CHEMICAL ENGINEERING TRANSACTIONS

VOL. 103, 2023

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.cetjournal.it

Guest Editors: Petar S. Varbanov, Panos Seferlis, Yee Van Fan, Athanasios Papadopoulos

ISBN 979-12-81206-02-1; **ISSN** 2283-9216

DOI: 10.3303/CET23103064

Environmental Impact Optimization of Microalgae Biorefinery Using Life Cycle Assessment and Evolutionary Computing

Andres Philip Mayol[a,*], Jayne Lois San Juan[b], Ronnie S. Concepcion II[a] , Aristotle T. Ubando[c] , Alvin B. Culaba[c]

[a]Department of Manufacturing Engineering and Management, De La Salle University, Manila, Philippines, 1004
[b]Department of Industrial and Systems Engineering, De La Salle University, Manila, Philippines, 1004
[c]Department of Mechanical Engineering, De La Salle University, Manila, Philippines, 1004
andres.mayol@dlsu.edu.ph

Technology has paved the way for economic growth and the reduction of poverty. To achieve this, an enormous amount of energy is required to sustain one's economic activity. However, due to industrialisation, global energy demand has been an issue for global sustainability. Biofuels from microalgae can be a potential alternative fuel for various applications to mitigate climate change. However, producing biofuels from microalgae is economically unfeasible due to its high capital and operation cost. Hence, a bio-refinery concept is a promising opportunity to valorise microalgae biomass to fill this gap. To investigate the environmental impact of microalgae bio-refinery with different scenarios, a Life Cycle Assessment (LCA) methodology will be utilised. Using computational intelligence (CI) algorithms such as genetic programming (GP) and genetic algorithm (GA) determined the relationships between the input parameters of the system and the environmental impact generated. LCA results showed that the transesterification process has the largest contribution, with 51.5 % of the total weight, followed by the cultivation process of the system. Lastly, environmental factors were minimised using GA, giving the best combination of input parameters.

1. Introduction

Technological innovation has paved the way for human evolution and increased economic growth. A significant contributor to this is energy consumption. In addition, the increase in global population also increased the energy global demand, and its anthropogenic activities cause harm to the environment (Pierro et al., 2023). Biofuels from biomass sources are one of the potential alternatives to mitigate climate change that can act as a carbon sink while providing energy (Caporusso et al., 2023). A candidate for this is microalgae, a third-generation biomass feedstock that thrives from sunlight through photosynthesis. Contrary to traditional biofuel feedstocks such as corn, canola, coconut, and soybean, it resolves the food versus fuel issue while achieving higher oil yield per hectare (Chisti, 2007). In addition, it is a feedstock that can be converted into different biofuels and other bioproducts, such as biogas, bioethanol, biohydrogen, and biodiesel, through a biorefinery (Kumar et al., 2022). However, producing biofuels from microalgae is still a challenge in terms of cost (Chisti, 2013). Hence, a microalgal biorefinery concept is introduced that can produce high-value products while minimising energy costs and greenhouse gas emissions (Chew et al., 2017). A biorefinery system involves two processing stages, upstream processing, which includes the cultivation process, and downstream processing, which includes the extraction and refining of the bioproducts extracted from microalgae. In addition, this concept plays a big role in resource utilisation of biomass resources to achieve a circular bio-economy (Khoshnevisan et al., 2020).
There have been works on biorefinery concepts such as resource circulation of an integrated algal biorefinery (Solis et al., 2021), co-production of protein and renewable fuel products (Karan et al., 2022), and optimisation of biorefinery pathways and biomass harvest scheduling (Lim et al., 2022).
Life cycle assessment (LCA) is a tool to investigate the potential environmental impact of a system. It can be used as a metric to assess circular economy requirements (Barkhausen et al., 2023). It has been used to investigate microalgae biorefineries in different scenarios, such as cultivation wastewater treatment (Josa and

Paper Received: 16 April 2023; Revised: 10 May 2023; Accepted: 28 May 2023
Please cite this article as: Mayol A.P., Juan J.L.S., Concepcion II R.S., Ubando A.T., Culaba A.B., 2023, Environmental Impact Optimization of Microalgae Biorefinery Using Life Cycle Assessment and Evolutionary Computing, Chemical Engineering Transactions, 103, 379-384 DOI:10.3303/CET23103064

