

# Study of microalgae cultivation systems based on integrated analytic hierarchy process–life cycle optimization

Jully Tan<sup>1,2</sup> · Raymond R. Tan<sup>3</sup> · Kathleen B. Aviso<sup>3</sup> · Michael Angelo B. Promentilla<sup>3</sup> · Nik Meriam Nik Sulaiman<sup>1</sup>

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**Abstract** Optimization of sustainable process plant configurations requires the use of systematic assessment methods based on the usage of natural resources, release of pollutants and generation of environmental impact. This paper presents an integrated life cycle optimization framework for the synthesis of microalgae cultivation systems, using a multiple objective linear program formulation; in the model, individual objective functions are aggregated and weighted using the analytic hierarchy process. Four different cultivation alternatives were used as case study to demonstrate the capability of this formulated integrated model. The model takes into account three main environmental criteria in assessing different cultivation alternatives, namely energy, water (direct and indirect water) and carbon footprints. It is determined in the case study that the open pond cultivation system is preferred compared to other alternatives.

**Keywords** Microalgae · Life cycle assessment · Life cycle optimization · Multiple objective linear programming · Analytic hierarchy process

## List of symbols

<b>A</b>	Technology matrix
<b>B</b>	Environment intervention matrix
<b>f(x)</b>	Objective function
<b>g</b>	Total value of the environmental footprint
<b>P</b>	Worst alternative matrix
<b>w<sub>i</sub></b>	Weight of each criterion <i>i</i> ( <i>i</i> = 1, 2, ..., <i>n</i> )
<b><math>\bar{w}_{fp}</math></b>	AHP weight vector
<b>x</b>	Gross output or scaling vector
<b>y</b>	Net output vector
<b>z</b>	Pairwise comparison matrix

## Introduction

Many alternative energy sources have been studied for the production of biofuels due to recent energy security concerns and environmental issues. It is predicted that the world energy demand will increase by as much as 53% from recent levels by year 2030 (Talebian-Kiakalaieh et al. 2013). The current course of fossil fuel consumption is unsustainable particularly due to the release of greenhouse gases (GHGs), such as carbon dioxide (CO<sub>2</sub>), into the atmosphere (Amaro et al. 2011). Thus, biofuels have gained worldwide interest as low-carbon alternatives for use in motor vehicles. Feedstocks for biofuel production include commercial crops like corn, sunflower, soybean, rapeseed, oil palm, as well as crop residues or biomass (Balat and Balat 2009). Global production of biofuels grew from 16 × 10<sup>9</sup> L in 2000 to more than 100 × 10<sup>9</sup> L in 2011 (Zhang et al. 2013). Among emerging biofuel feedstocks, microalgae are one of the most promising due to its high yield (i.e., fuel production per hectare) and fast growth rate (Avagyan 2008). Microalgae are classified as

✉ Nik Meriam Nik Sulaiman  
meriam@um.edu.my

<sup>1</sup> Department of Chemical Engineering, Faculty of Engineering, Universiti Malaya, 50603 Kuala Lumpur, Malaysia

<sup>2</sup> Department of Chemical and Petroleum Engineering, Faculty of Engineering, Technology and Built Environment, UCSI University, No. 1, Jalan Menara Gading, UCSI Heights, 56000 Cheras, Kuala Lumpur, Malaysia

<sup>3</sup> Chemical Engineering Department/Center for Engineering and Sustainable Development Research, De La Salle University, 2401 Taft Avenue, 0922 Manila, Philippines

third-generation biofuel feedstocks (Chisti 2007). Furthermore, integrated systems involving microalgae production and wastewater treatment allow pollutants to be used as nutrients for microalgae (Mata et al. 2010).

Unlike first-generation biofuel feedstocks which often require high-quality agricultural land, the production of biodiesel from microalgae will not compromise food production (Demirbas 2009). It is estimated that microalgae can produce 20–760 times more oil per unit of land area than other conventional crops (Chisti 2007). Favorable properties of microalgae result from their high photosynthetic efficiency and have benefits for large-scale cultivation systems (Aslan and Kapdan 2006). In addition, some varieties of microalgae can use wastewater, brackish water or seawater, thus reducing competition for fresh water resources (Rawat et al. 2013). Microalgae can also be grown under heterotrophic conditions to achieve higher yields by using carbon sources dissolved or suspended in water (Liang 2013).

Nevertheless, there are still questions that remain about the best pathway for the production of microalgae biomass for fuel production (Handler et al. 2014). Some works on microalgae derived biofuels have focused on the improvement or selection of the various processing steps starting from the production of feedstock up to fuel conversion (Quinn and Davis 2015). A holistic evaluation of the environmental impacts of microalgae derived biofuels can be accomplished using life cycle assessment (LCA). LCA is a tool used to analyze the overall environmental impact of the product from the initial stage of raw material acquisition until the end of life of the product. It is a quantitative tool for analyzing the impacts related to a product or service from the initial stage of raw material acquisition to the end of life or disposal of the product (Guinée 2002). LCA enables the comparison of environmental performance between products and processes which perform the same function (Guinée 2002). Several studies of LCA for the different process paths for biodiesel/biogas production from microalgae have been conducted in the past years. Table 1 shows a summary of LCA studies of different microalgae production systems.

Despite improvements in the cultivation and processing of microalgae, the overall sustainability of algal biofuels remains controversial (Azadi et al. 2014). Technologies need to be assessed based on environmental impacts, quantified via metrics such as energy, water and carbon footprints. De Benedetto and Klemeš (2009) also proposed that carbon footprint, water footprint, energy footprint and workplace footprint be evaluated in the context of streamlined LCA as input for strategic decision-making. Čuček et al. (2012) conducted a comprehensive review of footprint analysis tools for monitoring impacts on sustainability. Razon (2014) discussed the

importance of the nitrogen cycle and its interplay with other footprints. These methods enable the comparison of different technologies, which will then facilitate the selection of the most promising ones. Numerous papers dealing with the optimization and environmental assessment of biomass energy supply chains have been published.

