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Research Article

Simulation of Multi-Loop PI Control Strategies for Optimizing Microalgae Cultivation and CO2 Capture in 3-Stage Bubble Column Photobioreactors

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Abstract: Microalgae holds several promising applications, such as renewable sources for biofuel production and CO_2 capture from industrial flue gases. There are limited studies so far focusing on the challenges of optimizing microalgae cultivation productivity and CO_2 capture efficiency in photobioreactor (PBR). The present work shows that one of the challenges to aim at high microalgae cultivation and CO_2 capture efficiency is maintaining the oxygen level in water below its maximum threshold value, beyond which microalgae photosynthesis switches to respiration. The current work explores various control strategies, attached to 3-state Bubble column PBR, such as directly maintaining the oxygen level, microalgae concentration and CO_2 capture efficiency. One of the findings revealed that the conditions that increase the microalgae concentration tend to reduce CO_2 capture and vice versa. The results emphasize the need to improve the mass transfer rates of CO_2 and O_2 across the liquid-gas phases by modification of the existing PBR design to improve microalgae productivity and CO_2 capture efficiency simultaneously.

Keywords: Microalgae Cultivation; PI Control; Algae Carbon Capture; Photobioreactor Simulation; Wastewater Treatment.

1. Introduction

Microalgae have shown great promise as a versatile feedstock with applications in various fields. They find use in pharmaceuticals, animal feed, cosmetics, and renewable energy [1-3]. As a feedstock for renewable fuels, microalgae have been proposed for several processes and routes. These include biodiesel production through hexane extraction [4], renewable diesel production via hydrothermal liquefaction [5], biomethane production [6], biohydrogen production [7], and bioethanol production through fermentation [8]. These applications demonstrate microalgae's potential as a sustainable renewable energy source. Moreover, microalgae production systems can be effectively integrated with wastewater systems to recover essential nutrients like nitrates and phosphorous [9]. This integration offers an environmentally friendly approach to nutrient recycling and helps to reduce the environmental impact of waste disposal and greenhouse gas emissions, especially CO_2.

As of November 2022, the concentration of CO_2 in the atmosphere has reached unprecedented levels, reaching approximately 420 parts per million ppm [10]. This increase in CO_2 concentration has contributed to a global average temperature rise of 1°C, with more significant impacts observed in the Arctic Circle, where temperatures have increased by 4°C [11]. The rising temperatures have also led to a

103 mm increase in sea levels since the start of the industrial era. Global warming and its associated greenhouse effect have become major concerns due to their significant impact on the climate [12]. In mitigating the average global temperature increase, there is a pressing need to implement carbon capture (CC), storage, and utilization technologies worldwide [13]. Continuous efforts are being made to develop improved CO_2 capture technologies that reduce emissions and have minimal environmental impact and energy wastage. European initiatives (is a set of policy initiatives by the European Commission with the overarching aim of making the European Union (EU) climate neutral) aim to transition to a low-carbon economy in the coming years [14]. However, one of the main challenges is the increasing demand for energy from the energy industry [15]. As fossil fuels are expected to remain the primary energy source in the foreseeable future, significant advancements in CC technologies are essential for achieving a sustainable global economy [16]. In summary, microalgae represent a promising and versatile feedstock with diverse applications across various industries, making them a valuable resource. Therefore, there is a need for production technologies that enable consistent and optimal microalgae production. A closed PBR system has been suggested as a potential production method due to its ability to achieve optimal production rates and yields. However, its high initial and operational costs make it economically viable only for high-value products and limit its use for large-scale production [17, 18]. Moreover, many industrial processes exhibit complex characteristics such as higher-order dynamics, instability, and integrating dynamics. These traits may be deliberately introduced or naturally occur due to the intricacies of the processes, aiming to enhance output yield and system stability.

Thus, controlling such processes has been challenging and often unsuccessful. Furthermore, many industrial processes have evolved intending to optimize output yield and maximize system stability, but these efforts have frequently needed to catch up. Notably, there needs to be more research on the controllability of dynamics in microalgae production using waste water while employing the First-Order plus Dead Time (FOPDT) method. Additionally, the existing literature needs more comprehensive information regarding the dynamics controllability of microalgae production using palm oil mill effluents (POME) with the FOPDT method. This paper introduces various controller design structures to address these gaps, specifically a multi-loop PI control strategy. It seeks to investigate the parameters responsible for the dynamic behavior of microalgae cultivation and CO_2 capture in a three-stage bubble column (PBR). Furthermore, the study aims to assess the barriers hindering the achievement of CO_2 capture rates and algae productivity.