Garfi, 2023). Another study by Bussa et al. (2021) conducted a sensitivity analysis on the target values of microalgae biorefineries using LCA. One important factor in designing biorefineries for sustainability is to minimise environmental impact. There are different mathematical models to enhance the design of biorefineries. However, with the rise of automation, such as the Internet of Things (IoT), biorefineries' production systems and processes will require the dynamicity of computational models due to the embedded systems installed. This will pose a problem due to the complex computational resource of mathematical models (Baba, 2021). Hence, there is a need to implement Computational intelligence models in designing biorefineries that involve IoT (Wang et al., 2022).

Computational Intelligence (CI) methods are bio-inspired algorithms that can enhance embedded systems' accuracy and precision (Jin et al., 2023). Examples are the Artificial Neural Network (ANN) which is inspired by the function of the human brain; Fuzzy Logic systems based on fuzzy sets used for decision-making applications; and evolutionary computing, which transpired from evolutionary theories of natural selection such as Genetic Algorithm (GA). Studies have utilised data-driven algorithms applied to LCA, such as ANN and Adaptive Neuro-Fuzzy Inference System (ANFIS) (Nabavi-Pelesaraei, 2018). Hence, multigene genetic programming (GP), a regression tree and a GA combination is a lightweight symbolic regression model that can generate a mathematical equation for sensitive prediction based on non-linear features (Concepcion et al., 2023). When the GP-generated equation is set as a fitness function for GA in determining the optimum (minimal environmental impact), the best set of values of endogenous parameters in the processes of biorefinery can be determined. The use of hybrid GP-GA in biorefinery is not yet existing as of this writing. Unlike other optimisation algorithms like ANN (Rivera et al., 2010) and the classical Life Cycle Optimization (Solis et al., 2021), which have been reported to be too sensitive and have the tendency to converge prematurely, the use of GP-GA will eliminate it through the built-in genetic hyperparameters with mathematical functions under GP.

The objectives of this study are to evaluate the environmental impact of microalgae biorefinery using LCA and combining it with CI methods such as a novel application-specific hybrid GP-GA model to investigate the relationship of the different process input parameters in the biorefinery system and predict environmental factors with respect to the process inputs and to optimise these factors for environmental impact minimisation. This study contributes to the following: (1) the development of a lightweight symbolic regression model intended for minimising the environmental factors in microalgae biorefinery system; (2) the identification of which among the input processes in microalgae biorefinery for biodiesel emits the environment significantly; and (3) initial development of a decision support tool (GP-GA model) to biorefinery plant managers to immediately determine the environmental impact in their system.

2. Methods

The general framework of the environmental impact optimisation combining LCA and GP-GA methods is shown in Figure 1. The data generated from the LCA are the environmental impact process parameters. Data-driven computational intelligence models such as genetic programming are used to identify the relationship between the input and output parameters of the processes and environmental impact; lastly, it is used to identify the best combination and optimise the environmental impact.

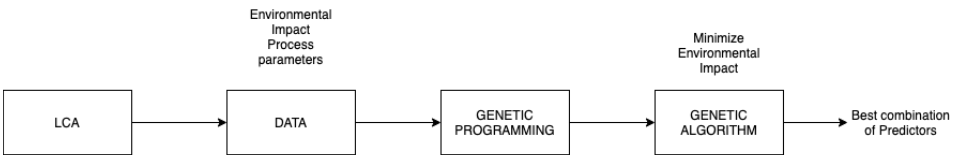

Figure 1: Environmental Impact optimisation process flow

2.1 Life cycle assessment

A Life Cycle Assessment was conducted using SimaPro software to evaluate the environmental impact of a microalgae biorefinery. The scope that was considered in this study is the different products produced by the refinery, such as biodiesel, biochar, regenerated heat, and power. In this study, a cradle-to-gate analysis was done, and 1.0 kg of biodiesel as the functional unit of the study. The life cycle inventory of the system boundary material and energy flow are derived from the study of Wu et al. (2018) and was encoded using similar transformation units and processes in the Ecoinvent database in the SimaPro software. The system boundary is shown in Figure 2. The main products of this biorefinery are biodiesel, glycerol, and biochar. The environmental impact assessment method used in this study is the EDIP 2003 impact assessment method.

