Uncertainty analysis and global sensitivity analysis of techno-economic assessments for biodiesel production

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HIGHLIGHTS

- Economical feasibility of biodiesel production with uncertainties was assessed.
- Uncertainty analysis and parameter screening was carried out.
- Global sensitivity analysis was performed using three efficient methods.
- Results identified influential parameters on the life cycle cost.

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ABSTRACT

There are various uncertain parameters in the techno-economic assessments (TEAs) of biodiesel production, including capital cost, interest rate, feedstock price, maintenance rate, biodiesel conversion efficiency, glycerol price and operating cost. However, fewer studies focus on the influence of these parameters on TEAs. This paper investigated the effects of these parameters on the life cycle cost (LCC) and the unit cost (UC) in the TEAs of biodiesel production. The results show that LCC and UC exhibit variations when involving uncertain parameters. Based on the uncertainty analysis, three global sensitivity analysis (GSA) methods are utilized to quantify the contribution of an individual uncertain parameter to LCC and UC. The GSA results reveal that the feedstock price and the interest rate produce considerable effects on the TEAs. These results can provide a useful guide for entrepreneurs when they plan plants.

1. Introduction

Conventional fossil fuels can produce many deleterious emissions when igniting in engines, including greenhouse gases, NOx, hydrocarbons and particulate matter, which have caused various harmful influences on the global climate and air quality (Höök and Tang, 2013; Van et al., 2014). It is desired to find alternative clean, economic and easy-to-use energy sources in the industry, the transport system, etc. As a renewable fuel, biodiesel has many advantages over the conventional fossil fuels in terms of environmental friendliness (Kalam et al., 2011; Frey and Kim, 2009; Fontaras et al., 2009; Chen et al., 2010). Thus, biodiesel has attracted more and more attention, and the biodiesel industry is growing rapidly. Many studies have focused on biodiesel production from various feedstocks, such as palm oil (Chen et al., 2010), Jatropha curcas L. (Yusuf et al., 2012), waste cooking oil (Zhang et al., 2003), soybean oil (You et al., 2008), castor oil (Santana et al., 2010) and vegetable oils (Apostolakou et al., 2009).

In order to understand the economical feasibility of biodiesel production, many researchers have conducted valuable studies on the techno-economic assessments (TEAs) of biodiesel production (Delrue et al., 2012; Nagarajan et al., 2013; Haas et al., 2006; Lozada et al., 2010; Jegannathan et al., 2011; Sakai et al., 2009; Ong et al., 2012). They focused on the life cycle cost (LCC) and the unit cost (UC) of biodiesel production within a project’s lifetime under the assumptions that all of the parameters were deterministic. In practice, many unavoidable, uncertain sources exist in the TEAs of biodiesel production during the project’s lifetime (Sotoft et al., 2010), such as the variation of the feedstock and biodiesel prices (Busse et al., 2012) and the fluctuation of the interest rate (Mankiw, 2011). As revealed by Borgonovo and Peccati (2006) and Brownbridge et al. (2014), the uncertainties in
the parameters may exert important effects on the investment projects. In order to decrease these effects, engineers may be interested in knowing the contribution that each parameter has produced on the output and, further, how this contribution can be quantified.

Global sensitivity analysis (GSA) is a beneficial tool to estimate the contribution of an individual parameter to the output. In this paper, three available GSA methods are employed to quantify the contribution of an individual parameter to LCC and UC, i.e., the variance-based importance measure (Saltelli et al., 2004), the moment-independent importance measure (Borgonovo et al., 2011) and the entropy-based importance measure (Tang et al., 2013). The GSA results can serve as a reasonable guide to the identification of the important parameters and the unimportant ones, which can tell the engineers which parameters require attention. The variance-based importance measure (Saltelli et al., 2004) is the most popular GSA tool to test the sensitivity of the output with respect to the random inputs, and it employs the expected reduction in the output variance due to the elimination of the uncertainty in the individual random input to define the effect of the random input on the output. However, as summarized by Borgonovo et al. (2011), the variance-based importance measure may no longer be a computationally advantageous method in the presence of the correlated model inputs. Therefore, the moment-independent importance measure was originally proposed by Borgonovo et al. (2011) as an alternative to the variance-based one. This GSA approach employs the expected shift in the probability density function (PDF) of the output after eliminating the uncertainty in the individual random input to measure the effect. Based on the fact that entropy can measure the uncertainty in a random variable, the authors also proposed an entropy-based GSA method (Tang et al., 2013), which used the expected shift in the entropy to assess the contribution of an individual random input to the output. The three GSA methods can measure the contribution of an individual random input to the output from different physical meanings, i.e., the output variance, the output PDF and the output entropy. Therefore, a combination of them can give a more comprehensive measurement of the contribution of the individual random input to the output.