Life cycle optimization (LCO) methodology is based on the combination of LCA with mathematical programming, which was first proposed by Azapagic and Clift (1998) and applied to industrial boron production (Azapagic and Clift 1999). The approach based on the matrix formalism of Heijungs and Suh (2002) was later extended into a LCA optimization model by Tan et al. (2008) using fuzzy linear programming. Many other studies have also been done by incorporating multi-objective optimization approach to identify the optimal point with regard to the different objectives, such as total environmental footprints (Čuček et al. 2014) as well as actuarial risk estimates of fatalities (Ramadhan et al. 2014). A recent robust formulation for LCO was also proposed by Wang and Work (2014). However, one of the challenges in multi-objective optimization is in identifying the appropriate aggregation method to integrate the objectives into a single performance index, which is typically done by assigning importance weights to the different objectives. As shown in Table 1, previous LCA studies for the microalgae cultivation system were mainly focused in comparing overall environmental impacts without taking into consideration the priority of the environmental concerns.

There have been recent studies on LCO applied to bioenergy systems. For example, Gong and You (2014) developed the global optimization of the microalgae processing for CO<sub>2</sub> mitigation and biofuel production. Murphy et al. (2016) performed optimization to assess biomass energy conversion technologies which ensure minimal greenhouse gas emissions. Meanwhile, Khila et al. (2016) used LCO for identifying the optimal operating condition for hydrogen production and Miret et al. (2016) performed multi-objective optimization for the design and operation of the biomass supply chain under economic, environmental and social criteria. Mousavi-Avval et al. (2017) applied multi-objective genetic algorithm to find the best combination of energy, economic and environmental indices for oilseed canola production. Escobar et al. (2017) developed a framework that combines LCA with economic optimization to determine the feedstock combination for biodiesel production in Spain. On the other hand, there is a notable gap in the literature on the LCO of microalgae production systems. For example, searching the Scopus database using “life cycle optimization” as key word

**Table 1** Summary of different life cycle impact assessment studies for cultivation and harvesting process in microalgae production

Author	Cultivation method	Summary
Lardon et al. (2009)	Open pond	LCA was conducted for two different culture conditions and harvesting methods. Microalgae show as potential energy sources
Liu and Ma (2009)	Open pond	LCA of microalgae-based fuel methanol was conducted to evaluate its energy efficiency and environmental emission compared with gasoline fuel
Clarens et al. (2010)	Open pond	Comparative studies of LCA for switchgrass, canola, corn farming and microalgae were conducted. Conventional crops show lower environmental impacts than algae. However, algae performed favorably in total land use
Jorquera et al. (2010)	Tubular PBR, flat-plate PBR and open pond	LCA of biomass production from <i>Nanochloropsis sp</i> using three different cultivation methods was conducted. Flat-plate PBR and open pond cultivation show better net energy ratio compared with tubular PBR
Sander and Murthy (2010)	Open pond	Energy analysis of microalgae dewatering process was conducted and showed high amount of energy required
Campbell et al. (2011)	Open pond	LCA study was conducted to compare biodiesel production from algae with canola and ultra-low sulfur diesel. Algae show favorable results in greenhouse gases emissions compared to the others
Collet et al. (2011)	Open pond	LCA of biogas production from the microalgae is performed and compared to algal biodiesel and to first-generation biodiesels
Murphy and Allen (2011)	Open pond	A preliminary study of energy and water consumption was studied and provided input to the energy and water management of the overall processes in microalgae production
Razon and Tan (2011)	Integrated PBR and open raceway pond	Energy deficiency was observed during post-harvest dewatering and oil recovery operation of microalgae production
Yang et al. (2011)	Open pond	Life cycle water and nutrients usage of microalgae-based biodiesel production for the 11 algae strains were conducted
Beach et al. (2012)	Not specify	LCA of three different flocculants used in harvesting process was conducted
Chowdhury et al. (2012)	Integrated PBR and open raceway pond	Energy consumption and global warming potential were analyzed for the microalgae production
Frank et al. (2013)	Open pond	LCA for the biogas production from microalgae using hydrothermal liquefaction and lipid extraction was evaluated
Liao et al. (2012)	Open pond	LCA of microalgae cultivation, harvesting, drying, oil extraction, anaerobic digestion, oil transportation, esterification, biodiesel transportation and biodiesel combustion was done
Sevigne Itoiz et al. (2012)	Bubble column PBR	LCA to compare the indoor and outdoor growth of algae in bubble column PBR. Outdoor production system shows better energy consumption and life cycle impact to the environment
Vasudevan et al. (2012)	Open pond	LCA for various technology options affected GHG and freshwater consumption for microalgae biofuel production
Adesanya et al. (2014)	Hybrid tubular PBR and open pond	LCA from the hybrid system of microalgae cultivation to biodiesel production. Environmental impacts were compared to fossil-derived diesel
Handler et al. (2014)	Open pond	LCA for cultivation techniques (raceway vs. effluent cultivation) and fuel conversion pathways (pyrolysis vs. oil extraction and hydrotreatment) was conducted
Quinn et al. (2014)	Open pond, bioreactor	LCA for four microalgae-to-biofuel production scenarios using process modeling on: baseline scenario, improved microalgae productivity, supercritical CO <sub>2</sub> extraction and no nutrient recycle
Soh et al. (2014)	Open pond	LCA to evaluate varying species/growth conditions (freshwater and marine)

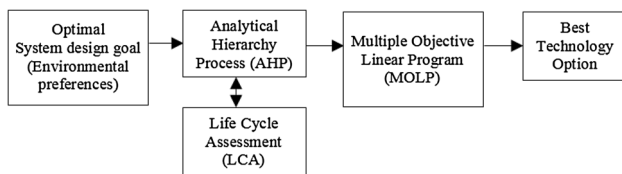
yields 161 published documents; however, filtering further using “microalgae cultivation” as an additional search parameter results in only one conference paper. Thus, a significant research gap can be identified in this specific application of LCO.

In this work, the analytic hierarchy process (AHP) (Saaty 1979) is utilized to develop an integrated AHP-LCO framework for determining the optimum system design for microalgae production. The methodology integrates the importance or preference weights of multiple

environmental footprints (i.e., energy, water and carbon footprint) to come up with a single environmental performance index. Through AHP, the subjective preferences of an expert can be captured in a quantitative form for use within a larger modeling framework (Ho 2008). These preferences are then utilized to generate the weights of the environmental footprints, which are then utilized to optimize the system. Different cultivation alternatives and carbon sources of microalgae production are evaluated with this proposed model to provide valuable insights in designing the microalgae production system. The rest of the paper is organized as follows. The next section discusses the formulation of the integrated AHP-LCO framework. Then, a case study based on literature values is utilized to illustrate the modeling approach. Finally, conclusion and prospects for future work are presented at the end of the paper.