2.2 Computational Intelligence Algorithms

The relationship of environmental impacts to the input parameters based on the system boundary of the microalgae biorefinery system (Figure 2) was determined using genetic programming to generate symbolic equations. MATLAB software was used to apply the orthogonal least squares algorithm (GP-OLS) (Madár et al., 2005). This method generates equations to predict the behaviour of modelled physical systems, including the non-linear relationships in the provided data. The following input parameters used in the study are power used in cultivation, methanol in transesterification, heat in transesterification, solid residue in biochar, liquid residue input in Anaerobic Digestion, methane input in CHP, and power used in transesterification. The data needed as input for the CI algorithm are the different input data combinations of the described process. This was generated using Monte Carlo simulation and has different environmental impact values per combination.

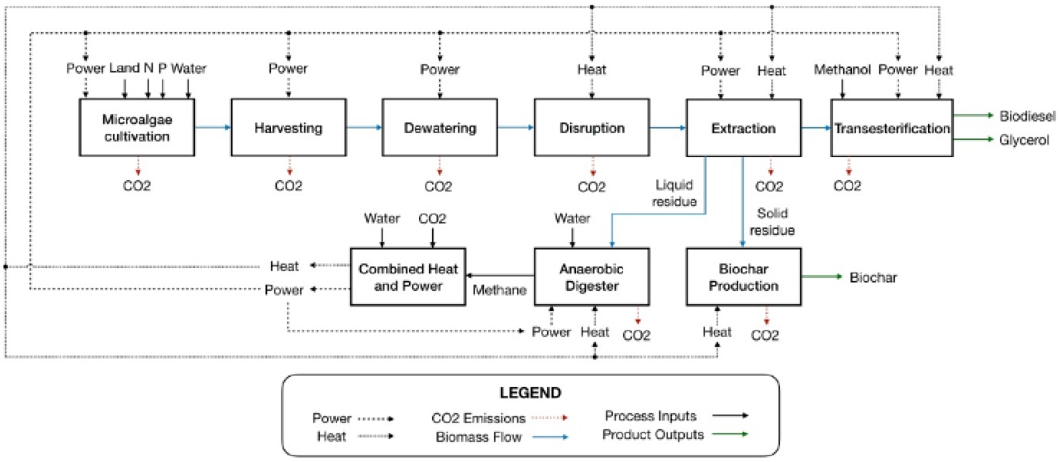

Figure 2: Microalgae biorefinery system boundary

Table 1: Genetic Algorithm hyperparameter values

Operators	Values
Population Size	100
Number of Generations	100
Selection rate	0.15
Crossover rate	0.5
Mutation rate	0.5

The generated symbolic or transcendental equations are the output of the GP as the fitness function to get the fittest chromosome. GA is a bio-inspired optimisation algorithm that can solve complex problems. This algorithm is inspired by the process of natural selection and evolution. Hence, in a large solution space, this method can search for the best solution or the optimal set of parameters based on the criteria of the fitness value (Espanola et al., 2019). This method creates the best parametric combination of inputs in the biorefinery that achieves the lowest environmental impact. The solution that has the highest fitness value is the best possible solution generated. Table 1 shows the GA operator values, which are population size, number of generations, selection rate, crossover rate, and mutation rate.

3. Results

3.1 Life cycle assessment

Different environmental impact categories are generated using the EDIP impact assessment method to characterise the impact of the biorefinery. Figure 3 and 4 shows that the transesterification process has the largest contribution of 51.5 % of the total weight. This is mainly to the chemicals and energy used in the process. This is followed by the cultivation process, which ranked second.

3.2 Minimization of environmental impact

Genetic Programming generated symbolic equations determining the relationship of the environmental impacts (Table 3). In each environmental impact, there are different numbers of genes generated. In addition, these equations capture the changes in the impact results based on the input parameters. These are ranked based on the highest R^2 to the lowest R^2 to determine which environmental impact has high relationships with the input parameters. Ozone formation had the highest value of R^2, while aquatic eutrophication had the lowest R^2. In terms of the prediction accuracy of the model, the generated equations were ranked using their RMSE results.

