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Sustainability Prioritization Framework of Biorefinery: A Novel Multi-Criteria Decision-Making Model under Uncertainty Based on An Improved Interval Goal Programming Method

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Abstract

As a sustainable substitute of traditional petroleum refining technology, the biorefinery, which has advantages of higher resource utilization efficiency, better sustainability and lower negative environmental impacts, have developed and applied. However, the variety of developed biorefinery system makes it difficult for decision-makers to determine the most sustainable biorefinery system. How to deal with the uncertainties in the decision-making process is another issue existing in biorefinery prioritization. In order to solve the decision-making problem under uncertainties in the selection process of biorefineries, a novel decision-making framework based on an improved interval goal programming was developed. In this study, a case study, which is to select the most sustainable biorefinery technology from grain ethanol (GE), cellulosic ethanol (CE), and Fischer-Tropsch diesel (FTD), was adopted to practice the proposed method. Three other methods were also employed to validate the results determined by the proposed method in this study. The results revealed that FTD was recognized as the most sustainable scenario by the proposed method and the proposed method was validated and recognized as the most robust method in uncertain decision-making problem.

Keywords: Biorefinery; sustainability assessment; multi-criteria decision-making; uncertainty

1. Introduction

As an effective way to substitute the traditional petrochemical refinery, biorefinery has greatly expanded the application of renewable plant-based raw materials, making it a means of chemical and energy economic transformation for environmental sustainable development (Cherubini, 2010; Espinoza Pérez et al., 2019). Biorefinery refers to the production of various chemicals, fuels and bio-based materials from agricultural wastes, plant-based starch, lignocellulose and other bio-based materials (Cherubini, 2010; Espinoza Pérez et al., 2019). With the increasing negative impacts of petroleum refining such as, the environmental pollution, the shortage of energy reserves and the rising price, biorefinery shows its advantages of less environmental impact (Ouda et al., 2017), higher reserves (Kokossis and Yang, 2010) and higher resource utilization efficiency (Dahiya et al., 2018). Therefore, biorefinery has been studied as a popular research topic in the field of energy development worldwide.

With continuous development and increasing maturity of biorefinery technology, the advantages of this technology, such as high resource utilization, low pollutant emission and renewable, have been amplified during the innovation. The existing biorefinery technologies can be divided into three categories: whole grain refining, green refinery and lignocellulose refining (Moncada et al., 2014). The whole grain refining, known as the first generation of biorefining technology, uses cereal or corn as raw materials corn (Hughes et al., 2013; Maity, 2015; Singh and Olsen, 2011). The green refinery , also known as the second generation of biorefinery technology, uses wet biomass in nature such as green grass, alfalfa, clover and immature grains as raw materials (Naik et al., 2010; Singh and Olsen, 2011). The lignocellulose refining is a biorefining technology using natural dry raw materials such as biomass and waste containing cellulose as raw materials (Abdul Hamid and Lim, 2019; Singh et al., 2011). These developed various biorefinery technologies have their own advantages and disadvantages in different aspects (Parajuli et al., 2015). Therefore, there is no single biorefinery technology with absolute advantages that makes the users of biorefinery technology encounter the situation of being unable to choose. To be specific, the whole grain refining has the advantage of low price, but the biomass it uses is also the daily food of human beings, which indirectly causes the situation of food shortage (Hughes et al., 2013; Singh and Olsen, 2011); the green refinery performs the best in the conversion rate, but the cost is high due to the increase of processing steps, and the existing technology is relatively immature compared with whole grain refinery (Moncada et al., 2015; Nagy and Hegedüs, 2015); the lignocellulose refining solves the problem of whole grain refining, but its high cost and strict requirements of technology restrict its application (Chew et al., 2017; Sawatdeenarunat et al., 2016). To consider all aspects mentioned above in the sustainability assessment, the decision-maker needs a multi-criteria based decision-making framework to assist the selection of technology.

As for solving the biorefinery selection issue, there are many studies focusing on developing decision-making tool. Among them, there are three kinds of selection mechanisms of biorefinery technology, one is to establish evaluation mechanism for analysis and to compare directly (Vlysidis et al., 2011), another is the decision-making model based on optimization model (Maronese et al., 2015; Sharma et al., 2011; Ubando et al., 2016), and the third is to use multi-criteria decision-making model for selection (Parajuli et al., 2015; Vyhmeister et al., 2018). The advantage of establishing evaluation mechanism and direct comparison lies in the unified evaluation standards established for assessment, and comparisons among alternatives for each criterion can be observed directly. However, the direct comparison leads to absence of ranking of alternatives, which still requires to be done by subjective judgment of decision makers. The decision-making models based on the optimization model can help to select the optimal processes and aggregate them as the optimal pathway, which were mostly used in process design. Those multi-criteria decision-making models were used to screen the biorefinery technology, considering various criteria and the different roles each criterion plays in each decision. These three categories of methods mentioned above can be combined to form a more complete decision system of biorefinery. Besides, there is still a literature gap in the selection of biorefinery. In the process of biorefinery, there are uncertainties caused by time fluctuation, inaccurate human judgment and incomplete reaction, so many criteria cannot be expressed in the form of constants or crisp numbers (Ubando et al., 2016). Uncertainty has not been considered in the previous studies of biorefinery selection. Therefore, we need to establish a multi-criteria decision-making model which can deal with uncertain data.

In addition to this section, the second section demonstrates the hybrid decision framework based on improved interval goal programming with detailed criteria system; the third section uses a case to validate the proposed selection framework by prioritizing grain ethanol biorefinery (GE), cellulosic ethanol biorefinery (CE) and Fischer-Tropsch diesel biorefinery (FTD); the fourth section analyzes the new method by comparing with other three decision methods and analyzing the original data; the fifth section summarizes the study.

2. Methods

In order to establish a multi-criteria decision-making model for the sustainable screening of biorefinery technologies under uncertainties, a hybrid decision-making framework based on improved interval objective programming is developed. This research is divided into two stages: establishing decision framework and verification. The decision-making model consists of three main steps: establishing criteria system, collecting alternative data, criteria weighting, and ranking based on uncertain data. In the verification part, the proposed decision-making framework under uncertainties is compared with other existing weighting methods and multi-criteria ranking methods (see **Fig. 1**). The steps of uncertain decision framework based on improved interval objective programming are explained in the following:

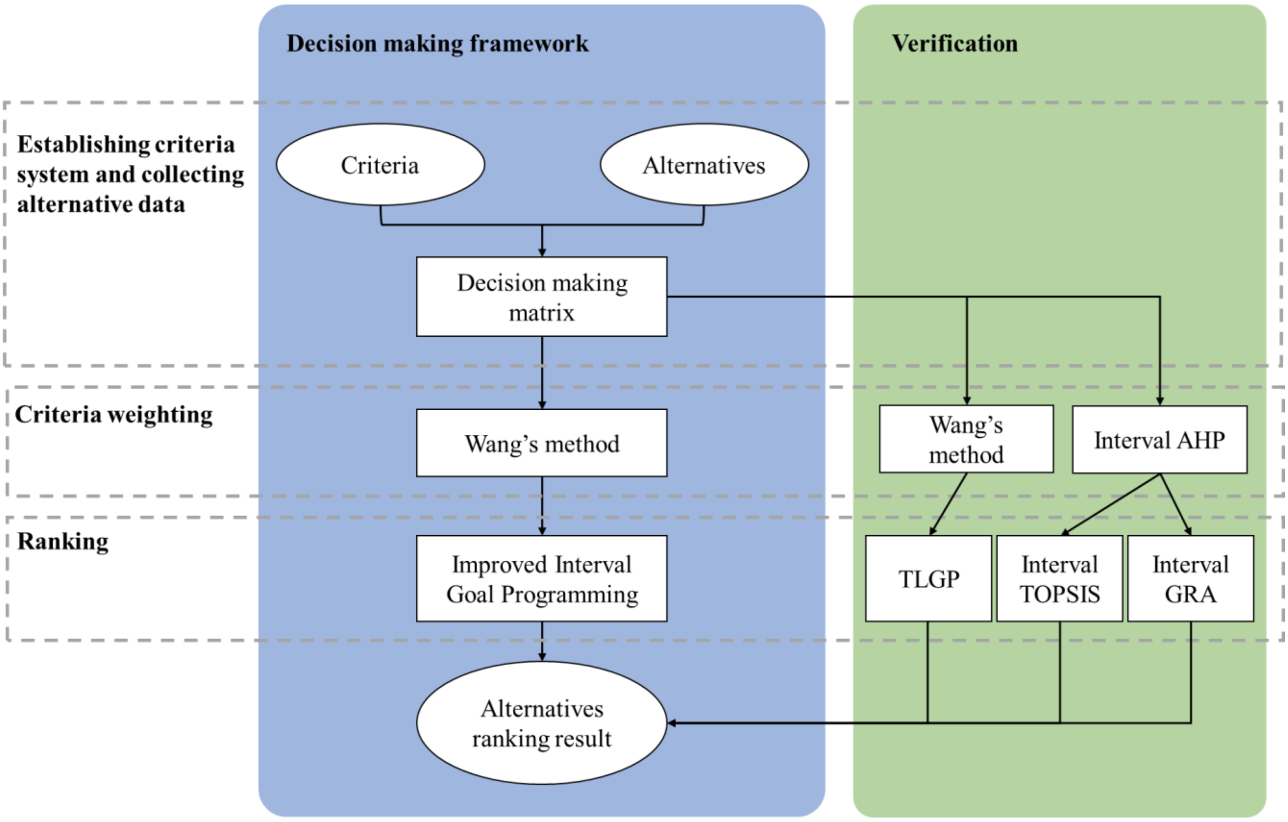


FIGURE 1. Research and verification process of the prioritization framework for sustainability of biorefinery technology under uncertainties