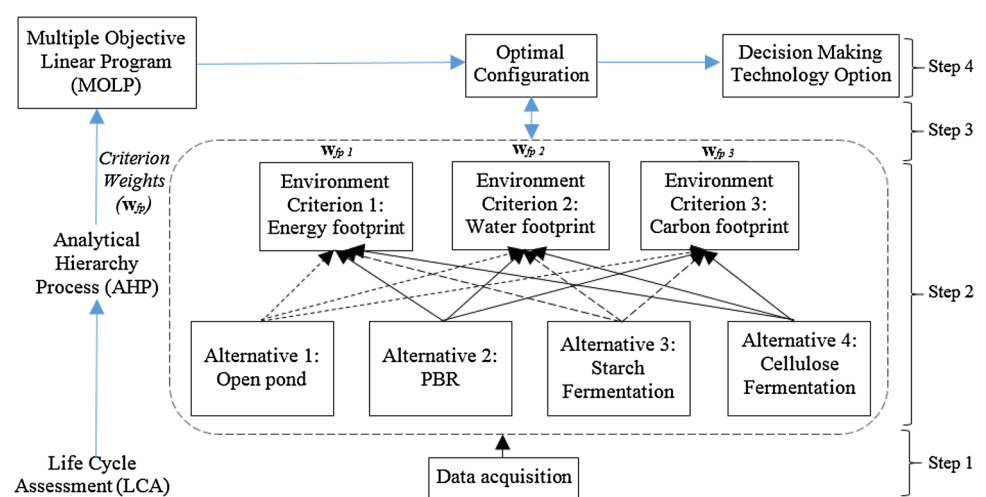
## Methodology

In general, the approach for LCO model development is comprised of four main steps, which are: acquiring the data for major processes in the life cycle, implementing AHP to determine the preference weights, formulating the multi-



**Fig. 1** Methodology framework of the integrated AHP-LCO model

**Fig. 2** Decision modeling framework for identifying the minimum footprints of cultivation options

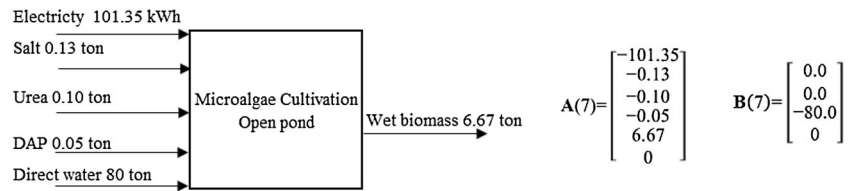


objective optimization problem within the LCA context and finally solving the model.

The methodological framework is shown in Fig. 1. The framework enables the determination of best cultivation option along with the optimum target value of preference environmental footprints. Identification of the system design goal (the environmental preferences in this case) is essential as it is required in the building of AHP hierarchy. LCA is integrated into AHP to assess different alternative technologies. Then, a multiple objective linear program (MOLP) model for the system is developed to minimize the overall environmental impact. Finally, the best technology option can be determined. A graphical representation of the sequential methodology is shown in Fig. 2. Using the LCA framework, the boundaries of the system are defined by identifying the functional unit, the processes and technology alternatives, material and energy streams to be included in the analysis, and the environmental footprints to be considered (Step 1). The relative importance of the environmental footprints is then derived using AHP (Step 2). The preference weights are needed to aggregate the footprints into a single environmental score. LCO is then implemented to identify the optimal process design for the system based on the objective function (Step 4), by taking into consideration of the environmental footprint limits or the worst environmental performance in each environmental footprint (Step 3). The integrated AHP-LCO model is formulated as a MOLP, which is used to determine the optimal solution. The weighted sum form of the composite objective function ensures that the solution is Pareto optimal (Clark and Westerberg 1983).

The process data can be used to generate the technology matrix  $\mathbf{A}$ , which is an  $n \times m$  matrix to represent  $n$  material or energy flows and  $m$  technology matrix processes. It consists of process inputs and outputs of material and

**Fig. 3** Example of column vector representation of a process



energy. The convention used denotes output streams with positive values and input streams with negative values (Heijungs and Suh 2002). The intervention matrix  $\mathbf{B}$  is a  $k \times m$  matrix representing  $k$  environmental flows associated with the  $m$  processes. The flows represent the interaction of the processes with the environment (i.e., primary energy and water resource consumption and CO<sub>2</sub> emissions). The  $m$  technology matrix is arranged from its left to the right, starting of resources by the facility to the main process of the system. The balance equations are as follows:

$$\mathbf{Ax} = \mathbf{y} \tag{1}$$

$$\mathbf{Bx} = \mathbf{g} \tag{2}$$

where the net output vector  $\mathbf{y}$  indicates the amount of material or energy flow that is needed or that exits the system as product; in the context of LCA, this is typically the functional unit. Meanwhile,  $\mathbf{x}$  is the gross output or scaling vector. Equation (1) indicates the overall material and energy balance of the system. The processes can be scaled up or down by the scaling vector,  $\mathbf{x}$ , to meet the desired net output vector. When  $\mathbf{A}$  has more columns than rows, Eq. (1) has excess degrees of freedom, which allows for optimization via selection from alternative technologies or processes. Meanwhile, Eq. (2) exhibits the interaction of the processes with the environment, where  $\mathbf{B}$  is the intervention matrix and  $\mathbf{g}$  is the environmental footprint matrix. Within this framework, a single process can be represented as vectors  $\mathbf{A}(j)$  and  $\mathbf{B}(j)$ . Figure 3 shows an example for the microalgae cultivation process using open pond. Note that zeroes indicate nonexistent streams in the respective process. Vector  $\mathbf{B}(7)$  contains only four rows to represent the four process environment flows, i.e., (1) energy, (2) carbon, (3) direct water footprint and (4) indirect water footprint. In this case, the zero values in vector  $\mathbf{B}(7)$  indicate that there are no energy and carbon flows associated with the process and that an input of 80 tons of direct water is needed. Negative and positive values in each process column vector denote inputs and outputs, respectively; further details of this convention are described by Heijungs and Suh (2002).