The paper is organized as follows. Section 2 introduces the TEAs of a biodiesel production and three available GSA methods. Section 3 performs the uncertainty analysis and the global sensitivity analysis for the techno-economic assessments of a biodiesel production under uncertain parameters. Conclusions are given in Section 4.

2. Methods

2.1. Techno-economic assessments of biodiesel production from crude palm oil

Ong et al. (2012) investigated the TEAs of a plant producing biodiesel from crude palm oil with deterministic parameters. Based on this study, LCC and UC are introduced in the following. Then, the variation range of an individual parameter is also provided.

The LCC of biodiesel production from crude palm oil within the project’s lifetime is defined by:

$$\text{LCC} = \sum_{i=1}^{n} \left( \text{FC}_i + \text{OC}_i + \text{MC}_i - \text{SV} \right) + BPC_i,$$

where $\text{LCC}$ is the life cycle cost; $\text{CC}$ indicates the capital cost; $\text{FC}$ is the feedstock cost; $\text{OC}$ denotes the operating cost; $\text{MC}$ represents the maintenance cost; $\text{SV}$ is the salvage value and $\text{BPC}$ is the byproduct credit.

Business and economics commonly employ the present value calculations to compare the cash flows at different times. Therefore, in the form of the present value, LCC is expressed by:

$$\text{LCC} = \sum_{i=1}^{n} \left( \text{FC}_i + \text{OC}_i + \text{MC}_i - \text{SV} \right) \left( \frac{1}{1+r} \right)^i + BPC_i \left( \frac{1}{1+r} \right)^n,$$

where $n$ is the project’s lifetime, i.e., $n = 20$; $r$ represents the interest rate, i.e., $r \in [4.44\%, 13.53\%]$ (TRADING ECONOMICS, 2014); $\text{FC}$, $\text{OC}$, $\text{MC}$ and $\text{BPC}$ are the feedstock cost, the operating cost, the maintenance cost and the byproduct credit of the $i$th year, respectively.

The definitions of all of the items in Eq. (1) will be given. According to Ong et al. (2012), the annual biodiesel production capacity of the plant is 50 ktons, i.e., $\text{PC} = 50\text{ktons}$. As revealed by Ong et al. (2012), the capital cost of the plant with such production capacity varies from $9$ million to $15$ million, i.e., $\text{CC} \in [9\text{ million}, 15\text{ million}]$.

The main cost of biodiesel production is $\text{FC}$ (i.e., the cost of the crude palm oil), which usually accounts for 80–90% of LCC (Hitchcock, 2014) and is expressed by:

$$\text{FC} = \sum_{i=1}^{n} \text{FP} \times \frac{\text{FU}}{\left(1+r\right)^i},$$

where $\text{FP}$ is the feedstock price or the crude palm oil price, which varied from $200/ton to $1200/ton in the past twelve years, $\text{FP} \in [200/ton, 1200/ton]$ (Ong et al., 2012); $\text{FU}$ is the annual total feedstock consumption; $\text{CE}$ represents the conversion efficiency from feedstock to biodiesel, which generally varies from 96% to 99%, i.e., $\text{CE} \in [96\%, 99\%]$ (Nagi et al., 2008).

The total OC within the project’s lifetime in the form of the present value model yields, which usually comprises less than 15% of LCC (Duncan, 2003), is defined by:

$$\text{OC} = \sum_{i=1}^{n} \left( \text{OR}_i \times \text{PC} \times 1000 \right) \left( \frac{1}{1+r} \right)^i,$$

where $\text{OR}$ is the operating rate or the operating cost of per-ton biodiesel production. Here, the percentage that $\text{FC}$ comprises in LCC takes the value of 80% (Hitchcock, 2014), and the percentage that $\text{OC}$ comprises in LCC is 15% (Duncan, 2003). Because the feedstock price is $\text{FP} \in [200/ton, 1200/ton]$ (Ong et al., 2012), the operating rate or the operating cost of per-ton biodiesel production can be approximated as $\text{OR} \in [37.5/ton, 225/ton]$ by the feedstock price.