2.1 Establishing criteria system and collecting alternative data

2.1.1 Criteria for sustainability assessment of biorefineries

The basis of decision-making is to establish an appropriate and complete index system. The indicators to evaluate the sustainability of biorefining technology mainly include four aspects: environment, economy, society and technology. Since some indicators can be included in more than one aspect, some studies have overlapping indicator classifications, such as socio-economic and tech-economic aspects. Environmental aspect is an indispensable aspect of sustainable development research, and some researches even used only environmental criteria to evaluate the sustainable development of biorefining technology (Krzyżaniak and Stolarski, 2019; Papadaskalopoulou et al., 2019; Salim et al., 2019; Vega et al., 2019). With the development of research, economic indicators have been taken into consideration in the evaluation of sustainable development (Budzinski and Nitzsche, 2016; Dimian et al., 2019; Ng et al., 2019; Nieder-Heitmann et al., 2018), and the environmental economic analysis of biorefinery technology has been carried out (Chia et al., 2018; Martinez-Hernandez et al., 2014; Rodrigues Gurgel da Silva et al., 2019). With further improvement of indicator classification, the sustainability research of three pillar model (environmental, economic and social indicators) has been widely used (Dale et al., 2015; Halog and Manik, 2011; Wang et al., 2009; Wellisch et al., 2010). In spite of these three aspects, many researches on biorefinery technology also mentioned technical indicators in their assessments (Keller et al., 2015; Rubio

Rodríguez et al., 2011; Sacramento-Rivero, 2012). The technological assessment sometimes was conducted together with economic assessment as techno-economic assessment (Ghayur et al., 2019; Han et al., 2016; Parsons et al., 2019). Based on the existing evaluation researches on biorefinery technology, the relevant indicators were listed in **Fig. 2**.

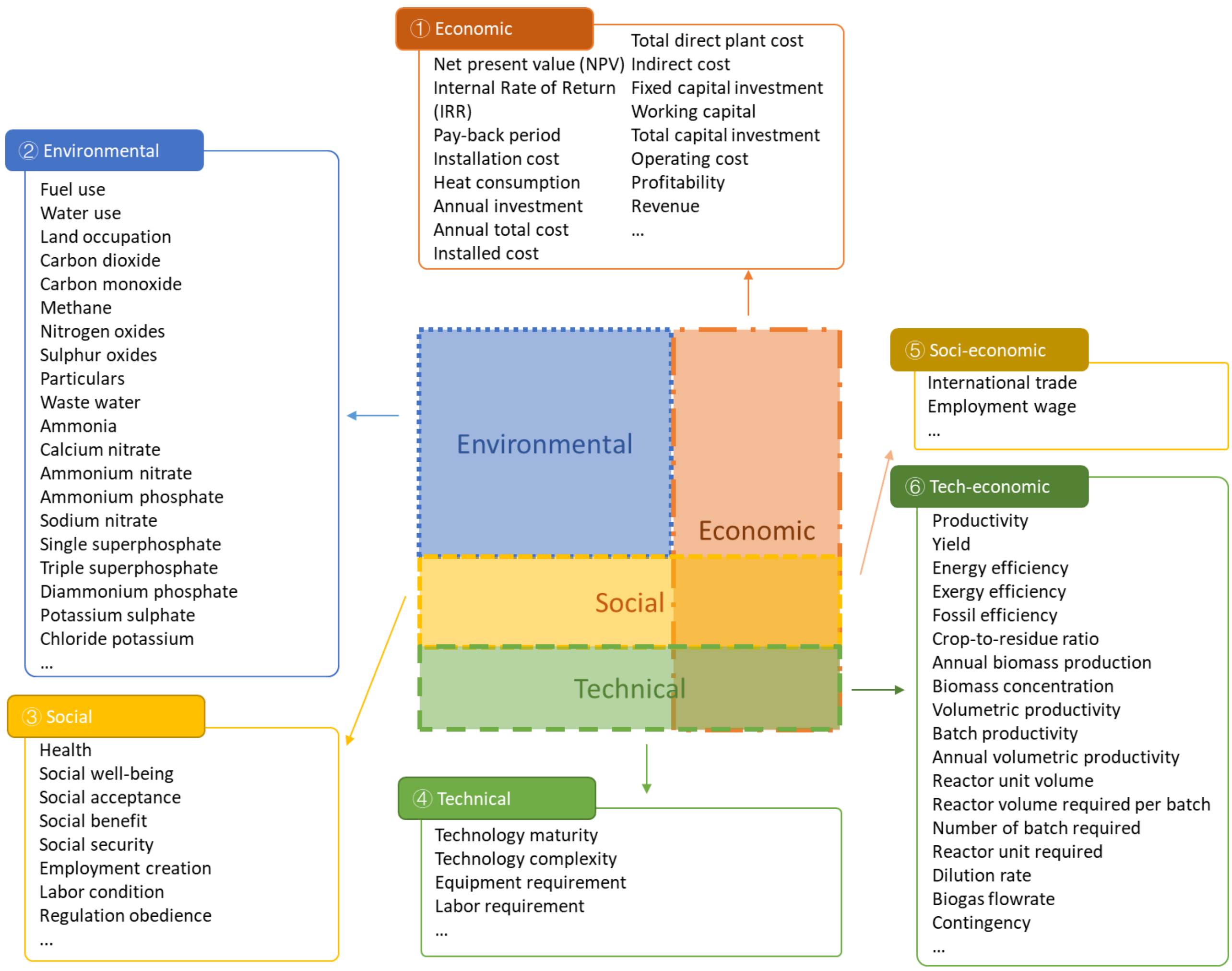


FIGURE 2. Sustainability indicators for biorefineries

Depending on the actual situation and the subjective preferences of the decision-makers, the decision maker may choose some of them or add some sub-indicators to make decisions. To select appropriate indicators for sustainability assessment, the decision maker should follow the following rules:

- No overlapping for two or more indicators. For example, NPV, ROI, IRR, and payback period are different methods to measure cost, so it is unnecessary to contain all of them in the criteria system. The decision maker should choose the most suitable one for technology description;
- The indicators in one aspect can sufficiently describe the aspect performance. For instance, the at least one criterion can describe cost performance and one for benefit performance in the economic aspect assessment;
- The indicators selected need to be measurable or can be converted into other quantitative indicators. As for the soft indicators and hard indicators conversion problem. There are two ways to convert soft indicators to hard indicators. The first one is to adapt quantitative sub-indicators for the indicators. For example, in this article, the *job creation* was adapted as the quantitative sub-indicator of the qualitative indicator *social benefit*. The other one is to use intuitional weighting method to quantify the qualitative indicator by pairwise comparison; and
- The indicators the decision makers think are significant to the project development should be selected.

The major categories of indicators for each aspect were introduced in the following to assist decision makers in selecting appropriate criteria for biorefinery technology assessment.

Economics: The economic considerations mainly include two aspects: whether it is costly, and whether it can make a profit. Therefore, indicators in economic aspect include at least cost and profit. The cost can be classified as fixed cost and variable cost. Fixed cost accounts for the majority of early investment, also known as capital cost, including equipment fees, starting up fees and patent. Variable cost is the main type of ongoing investment. Variable cost includes labor cost, maintenance cost, resource costs for water, fuel, and power. The profit is the other necessary category of indicators to examine the economic performance of biorefinery technologies. Non-profitable technology cannot be serviced for a long time, and it will be replaced by technology that can be long-lived as the time passing by. The indicators for profit usually include Return on Investment (ROI), payback period and Net Present Value (NPV).

Environmental: The environmental impact of the biorefinery is mainly reflected in the two aspects of pollution and resource occupation (Al-Jebouri et al., 2017). Pollution can lead to scarcity of limited resources and affect the existence of living things, which in turn affects human survival. The fewer pollutants are more conducive to sustainable development. All the pollution indicators are cost-type indicators. The pollution comes from the gas, solid and liquid wastes produced in the biorefinery process. Gaseous emissions contain greenhouse gases and harmful gases such as SOx and NOx. Solid wastes take up land and pollute the land and sea. Especially now, the landfill is the main industrial waste treatment. In addition, liquid wastes are mostly sewage containing harmful or toxic substances. The flow of water to rivers and oceans will destroy the quality of water bodies, affect marine life and destroy the ecological balance. The resources occupied are used as the raw materials of the manufacturing process. In this indicator, land, water, food and fuels are the main resources possibly occupied by biorefinery manufacturing.

Social: Biorefinery has an impact on society and can be divided into two main categories: Social well-being and social acceptability (Falcone and Imbert, 2018; Ikhlayel, 2018). Social benefits can be reflected in job creation, local family income change, the health of local residents and labors, food security, and international relationship. This standard cannot be quantified. It is determined by the attitude of the residents, the degree of project openness, and the participation of the stakeholders.

Technical: The technical indicators describe the technical performance of biorefinery technology. However, the maturity of technology is usually quantified by the operating data and output profit. Therefore, the technical aspect of biorefinery sustainability assessment sometimes overlapped with the indicators of economic aspect, for example, the productivity, energy efficiency, and exergy efficiency. The criteria selection of technical aspect should follow the first rule of selection mentioned before: "no overlapping among indicators."

2.1.2 Completeness rate

The framework proposed can have very distinct results if different criteria are used by the decision makers. To reduce the limitations brought by the high flexibility of this framework, an index *completeness rate* is introduced to this study. The *completeness rate* can be determined by **Eq.1**.

$$CR = 0.25 \times CR_{EN} + 0.25 \times CR_{EC} + 0.25 \times CR_{S} + 0.25 \times CR_{T} \tag{1}$$

where CR_{EN}, CR_{EC}, CR_{S} and CR_{T} indicate the completeness rate of each aspect respectively.