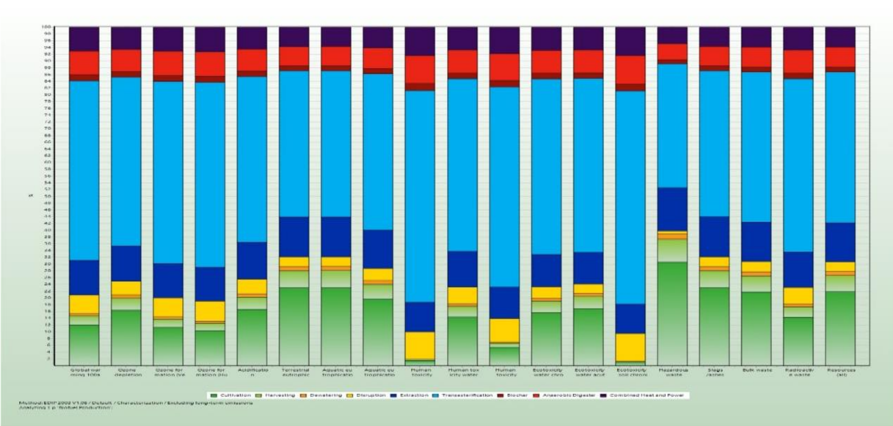

Figure 3: Environmental impact of microalgae on biofuel production

Results show that hazardous waste, terrestrial eutrophication, ozone depletion, human toxicity (water), aquatic eutrophication (P), and radioactive waste had the lowest RMSE, meaning these models are accurate in prediction.

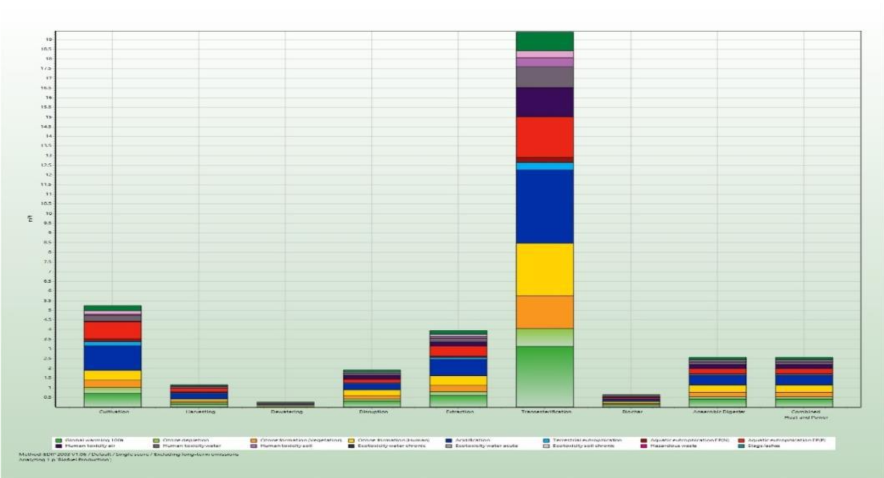

Figure 4: Single-weighted environmental impact of each process in the system

For this study, an example of global warming potential generated equations using GP and is used as input to the GA model. Equation 1 shows the generated equation of global warming potential generated by GP.

$$y = 0.0296x_1 + 0.0242x_3 + 2.38x_5 + 21.6x_6 + 0.0381x_7 + 7.17abs(\sin(x_5)) - 22.3\sin\left(x_4^{\frac{3}{2}}x_6^3x_7^3\right) - 0.00101\sin(x_3 - 1.0\sin(x_3)) - 7.36\sin(x_2) - 23.8x_2^3 + 0.0296x_4^{\frac{1}{4}}x_6x_7 + 9.22 \quad (1)$$

There are seven variables in this equation as a function of environmental impact. These variables are the input parameters in the processes in the biorefinery such as power used in cultivation, methanol in transesterification, heat in transesterification, solid residue input in biochar, liquid residue input in anaerobic digestion, methane input in CHP, and the power used in transesterification. The variables were selected and used for input variables due to the different attributions to the environmental impact. For example, the energy consumed in the cultivation process will significantly impact the environment. In addition, the chemical used in the process, such as the transesterification process, can affect the ecosystem and human health. In the results, the Ozone formation human is one of the highest correlations with the input parameters. Reasons for this are the emissions, such as the different compounds such as nitrogen oxides or hydrocarbons generated by the system.

