzzy BW method;

Case 1: $\omega_1 = \omega_2 = \cdots = \omega_{11} = \frac{1}{11}$;

Case 2-12(i=1,2,…,11): $\omega_i = 0.4, \omega_1 = \omega_2 = \cdots = \omega_{11} \neq \omega_i = 0.06$;

The results of sensitivity analysis were presented in Figure 6, and the results reveal that the final sustainability ranking of the four polygeneration systems are sensitive to the weights of the criteria for sustainability assessment of polygeneration systems. However, A_4 was recognized as the most sustainable polygeneration among these four alternatives in most of the cases excepting case 12, to some extent, it means that the selection of A_4 (Series polygeneration, CO-rich once through methanol method) as the most sustainable polygeneration system is reliable.

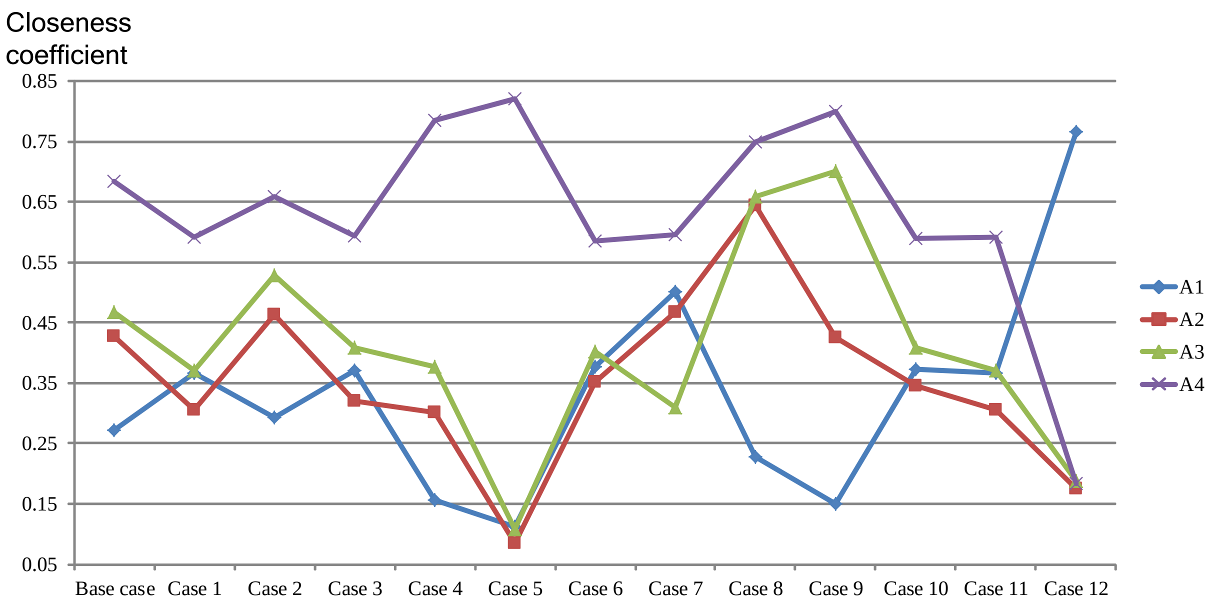

Figure 6: The results of sensitivity analysis

5. Insights and implications

Accordingly, the polygeneration systems including A_4 (Series polygeneration, CO-rich once through methanol method) and A_3 (Parallel polygeneration, liquid-phase CO-rich cycle, and circle ratio is 1:1) should be vigorously promoted. Polygeneration system has high potential to decrease the environmental pollution and to meet the future CO2 reduction requirements, but there are still few cases in practice all over the world. Only 10% of the global power is generated by polygeneration system. This ratio can be increased to 30%-50% in Denmark, Finland, Russia and Latvia (Calise and D'Accadia 2016). Fortunately, many countries have listed it as a priority developing item. European Union (EU) issued the "Directive 2004/8/EC of the European parliament and of the council of 11 February 2004 on the promotion of cogeneration based on a useful heat demand in the internal energy market and amending directive 92/42/EEC", which was well-known as "Combined heat and power (CHP) directive", for promoting the use of cogeneration to increase domestic energy efficiency and reduce the important dependency (Directive 2004). Other countries like America, Japan and Netherland also have its own plan to develop the polygeneration system (Pehnt *et al*. 2006).