The aspect completeness rates could be calculated as **Eq.2**.

$$CR_{EN} = \frac{n_{EN} - n_{EN}^{-}}{n_{EN}^{+} - n_{EN}^{-}} \tag{2}$$

where n_{EN} represents the number of effective environmental indicators used in the study, n_{EN}^{-} represents the threshold number of effective environmental indicators used in the study, and n_{EN}^{+} represents the number of all environmental indicators used in the study.

$$CR_{EC} = \frac{(n_{EC} + 0.5 \times n_{SE} + 0.5 \times n_{TE}) - n_{EC}^{-}}{(n_{EC}^{+} + 0.5 \times n_{SE}^{+} + 0.5 \times n_{TE}^{+}) - n_{EC}^{-}} \tag{3}$$

where n_{EC}, n_{SE} and n_{TE} represent the number of effective economic, soci-economic, and tech-economic indicators used in the study respectively, n_{EC}^{-} represents the threshold number of effective economic indicators used in the study, and n_{EC}^{+}, n_{SE}^{+} and n_{TE}^{+} represent the number of all effective economic, soci-economic, and tech-economic indicators respectively. Similarly, the completeness rates of social and technical aspects are determined by:

$$CR_{S} = \frac{(n_{S} + 0.5 \times n_{SE}) - n_{S}^{-}}{(n_{S}^{+} + 0.5 \times n_{SE}^{+}) - n_{S}^{-}} \tag{4}$$

$$CR_{T} = \frac{(n_{T} + 0.5 \times n_{TE}) - n_{T}^{-}}{(n_{T}^{+} + 0.5 \times n_{TE}^{+}) - n_{T}^{-}} \tag{5}$$

The number of all indicators in each aspect can be seen in **Fig.2** and the threshold number of indicators in each aspect is determined by the major categories described above. Therefore, the values of the number are shown in the **Table 1**.

Table 1. Parameter values of completeness rate calculation

Aspect	n^+	n^-
Environmental	20	2
Economic	16	2
Social	8	2
Technical	4	1
Soci-economic	2	-
Techo-economic	18	-

If any value of aspect completeness rates (i.e. $CR_{EN}, CR_{EC}, CR_S\ and\ CR_T$) is negative, the selected criteria is unsatisfying in the sustainability assessment and re-selection of criteria should be conducted. On the other word, the selected criteria are satisfactory and can be adopted in the sustainability assessment, when the aspect completeness rates are non-negative. Accordingly, the closer to 1 the value of the completeness rate is, the more completed the sustainability assessment is.

2.1.3 Criteria system and data collection

After the establishment of the criteria system, the criteria system presents a two-tier hierarchical structure with several indicators under each aspect $\boldsymbol{P_i}$. The $\boldsymbol{P_1}, \boldsymbol{P_2}, \boldsymbol{P_3}, \boldsymbol{P_4}$ represent the economic, environmental, social and technological aspects respectively. The *j*-th criterion under the *i*-th aspect is expressed as $\boldsymbol{C_j^i}$. The number of criteria under the *i*-th aspect is $\boldsymbol{u_i}$. The Assume that *m* criteria in total are selected for *n* alternatives, the *i*-th criterion is also expressed as $\boldsymbol{C_i}$ (*i*=1, 2, … m) as shown in **Table 2.**

Table 2. Hierarchical structure of indicators.

Aspect	$\boldsymbol{P_1}$			$\boldsymbol{P_2}$			…	$\boldsymbol{P_4}$		
Criterion	$\boldsymbol{C_1^1}$	…	$\boldsymbol{C_{u_1}^1}$	$\boldsymbol{C_1^2}$	…	$\boldsymbol{C_{u_2}^2}$	…	$\boldsymbol{C_1^4}$	…	$\boldsymbol{C_{u_4}^4}$
	$\boldsymbol{C_1}$				…					$\boldsymbol{C_m}$

The interval decision-making matrix is given by **Eq.6** after all data are collected.

$$A=\begin{bmatrix} [a_{11}^L,a_{11}^U] & [a_{12}^L,a_{12}^U] & \cdots & [a_{1n}^L,a_{1n}^U] \\ [a_{21}^L,a_{21}^U] & [a_{22}^L,a_{22}^U] & & [a_{2n}^L,a_{2n}^U] \\ \vdots & & \ddots & \vdots \\ [a_{m1}^L,a_{m1}^U] & [a_{m1}^L,a_{m1}^U] & \cdots & [a_{mn}^L,a_{mn}^U] \end{bmatrix}. \quad (6)$$

where a_{ij}^L and a_{ij}^U represent the minimum value and the maximum value of the *i*-th criterion with respect to the *j*-th alternative respectively, and *i*=1, 2, …m, *j*=1, 2, …n.

2.2 Criteria weighting

During the biorefinery selection process, the weights of criteria should be vague and fuzzy because there are some uncertainties caused by uncertain human judgement, the vagueness of level description and the knowledge limitation of human. To generate fuzzy weights from linguistic expressions, the Wang's method (Wang et al., 2005) is adopted since it is an efficient weighting method to deal with uncertainties. The calculation process of Wang's method is shown below.

Step 1. *Build pairwise comparison matrix*

The pairwise comparison should be conducted among aspects or among indicators in the same aspect to obtain local weights. The pairwise comparison matrix is given as **Eq.7**.

$$B = \begin{bmatrix} 1 & [l_{12}, u_{12}] & \cdots & [l_{1n}, u_{1n}] \\ [l_{21}, u_{21}] & 1 & & [l_{2n}, u_{2n}] \\ \vdots & & \ddots & \vdots \\ [l_{n1}, u_{n1}] & [l_{n2}, u_{n2}] & \cdots & 1 \end{bmatrix}, \tag{7}$$

where l_{ij} and u_{ij} are the minimum and maximum values of the ratio of criterion *i* comparing with criterion *j* respectively, l_{ij} and u_{ij} are nonnegative real numbers and $l_{ij} \leq u_{ij}$. $l_{ij} \leq 1/u_{ji}$ and $u_{ij} \leq 1/l_{ji}$. The values of l_{ij} and u_{ij} are marked among 1 to 9 according to Saaty's priority standard (see **Table 3**) (Saaty, 1987).

Table 3. Priority standard table (Saaty, 1987)

Score	**Priority**
1	Equal important
2	Weak or slight
3	Moderate important
4	Moderate plus
5	Strong important
6	Strong plus
7	Very strong or demonstrated important
8	Very, very strong
9	Extreme important

Step 2. *Calculate local weights*

The weight vector $\mathrm{W} = (\mathrm{w}_1, \ldots, \mathrm{w}_n)$ imposes multiplicative constraint in this method, so the constraint is equivalent to **Eq.8.**

$$\sum_{i=1}^{n} \ln w_i = 0, \quad i = 1, \dots, n. \tag{8}$$

To provide the interval value $[l_{ij}, u_{ij}]$ an acceptable error range to make inequation $l_{ij} \le w_i/w_j \le u_{ij}$ workable, p_{ij} and q_{ij} are introduced as deviation variables, given by **Eq.9**.

$$\ln l_{ij} - p_{ij} \le \ln w_i - \ln w_j \le \ln u_{ij} + p_{ij}, \; i, j = 1, 2, \dots, n, \tag{9}$$

where p_{ij} and q_{ij} are both non-negative real numbers. To simplify the equation, variables x_i and y_i are introduced in **Eq.10** and **Eq.11**.

$$x_i = \frac{\ln w_i + |\ln w_i|}{2}, \quad i = 1, 2, \dots, n, \tag{10}$$

$$y_i = \frac{-\ln w_i + |\ln w_i|}{2}, \quad i = 1, 2, \dots, n. \tag{11}$$

To minimize the inconsistency shown by deviation variables p_{ij} and q_{ij}, the programming is given by **Eq.12**.

$$\text{Minimize} \quad J = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} (p_{ij} + q_{ij}) \tag{12}$$

Subject to $x_i - y_i - x_j + y_j + p_{ij} \ge \ln l_{ij}, i = 1, 2, \dots, n-1, \; j = i+1, \dots, n,$

$$x_i - y_i - x_j + y_j - q_{ij} \le \ln u_{ij}, i = 1, 2, \dots, n-1, \; j = i+1, \dots, n,$$

$$\sum_{i=1}^{n} (x_i - y_i) = 0,$$

$$x_i, y_i \ge 0, \quad x_i y_i = 0, \quad i = 1, 2, \dots, n,$$

$$p_{ij}, q_{ij} \ge 0, \quad p_{ij} q_{ij} = 0, \quad i = 1, 2, \dots, n-1, \; j = i+1, \dots, n.$$

where J represents the inconsistency value.

The local weights of indicators in each aspect and the aspect weights are calculated by repeating the processes mentioned above.

Step 3 *Calculate global weights*

As shown in **Table 4**, the global weights of criteria could be calculated by the weights of aspects and the local weights of criteria in this aspect.