2. Methodology

2.1. FOPDT model identification

The model from this study was obtained and modified from previous studies [19], ensuring that the analysis is based on relevant and validated information. By using the loop gain of the PI controller as a measure of controllability, the study aims to provide insights into the effectiveness of the control system for the microalgae production process and assess its potential for high control performance. Ultimately, this analysis can contribute to improving the control strategies and optimizing the microalgae production process for better productivity and stability. FOPDT models are widely utilized in the fields of process control and system identification. They offer a highly efficient way to represent dynamic systems. FOPDT models are particularly useful for capturing the dynamics of processes with a single dominant time constant and a time delay before the response starts. Determine whether a FOPDT model is appropriate for the system by analyzing the step response of the data as illustrated in Fig.1 which uses the identification techniques such as regression analysis, least squares, or optimization algorithms to estimate the parameters K, τ, and θ. In this work, visual identification technique is adopted.

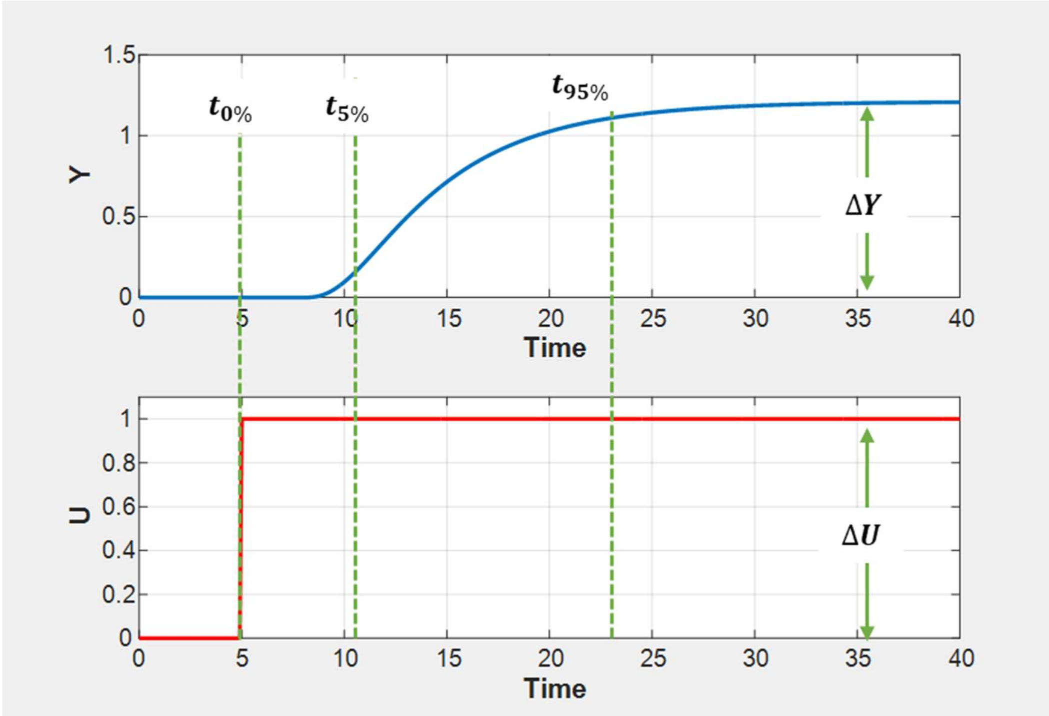

Fig. 1. Step response data for the FOPDT identification (Y = output, U = input).

The FOPDT model parameters are identified using the equation (1):

$$\begin{cases} K_p = \dfrac{\Delta Y}{\Delta U} \\ \tau_p = \dfrac{t_{95\%} - t_{0\%}}{4} \\ \theta_p = t_{5\%} - t_{0\%} \end{cases} \tag{1}$$

where K_p denotes the process gain, τ_p the time constant and θ_p the deadtime. The FOPDT transfer function is expressed as $G_p(s) = K_p \exp(-\theta_p s)/(\tau_p s + 1)$.