The total MC within the project’s lifetime is formulated by:

$$\text{MC} = \sum_{i=1}^{n} \text{MR} \times \text{CC},$$

where $\text{MR}$ denotes the maintenance rate. $\text{MR}$ takes a value of 2% in the research of Ong et al., 2012, and it is 1% in the work of Haas et al., 2006. Here, $\text{MR}$ varies from 1% to 2%, i.e., $\text{MR} \in [1\%, 2\%]$.

Salvage value (SV) is the remaining value of the components of the assets of the plant at the end of the project’s lifetime, i.e., $\text{SV} = \text{MR} \times \text{CC}$. Therefore, in the form of the present value, MC is expressed by:

$$\text{MC} = \sum_{i=1}^{n} \frac{\text{MR} \times \text{CC}}{\left(1+r\right)^i},$$

where $\text{MR}$ represents the maintenance rate, $\text{MR}$ takes a value of 2% in the research of Ong et al., 2012, and it is 1% in the work of Haas et al., 2006. Here, $\text{MR}$ varies from 1% to 2%, i.e., $\text{MR} \in [1\%, 2\%]$.

For the plant producing biodiesel from the crude palm oil, the byproduct credit comes from the sale of glycerol, which is yielded during biodiesel production. The total amount of the byproduct credit during the project’s lifetime is defined by:
where $GP$ is the glycerol price, i.e., $GP \in \{\$0.08/kg, \$0.02/kg\}$ (Nanda et al., 2014); $GCF$ represents the glycerol conversion factor, i.e., $GCF = 0.0985$ (Ong et al., 2012).

Unit cost (UC) of biodiesel production from the crude palm oil is defined as the cost per-liter of the biodiesel during the project’s lifetime. Therefore, the definition can be given by:

$$UC = \frac{LCC}{\text{PC} \times 10^6 / \rho \times n}$$

where $\rho$ represents the density of the biodiesel, i.e., $\rho = 0.95$ kg/l; PC is the annual biodiesel production capacity, i.e., $\text{PC} = 50$ ktons; $n = 20$ is the project’s lifetime.

Some key input parameters are summarized in Table 1. Their ranges are also provided. The ranges of the capital cost ($x_1$) (Ong et al., 2012), the interest rate ($x_2$) (TRADING ECONOMICS, 2014), the operating rate ($x_5$) (Hitchcock, 2014; Duncan, 2003; Ong et al., 2012), the feedstock price ($x_4$) (Ong et al., 2012), the glycerol price ($x_6$) (Nanda et al., 2014), the maintenance rate ($x_6$) (Ong et al., 2012, Haas et al., 2006) and the biodiesel conversion efficiency ($x_7$) (Nagi et al., 2008) are determined by the available data. All of the uncertain parameters follow the uniform distributions within their ranges.

### 2.2. Global sensitivity analysis using three methods

Sensitivity analysis (SA) can be grouped into the local sensitivity analysis (LSA) and GSA (Haaker and Verheijen, 2004). LSA investigates how much the output is changed by the small variation of the random input around a reference point (such as the nominal value), which depends on the choice of the reference point. Instead, GSA measures the contribution of an individual random input to the output within the entire range space of the input, which is independent of the choice of the reference point. Three GSA methods used in this paper are briefly introduced.

#### 2.2.1. Variance-based importance measure

In general, the chosen model can be written in the form of $Y = g(x_1, x_2, \ldots, x_m)$, where $x_1, x_2, \ldots, x_m$ are random inputs, and $Y$ is the output of the model. In this paper, $Y$ is LCC or UC of biodiesel production from the crude palm oil, and $x_1, x_2, \ldots, x_m$ represent the random inputs of the techno-economic assessments, including the capital cost, the interest rate, the operating rate, the feedstock price, the glycerol price, the maintenance rate and the biodiesel conversion efficiency.