The second step involves weighting of priorities for the environmental footprint. Multiple objective optimization models can be integrated with AHP to determine priorities (Olson 1988). Some hybrid approaches are described in a

**Table 2** AHP fundamental nine-point scale (Saaty 1990)

Value of $z_{jk}$	Definition
1	$j$ and $k$ are equally important
3	$j$ is slightly more important than $k$
5	$j$ is more important than $k$
7	$j$ is strongly more important than $k$
9	$j$ is absolutely more important than $k$

review by Ho (2008). In such approaches, criterion weights of the environment footprint,  $\bar{w}_{fp}$ , are measured using the AHP technique. AHP is the versatile multi-criterion decision-making methodology which decomposes the problem structure into a hierarchical model and derives priorities from pairwise comparisons. These priorities are ratio scales derived from value judgments in a pairwise comparison matrix,  $\mathbf{z}$ , as described in Eq. (3) (Saaty 1990).

$$\mathbf{z} = \begin{bmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \dots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \dots & \frac{w_2}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_i}{w_1} & \frac{w_i}{w_2} & \dots & \frac{w_i}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \dots & \frac{w_n}{w_n} \end{bmatrix} \tag{3}$$

where  $w_i$  is the weight of each criterion  $i$  ( $i = 1, 2, \dots, n$ ). A ratio scale is given based on the intensity of importance of one criterion over another. The subscript  $i$  refers to the row. Table 2 indicates the fundamental nine-point scale used when carrying out the pairwise comparison. Based on the hierarchical model shown in Fig. 2, a set of questions is prepared to elicit value judgment of an expert to generate the pairwise comparison matrix. Then, the weight vector  $\bar{w}_{fp}$  can be computed via eigenvector method (Saaty 2003). The third step is to normalize the environmental footprints from the different technology options relative to the performance of the worst alternative matrix,  $\mathbf{P}$ . This step ensures that all the values are properly scaled and lie in the interval [0, 1].

The fourth step is performing the LCO by integrating the priority weights with the optimization model, via the



objective function,  $\mathbf{f}(\mathbf{x})$ . Equation (4) represents the overall result upon performing steps outlined above.

$$\text{minimize } \mathbf{f}(\mathbf{x}) = \bar{\mathbf{w}}_{\text{fp}}(\mathbf{P})^{-1}\mathbf{g} \quad (4)$$

In order to satisfy this optimization model, the limitations of the linearity assumption are the following: (1) the input and output data are constant, (2) the relationship between objective function and constraints is linear, and (3) the value of variables must be nonnegative. Note that the resulting model is a linear program, for which a global optimum can be readily determined without significant computational issues. In this work, the model template is built using Microsoft Excel spreadsheet file and solved using the standard Solver add-in in an Intel® iCore™ i5-3317U CPU 1.7 Ghz, with 4 GB memory. For the case study described in the next section, the computational time was negligible.

## Case study: integrated AHP-LCO

### Goal and scope

Life cycle assessment is typically conducted either to compare technology alternatives and identify the best option or to identify hot spots within the product's life cycle. In this work, the goal is to determine the optimal technology alternative that minimizes the overall environmental impact. A functional unit of one ton of dry microalgae biomass produced is used as the basis for the calculations. The integrated AHP-LCO framework is used to select which is the best among the four microalgae cultivation systems. The life cycle system includes inputs of material and energy from microalgae cultivation to microalgae dry biomass production. The environmental footprints being considered are energy, water and carbon footprint. Energy footprint takes into account energy inputs, such as process energy and electricity, which are obtained from nonrenewable resources (Schindler 2015). Carbon footprint calculates the amount of net greenhouse gases released from a system directly or indirectly. In this work, total CO<sub>2</sub> emissions are used as an approximation of the total carbon footprint; it does not include other greenhouse gases. Although the energy footprint is correlated with the carbon footprint, the correlation is imperfect and dependent on the carbon intensity of the energy mix of a given location. For example, if electricity comes from renewable sources, then the correlation is much weaker. Water footprint, which is an indicator of water usage, measures the water used directly and indirectly at different stages of the supply chain (Hoekstra and Chapagain 2007).

### Functional unit

Functional unit is defined as the physical quantity of output that is used as a basis to normalize all other computations throughout the LCA. It also enables different systems to be treated as functionally equivalent (Guinée 2002). To compare microalgae cultivation alternatives in this study, all the data are normalized to a functional unit of one ton of dry biomass. It is the net output vector  $\mathbf{y}$  indicated in Eq. (1). One ton of dry microalgae biomass is used as the functional unit in this work.

### Data sources/assumptions

This step involves setting the system boundaries, designing the flow diagram with unit processes and collecting the data for each of these processes in order to complete the final LCA calculations. The process data are often organized around the unit processes, providing information on the material and energy input and output flows, as well as environmental inputs and outputs. The process data are typically quantified in relation to a reference flow (e.g., one ton of material or 1 kWh of electricity). Data sources used here include previously published data from the literature and from EIO/LCA.net (Carnegie Mellon University Green Design Institute 2013). The technology matrix ( $\mathbf{A}$ ) and the environment intervention matrix ( $\mathbf{B}$ ) are obtained. The inventory of the data is divided into two stages. Stage one is data collection for the technology matrix ( $\mathbf{A}$ ) and the environment intervention matrix ( $\mathbf{B}$ ) of the resources inputs (i.e., urea, salt, diammonium phosphate (DAP) and electricity) into the main systems. These upstream systems can

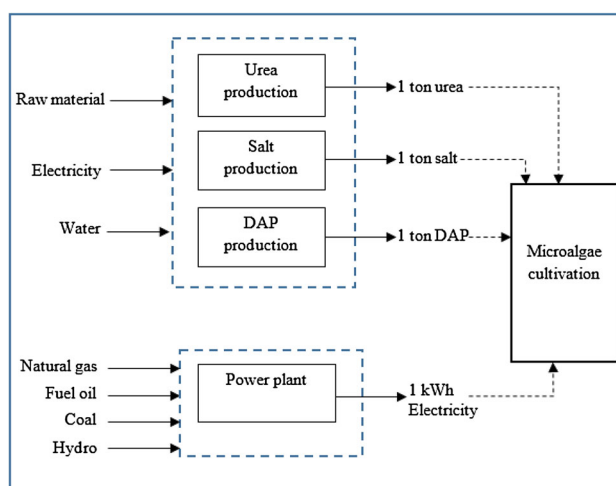


Fig. 4 Partial LCA of key upstream inputs

then be represented as a single consolidated process within the LCO model. The system boundary is illustrated in Fig. 4. The second stage is to consider the input and output data of the main systems (each single process involves in the operation). The assumptions and limitations of the processes are:

1. CO<sub>2</sub> was sequestered from the atmosphere via photosynthesis during microalgae cultivation. This CO<sub>2</sub> is eventually released to the atmosphere when the final product is used. Hence, the contribution of biomass carbon to system carbon footprint is virtually zero (Handler et al. 2014). The carbon footprint results mainly from the use of fossil fuel within the life cycle system.
2. The amount of nutrients added is determined based on the nitrogen and phosphorous contents of the algae cell (around 5.5% N of the algae dry weight and around 1.1% P of the algae dry weight) (Borowitzka 1992).
3. Significant mixing is required during microalgae cultivation. Aeration is used to accomplish appropriate mixing (Zhang et al. 2013).
4. The amount of water lost due to evaporation depends on the climatic conditions. It is estimated to be 0.88 m<sup>3</sup> for each m<sup>2</sup> of cultivation open pond area per year (Murphy and Allen 2011).
5. Microalgae biomass concentration of 0.5 kg/m<sup>3</sup> is assumed at the harvesting stage (Borowitzka 1999).
6. The water obtained from the dewatering step is sent back to the microalgae cultivation pond for reuse. Thus, the water discharged to the environment during the dewatering process is negligible.
7. Steam drying system is used for drying wet biomass. This step consumes 134 kWh to produce one ton of dry microalgae biomass (Zhang et al. 2013).
8. During the dewatering process by centrifugation, dry biomass with solid content of 15% w/w is obtained (Zhang et al. 2013).

The use of AHP-LCO model is illustrated by a simplified case study involving microalgae cultivation system. The case study is intended solely as an illustrative example for the purposes of explaining the general methodology proposed in “Methodology” section. Hence, the life cycle system is a small one, with just four different cultivation systems, six material or energy flows and four environmental flows. There are four cultivation systems considered: (1) open pond, (2) PBR, (3) cultivation by starch and (4) cultivation by cellulose. The alternative systems are generated based on the literature review. The material and energy inputs per ton of dry biomass produced by different cultivation options are presented in Table 3. These data are normalized to the production of one ton of dry biomass in

order to fit into the matrix calculation. Note that the material and energy requirements in harvesting process (as shown in Table 3) are similar for all the four alternatives. Meanwhile, the data sources for the background processes such as electricity generation and chemicals production are presented in Table 4. The chemicals production data are obtained through the EIO-LCA.net (Carnegie Mellon University Green Design Institute 2013). Table 5 shows the technology and intervention matrices (**A** and **B**) of these background processes.

Figure 5 shows the process block diagram for the microalgae cultivation open pond. Mixing with paddle wheel is performed during the entire cultivation period, which required electricity. Additional nutrients, particularly urea, salt and DAP, are added into the pond for the growing of microalgae. When the algae concentration of the open pond reaches 0.5 kg/m<sup>3</sup>, the algae solution will pass through the harvesting screen and the process of centrifugation to get a cake with solid content of 15% w/w. The water obtained from the dewatering (centrifuge) step is sent back to the algae cultivation pond to be reused. In alternative 2, microalgae cultivation is performed in PBR system. The process of biomass production from microalgae obtained from PBR is schematically shown in Fig. 6. Apart from the cultivation step, other steps of biomass production, i.e., microalgae harvesting and dewatering, are similar to that of open pond system; therefore, only the cultivation in the photobioreactor is discussed in detail in this section. In a PBR cultivation system, sunlight is important as energy source for the photosynthesis process.

In alternative 3, microalgae cultivation is carried out in a fermenter system with starch as carbon source as illustrated in Fig. 7. Carbon source has to be provided in the cultivation medium. In this case, starch, which is considered as a cheaper carbon source, is the main carbon source during the cultivation process. When starch is used as carbon source, the dissolved starch and nutrients are well mixed before being fed into the cultivation fermenter. Meanwhile, other steps of biomass production are similar to the open pond system. Finally, in alternative 4, cellulose is employed as the carbon source. Hydrolysis of cellulose will be performed prior to feeding in the fermenter, and then, the hydrolyzed cellulose and dissolved nutrients will be fed to the fermenter. The schematic process is shown in Fig. 8.

The system considers four environment flows, energy, CO<sub>2</sub>, indirect water and direct water. Based on the input data to the systems, the matrices in model (Eqs. 1, 2) are determined. Matrices **A** (Eq. 5) and **B** (Eq. 6) contain coefficients derived from Tables 3 and 5.

$$\mathbf{A} = \begin{pmatrix} 1 & -3055.6 & -6388.9 & -8333.3 & -5000 & -1388.9 & -101.4 & -555.7 & -301 & -301 & -134 \\ 0 & 1 & 0 & 0 & 0 & 0 & -0.1 & -0.1 & -0.1 & -0.1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & -0.1 & -0.1 & -0.1 & -0.1 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & -0.05 & -0.05 & -0.05 & -0.05 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 6.67 & 6.67 & 6.67 & 6.67 & -6.67 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix} \quad (5)$$

$$\mathbf{B} = \begin{pmatrix} -2.2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.0007 & 0.6 & 0.004 & 0.005 & 1 & 0.3 & 0 & 0 & 0 & 0 & 0 \\ -1.5 & -41.3 & -62.8 & -81.5 & -646 & -23 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & -80 & -3.4 & -0.6 & -0.6 & 0 \end{pmatrix} \quad (6)$$

**Table 3** Technology and intervention matrices for one ton of dry biomass production (Zhang et al. 2013)

	Cultivation (open pond)	Cultivation (PBR)	Cultivation (starch)	Cultivation (cellulose)	Harvesting
Process input (technology matrix <b>A</b> )					
Electricity (kWh)	-101.35	-555.72	-301.26	-301.26	-134.0
Salt (ton)	-0.13	-0.13	-0.13	-0.13	0
Urea (ton)	-0.097	-0.096	-0.095	-0.095	0
DAP (ton)	-0.048	-0.047	-0.048	-0.048	0
Starch (ton)	0	0	-1.024	0	0
Cellulose (ton)	0	0	0	-1.076	0
Wet microalgae	6.67	6.67	6.67	6.67	-6.67
Dry biomass	0	0	0	0	1
Environmental footprint (intervention matrix <b>B</b> )					
Energy (kWh)	0.0	0.0	0.0	0.0	0.0
CO <sub>2</sub> (ton)	0.0	0.0	0.0	0.0	0.0
Indirect water (ton)	0.0	0.0	0.0	0.0	0.0
Direct water (ton)	-79.98	-3.36	-0.57	-0.57	0.0