Table 3: Generated environmental impact equations and their accuracy.

Environmental impact	R^2	RMSE
Ozone Formation Human	0.998	0.092908
Radioactive Waste	0.994	0.01954
Global Warming Potential	0.993	0.026599
Human Toxicity (Water)	0.993	0.017531
Hazardous Waste	0.991	8.61E-05
Acidification	0.984	0.17017
Ozone Formation Vegetation	0.976	0.10528
Human Toxicity (Air)	0.935	0.032723
Human Toxicity (Soil)	0.917	0.027483
Slags and Ashes	0.843	0.02468
Aquatic Eutrophication (N)	0.843	0.05702
Ozone Depletion	0.841	0.014432
Terrestrial eutrophication	0.841	0.00082067
Bulk waste	0.827	0.027483
Aquatic Eutrophication (P)	0.802	0.017531

Another example case is where not all equations generated by GP have a relationship with all parameters. Equation 2 shows that there are only 3 variables considered in the equation for Human Toxicity (soil).

$$y = 0.00725x_3 + 1.61x_4 + 0.00641\sin\left(x_3^{1/2}\right) - 0.0135\cos\left(x_3 - 1.0x_3^{\frac{1}{2}}\right) - 41.7x_4^2 + 25.4x_6^2 + 0.245 \quad (2)$$

The only input parameters that affected this environmental impact are the heat in transesterification, solid residue input in biochar, and methane input in CHP. This was the same on the other environmental impact, which are Aquatic eutrophication (N) and (P), bulk waste, human toxicity (Air), and Slags and ashes had minimal relationships with four process inputs.

Environmental impact minimisation was achieved by using GA, and the factors were individually optimised as a single objective function and treated separately. Table 4 shows the optimisation result of the minimised environmental impact. For example, Eq(1) above represents the global warming potential associated with seven input parameters.

Table 4: Genetic Algorithm optimisation result

Environmental impact	Optimised value	X1 (MJ)	X2 (kg)	X3 (MJ)	X4 (kg)	X5 (kg)	X6 (kg)	X7 (MJ)
Global warming potential	2.03	0.074	0.004	2.61	0.003	0.015	0.001	0.2
Human Toxicity (Soil)	0.258			2.61	0.043		0.001	

The values generated in the GA optimisation result per environmental impact can be a guide to designers. In addition, this model can be used to implement IoT and have embedded systems in a biorefinery to adjust the input parameters adhering to minimise environmental impact and improve sustainability.

4. Conclusions

The environmental impact optimisation of microalgae to biorefinery having multiple products with the combination of LCA and CI models such as GP-GA. The GP method generated transcendental equations that relate the environmental impact to the input parameters. These equations were optimised using GA by minimising environmental impact and selecting the best combination of process input amounts. The transesterification process had the highest environmental impact potential having 51.5 % of the total weight, followed by the cultivation process. In addition, the generated equations for global warming potential and human toxicity (soil) gave insights into how the identified input is related to the environmental impact. Lastly, environmental impacts were optimised using GA. An extension of this study is to have multiple objective functions resulting in a multi-objective optimisation considering the interactions of these environmental factors. The integration of an AI-based decision support system through digital twin technology that can trigger certain feedback to the system when reaching a certain threshold can also be developed for on-the-fly microalgae biorefinery optimisation.

References

Baba A., 2021, Advanced AI-based techniques to predict daily energy consumption: A case study. Expert Systems with Applications, 184, 1–9.

Barkhausen R., Rostek L., Miao Z.C., Zeller V., 2023, Combinations of material flow analysis and life cycle assessment and their applicability to assess circular economy requirements in EU product regulations A systematic literature review. Journal of Cleaner Production, 407, 137017.

Bussa M., Zollfrank C., Röder H., 2021, Life cycle assessment with parameterised inventory to derive target values for process parameters of microalgae biorefineries. Algal Research, 57, 102352.

Caporusso A., Giuliano A., Liuzzi F., Barletta D., De Bari I., 2023, Techno-economic Analysis of Green Diesel Production Process from Vegetable Oils. Chemical Engineering Transactions, 100, 13-18.