The total variance of the output can be decomposed into

$$\text{Var}(Y) = \sum_{i=1}^{m} \text{Var}(Y|x_i) + \sum_{i<j} \text{Cov}(Y|x_i,x_j) + \sum_{i<j<k} \text{Cov}(Y|x_i,x_j,x_k) + \cdots$$

where $\text{Var}(Y|x_i)$ is the main effect of $x_i$ (i.e., all other random inputs, except $x_i$). $\text{Cov}(Y|x_i,x_j)$ captures how much the output is changed by the small variation of $x_i$ and $x_j$.

#### 2.2.2. Moment-independent importance measure

The moment-independent importance measure $\delta_i$ is expressed by Borgonovo et al. (2011):

$$\delta_i = \frac{1}{2} \int_{D_x} \left| \frac{f_{Y|x_i}}{f_Y} - f_{Y|x_i=0} \right| dy$$

with $D_x$ representing the support of the output $Y$; $f_{Y|x_i}$ is the original PDF of $Y$ and $f_{Y|x_i=0}$ is the conditional PDF of $Y$ given $x_i$.

### Table 1

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Lower bound ($x_i^l$)</th>
<th>Upper bound ($x_i^u$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Capital cost (CC: $x_1$) (Ong et al., 2012)</td>
<td>$9$ million</td>
<td>$15$ million</td>
</tr>
<tr>
<td>Interest rate ($r$: $x_2$) (TRADING ECONOMICS, 2014)</td>
<td>$4.44%$</td>
<td>$13.53%$</td>
</tr>
<tr>
<td>Operating rate (OR: $x_5$) (Hitchcock, 2014; Duncan, 2003; Ong et al., 2012)</td>
<td>$37.5$/ton</td>
<td>$225$/ton</td>
</tr>
<tr>
<td>Feedstock price (FF: $x_4$) (Ong et al., 2012)</td>
<td>$200$/ton</td>
<td>$1200$/ton</td>
</tr>
<tr>
<td>Glycerol price (GP: $x_6$) (Nanda et al., 2014)</td>
<td>$0.08$/kg</td>
<td>$0.2$/kg</td>
</tr>
<tr>
<td>Maintenance rate (MR: $x_6$) (Ong et al., 2012; Haas et al., 2006)</td>
<td>$1%$</td>
<td>$2%$</td>
</tr>
<tr>
<td>Biodiesel conversion efficiency (CE: $x_7$) (Nagi et al., 2008)</td>
<td>$96%$</td>
<td>$99%$</td>
</tr>
</tbody>
</table>

Fig. 1. Original probability density function $f_I(y)$ (solid) and conditional probability density function $f_{I|x=x_0}(y)$ (dashed).
measures the expected can measure and are based on the output variance. is based on the output PDF and is a sensitive indicator. It can and are the conditional PDF and the support of are the PDF and the support of where \( H_Y(y) \) is the original entropy of \( Y \); \( H_{Y|X_i}(y) \) is the conditional entropy of \( Y \) given \( x_i \).

According to the information theory, the definitions of \( H_Y(y) \) and \( H_{Y|X_i}(y) \) are given by:

\[
H_Y(y) = - \int_{D_Y} f_Y(y) \ln(f_Y(y)) \, dy,  
\]

\[
H_{Y|X_i}(y) = - \int_{D_{Y|X_i}} f_{Y|X_i}(y) \ln(f_{Y|X_i}(y)) \, dy, 
\]

where \( f_Y(y) \) and \( D_Y \) are the PDF and the support of \( Y \); \( f_{Y|X_i}(y) \) and \( D_{Y|X_i} \) are the conditional PDF and the support of \( Y \) given \( x_i \).

In this paper, four GSA indicators including \( S_i \), \( ST_i \), \( \delta_i \) and \( \epsilon_i \) are utilized to perform the global sensitivity analysis for the TEAs of biodiesel production. The main purpose is to assess the effect of an individual input parameter on the TEAs from different perspectives, i.e., the output variance, the output PDF and the output entropy. \( S_i \) and \( ST_i \) are based on the output variance. \( S_i \) can measure the main effect of a variable on the output, while \( ST_i \) can measure the intersection between a variable and other ones. \( S_i \) and \( ST_i \) are easy to execute by the program. Their disadvantages are that they depend on the second moment, or the variance of the output, but the variance cannot include all of the uncertainty in the output. \( \delta_i \) is based on the output PDF and is a sensitive indicator. It can provide a very efficient assessment of the effect of the parameter

\[
\delta_i = E_x [t(X_i)] 
\]

\[
t(X_i) = |H_Y(y) - H_{Y|X_i}(y)|, 
\]

The total area with shading represents the shift between \( f_Y(y) \) and \( f_{Y|X_i}(y) \), as sketched in Fig. 1, in which the intersection between a variable and other ones.