Table 4. Synthesis of interval weights

Aspect	$\boldsymbol{P_1}$			**…**	$\boldsymbol{P_4}$		
	$[w_{p1}^{L}, w_{p1}^{U}]$			…	$[w_{p4}^{L}, w_{p4}^{U}]$		
Criterion	$\boldsymbol{C_1^1}$	**…**	$\boldsymbol{C_{u_1}^1}$	**…**	$\boldsymbol{C_1^4}$	**…**	$\boldsymbol{C_{u_4}^4}$
Local weight	$[w_{l11}^{L}, w_{l1}^{U}$	…	$[w_{l1\boldsymbol{u_1}}^{L}, w_{l1\boldsymbol{u_1}}^{U}]$	…	$[w_{l41}^{L}, w_{l41}^{U}]$	…	$[w_{l4\boldsymbol{u_4}}^{L}, w_{l4\boldsymbol{u_4}}^{U}]$
Global weight	$[w_{g11}^{L}, w_{g}^{U}$	…	$[w_{g1\boldsymbol{u_1}}^{L}, w_{g1\boldsymbol{u_1}}^{U}]$	…	$[w_{gn1}^{L}, w_{gn1}^{U}]$	…	$[w_{g4\boldsymbol{u_4}}^{L}, w_{g4\boldsymbol{u_4}}^{U}]$

The global weights $[w_{gij}^{L}, w_{gij}^{U}]$ of *j*-th criteria under *i*-th the aspect is determined by *i*-th aspect weight $[w_{pi}^{L}, w_{pi}^{U}]$ multiplicated by local weight $[w_{lij}^{L}, w_{lij}^{U}]$ of *j*-th criteria under *i*-th aspect, which are given by **Eq.13** and **Eq.14**:

$$w_{gij}^{L} = \sqrt[m]{(w_{pi}^{L} \,/\, \prod_{j}^{m} w_{lij}^{U})} \times w_{lij}^{L}, \qquad i = 1,2,\dots,n,\;\; j = 1,\dots,m, \tag{13}$$

$$w_{gij}^{U} = \sqrt[m]{(w_{pi}^{U} \,/\, \prod_{j}^{m} w_{lij}^{L})} \times w_{lij}^{U}, \qquad i = 1,2,\dots,n,\;\; j = 1,\dots,m. \tag{14}$$

where *m* represents the number of criteria in a certain aspect and *n* represents the number of aspects.

2.3 Ranking

The multi-criteria decision-making method helps to prioritize the alternatives based on criteria data with respect to each alternative and the criteria weights. The uncertainties existing in the selection process of biorefinery technologies haven't been solved by previous decision-making methods. Since goal programming is an efficient optimization model that has been used for assignment allocation, scheduling and selection (Ren et al., 2015), the principle of goal programming is suitable in the decision-making ranking process. Therefore, an improved interval goal programming method was proposed in this study based on traditional goal programming method to provide a solution to prioritization problem under uncertainties.

Step 1. *Normalization*

The criteria can be categorized into two types: benefit-type and cost-type. The benefit-type criterion is the one who has higher the value, the better performance the alternative has. On the contrary, the higher the value of cost-type criterion, the worse performance the alternative has. To eliminate the errors brought by different units and criteria types, the normalization process should be conducted. In the goal programming method, the normalization process is given by **Eq.15** and **Eq.16**.

For benefit-type criterion, the normalization equation is given by

$$y_{ij} = \frac{a_{ij} - \min_j a_{ij}}{\max_j a_{ij} - \min_j a_{ij}}, \quad i = 1, \dots, m, \;\; j = 1, \dots, n \, , \tag{15}$$

For cost-type criterion, the normalization equation is given by

$$y_{ij} = \frac{\max_j a_{ij} - a_{ij}}{\max_j a_{ij} - \min_j a_{ij}}, \quad i = 1, \dots, m, \; j = 1, \dots, n \,, \tag{16}$$

To extend the goal programming process into interval goal programming process, the upper boundary of and the lower boundary of interval data should be considered in the normalization process. Since TLGP (Wang et al., 2005) cannot proceed 0 value, both lower boundary and upper boundary add extra 0.1 to avoid the existence of 0 as a normalization result. To consist of another method, the normalization process is given by **Eq.17 – Eq.21** is applied in interval goal programming as well.

As for benefit-type criterion, the normalization equations are given by **Eq.17** and **Eq.18**.

$$y_{ij}^L = \frac{a_{ij}^L - \min_j a_{ij}^L}{\max_j a_{ij}^U - \min_j a_{ij}^L} + 0.1, \quad i = 1, \dots, m, \; j = 1, \dots, n \,, \tag{17}$$

$$y_{ij}^U = \frac{a_{ij}^U - \min_j a_{ij}^L}{\max_j a_{ij}^U - \min_j a_{ij}^L} + 0.1, \quad i = 1, \dots, m, \; j = 1, \dots, n \,. \tag{18}$$

As for cost-type criterion, the normalization equations are given by **Eq.19** and **Eq.20**.

$$y_{ij}^L = \frac{\max_j a_{ij}^U - a_{ij}^U}{\max_j a_{ij}^U - \min_j a_{ij}^L} + 0.1, \quad i = 1, \dots, m, \; j = 1, \dots, n \,, \tag{19}$$

$$y_{ij}^U = \frac{\max_j a_{ij}^U - a_{ij}^L}{\max_j a_{ij}^U - \min_j a_{ij}^L} + 0.1, \quad i = 1, \dots, m, \; j = 1, \dots, n \,. \tag{20}$$

For the *j*-th alternative, the minimum value and the maximum value of the *i*-th normalized criterion are y_{ij}^L and y_{ij}^U respectively, while $y_{ij}^L \le y_{ij}^U$. The interval normalized decision-making matrix is given by **Eq.21**.

$$Y = \begin{bmatrix} [y_{11}^L, y_{11}^U] & [y_{12}^L, y_{12}^U] & \cdots & [y_{1n}^L, y_{1n}^U] \\ [y_{21}^L, y_{21}^U] & [y_{22}^L, y_{22}^U] & & [y_{2n}^L, y_{2n}^U] \\ \vdots & & \ddots & \vdots \\ [y_{m1}^L, y_{m1}^U] & [y_{m1}^L, y_{m1}^U] & \cdots & [y_{mn}^L, y_{mn}^U] \end{bmatrix}. \tag{21}$$

Step 2. *Goal programming*

In the goal programming method, any alternative with its decision z_j=1 is the best alternative among all alternatives. The z_j is generated through non-linear programming model **Eq.22**.

$$\text{Minimize} \quad \sum_{i=1}^{m} w_i(d_i^+ + d_i^-), \qquad i = 1,2,\ldots,m, \tag{22}$$

$$\text{Subject to} \quad \sum_{j=1}^{n} y_{ij} z_j - d_i^+ + d_i^- = g_i, \qquad i = 1,2,\ldots,m, j = 1,\ldots,\text{n},$$

$$z_j = \begin{cases} 1, & if\ the\ \ j-th\ alternative\ has\ been\ selected \\ 0, & otherwise \end{cases}, j = 1,\ldots, \text{n},$$

$$\sum_{j=1}^{n} z_j = 1, \qquad j = 1,\ldots,\text{n},$$

$$\sum_{i}^{m} w_i = 1, \qquad i = 1,2,\ldots,m,$$

$$d_i^+, d_i^- \geq 0, \qquad i = 1,2,\ldots,m,$$

where y_{ij} is the value of the *i*-th criterion with respect to the *j*-th alternative, g_i represents the value of the best option for *i*-th criterion, and z_j represents the decision variable. d_i^+ and d_i^- show the over and under-achievement of the *i*-th goal, respectively.

In the interval goal programming method, as the weights are interval values and are multiplicative constraints, some adjustments are applied to this method. The objective uses a multiplicative function instead of an additive function. $\sum_{i}^{m} w_i = 1$ is replaced by $\prod_{i}^{m} w_i = 1$, as the criteria weights generated by Wang's method (Wang et al., 2005) are constrained multiplicatively, so the objective function is replaced by **Eq.23**.

$$\text{Minimize} \qquad \prod_{i=1}^{m}(d_i^{+} + d_i^{-})^{w_i}, \qquad i = 1,2,\dots,m, \tag{23}$$

In this method, the interval number is adopted instead of the crisp number, so $[d_i^{L+}, d_i^{U+}]$ and $[d_i^{L-}, d_i^{U-}]$ replace d_i^{+} and d_i^{-} forming two constraints to achieve lower bound of goal and the higher bound of goal respectively. The overall performance of an interval value is determined by **Eq.24** and **Eq.25**.

$$d_i^{+} = \sqrt{\frac{\left(d_i^{L+}+d_i^{U+}\right)^2}{2}}, \qquad i = 1,2,\dots,m, \tag{24}$$

$$d_i^{-} = \sqrt{\frac{\left(d_i^{L-}+d_i^{U-}\right)^2}{2}}, \qquad i = 1,2,\dots,m. \tag{25}$$

The non-linear programming model is adapted accordingly given by programming model **Eq.26**.

$$\text{Minimize} \qquad \sum_{i=1}^{m}\left(\sqrt{\frac{\left(d_i^{L+}+d_i^{U+}\right)^2}{2}} + \sqrt{\frac{\left(d_i^{L-}+d_i^{U-}\right)^2}{2}}\right)^{w_i} \tag{26}$$

$$\text{Subject to} \qquad \sum_{j=1}^{n} y_{ij}^{L} z_j - d_i^{L+} + d_i^{L-} = g_i^{L}, \qquad i = 1,2,\dots,m,$$

$$\sum_{j=1}^{n} y_{ij}^{U} z_j - d_i^{U+} + d_i^{U-} = g_i^{U}, \qquad i = 1,2,\dots,m,$$

$$z_j = \begin{cases} 1, & if\ the\ j-th\ alternative\ has\ been\ selected \\ 0, & otherwise \end{cases}, j = 1,\dots, n,$$

$$\sum_{j=1}^{n} z_j = 1, \qquad j = 1,\dots,n,$$

$$w_i \in [w_i^{L}, w_i^{U}], \qquad i = 1,2,\dots,m,$$

$$\prod_{i}^{m} w_i = 1, \qquad i = 1,2,\dots,m,$$

$$d_i^{L+}, d_i^{U+}, d_i^{L-}, d_i^{U-} \geq 0,$$

where $[y_{ij}^L, y_{ij}^U]$ is the value of the i-th criterion with respect to the j-th alternative, $[g_i^L, g_i^U]$ represents the value of i-th criterion with respect to the best option , and z_j represents the decision variable. $[d_i^{L+}, d_i^{U+}]$ and $[d_i^{L-}, d_i^{U-}]$ show the over and under-achievement of the i-th goal, respectively. $[g_i^L, g_i^U]$ is determined by **Eq.27** and **Eq.28**.