Chew K.W., Yap J.Y., Show P.L., Suan N.H., Juan J.C., Ling T.C., Lee D.J., Chang J.S., 2017, Microalgae biorefinery: High value products perspectives. Bioresource Technology, 229, 53–62.

Chisti Y. 2007, Biodiesel from microalgae. Biotechnology Advances, 25(3), 294-306.

Chisti Y., 2013, Constraints to commercialization of algal fuels. Journal of Biotechnology, 167, 201–214.

Concepcion II R., Duarte B., Palconit M.G., Baun J.J., Bandala A., Vicerra R.R., Dadios E., 2023, Screen-printed graphite electrode on polyvinyl chloride and parchment strips integrated with genetic programming for in situ nitrate sensing of aquaponic pond water, Information Processing in Agriculture, In Press, DOI: 10.1016/j.inpa.2023.02.002.

Espanola J.L., Bandala A.A., Vicerra R.R.P., Dadios E.P., 2019, Design of a Fuzzy-Genetic Controller for an Articulated Robot Gripper, IEEE Region 10 Annual International Conference, Proceedings/TENCON, 2018-October, 1701–1706.

Josa I., Garfí M., 2023, Social life cycle assessment of microalgae-based systems for wastewater treatment and resource recovery. Journal of Cleaner Production, 407, 137121.

Karan H., Roles J., Ross I.L., Ebrahimi M., Rackemann D., Rainey T., Hankamer B., 2022, Solar biorefinery concept for sustainable co-production of microalgae-based protein and renewable fuel, Journal of Cleaner Production, 368, 132981.

Khoshnevisan B., Duan N., Tsapekos P., Awasthi M., Liu H., 2020. A critical review on livestock manure biorefinery technologies: sustainability, challenges, and future perspectives. Renew. Sust. Energ. Rev., 135, 110033.

Kumar N., Banerjee C., Chang J.S., Shukla P., 2022, Valorization of wastewater through microalgae as a prospect for generation of biofuel and high-value products, Journal of Cleaner Production, 362, 132114.

Jin B., Khan F., Alturki R., Ikram M.A., 2023, Computational intelligence-enabled prediction and communication mechanism for IoT-based autonomous systems. ISA transactions, 132, 146-154.

Lim J.Y., Teng S.Y., How B.S. Nam K., Heo S., Máša V., Stehlik, P., Yoo C.K., 2022, From microalgae to bioenergy: Identifying optimally integrated biorefinery pathways and harvest scheduling under uncertainties in predicted climate. Renewable and Sustainable Energy Reviews, 168, 112865.

Madár J., Abonyi J., Szeifert F., 2005, Genetic programming for the identification of nonlinear input− output models, Industrial & Engineering Chemistry Research, 44, 3178-3186.

Nabavi-Pelesaraei A., Rafiee S., Mohtasebi S.S., Hosseinzadeh-Bandbafha H., Chau K.W., 2018, Integration of artificial intelligence methods and life cycle assessment to predict energy output and environmental impacts of paddy production. Science of the Total Environment, 631, 1279-1294.

Pierro N., Giuliano A., Giocoli A., Barletta D., De Bari I., 2023, Process Design of the Biogas Upgrading to Biomethane Using Green Hydrogen. Chemical Engineering Transactions, 100, 7-12.

Rivera E.C., Rabelo S.C., dos Reis Garcia D., Filho R.M., da Costa A.C., 2010, Enzymatic hydrolysis of sugarcane bagasse for bioethanol production: Determining optimal enzyme loading using neural networks, Journal of Chemical Technology and Biotechnology, 85, 7, 983–992.

Solis C.M.A., San Juan J.L.G., Mayol A.P., Sy C. L., Ubando A.T., Culaba A.B., 2021, A multi-objective life cycle optimization model of an integrated algal biorefinery toward a sustainable circular bioeconomy considering resource recirculation. Energies, 14, 1416.

Wang K., Khoo K.S., Leong H. Y., Nagarajan D., Chew K.W., Ting H.Y., Selvarajoo A., Chang J.S., Show P.L., 2022, How does the Internet of Things (IoT) help in microalgae biorefinery? Biotechnology Advances, 54, 107819.

Wu W., Lin K.H., Chang J.S., 2018, Economic and life-cycle greenhouse gas optimization of microalgae-to-biofuels chains. Bioresource Technology, 267, 550–559.