The block diagram of the standard single-loop control system where the corresponding process and controller transfer functions as shown in **Fig 2.** The block diagram assumes the dynamics of the actuator and sensor are fast compared to the dynamics of the process (i.e., pseudo-steady state of actuator and sensor). Thus, there is no need to include the actuator and sensor in the block diagram. Refer to **Fig 2**, R, E, U, D, and Y denote the desired input, set point, error, controller output, input disturbance, output disturbance, and controlled variable signals; G_c and G_p are the controller and process transfer functions, respectively.

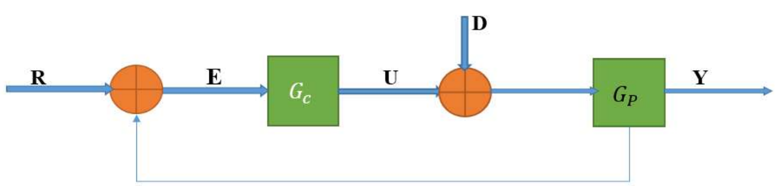

Fig. 2. Block diagram of the standard single-loop feedback control.

Based on the block diagram, one can derive the closed-loop set point transfer function as in the following steps.

The closed loop set point transfer function is given as:

$$H_r(s) = \frac{G_c(s)G_p(s)}{1 + G_c(s)G_p(s)} \tag{2}$$

Closed-loop input disturbance transfer function:

$$H_{d_i}(s) = \frac{G_p(s)}{1 + G_c(s)G_p(s)} \tag{3}$$

Closed-loop output disturbance transfer function:

$$H_{d_o}(s) = \frac{1}{1 + G_c(s)G_p(s)} \tag{4}$$

where R is a set point, E is an error, U is a controller output, D is the input and output disturbance are an output disturbance, Y is output or controlled variable, G_c is a controller transfer function or sub-system and G_p is a process transfer function or sub-system.

The closed-loop characteristic equation is expressible by general characteristics:

$$\psi = (h_n + K_L f_n)s^n + \cdots + (h_1 + K_L f_1)s + (h_0 + K_L f_0) = 0 \tag{5}$$

Note that the parameters h_i and f_i for $i = 0, 1, \ldots, n$ are often functions of the model parameters and the reset time. Meanwhile, K_L denotes the loop gain of the control system, i.e., $K_L = K_c K_p$ where K_c denotes the PI controller gain and K_p the process gain. Remember that the loop gain K_L is a dimensionless parameter directly related to the control performance. A high value of K_L means that the control system can exhibit higher performance than the smaller value of K_L and vice versa. Since K_L is directly related to the control performance, the loop gain value should be practically above zero. If its value is less than zero, then this implies that the control performance is lower than the open-loop system, i.e., the control system is practically useless.

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2.2 Stability of PI Control

Assume the FOPDT model can represent: the process, i.e.:

$$G_p = \frac{K_p e^{-\theta_p s}}{\tau_p s + 1} \tag{6}$$

Notations K_p, τ_p and θ_p denote the process gain, time constant, and dead time, respectively. Meanwhile, the PI controller transfer function in its ideal form is as follows:

$$G_c = K_c\left(1 + \frac{1}{\tau_I s}\right) \tag{7}$$

where K_c and τ_I represent the tunable parameters viz. controller gain and reset time, respectively. The controller gain is obtained from the equation (8):

$$K_c = \frac{r_p}{K_p}\left(\frac{\theta_p}{\tau_p}\right) \tag{8}$$

where r_p denotes the dimensionless tuning parameter bounded between 0 and 1for stability, i.e., $0 < r_p < 1$.

The process gain K_p, representing the steady-state relationship between the input and output variables. Process gain, also known as process transfer function gain, is a crucial parameter in process control and system analysis. It quantifies the relationship between the change in the output variable of a process and the change in the input variable. In simpler terms, process gain indicates how much the output of a system will change in response to a given change in the input.