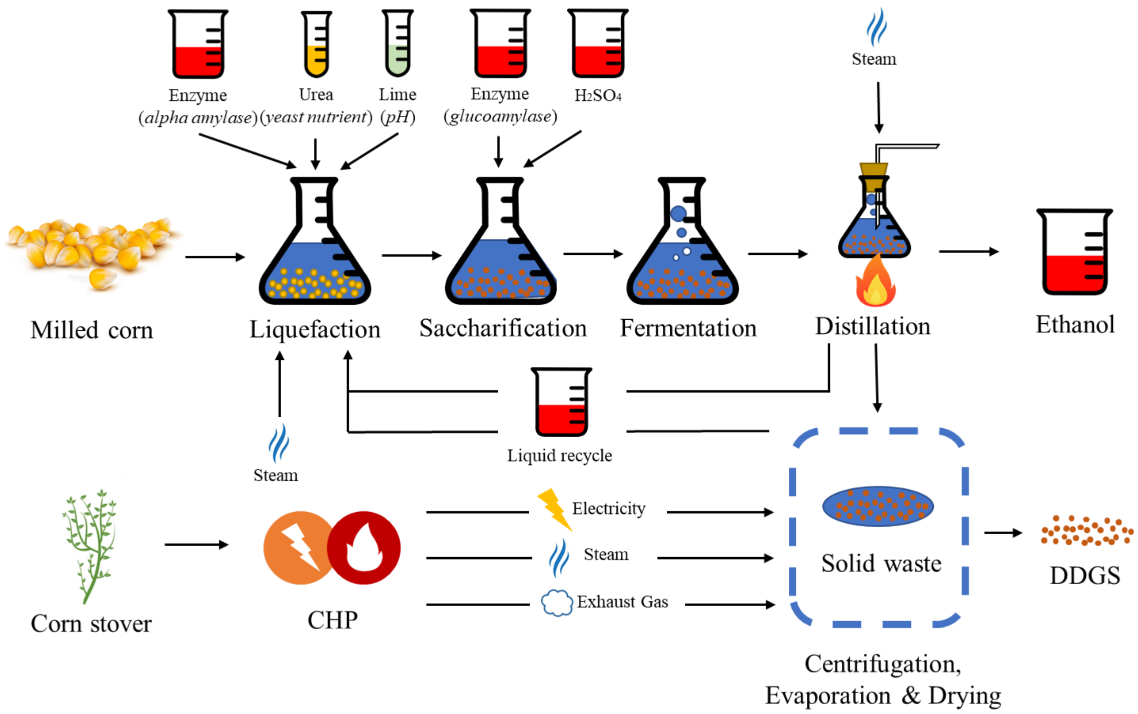
$$g_i^U = \max_j y_{ij}^U, \quad i = 1,2, \dots, \mathrm{m}, \; j = 1, \dots, \mathrm{n}, \tag{27}$$

$$g_i^L = \max_j y_{ij}^L, \quad i = 1,2, \dots, \mathrm{m}, \; j = 1, \dots, \mathrm{n}, \tag{28}$$

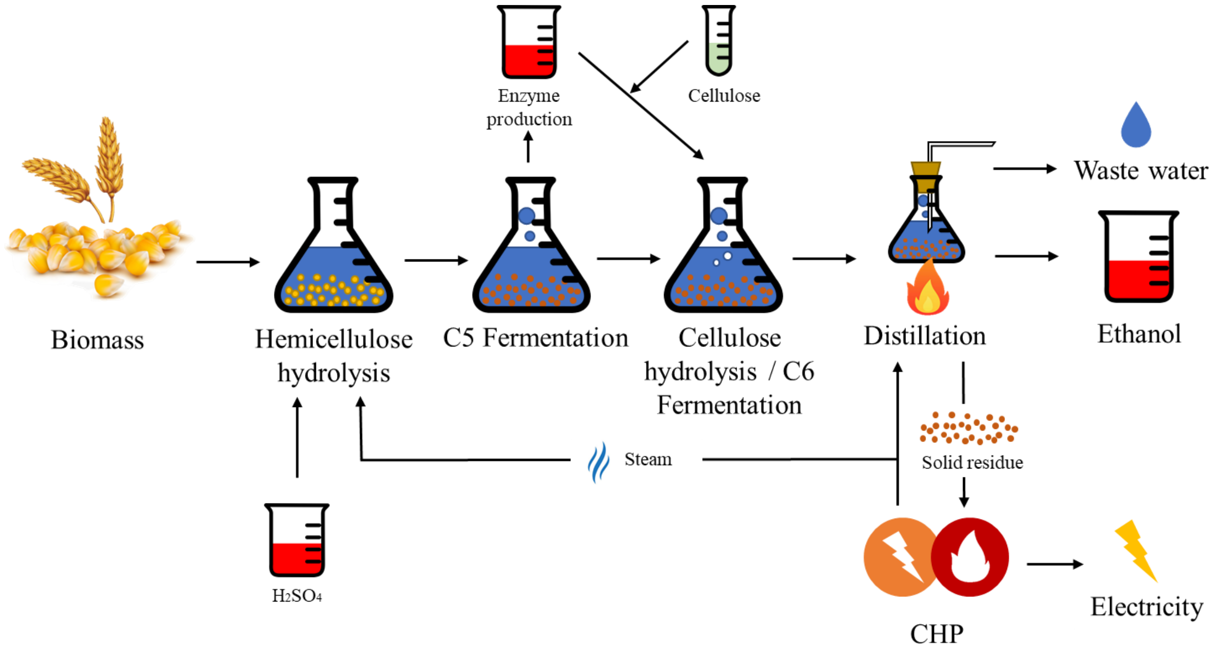
3. **Case study**

In this study, three alternatives of biorefinery technologies, the grain ethanol biorefinery (GE), cellulosic ethanol biorefinery (CE) and Fischer-Tropsch diesel biorefinery (FTD), were used for case analysis.

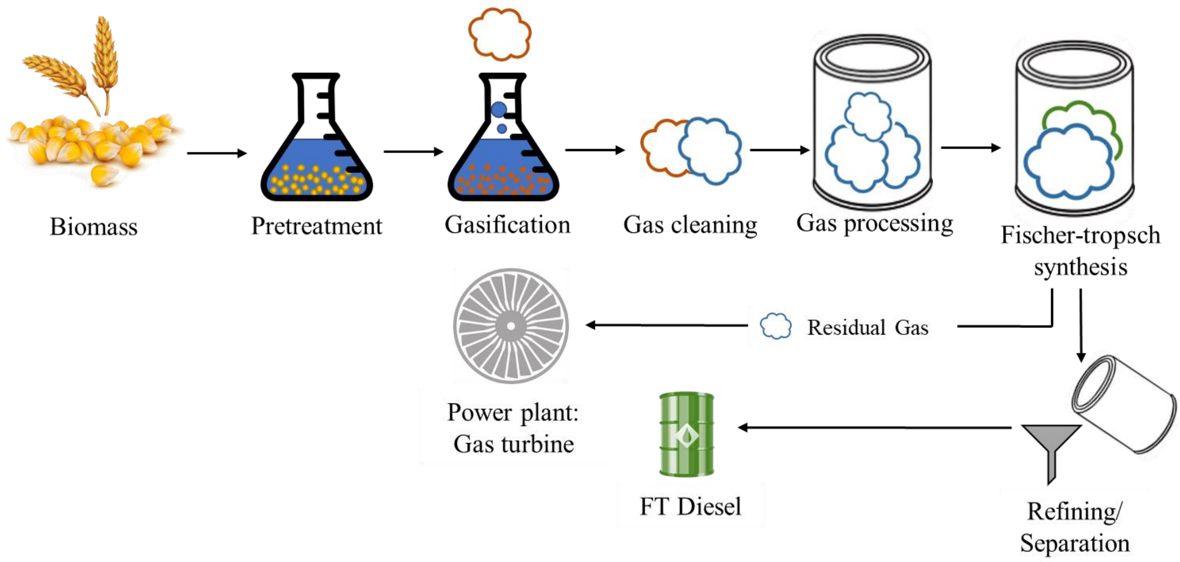
GE, CE and FTD are three typical biorefinery technologies. The dry mill GE process is a mature technology producing ethanol from corn starches. The main process steps include liquefaction, saccharification, fermentation, and distillation (see **Fig. 3a**). The GE system also cooperates with combined heat and power (CHP) systems, which could provide heat, gas, and power to the GE process while corn stove could be the energy resource for the CHP system. This additional system helps to increase plant energy efficiency by 25% (Schaidle et al., 2011). The CE technology is comparatively immature technology but complex in processes. The production process of CE technology starts from hemicellulose hydrolysis, followed by C5 fermentation, cellulose hydrolysis or C6 fermentation and distillation (see **Fig. 3b**). CE technology combined with a CHP system where CHP provides heat to CE production only and CHP adapts solid residues from the CE production process (Schaidle et al., 2011). An FTD produces diesel fuel instead of ethanol, comparing to other biorefinery technologies. Main production processes include pretreatment, gasification, gas cleaning, gas processing, Fischer-Tropsch Synthesis (FTS), and fuel refining or separation (see **Fig. 3c**). According to the decision-making method described in section 2, the analysis is explained in the following:



(a) Flowchart of Grain Ethanol Biorefinery



(b) Flowchart of Cellulosic Ethanol Biorefinery



(c) Flowchart of Fischer-Tropsch Diesel Biorefinery with Gas Turbine Combined Power Cycle

FIGURE 3. Flowcharts of biorefinery techniques

3.1 Establishing criteria system and collecting alternative data

According to the index system described in section 2.1 and the conditions for selecting the index system, the experts of biorefinery technology selected the following four indicators to become the index system of this study. There are thirteen enablers in technical, environmental, economic and social aspects that were selected to evaluate this case study. There were energy efficiencies for technical aspect, greenhouse gas emission, SOx, and NOx emission, and water use for environmental aspect, capital cost, operating cost, return on investment (ROI) for economic aspect and job creation, health effects for social aspect. There is no overlapping for those thirteen indicators. The indicators in one aspect can sufficiently describe the aspect performance. In technical aspect, energy efficiency can indicate the technical performance of biorefinery. In environmental aspect, greenhouse gas emission, SOx, and NOx emission describe the pollution caused by biorefinery, and the water use describes the resources occupied by this activity. In economic aspect, capital cost and operating cost assess the performance of cost and ROI indicates the profit made by this project. In social aspect, job creation is the sub-indicator of social well-being and the rest describe health under social acceptance. The indicators selected were measurable and the indicators the decision makers think are significant to the project development were selected. The completeness rate of this study calculated according to the **Eq.1** is given by **Eqs.29-33**.

$$CR_{EN} = \frac{n_{EN} - n_{EN}^{-}}{n_{EN}^{+} - n_{EN}^{-}} = \frac{4-2}{20-2} = 0.1111 \geq 0 \tag{29}$$

$$CR_{EC} = \frac{(n_{EC} + 0.5\times n_{SE} + 0.5\times n_{TE}) - n_{EC}^{-}}{(n_{EC}^{+} + 0.5\times n_{SE}^{+} + 0.5\times n_{TE}^{+}) - n_{EC}^{-}} = \frac{3-2}{16+0.5\times 2+0.5\times 17-2} = 0.0426 \geq 0 \tag{30}$$

$$CR_S = \frac{(n_S + 0.5 \times n_{SE}) - n_S^-}{(n_S^+ + 0.5 \times n_{SE}^+) - n_S^-} = \frac{4-2}{8+0.5\times2-2} = 0.2857 \geq 0 \quad (31)$$

$$CR_T = \frac{(n_T + 0.5 \times n_{TE}) - n_T^-}{(n_T^+ + 0.5 \times n_{TE}^+) - n_T^-} = \frac{2-1}{4+0.5\times18-1} = 0.0833 \geq 0 \quad (32)$$

$$CR = 0.25 \times C_{EN} + 0.25 \times C_{EC} + 0.25 \times C_S + 0.25 \times C_T = 0.0398 \quad (33)$$

Since the aspect completeness rates are non-negative, the criteria selected for the sustainability assessment are satisfactory and feasible.

The article (Schaidle et al., 2011) provided data for those 13 enablers as shown in **Table A1.** Since the uncertainties in the decision-making should be considered, information from several sources regarding GE, CE, and FTD was collected to determine the range of possible impact information (Farrell et al., 2006; Pate et al., 2007; Phillips et al., 2010; Sheehan et al., 2004; Spatari et al., 2005; Wang et al., 2007; M. Wu et al., 2006; May Wu et al., 2006).

3.2 Criteria weighting

The index weight is obtained according to the judgment of experts and the method of obtaining the weight as described in section 2.2. The detailed steps are explained as following.

To determine the local weights, pairwise matrixes for environmental, economic aspect and social aspect were determined and listed in **Table 5-9**.

Table 5. Pairwise matrix among aspects

	Technical	**Economic**	**Social**	**Environmental**
Technical	1	1	[2,3]	[6,7]

Economic	1	1	[2,3]	[6,7]
Social	[1/3,1/2]	[1/3,1/2]	1	[4,5]
Environmental	[1/7,1/6]	[1/7,1/6]	[1/5,1/4]	1

Table 6. Pairwise matrix of technical aspect

	$\mathbf{E_{total}}$	$\mathbf{E_{fossil}}$
E_{total}	1	[1/3,1/2]
E_{fossil}	[2,3]	1

Table 7. Pairwise matrix of environmental aspect

	GHG emissions	**SOx emissions**	**NOx emissions**	**Water use**
GHG emissions	1	[3,4]	[3,4]	[5,6]
SOx emissions	[1/4,1/3]	1	1	[1,2]
NOx emissions	[1/4,1/3]	1	1	1
Water use	[1/6,1/5]	[1/2,1]	1	1

Table 8. Pairwise matrix of economic aspect

	Capital cost	**Operating cost**	**ROI**
Capital cost	1	[1/3,1/2]	[1/4,1/3]
Operating cost	[2,3]	1	[1/3,1/2]
ROI	[3,4]	[3,4]	1

Table 9. Pairwise matrix of social aspect

	Jobs created	PM-10 for health assessment	CO for health assessment	VOC for health assessment
Jobs created	1	[1/3,1/2]	[1/2,1]	[1/3,1/2]
PM-10 for health assessment	[2,3]	1	[2,3]	[3,4]
CO for health assessment	[1,2]	[1/2,1]	1	[2,3]
VOC for health assessment	[2,3]	[1/4,1/3]	[1/3,1/2]	1

Hence, their local weights were calculated through programming model **Eq.6** respectively, as shown in **Table 10**. The global weights were generated through **Eq.7** and **Eq.8**.

Table 10. Criteria weights

Enablers	Local weights	Global weights
Technical	**[1.9343,1.9343]**	
E_{total}	[0.5774,0.7071]	[0.7256,1.0883]
E_{fossil}	[1.4142,1.7321]	[1.7773,2.6659]
Environmental	**[0.2763,0.2763]**	
GHG emission	[1,8.1072]	[0.4297,16.6464]
SO_x	[0.2866,1]	[0.1231,2.0533]
NO_x emissions	[0.273,1]	[0.1173,2.0533]

Water use	[0.1987,1]	[0.0854,2.0533]
Economic	**[1.9343,1.9343]**	
Capital cost	[0.5,0.5]	[0.5581,0.5581]
Operating cost	[1,1]	[1.1162,1.1162]
ROI	[2,2]	[2.2325,2.2325]
Social	**[1,1]**	
Jobs created	[0.5533,0.7378]	[0.5088,0.8024]
PM-10 for health assessment	[1.9168,2.3784]	[1.7626,2.5866]
CO for health assessment	[1.0299,1.2779]	[0.947,1.3897]
VOC for health assessment	[0.5533,0.7378]	[0.5088,0.8024]

3.3 Ranking

The ranking results of multi criteria decision are obtained by the method described in 2.3. The detailed steps are explained as following.

After the calculation through programming model **Eq.21**, the result of interval goal programming method shows that $z_1 = 0$, $z_2 = 0$ and $z_3 = 1$, which represents that the third option FTD technology was picked as the first priority. Then, FTD is excluded from the alternative list and the processes of interval goal programming are repeated to compare the remain two options – GE and CE. The interval goal programming shows the result that $z_1 = 0$ and $z_2 = 1$, which indicates that CE was ranked as the second priority and the GE was the last one to choose (**Fig. 4**).

FIGURE 4. The prioritization results of interval goal programming

4. Result and Discussions

After analyzing the case study, comparing the results with other methods and sensitivity analysis with other methods, the feasibility of the proposed method can be examined. The practical application of this framework and the shortcomings of this study will be discussed in this section afterwards.

4.1 Result analysis of case study

According to the results of case analysis, FTD was the best result under the evaluation of selected indexes and the ranking of decision makers' preference for indexes. From the original data, more than half of indicators of FTD were optimal among all the alternatives. To be specific, those dominated indicators of FTD included fossil fuel input-output ratio, oxygen sulphide emission, oxygen nitrogen compound emission, and all social indicators. Furthermore, FTD was not the worst in terms of greenhouse gas emissions and operating costs. In contrast, GE's performance in ROI index and input cost was good while the other indexes were not. Known from the original result, the majority of the indicators for CE were disadvantaged among three alternatives. This result was consistent with the trend of increasing use of FTD (Gruber et al., 2019). Therefore, the ranking sequence of FTD first, CE second and GE last proved that the decision model proposed in this study was feasible in sustainable selection of biorefinery under uncertainties.

4.2 Feasibility analysis

In order to distinguish this decision framework from other interval decision frameworks, the case data will be processed by three interval decision-making methods (see **Fig.1)** and compared with the results obtained by the newly proposed interval decision-making framework. The three interval decision-making methods for validation are 1) TLGP (Wang et al., 2005); 2) interval Analytic Hierarchical Process(interval AHP) (Sugihara and Tanaka, 2001) as the criteria weighting method with interval Grey Relational Analysis (interval GRA) (Wei et al., 2011) as the decision-making method; 3) interval AHP with Technique for Order of Preference by Similarity to Ideal Solution (interval TOPSIS) (Dymova et al., 2013). The three decision-making methods and related calculations are explained in detail in supporting material.