The eight rows of **A** correspond to flows of electricity (in kWh), salt (in ton), urea (in ton), DAP (in ton), starch (in ton), cellulose (in ton), wet microalgae (in ton) and the dry biomass of microalgae (in ton). The columns one to six are corresponded to the background processes input and output as shown in Table 5. Meanwhile, the columns seven to ten represent the data for the four cultivation technologies: (1) open pond, (2) PBR, (3) cultivation by starch and (4) cultivation by cellulose. The four rows in **B** correspond to the flows for energy (in kWh), CO<sub>2</sub>, indirect water and direct water (in ton). The net output or functional unit

vector, **y**, specifies a net output of 1 ton of dry biomass in the eighth row (Eq. 7):

$$\mathbf{y} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{pmatrix} \quad (7)$$

By utilizing matrices **A** and **B**, and Eqs. (1) and (2), it is possible to solve for the environmental footprint, **g**, of each

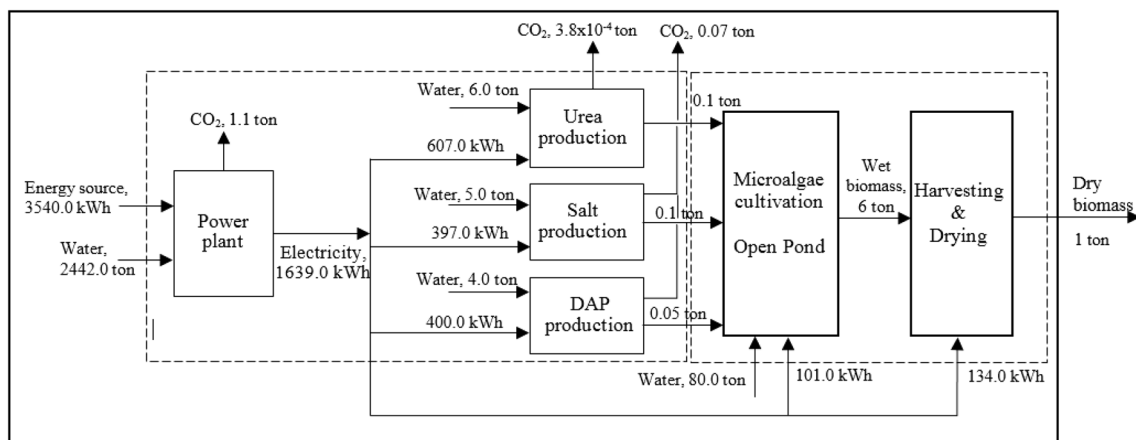


**Table 4** Data source for the environmental footprint for background processes

Environmental footprint	Source
Generates 1 kWh electricity	
Energy consumption	Tan et al. (2010), Mahlia (2003) and Shekarchiana et al. (2011)
Indirect water consumption	Fthenakis and Kim (2009)
CO <sub>2</sub> emission	Mahlia (2003) and Shekarchiana et al. (2011)
Produces 1 ton of chemical (salt, urea, DAP, starch and cellulose)	
Energy consumption	Carnegie Mellon University Green Design Institute (2013)
Indirect water consumption	
CO <sub>2</sub> emission	

**Table 5** Technology and intervention matrices for electricity and chemicals production

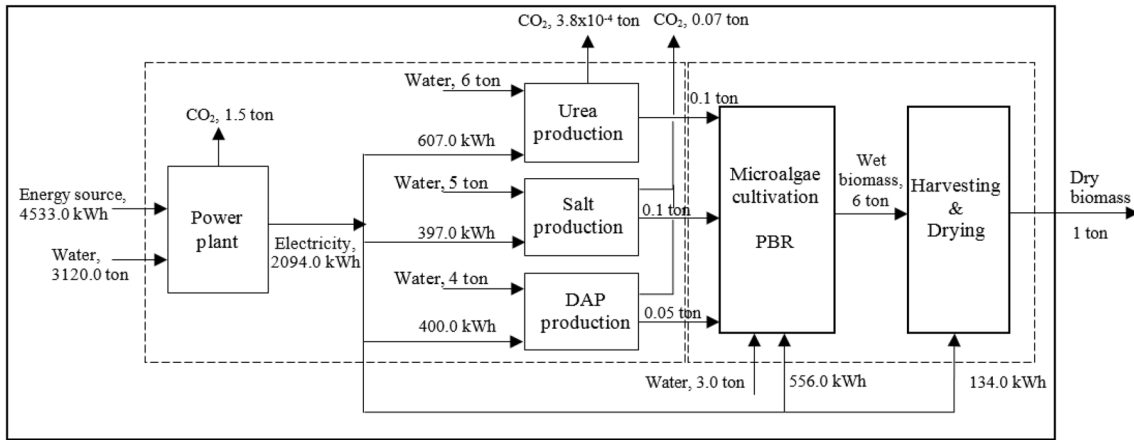
	Electricity	Salt	Urea	DAP	Starch	Cellulose
Process input (technology matrix <b>A</b> )						
Electricity (kWh)	1.0	-3055.6	-6388.9	-8333.3	-5000.0	-1388.9
Salt (ton)	0.0	1.0	0.0	0.0	0.0	0.0
Urea (ton)	0.0	0.0	1.0	0.0	0.0	0.0
DAP (ton)	0.0	0.0	0.0	1.0	0.0	0.0
Starch (ton)	0.0	0.0	0.0	0.0	1.0	0.0
Cellulose (ton)	0.0	0.0	0.0	0.0	0.0	1.0
Environmental footprint (intervention matrix <b>B</b> )						
Energy (kWh)	-2.16	0.0	0.0	0.0	0.0	0.0
CO <sub>2</sub> (ton)	0.0007	0.56	0.004	0.005	1.14	0.31
Indirect water (ton)	-1.49	-41.3	-62.8	-81.5	-646.1	-23.3
Direct water (ton)	0.0	0.0	0.0	0.0	0.0	0.0