China is rich in coal reserve, and the coal production and consumption of China also experienced a rapid increase since 1980 (Shen *et al*. 2012). In order to increase the coal efficiency and decrease the pollution emissions, the relentless pursuit leads to 82.86% of CO_2 emissions contributed by coal combustion (NBS 2015; IEA 2016). As early as 1995, Chinese government had deployed clean coal technologies nationwide. In "National Program for Long- and Medium-Term Scientific and Technological Development" published in 2006, polygeneration was listed as the priority development technology (Lin 2008). Coal related polygeneration system developed rapidly by combining with oil and chemical production, which can bring lots of economic and environmental benefits (Xie *et al*. 2010). The following implications can be obtained for stakeholders/decision-makers to promote the development of polygeneration:

(1) Setting special funding for R&DD (Research, Development and Demonstration) of polygeneration projects to reduce the investment and improve the maturity of polygeneration technologies;

(2) Breaking the technical bottleneck through technical innovations to simplify the complex installations architecture.

(3) Setting special subsidies or low/zero interest loan for the companies adopting polygeneration technologies.

6. Conclusions

This study aims at developing a multi-attribute sustainability assessment method for assessing the sustainability of polygeneration systems under uncertainty conditions, and the proposed method can determine the sustainability sequence of multiple polygeneration systems by using the interval data which can represent uncertainties. The fuzzy best-worst network method was developed for calculating the weights of the indicators for sustainability assessment of polygeneration systems, and this method for calculating the weights have the following three advantages:

(1) Less times of comparisons comparing with AHP and various methods derived from AHP;

(2) The BO and OW vectors are more consistent than the comparison matrices used in AHP;

(3) The independent relationships among the indicators or sustainability assessment of polygeneration systems can be incorporated.

Meanwhile, the interval best-worst method was used to quantify the data of the polygeneration systems with respect to the soft criteria.

The interval TOPSIS has been used to rank the alternative polygeneration systems, in which, the data (the weights and the performances of the alternative polygeneration systems with respect to the indicators for sustainability assessment) in the decision-making matrix are interval numbers.

The developed multi-attribute decision analysis method in this study based on fuzzy best-worst network method and interval TOPSIS method can be popularized for selecting the most sustainable polygeneration systems among multiple alternatives, and it can also be applied in selecting the most sustainable sub-system of a polygeneration system. The results determined by the proposed framework can be used as the foundation for polygenetaion system synthesis, design and optimization. In other words, the developed multi-attribute decision analysis method can firstly help the decision-makers to select the best or the most sustainable elements, then, some decision-supporting tools (i.e. multi-objective optimization model, two-stage programming, and mixed integer non-linear optimization model) can be used to further optimize the selected polygeneration system or synthesis these elements (Rubio-Maya *et al*., 2011; Chen *et al*., 2011; Piacentino and Cardona, 2008). In one word, the proposed multi-attribute decision analysis method can initially help the stakeholders to make decision on selecting the most sustainable configuration of polygeneration system among several alternative configurations, but they can employ the optimization tools for optimizing the selected system for improving its sustainability.

7. Limitations and future work

Besides the advantages of the proposed multi-attribute decision-support framework for sustainability assessment of polygeneration systems under uncertainties, there are also some limitations in the proposed method:

(1) the lack of the incorporation of multiple decision-makers in sustainability assessment: there are usually multiple stakeholders involved in the selection of the most sustainable polygeneration system; thus, the future work is to develop a multi-actor multi-attribute sustainability assessment model for assessing the sustainability of polygeneration systems;

(2) the lack of the method for selecting the evaluation indicators: there are usually various overlaps and intersections among the concepts of the indicators for sustainability assessment of polygeneration systems; thus, the future work also needs to developing the standards for screening the evaluation indicators.

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