It can be seen in the **Fig.5**, the ranking results of the case study generated by four decision-making method were different. Even the two classical methods, interval GRA and interval TOPSIS, have reached different conclusions. This shows that when decision makers use different decision rules and different emphases, the decision results will also change. According to the description of the original data in section 4.1, it can be seen that the method proposed in this study can draw more practical conclusions.

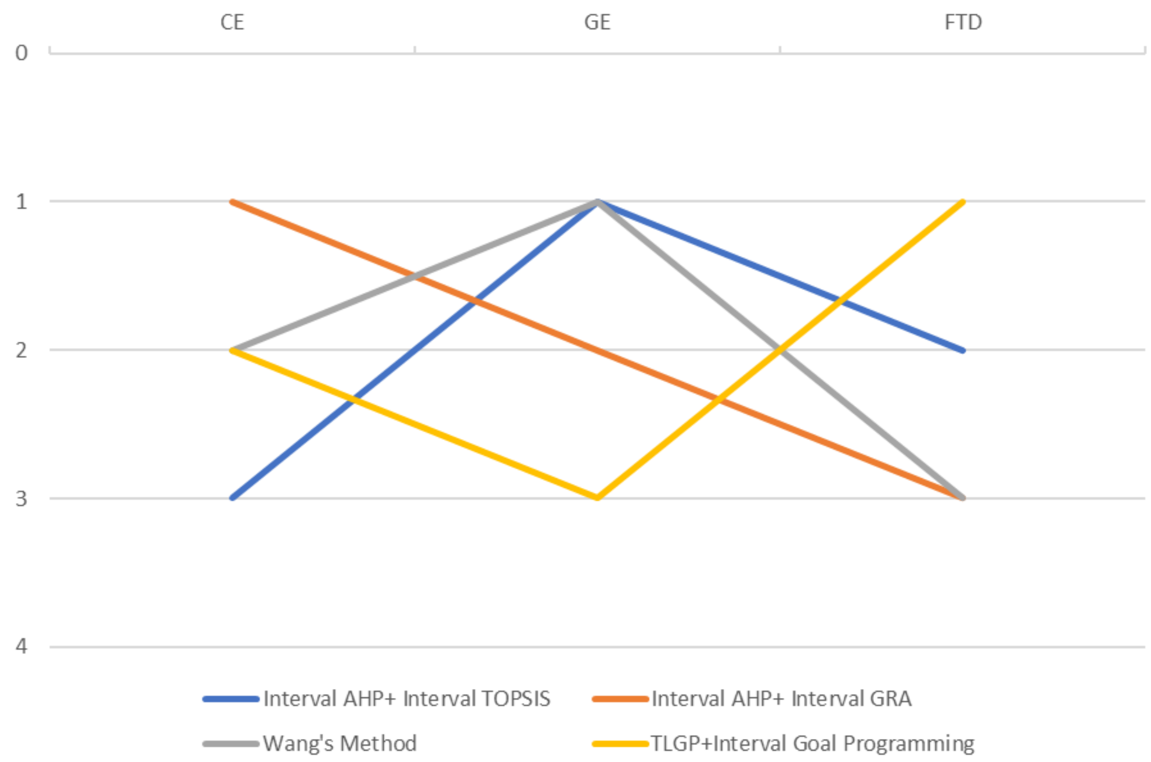
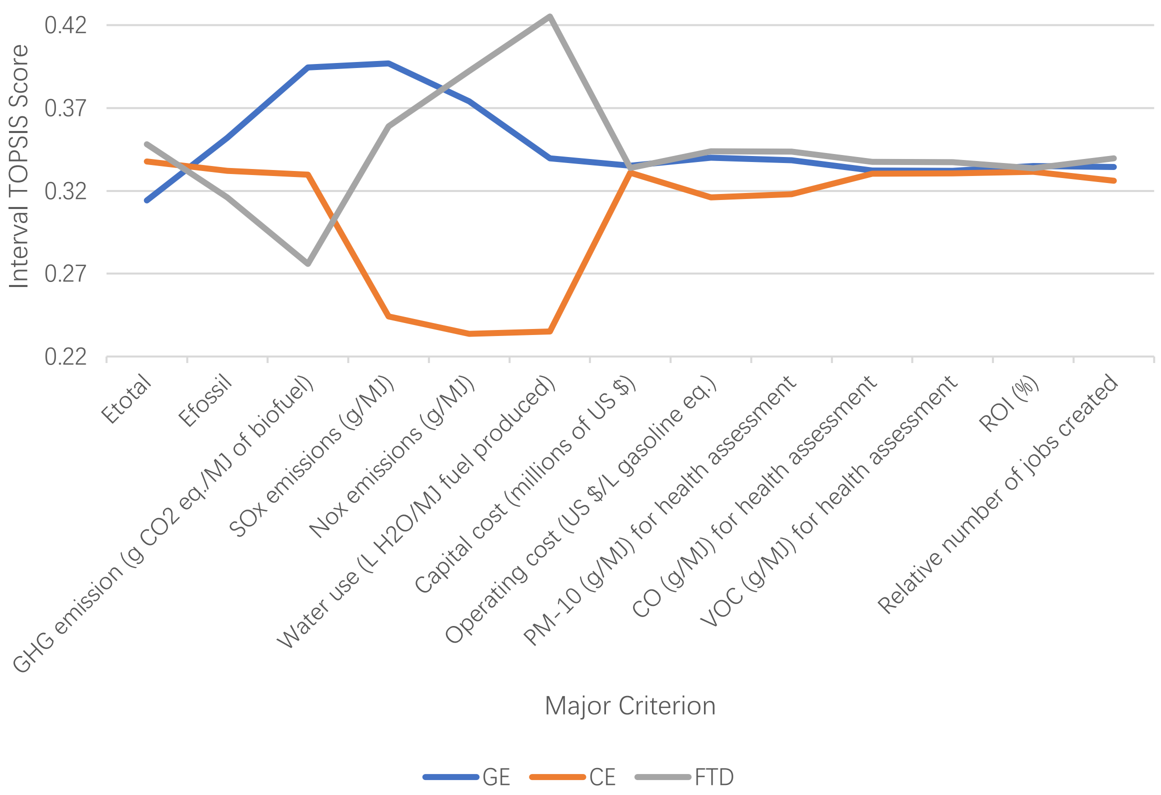


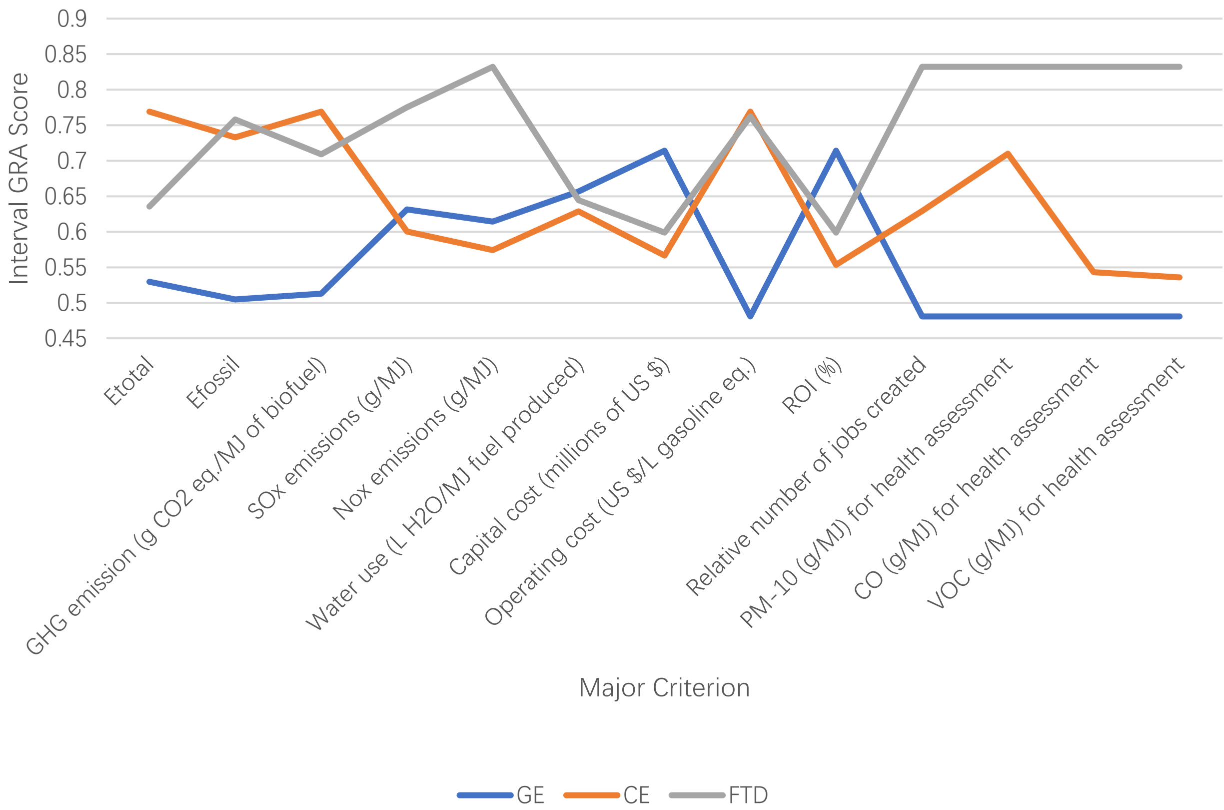
FIGURE 5. Alternative ranking results generated by four decision-making frameworks