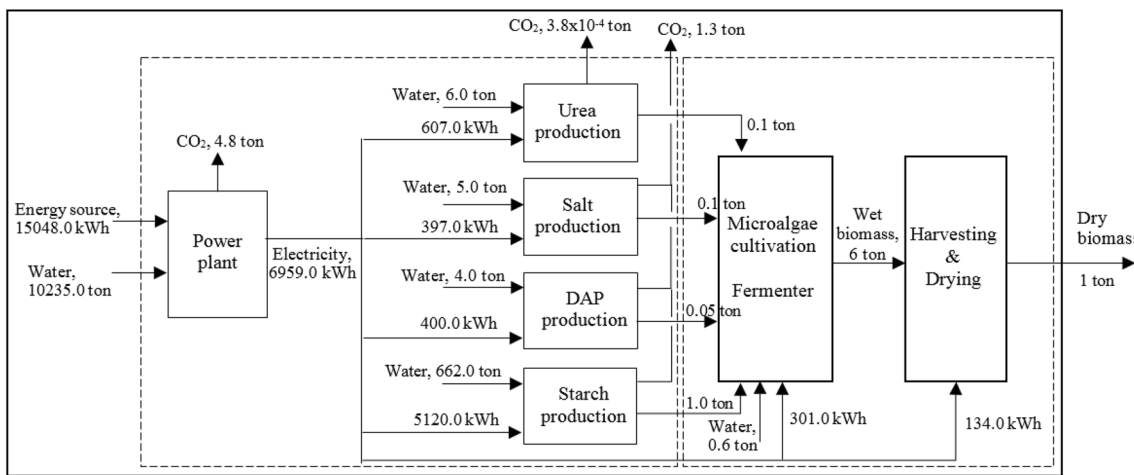
**Fig. 5** Material and energy system boundary for alternative 1, microalgae cultivation in open pond followed by dry biomass production

cultivation technology alternative by setting the scaling factor ( $x_j$ ) of unselected technologies to zero. This then limits the model to scaling only the selected cultivation technology and generating the corresponding environmental footprint. To determine the preference AHP weights of the environmental footprint criteria, pairwise comparison was done using the nine-point scale (as defined in Table 2). The criteria are evaluated in a pairwise manner to determine their relative significance based on expert

judgment. The matrix of pairwise comparisons ( $z$ ) of the environmental footprint for the microalgae cultivation is shown in Table 6 as expressed in Eq. (3). The expert considered is someone who is experienced in the field of microalgae biofuel production. Then,  $\bar{w}_{fp}$  is calculated via eigenvector method from  $z$ . Equation (8) shows the vector of  $\bar{w}_{fp}$  for the environmental footprint (energy, CO<sub>2</sub>, indirect water and direct water):



**Fig. 6** Material and energy system boundary for alternative 2, microalgae cultivation in photobioreactor (PBR) followed by dry biomass production



**Fig. 7** Material and energy system boundary for alternative 3, microalgae cultivation in fermenter (carbon source—starch) followed by dry biomass production

**Table 6** Pairwise comparison matrix of environmental footprints, *z*

Environment footprint	Energy	CO <sub>2</sub>	Indirect water	Direct water
Energy	1.00	0.14	0.14	0.14
CO <sub>2</sub>	7.00	1.00	0.14	0.14
Indirect water	7.00	7.00	1.00	1.00
Direct water	7.00	7.00	1.00	1.00

**Table 7** Summary of environmental output for each process option

Environmental footprint	Open pond	PBR	Cultivation (starch)	Cultivation (cellulose)
Energy (kWh)	-3585.31	-4533.64	-15,048.74	-7220.17
CO <sub>2</sub> (ton)	1.25	1.57	6.19	2.78
Indirect water (ton)	-2492.24	-3147.21	-11,072.67	-5028.20
Direct water (ton)	-79.98	-3.36	-0.57	-0.57

$$\bar{w}_{ip} = ( 0.04 \quad 0.1 \quad 0.43 \quad 0.43 ) \quad (8)$$

The environmental footprints of the different technologies are compared to determine the worst environmental

performance in each environmental footprint considered as shown in Table 7. Negatively signed entries indicate consumption, while those that are positively signed indicate

**Table 8** Integrated AHP-LCO optimum solution

Environmental footprint	Weight, $\bar{w}_{fp}$	Normalized value, $g(P)^{-1}$	Optimized value
Energy (kWh)	0.04	0.30	-4533.64
CO <sub>2</sub> (ton)	0.10	0.25	1.57
Indirect water (ton)	0.43	0.28	-3147.21
Direct water (ton)	0.43	0.04	-3.36

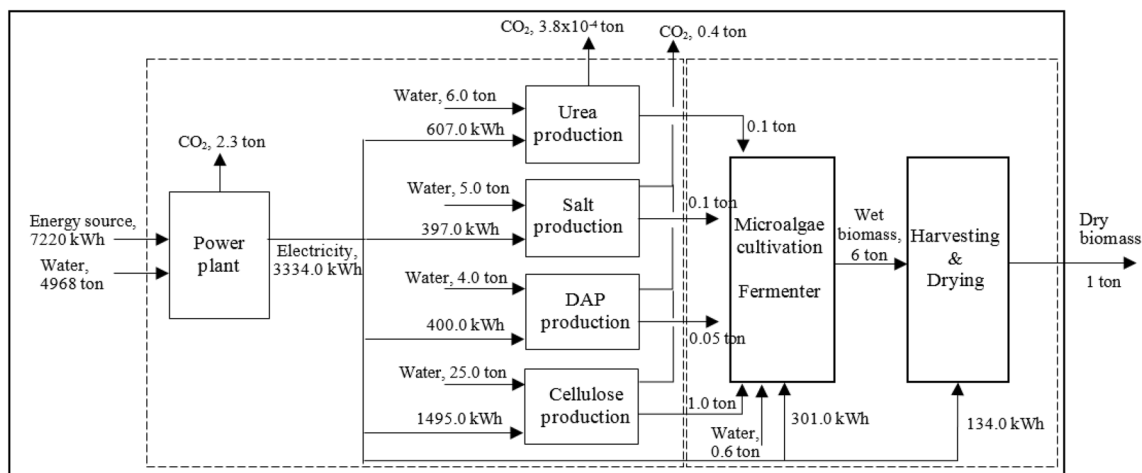
release to the environment. The italic data show the worst performance in each environmental footprint category which are then used in the optimization function as  $(P)^{-1}$  in the optimization function to normalize the output data. Alternatively, environmental footprint limits, based on the performance of current technologies, may be identified and used as the normalizing factors. The optimization function is to minimize the overall environmental output, where AHP weights ( $\bar{w}_{fp}$ ) in relation with the worst alternative output  $(P)^{-1}$  and environment footprint ( $g$ ) of the cultivation system. It is expressed in Eq. (9):

$$\text{minimize } f(x) = (0.040.10.430.43) \begin{pmatrix} 15058 & & & \\ 0 & 6.2 & & \\ 0 & 0 & 11072 & \\ 0 & 0 & 0 & 80 \end{pmatrix}^{-1} \begin{pmatrix} g_1 \\ g_2 \\ g_3 \\ g_4 \end{pmatrix} \tag{9}$$