**2.2.3. Entropy-based importance measure**

Similar to \( \delta_i \), the entropy-based importance measure is defined by Tang et al. (2013):

\[
\epsilon_i = E_x [t(X_i)] 
\]

with

\[
t(X_i) = |H_Y(y) - H_{Y|X_i}(y)|, 
\]

Table 2

<table>
<thead>
<tr>
<th>Random input</th>
<th>( x_1 )</th>
<th>( x_2 )</th>
<th>( x_3 )</th>
<th>( x_4 )</th>
<th>( x_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>LCC(( x_1 ), ( x_2 ), ( x_3 ), ( x_4 ), ( x_5 ))</td>
<td>1.647 x 10^3</td>
<td>1.647 x 10^3</td>
<td>1.647 x 10^3</td>
<td>1.647 x 10^3</td>
<td>1.647 x 10^3</td>
</tr>
<tr>
<td>LCC(( x_1 ), ( x_2 ), ( x_3 ), ( x_4 ), ( x_5 ))</td>
<td>1.715 x 10^3</td>
<td>0.903 x 10^3</td>
<td>2.877 x 10^3</td>
<td>8.481 x 10^3</td>
<td>1.569 x 10^3</td>
</tr>
</tbody>
</table>

Table 3

<table>
<thead>
<tr>
<th>Random input</th>
<th>( x_1 )</th>
<th>( x_2 )</th>
<th>( x_3 )</th>
<th>( x_4 )</th>
<th>( x_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>UC(( x_1 ), ( x_2 ), ( x_3 ), ( x_4 ), ( x_5 ))</td>
<td>0.1565</td>
<td>0.1565</td>
<td>0.1565</td>
<td>0.1565</td>
<td>0.1565</td>
</tr>
<tr>
<td>UC(( x_1 ), ( x_2 ), ( x_3 ), ( x_4 ), ( x_5 ))</td>
<td>0.1629</td>
<td>0.0858</td>
<td>0.2733</td>
<td>0.8057</td>
<td>0.1491</td>
</tr>
<tr>
<td>UC(( x_1 ), ( x_2 ), ( x_3 ), ( x_4 ), ( x_5 ))</td>
<td>0.1565</td>
<td>0.1565</td>
<td>0.1576</td>
<td>0.1525</td>
<td></td>
</tr>
</tbody>
</table>

Fig. 2. Original and conditional probability density functions of the life cycle cost and the unit cost, (a) the life cycle cost, (b) the unit cost.
due to the fact that PDF can include all of the uncertainty in the output. The main drawback of $s_i$ is the dependence on the accuracy of the estimated output PDF. $e_i$ is based on the output entropy. This indicator can measure the effect of the parameter in terms of information. The shortcoming of $e_i$ is that it depends on the accuracy of the estimated output PDF and the entropy, as shown by Eqs. (15)–(18). $e_i$ is not suitable for identifying the parameters with low effects due to this demerit.

3. Results and discussion

In this section, parameter screening is first carried out. Then, the uncertainty analysis for the LCC and UC are performed. Finally, the global sensitivity analysis is accomplished.
constant at the baseline level. After all of the tests are performed, a series of graphs are usually constructed showing how the response variable is affected by varying each factor with all other factors held constant (Montgomery, 2013). Tables 2 and 3 provide the results for the LCC and the UC when one input random variable \( x_i \) varies from the lower bound \( x_{iL} \) to the upper bound \( x_{iU} \) with the other variables held constant at the lower bounds. The results show that the values of the LCC and UC are insensitive to the variations of \( x_6 \) and \( x_7 \).

The low-discrepancy sampling method (Dai and Wang, 2009) is employed to generate the samples of the random parameters due to the fact that it can yield better results than the conventional pseudo-random generator because the sequences produced by the low-discrepancy sampling method are more uniform than those from the pseudo-random generator within the ranges of parameters. Substituting these samples into Eqs. (2) and (8) can obtain the samples of LCC and UC. The work by Tang et al. (2013) has proven that the GSA results for LCC and UC, including \( S_i, S_{Ti}, d_i \) and \( e_i \), are equal to each other. Therefore, only LCC is focused on here.