4.2 Sensitivity Analysis

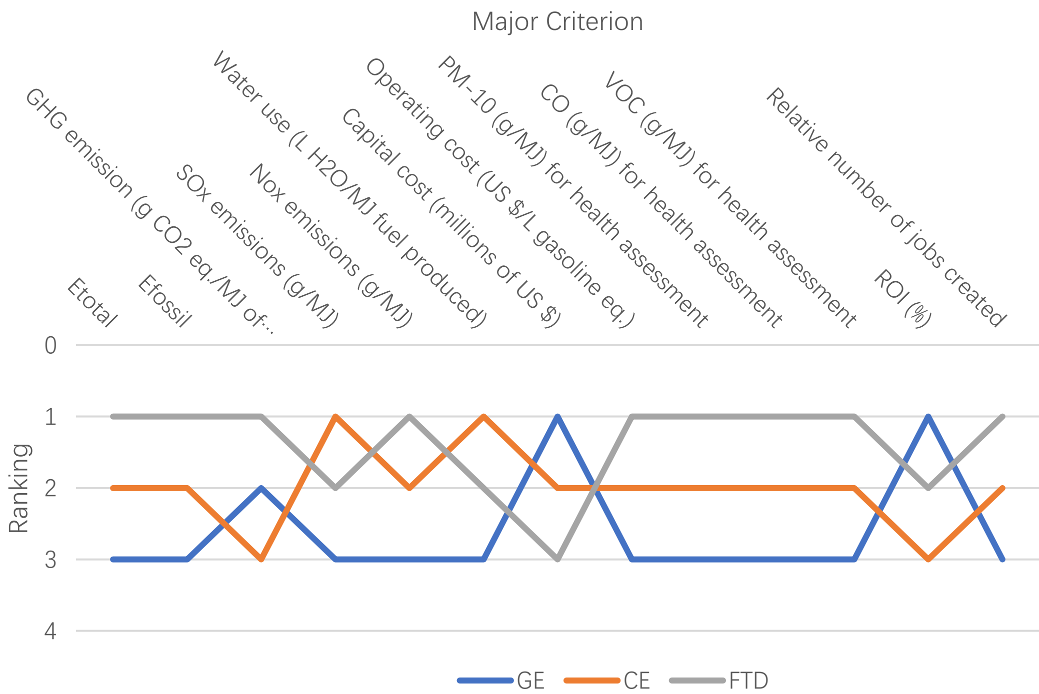
Sensitivity analysis can be used to detect the robustness of the method, that is, the stability of the result. The sensitivity analysis has done for the newly proposed decision-making framework and the other three decision frameworks, and the results can be seen in **Fig.6**. In this sensitivity analysis, one of the indicators was defined as the main indicator and the other indicators as the common indicators. Sensitivity analysis is to highlight one of the indicators and keep other indicators the same to determine the ease of the results affected by the main indicators. In this study, Wang's method, as the two methods of index weighting, adopts the main index of 3.54 and the other index of 0.9, which has met the requirement of index weight product of 1 in the method; interval AHP, as the two methods of index weighting, adopts the main index of 0.4 and the other index of 0.05, which can meet the requirement of index weight sum of 1 in the method. The greater the floating of the line, the greater the change of the order, the lower the stability of the decision. Obviously, the framework of this study can output the most stable results in the decision-making of uncertain data of biorefinery technology.



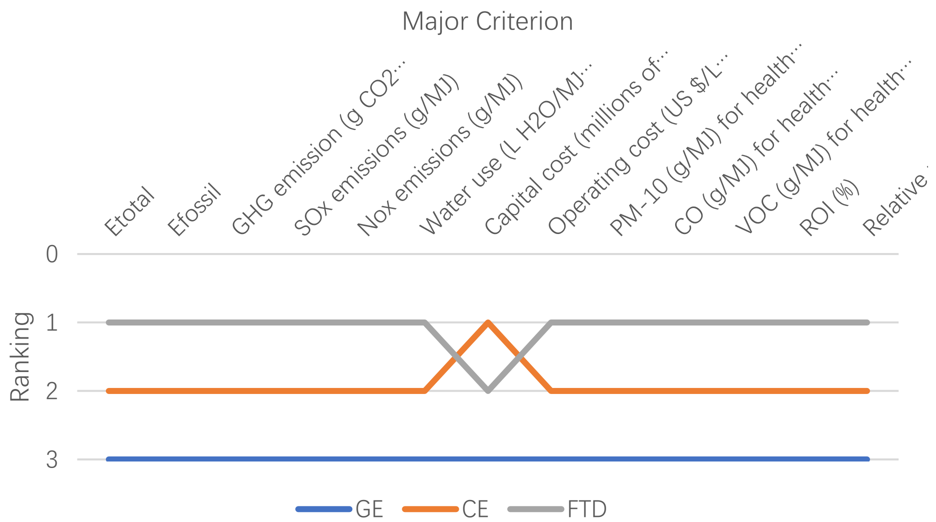
(a) Sensitivity analysis result of iTOPSIS based on biorefinery case study



(b) Sensitivity analysis result of iGRA based on biorefinery case study



(c). Sensitivity analysis result of Wang's method based on biorefinery case study



d). Sensitivity analysis result of revised interval goal programming method

FIGURE 6. Sensitivity analysis results

4.4 Discussion

This decision framework can not only be applied to the decision-makers of the construction of biological refining plants for decision-making, but also to the following scenarios:

(1) This framework also can assist policy development process. The policymakers could use this method to assess multiple alternatives comprehensively with more criteria and equal criteria weights, to determine the biorefinery technology to support.

(2) It is helpful for technicians to discover the parts that need to be improved in the biological refining technology. The key factors of the development of a certain biorefinery technology comparing to other biorefinery technologies can be generated through the framework and the

sensitivity analysis. The method can be used before implementation for technology selection, and also can be used for monitoring the performance of the study object and comparing to that of competitors.

(3) This framework can help researchers to evaluate the new biorefinery technology. When a new biorefinery technology is developed, this framework could help to examine the strengths and priority of the new technology.

Subject to restrictions on knowledge and research methods, there must be deficiencies in this article and demands for further research. The main limitations of this method include:

1) this method partially depending on subjective judgement of decision makers;

2) this method lacking considering more data types such as fuzzy number and linguistic terms. There are several forms of data types to express uncertainty, and the interval number is one of forms; and

3) the criteria analyzed in this article did not consider all the criteria in the sustainable assessment system due to limitations of data resources. Since this framework is designed to assist decision makers to make decision under uncertainty when they have clear preference of criteria, the results generated from the framework are different when decision makers have different preference of criteria selection and criteria weighting.

Therefore, other data types such as natural language descriptions, fuzzy numbers or hybrid data types will be discussed in the future. Experiments and tests are required to acquire more data resources for more accurate research assessment;

5. Conclusions

This study developed a sustainability prioritization framework for biorefinery system based on improved interval goal programming for the screening of biorefinery technology under uncertain conditions. In order to evaluate the sustainability of biorefinery technology more accurately, this study provided a complete list of criteria for biorefinery technology and the rules for selecting evaluation criteria. By comparing the case of GE, CE, and FTD biorefineries as examples, the results of other three decision frameworks, the feasibility and stability of this decision framework for the sustainability evaluation and sequencing of biorefinery technology with uncertain data are determined. The results reveal that FTD was recognized as the most sustainable scenario by the proposed method and criteria weighting method choosing has great impacts on decision-making results. The TLGP, interval AHP combined with interval GRA method, and the interval AHP combined with interval TOPSIS were also employed to validate the results. According to the validation results, the new model is feasible in solving biorefinery prioritization problems under uncertainties and the differences in weighting methods lead to the difference in selection results. Proven by the sensitivity analysis, the new model is more robust in selection result comparing with other validation methods. This framework can be used in policy making, problem diagnosis, process monitoring and optimization. However, this study still has some shortcomings such as limited data types and limited number of criteria. Therefore, the decision-making framework of biorefinery that can handle more data types such as natural language descriptions, fuzzy numbers or hybrid data types will be discussed in the future. Experiments and tests are required to acquire more data resources for more accurate research assessment.

Acknowledgment

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Appendix

Table A1. Values of enablers for grain ethanol biorefinery, cellulosic ethanol biorefinery and Fischer-Tropsch diesel biorefinery (Schaidle et al., 2011)

Enablers	**GE**	**CE**	**FTD**
Technical			
E_{total}	[2.15, 2.30]	[2.05, 2.30]	[2.20, 2.30]
E_{fossil}	[0.33, 0.42]	[0.08, 0.42]	[0.05, 0.42]
Environmental			
GHG emissions (g CO2 eq./MJ of biofuel)	[44, 57]	[-9, 23]	[-5, 48]
SO_x emissions (g/MJ)	[0.055, 0.081]	[0.009, 0.220]	[0.009, 0.110]
NO_x emissions (g/MJ)	[0.12, 0.25]	[0.05, 0.65]	[0.03, 0.10]
Water use (L H_2O/MJ fuel produced)	[0.14, 0.28]	[0.09, 0.45]	[0.37, 0.37]
Economic			
Capital cost (millions of US $)	[143, 143]	[585, 585]	[786, 786]
Operating cost (US $/L gasoline eq.)	[0.61, 0.61]	[0.53, 0.53]	[0.54, 0.54]
ROI (%)	[24.1, 24.1]	[11.1, 11.1]	[7.9, 7.9]
Social			
Relative number of jobs created	[1, 1]	[2, 2]	[2.5, 2.5]
PM-10 (g/MJ) for health assessment	[0.07, 0.07]	[0.017, 0.017]	[0.011, 0.011]
CO (g/MJ) for health assessment	[1.66, 1.66]	[1.63, 1.63]	[1.32, 1.32]
VOC (g/MJ) for health assessment	[0.1, 0.1]	[0.1, 0.1]	[0.05, 0.05]

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