Multiobjective optimization of synechocytis culture in flat-plate photobioreactor toward optimal growth and exergy

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Abstract. Many researchers are analyzing microalgae as a fuel source due to their high potential. Since microalgae are grown on a narrow area of land and less water, microalgae can contain high lipids. Carbon dioxide, water, inorganic salts, temperature and degree of acidity (pH), and light intensity in photobioreactors affect microalgae growth. Microalgae Synechocystis cultivated in BG-11 medium on closed PBRs with an addition of 10 mM NaHCO$_3$. Culture medium illuminated at one side with Orange-red LED (636 nm) at light intensities of 50, 200, 300, 500, 800, 950, and 1,460 µmol photon/m$^2$.s with light intensity adjustment every 24 hours. Optical density and exergy destruction also optimize for artificial neural network training and Multiobjective Genetic Algorithms. The optimum value from the TOPSIS approach is the OD 12.957 OD730 and 8660.35 kJ exergy destruction. The optimum condition is derived from the optimum value. The light intensity of 71 µmol photon/m$^2$.s and the dry cell weight of 0.119 g/OD730L are ideal conditions for optimal microalgae development.

1. Introduction
Microalgae need relatively limited land for growth as biomass sources, less freshwater, not affecting food supply, high growth rates, and more elevated lipids [1, 3]. In Indonesia, there is enormous potential to grow microalgae as energy resources. However, microalgae study in Indonesia is still on a laboratory scale and not yet optimum. The explanation is that each species of microalgae has different characteristics. The various cultivation conditions have to be tailored to each microalga, and the operating cost is expensive [4]. Microalgae growth is affected by carbon dioxide, water, inorganic salts, temperature and degree of acidity (pH), and light intensity. Optimal growth conditions, the amount of lipid content, the capacity for wide-scale production, and the importance of algae by-products must be considered in the species selection process [5].

Microalgae productivity increased by changing light sources, light intensity, solar irradiance, wavelength, and photoperiod [6–8, 10]. Cordara A, Re A [11] searched for the effect of different light intensities on Synechocytis growth. They found that light intensity of 1460 µmol photon/m$^2$.s causes Synechocytis to enter the photoinhibition period, but light intensity moves to 200 µmol photon/m$^2$.s, synechocytis can recover its growth rate. Multiobjective optimization of microalgae has also been done a lot [12, 13, 15–17]. Microalgae’s optimum growth conditions differ in different photobioreactor configurations. For instance, Hossain S Z, Alnoaimi A [13] optimized CO2 capture rate, biomass productivity, and specific growth rate of Chlorella vulgaris. Meanwhile, Rahman A, Nasution S B [12]...
had optimized the flat plate photobioreactor’s in exergy and economics. They find that variations in light intensity and pressure gauge will have different effects on the photobioreactor.

This paper will optimize Synechocystis cultivation data using multiobjective optimization (MOO) by considering exergy destruction in cultivation and growth rate. Variations in light intensity and the number of microorganisms can influence the photobioreactor system’s energy and energy. Therefore, this analysis aims to decide the optimal conditions for light intensity and dry cell weight required to achieve maximum growth and energy destruction.

2. Research Method

PBR FMT150.2 / 400 flat plate photobioreactor (Photon System-Instrument) coupled with a combination of Clark Probe (Mattler-Toledo) temperature / pH probe type and then integrated with the use of a densitometer used to measure optical density (OD) so that the desired criteria are achieved, namely level scale from 720 to 680 nm. Synechocystis culture was grown on BG-11 medium with the addition of 10 mM NaHCO$_3$. Orange-red LED (636 nm) is used for irradiation on one side of the culture medium at light intensities of 50, 200, 300, 500, 800, 950, and 1,460 µmol photon/m$^2$s with a light intensity adjustment every 24 hours [11].

2.1. Artificial Neural Network models and optimization using Genetic Algorithms

The Artificial Neural Network (ANN) is a computational system where architecture and computation are inspired by brain nerve cells. By conducting the learning process, artificial neural networks may generate a coherent response to the input series. Neurons divide into layers of input neurons, layers of output neurons, and layers of hidden layers that intertwined throughout the ANN structure. An artificial neural network is used in Matlab applications by calculating the sum by trial and error to achieve the stated goal. If the research data used has a large degree of dimension, then a dimensional reduction method can be used to reduce it. Researchers [14] use KPCA to reduce the features of complex data dimensions. Meanwhile, some of the following researchers [2, 9, 24] have recently succeeded in using dimension reduction for large amounts of small-scale data through the use of machine learning methods. Inputs on ANN are light intensity (I) and biomass dry weight ($\dot{m}_{MO}$) and the optical density (OD) and destructive exergy ($\dot{E}_D$) as output. A Multiobjective Genetic Algorithm will optimize the ANN results. The optimal value is determined using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method [15, 18, 19].