Fig. 3 shows the relations of the estimated values of \( S_i, S_{Ti}, d_i \) and \( e_i \) with respect to the increasing samples. Fig. 2a and b shows two important observations. The first is that the elimination of the uncertainties in the unimportant parameters \( x_6 \) and \( x_7 \) (fixing them to their central values) yields a negligible influence on the PDFs of LCC and UC. The difference between the original PDF and the conditional PDF is so small that they appear to be overlapping with each other in the figure. Thus, \( x_6 \) and \( x_7 \) can be fixed to their central values without considerably affecting LCC and UC. The second observation is that the ranges of parameters have resulted in the variation of LCC and UC. The variation ranges of LCC (units: USD) and UC (units: USD/liter) are \([0.2, 9.8] \times 10^6\) and \([0.02, 0.92]\), respectively, indicating that the uncertainties in the parameters have yielded a considerable impact on LCC and UC.

In summary, the parameter uncertainties can considerably affect the techno-economic assessments. Neglecting the parameter uncertainties may lead to misleading results of the techno-economic assessments. The OFAT method is a simple strategy to assess the effect of one factor, but it fails to consider any possible interaction between the factors (Montgomery, 2013). The following will employ the three available GSA methods in Section 2.2 to quantify the contribution of each parameter.

### 3.2. Global sensitivity analysis of the life cycle cost

Eq. (8) points out that LCC and UC are just constant multiples of each other. The work by Tang et al. (2013) has proven that the GSA results for LCC and UC, including \( S_i, S_{Ti}, d_i \) and \( e_i \), are equal to each other. Therefore, only LCC is focused on here.

Fig. 4 provides a comparison of the estimated sensitivity values of \( S_i, S_{Ti}, d_i \) and \( e_i \). It can be seen that \( x_2 \) (the interest rate), \( x_3 \) (the operating rate) and \( x_4 \) (the feedstock price or the crude palm oil...
price) have important effects on LCC, but the other parameters have negligible impacts on LCC, indicating that the importance ranking of the parameters is as follows: \( x_4 > x_2 > x_3 \geq x_1, x_5 \).

Based on the GSA results shown in Fig. 4, the important parameters and the unimportant parameters can be identified. The important parameters are \( x_1, x_2, \) and \( x_3 \), while the unimportant parameters include \( x_4 \) and \( x_5 \). For these unimportant parameters, their uncertainties can be removed, and they can be fixed to any values within their variation ranges without considerably affecting LCC. Fig. 5 shows the original and conditional PDFs of LCC, in which the conditional PDF of LCC is obtained when the unimportant parameters \( x_1 \) and \( x_3 \) are fixed to their central values. The differences between the original PDF and the conditional PDF are very small, indicating that eliminating the uncertainties of the unimportant parameters does not considerably affect LCC.

For the important parameters \( x_1, x_2, \) and \( x_3 \), Fig. 6 further shows the original and conditional PDFs of the LCC when \( x_2, x_4, \) and \( x_3 \) are fixed to their central values. Fig. 6 reveals that the elimination of the uncertainties in the important parameters will lead to a distinct change of LCC variance. Another observation is that eliminating the uncertainties of the important parameters can shorten the variation range of LCC. For example, Fig. 6c shows that the original range of LCC (units: USD) is \([0.2, 9.8] \times 10^8\), while the conditional range of LCC becomes \([2.4, 6.5] \times 10^8\) after eliminating the uncertainty in \( x_4 \).

The previous results reveal that more attention should be paid to the important parameters including \( x_2 \) (the interest rate), \( x_3 \) (the operating rate) and \( x_4 \) (the feedstock price or the crude palm oil price). But the uncertainties in other unimportant parameters can be ignored, and they can be fixed to any values within their ranges.

4. Conclusions

The uncertainty and global sensitivity analysis have been carried out for the techno-economic assessments of a plant producing biodiesel from the crude palm oil with seven random input variables. The influence of parameters such as the capital cost, the interest rate, the operating rate, the feedstock price, the glycerol price, the maintenance rate and the biodiesel conversion efficiency on the life cycle cost has been considered. The results show that the interest rate and the feedstock price have a major influence on the life cycle cost.

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