Environmental impact prediction of microalgae to biofuels chains using artificial intelligence: A life cycle perspective

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Abstract. Biofuels derived from microalgae is an emerging technology that can supply fuel demand and alleviate greenhouse gas emissions. However, exclusively producing biofuels from microalgae remains to be commercially unsustainable because of its high investment and operating costs. A promising opportunity to address this are algal bio-refineries. Nonetheless, there is still a need to verify the environmental sustainability of this system along its entire process chain, from raw material acquisition to end-of-life. This study utilizes a life-cycle perspective approach to assess the sustainability of the algal bio-refinery and developed environmental impact prediction model using artificial intelligence, particularly adaptive neuro fuzzy inference system. Results will indicate the environmental impacts of a bio-refinery system identifying its major hotspots on different environmental impact categories. Results show that in the investigated proposed algal bio-refinery, the transesterification process had a huge contribution on the overall environmental impact having over 51.5 % of the total weight. In addition, ANFIS results showed the correlation of input parameters with respect to the environmental impact of the system. The model also indicated that there is a perfect correlation between the two parameters. The model and its accuracy should be further validated with the use of real data.

Keywords: Microalgal bio-refinery chains, Adaptive Neuro Fuzzy Inference System (ANFIS), Environmental impact prediction, Life Cycle Assessment
1. Introduction
Microalgae is one of the best alternatives for biofuel production due to its high oil content and productivity in other compounds such as lipid and carbohydrate [1]. This microorganism offers several advantages such as less arable land use for cultivation, high productivity compared to other biomass sources, and can be a possible solution to the food versus fuel issue that is a threat to food security [2]. In addition, it can alleviate the impact of climate change and global warming by removing 1.83 kg of CO₂ per 1 kg of dry microalgae biomass [3]. Biofuel production from microalgae can cater global fuel demand for transportation since most microalgae species exhibits a great range of lipid content that varies from 20%-50% per microalgae cell [4]. Several processes have to be undergone by microalgae to be transformed into biofuel, namely cultivation, harvesting, pre-treatment, compound extraction, and biofuel production [5]. Algal biofuel production is a promising alternative energy source. However, there are still challenges that needs to be addressed, such as scale up for commercialization of the cultivation system, unstable productivity of algal bio compounds, the energy cost of the system, and its environmental implications [6].

Life Cycle Assessment (LCA) is a standardized methodology that is structured and internationally known to analyse the environmental profile of a system on a life cycle perspective [7]. There have been several studies that involved the investigation of the environmental sustainability of microalgae to biodiesel production through LCA [8], [9], [10].

Artificial intelligence (AI) is another useful tool to develop modelling techniques for various complex systems. It has been widely used in the field of computer science, business, agriculture, microorganisms, and energy systems. Adaptive Neuro-Fuzzy Inference Systems (ANFIS), is a combination of neural networks and fuzzy systems [11]. It has been applied to different applications such as crop yield production with respect to energy consumption in agricultural systems [12], and has been used to evaluate ecological conditions using categorized bio-indicators. Recently, a combination of AI and LCA has been utilized to investigate the economic and environmental assessment of canola production using ANFIS to predict energy and environmental impacts of the production system [13].

This study utilized the combination of AI and LCA as a tool to investigate the potential environmental impacts of microalgae to biodiesel chains. In addition, ANFIS was used in predicting the environmental impact under process unit uncertainties. Thus, ANFIS may be used to predict the environmental impact of similar systems in case of missing or inaccurate data regarding the process inputs.

2. Methodology
The LCA of microalgae to biofuels was in accordance with the ISO guidance within the series of 14040 and 14044 [14]. This work includes four LCA phases which is the goal and scope definition, inventory analysis, impact assessment, and LCA data interpretation.

2.1. Life Cycle Assessment
This study conducted a cradle-to-gate assessment in which analyses the system from the growth of raw material to the production gate. A cradle-to-gate life cycle analysis is used for the production of 1 kg biodiesel using the Ecoinvent database as compiled in SimaPro 9.0.0.35. The boundary of the system is shown in Figure 1. The mass and energy balances are based from a study of the life cycle analysis of the biodiesel production from algae [15]. The impact used is EDIP 2003 V1.06. Nineteen (19) impact categories are considered.

2.2. Adaptive Neuro Fuzzy Inference System
ANFIS is a type of learning methodology that combines FIS and ANN. It is a network that trains the fuzzy membership function parameters using a back-propagation algorithm or a least squares method. In this study, 7 environmental inputs, namely power used in cultivation, methanol in transesterification, heat in transesterification, solid residue input in biochar production, liquid residue input in anaerobic digestion (AD), methane input in combined heat and power (CHP), and power used in transesterification, were used as inputs in the 3 level ANFIS model to predict the environmental index, which is global warming.
3. Results and Discussion