2.2. Governing Equation

2.2.1. Exergy: Exergy is the maximum useful work in the system that brings the design to equilibrium. There is a balance of incoming and outgoing energy in the photobioreactor, which consists of the medium of society, biomass, and light energy. In this calculation, the photobioreactor serves as a control volume. Exergy measurement will involve culture media workout, input gas flow rate (CO$_2$), culture-accumulated microorganism, and light delivered. Table 1 lists the equations for calculating exergy, and table 2 contains the exergy standard of each chemical in the culture media [20].

| Table 1. Exergy equation [20] |
|--------------------------------|
| (i) Exergy of culture media |
| $\dot{E}_{CM} = \sum n_i \dot{E}_i$ | (1) |
| (ii) Exergy flow rate of CO$_2$ |
| $\dot{E}_{CO2} = \dot{n}_{CO2} \sum x_m \dot{E}_m + RT_0 \sum x_m \ln(x_m)$ | (2) |
(iii) Exergy of the microorganism accumulated

\[ \dot{E}_{X_{MO}} = 18.7m_{MO} \]  

(iv) Exergy of delivered light

\[ \dot{E}_{X_{DL}} = (1 - C_r)\alpha AI_{TL} \]  

(v) Exergy destruction

\[ \dot{E}_D = E_F - E_P \]  

### Table 2. Standard exergy of chemical components in culture media

| Chemical Components               | Standard Chemical Exergy (kJ/mol) | Ref. |
|-----------------------------------|-----------------------------------|------|
| Ferric ammonium citrate           | 2076.735                          | [20] |
| CaCl\(_2\).2H\(_2\)O              | 38.83                             | [21] |
| MgSO\(_4\).7H\(_2\)O              | 87                                | [20] |
| K\(_2\)HPO\(_4\)                  | 78.92                             | [20] |
| H\(_3\)BO\(_3\)                   | 21.97                             | [20] |
| MnCl\(_2\).4H\(_2\)O              | 179.57                            | [21] |
| ZnSO\(_4\).7H\(_2\)O              | 88.6                              | [20] |
| CuSO\(_4\).5H\(_2\)O              | 91.39                             | [20] |
| MoO\(_4\)                         | -98.73                            | [21] |

### Table 3. Biomass dry cell weight per light intensity [11]

| Light intensity (µmol photon/m\(^2\)s) | Dry cell weight (g/OD730·L) |
|----------------------------------------|-----------------------------|
| 50                                     | 0.145                       |
| 200                                    | 0.14                        |
| 300                                    | 0.145                       |
| 800                                    | 0.152                       |
| 950                                    | 0.153                       |
| 1,460                                  | 0.158                       |
| 200*                                   | 0.15                        |

(*) Recovery at 200 µmol photons m\(^{-2}\)s\(^{-1}\)

2.2.2. Microalgae growth. The productivity of microalgae influenced by many aspects of the cultivation system. Nutritional requirements and salt concentration in various microalgae strains can be distinct. Different numbers of temperature, pH, and light both allow significant improvements in microalgae’s productivity, but the light strength has a substantial impact on microalgae growth. The growth rate of microalgae can be seen from biomass density [22].

\[ S = I_0(S_fV^{-1})e_X X \]  

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2.3. Variable of Optimization

2.3.1. Light Intensity. Light intensity is one of the factors that affect the cultivation of microalgae and the concentration of nutrients and temperature. Light applied to microalgae affects the growth of microalgae before the point of light saturation is reached. As microalgae hit the point of light saturation, the microalgae’s growth rate will decrease to photoinhibition. Artificial light sources, such as LEDs and fluorescent lamps, prefer to minimize the photoinhibition effect. The light intensity in this optimization is varied at 50, 200, 300, 500, 800, 950, and 1,460 \( \mu \text{mol photon/m}^2\text{s} \) [1, 11].

2.3.2. Weight of Biomass. Microalgae are known for their rapid growth, the capacity to accumulate various biomolecules, and the need for a small area to become good energy-producing biomass sources. Biomass energy comes in many ways. Microalgae biomass can be converted to biofuel, while residual biomass and organic waste can also be converted to biomethane by-products using anaerobic digestion. Dry biomass in optimization has varied depending on the weight of the biomass-derived from cultivation. Table 3 indicates the yield of biomass mass yield per light intensity [23].