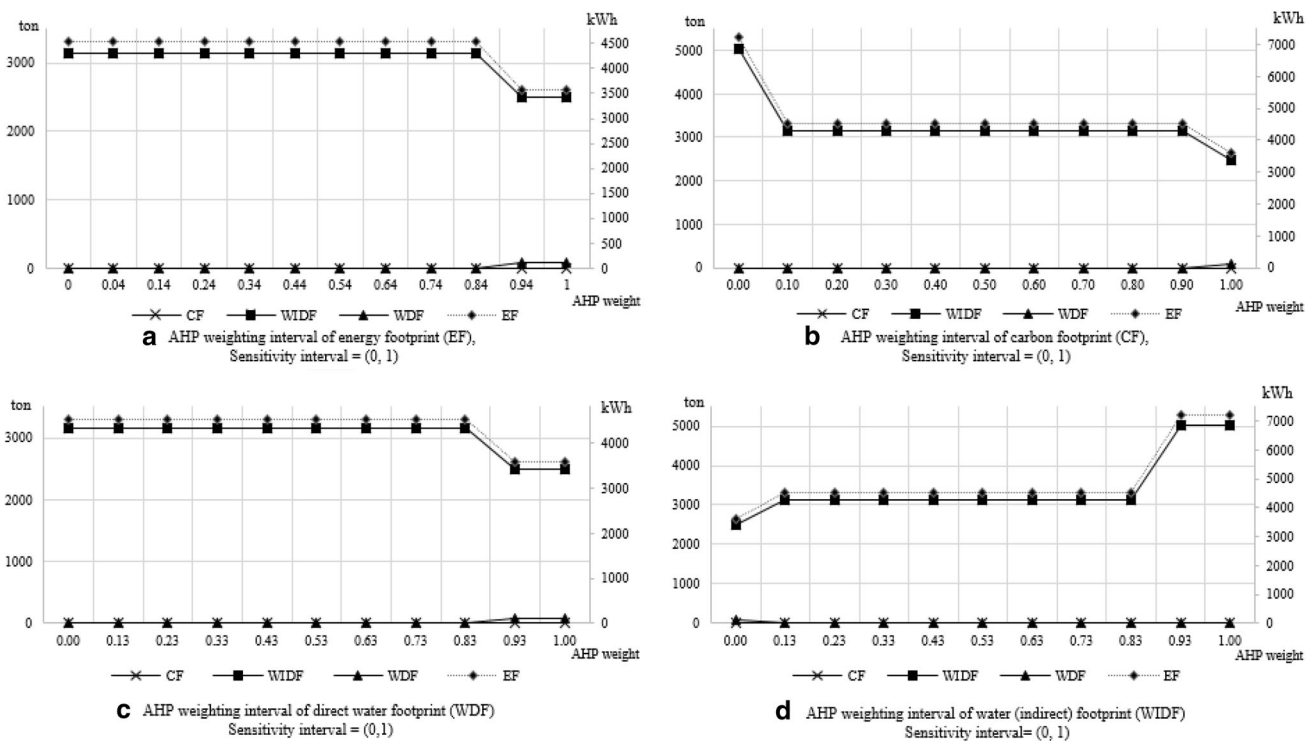
Cultivation of microalgae with starch fermentation system performs the worst in three environmental footprints mainly due to the involvement of starch which requires large amounts of water. In addition, the consumption of high electricity also adds into the water footprint as electricity generation consumes water. However, cultivation of microalgae with open pond system shows the highest amount of direct water usage due to the nature of the cultivation method.

From these results, open pond cultivation system seems to be chosen as the best technology option as it shows the overall lesser impact to the environment (energy footprint, carbon footprint and indirect water footprint) as compared to the others. This is justified as 98% of the commercial microalgae are using open pond system due to its cost-efficiency and effectiveness, simplicity and ease in maintenance with scale-up feasibility (Bharathiraja et al. 2015). However, open pond cultivation systems may require more fertilizer due to its poor productivity rate and because it is difficult to culture microalgae for longer periods of time (Ugwu et al. 2008).

The results are further optimized by integrating the AHP weights to determine the environmental concern preference



**Fig. 8** Material and energy system boundary involved for alternative 4, microalgae cultivation in fermenter (carbon source—cellulose) followed by dry biomass production



**Fig. 9** Sensitivity analysis for the AHP weights of environmental footprint for cultivation system at each different footprint's weight interval (0, 1): **a** energy footprint, **b** carbon footprint, **c** water (direct) footprint, **d** water (indirect) footprint

and the best process configuration as shown in Table 8. The integrated AHP-LCO model has shown that the PBR system is the best technology option based on these weights. This is due to the associated weights for water footprint (both indirect and direct water at 43%, respectively) which are relatively more important when compared with the other environmental footprints. Energy use (4%) and carbon footprint (10%) for PBR seem to be moderate compared to the other three options. Sensitivity analysis was conducted to examine how variations in criteria weights influence the selection of options. Figure 9 summarizes the results from the sensitivity analysis by changing the respective footprint weights. This is done by parametrically adjusting the weight of one footprint, while keeping constant the relative proportions of all the other criteria. For instance, Fig. 9a shows how the environmental output changes when the energy footprint's preference weight varies from 0 to 1. The environmental output can be compared with Table 7 for each process option's output. It can be seen that when the energy footprint is not taken into consideration as one of the criteria of environmental concern, PBR is still the dominant option. In contrast, if energy footprint is considered as the sole criterion for environmental consideration, open pond system is the most preferred option. Note that PBR was still ranked first regardless of the changes in weights for each environmental impact criterion. No significant changes in the

selection option were observed as the weights of the environmental footprint change between intervals of 0.1–0.8. The ranking of the cultivation selection options is reversed mainly at the sole criterion environmental impact. Microalgae cultivation with cellulose as carbon source is selected as the best option when the direct water footprint (DWF) is the sole environmental impact-considered criteria during the selection process (Fig. 9b, d).

## Conclusion

In this paper, an integrated LCO methodology has been developed and applied in the selection of the best technology option and process configuration for the cultivation system of microalgae. In this approach, AHP is used to identify the environmental criteria weights, which are then utilized within a hybrid MOLP model to integrate the energy, carbon dioxide and water footprint limits. The priority weights are systematically elicited from an expert's opinion via AHP. The proposed modeling framework is then applied to a case study with multiple microalgae cultivation pathways. By solving the model, it is found that the PBR cultivation system is the optimum solution. Sensitivity analysis is performed to give insights into the robustness of the decision model particularly with respect to criteria weights. Future work can focus on extensions of

the model incorporating different harvesting, dewatering and downstream processing alternatives.

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