3.1. Baseline Life Cycle Assessment

In quantifying the environmental hotspots of microalgae to biofuel production 19 environmental impact categories were considered namely global warming potential, ozone depletion, ozone formation (vegetation), ozone formation (human), acidification, terrestrial eutrophication, aquatic eutrophication, human toxicity air, human toxicity soil, ecotoxicity water chronic, ecotoxicity water acute, ecotoxicity soil chronic, hazardous waste, slags/ashes, radioactive waste, bulk waste, and all resources. In Figure 2, transesterification process contributes a huge percentage in all environmental factors, this is due to the chemicals and energy used in the process. Moreover, the cultivation process is second to the transesterification process on the single score impact making both processes a hotspot for the environment. From the single score values, the transesterification process has the highest environmental impact (19.40 mPts) having over 51.5% of the total weight. Dewatering and production of biochar having the least environmental burden of all processes with 0.267 mPts (0.71%) and 0.633 mPts (1.68%) respectively. The result suggests that other models and designs should be considered in the transesterification process which produces biodiesel and its co-products (glycerol and wet biomass) to lower the environmental impacts of the whole life cycle.
3.2. ANFIS Results

Shown in Figure 3 is the fuzzy inference system to predict the global warming 100a from the impact category such as power used in cultivation, methanol in transesterification, heat in transesterification, solid residue input in biochar production, liquid residue input in anaerobic digestion (AD), methane input in combined heat and power (CHP), and power used in transesterification.

The membership function used in the impact category is a generalized bell-shaped function defined by

\[ f(x, a, b, c) = \frac{1}{1 + \left(\frac{x-c}{a}\right)^{2b}} \]

where \(a\) is the width, \(b\) is the shape of the curve, and \(c\) is the center of the membership function.

To determine the membership function parameters, the neuro-fuzzy designer is used to train the ANFIS model structure shown in Figure 4. It has a single output that uses weighted average defuzzification. Table 1 shows the rules used to define the behavior of the global warming from the impact category. After the training, the parameters of the output membership functions were obtained and summarized in Table 2.

![Figure 3. ANFIS Model Structure for Predicting Global Warming](image1)

![Figure 4. ANFIS Model Structure in Neuro-Fuzzy Designer](image2)

Table 1. Rules of the ANFIS Model

| No. | Rule |
|-----|------|
| 1   | “power_used_in_cultivation==low|methanol_in_transesterification==low|heat_in_transesterification==low|solid_residue_input_in_biochar==low|liquid_residue_input_in_AD==low | methane_input_in_CHP==low |power_used_in_transesterification==low => Global_warming_100a=mfl (1)” |
| 2   | “power_used_in_cultivation==high | methanol_in_transesterification==high | heat_in_transesterification==high | solid_residue_input_in_biochar==high | liquid_residue_input_in_AD==high | methane_input_in_CHP==high | power_used_in_transesterification==high => Global_warming_100a=mfl2 (1)” |

Table 2. Membership Function Parameters

| Membership Function No. | Parameters |
|-------------------------|------------|
|                         | \(a_7\) | \(a_6\) | \(a_5\) | \(a_4\) | \(a_3\) | \(a_2\) | \(a_1\) | \(a_0\) |
| 1                       | 0.0289 | 0.5278 | 0.0175 | 2.6401 | 5.0644 | 24.5338 | 0.0358 | 2.1958 |
| 2                       | 0.0333 | -2.7552 | 0.0612 | 0.2669 | 1.3120 | 4.3678 | 0.0495 | 0.3909 |

Shown in Figure 5 is the fuzzy inference output surface for the following inputs: heat in transesterification vs power used in cultivation, solid residue vs methanol in transesterification, methane input in CHP vs liquid residue input in AD, and power used in transesterification vs methane input in CHP. Since it has been previously established that transesterification and cultivation are major environmental hotspots, the response surface for heat in transesterification vs power in cultivation show a positive relationship, wherein an increase in both or either variables would result in an increase of the...
System’s global warming potential. However, it is noticeable that between the two variables, heat in transesterification has a more significant impact as evidenced by its slope. On the other hand, it can be observed in the response surface for solid residue input in biochar vs methanol in transesterification that although transesterification is the primary source of environmental impact of the biorefinery chain, methanol does not contribute significantly and positively to this. In fact, an increase in its use slightly decreases global warming. Similarly, increasing the solid residue input in biochar increases global warming potential because of the carbon emissions of the process. Lastly, both methane in CHP vs liquid residue in AD and methane in CHP vs power in transesterification demonstrate increasing response surfaces indicating positive relationships between the said variables and global warming potential. It is important to note that AD and biochar production were added into the system for the purpose of promoting circular economy and reducing environmental impact. However, as their inclusions seem to encourage global warming, further analysis would be required to determine whether excluding them would be more environmentally sustainable.

Figure 5. Fuzzy Inference Output Surface

Figure 6 illustrates the scatterplot between the predicted and actual global warming. The linear behavior of the graph indicates the high accuracy of the ANFIS model in predicting the global warming potential of a system given different data sets for the inputs.

Figure 6. Scatterplot between Predicted and Actual Global Warming

4. Conclusion and Recommendations
The objective of this study was to evaluate the environmental impact of microalgae to biofuel as a biorefinery having co-products. This was possible with the aid of LCA and ANFIS. The LCA model
was able to determine the environmental hotspots in the system and pointed out that the transesterification process has a huge contribution in the overall results. Moreover, ANFIS was able to accurately model the relationship between the input parameters and the environmental impact, specifically the environmental impact. However, it is evident that the model showed perfect relationship of the two parameters. Hence, further analysis using real data from such system will enhance the overall model in predicting the global warming potential and other environmental impacts of algal bio-refinery systems.

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