3. Results

3.1. Artificial Neural Network training results

The data of light intensity and biomass weight are used as input, and optical density and exergy destruction are used as output in ANN. The Algorithm run in the Matlab program uses 70% of data for learning and 30% of data for calculation. This calculation uses the feed-forward backpropagation and the Levenberg-Marquardt backpropagation (trainlm) function. ANN performance results expressed in root square mean error (RMSE) with the regression value at the output seen in figure 1, where training stops when \( R = 0.88251 \). The RMSE value will indicate the ANN’s accuracy when predicting the stated target value and its similarity to the actual data. ANN training results suggest that the best validation result is 0.11759 in epoch 7, as shown in figure 2. The optimal ANN output graph results are the relationship between MSE and the number of training iterations or epochs. The optimal ANN training status results separated into three graphs: gradient, mu (momentum update), and danval failure. The optimum results occur at \( 1.0455 \times 10^{-9} \), then mu at \( 1 \times 10^{-9} \), and validation checks occur at 0, and all of the results appear in epoch 7, as shown in figure 3.

Figure 1. \( R^2 \) results of ANN training

Figure 2. Best validation results of ANN training
3.2. Optimization results

Previous studies concluded that light intensity had a substantial effect on the growth of microalgae. Light intensity variations can produce a different outcome in microalgae development, and biomass production may affect energy destruction. Optimization is carried out to determine the system’s optimal state so that the system can run efficiently. The light intensity and weight of the biomass produced in the experiment are limitations of optimization. The objective functions used for optimization are exergy destructive and optical density. Optical density describes the growth rate in microalgae, while exergy destruction describes the energy efficiency that occurs due to microalgae cultivation. The results of the optimization aimed at the Pareto Front can be seen in figure 4.

The previous work has not concluded the optimum point for the system to work efficiently. From the optimum value obtained, the most optimum point is selected using the TOPSIS method. This method will choose the non-ideal topic from the Pareto front’s value, then select the point farthest from the non-ideal point as the optimum value point. The optimization results show that the optimum optical density and minimum exergy destruction occur at a light intensity of 71 $\mu$mol photon/m$^2$s and biomass weight 0.119 g/OD730L with an OD value of 12.957 OD730 and exergy 8660.35 kJ. Microalgae can receive an intensity of 71 $\mu$mol photon/m$^2$s well. Hence, the system works efficiently from this optimization result and has minimum environmental impact and exergy destruction while maintaining effective biomass outcome.

4. Conclusion

Use From the optimization result using artificial neural network and Multiobjective optimization. We can conclude that the system will work efficiently at a light intensity of 71 $\mu$mol photon/m$^2$s and a dry cell weight of 0.119 g/OD730L. This optimum value generates optimum growth of 12.957 OD730 and exergy destructive of 8660.35 kJ.
5. Nomenclature

\[ \dot{E}_{CM} = \text{exergy value of culture media (kJ)} \]
\[ n_i = \text{mol number of chemical substance} \]
\[ \dot{E}_i = \text{exergy value of chemical substance (kJ)} \]
\[ \dot{E}_{CO_2} = \text{exergy of CO}_2 \text{ flow rate (kJ)} \]
\[ \dot{n}_{CO_2} = \text{mol rates} \]
\[ x_m = \text{molar fraction} \]
\[ \varepsilon_m = \text{standar chemical exergy of chemical component (kJ/mol)} \]
\[ R = \text{gas constant (8.314 J/mol K)} \]
\[ T_0 = \text{dead state temperature (K)} \]
\[ \dot{E}_{MO} = \text{exergy of microorganism accumulated (kJ)} \]
\[ \dot{m}_{MO} = \text{mass of microorganism (g)} \]
\[ \dot{E}_{DL} = \text{exergy of delivered light} \]
\[ C_r = \text{reflection coefficient of unpolarized light} \]
\[ \alpha = \text{energy to exergy ratio} \]
\[ A = \text{surface area of photobiorector light receiving side (m}^2) \]
\[ I_{TL} = \text{light intensity} \]
\[ \dot{E}_{D} = \text{Exergy destruction (kJ)} \]
\[ \dot{E}_{F} = \text{Exergy fuel (kJ)} \]
\[ \dot{E}_{P} = \text{Exergy product (kJ)} \]
\[ S = \text{substrate} \]
\[ I_0 = \text{light intensity (\mu} \text{mol photon/m}^2 \text{s)} \]
\[ S_f = \text{illuminated surface area (m}^2) \]
\[ V = \text{liquid volume (m}^3) \]
\[ \varepsilon_x = \text{extinction coefficient of the culture} \]
\[ X = \text{biomass concentration} \]

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