2.3 Modeling of PBR

Fig. 3 shows the schematic of the configuration of the bubble column photobioreactors (PBRs) for algal cultivation arranged in modules, each containing three PBRs. Multiple PBRs are organized in series based on modules, as the flow rate OF effluent (POME) from the process enters the first modules. Subsequently, liquid POME from PBR flows into the second module, and this sequence repeats for 'n' iterations. Concurrently, flue gas from the palm oil mill furnace is supplied to the n PBRs in parallel, with varying flow rates to each PBR present in the module, depending on the algal concentration in each PBR. In **Fig 3**, the overview of the microalgae PBR is presented indication the source of CO_2 supply essential for photosynthesis through flue gas. The key variables and parameters considered in this study include F_P (flow rate), X_{in} (vector of relevant substrate/nutrient concentrations in the effluent), $y_{co2,in}$ (molar fraction of CO_2 in the feed), $y_{o2,in}$ (molar fraction of O_2 in the feed), $y_{nh3,in}$ (molar fraction of ammonia in the feed flue gas), $F_{gin,j}$ is the flue gas flow rate to j^{th} PBR, $F_{gout,j}$ is the gas leaving the j^{th} PBR, $y_{co2,out,j}$ is the exit molar fraction of CO_2, $y_{o2,out,j}$ is the exit molar fraction of O_2, $y_{nh3,out,j}$ is the exit molar fraction of ammonia in from j^{th} PBR, $X_{out,j}$ is the vector of substrate/nutrient concentrations leaving the j^{th} PBR, and F_{gT} (total flue gas supplied to all PBRs).

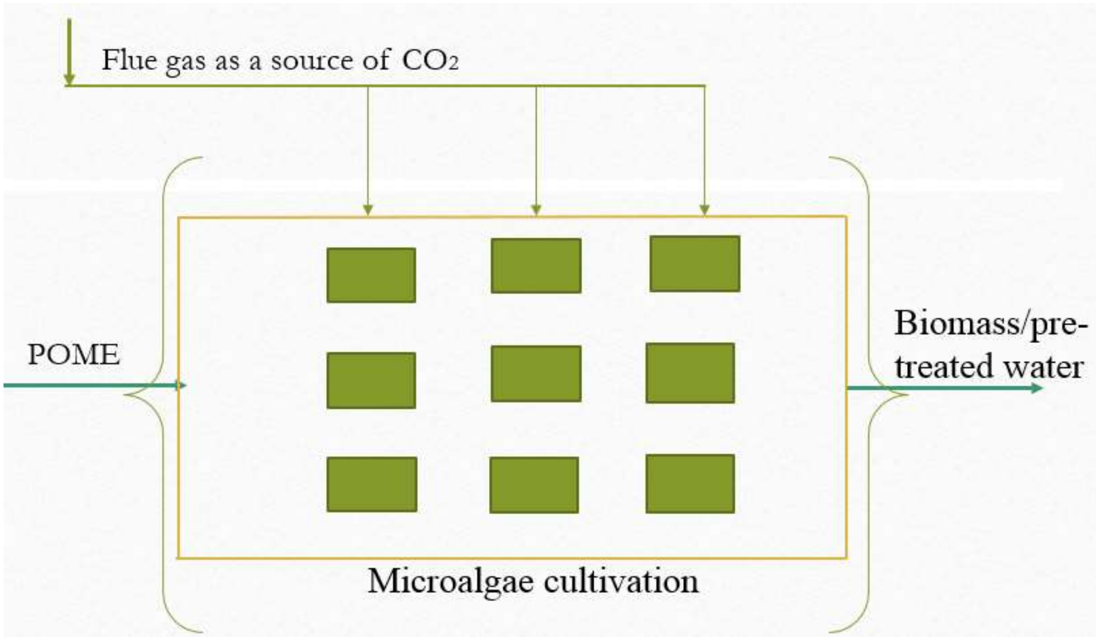


Fig. 3. Algal cultivation PBRs configuration arranged in modules.

It is important to note that the concentration of relevant substrates/nutrients (X_{out}) leaving the PBRs is expected to be very low at this point, as a significant portion, if not all (about 98%), has been utilized by bacteria during the microalgae cultivation. Consequently, the consumption of flue gas depends on the nutrient concentration in the substrates, with higher concentrations leading to increased algae growth and, in turn, greater flue gas utilization.

The substrate or nutrient concentrations X_in∈R^7 considered in the feed to a PBR can be represented by equation (9):

$$X_{in} = [S_{nh3i}, S_{nh4i}, S_{co2i}, S_{hco3i}, S_{co3i}, S_{no3i}, S_{o2i}]^T \quad (9)$$

where $S_{nh3i}, S_{nh4i}, S_{co2i}, S_{hco3i}, S_{co3i}, S_{no3i}$ and S_{o2i} denote the inlet concentrations of ammonia, ammonium, dissolved CO_2, bicarbonate, carbonate, nitrate, and dissolved O_2 in the feed POME to the PBRs in module 1, respectively.

2.4 Modelling assumptions

In this study, a model is developed for process integration and dynamic simulations of various (PBRs) used in microalgae cultivation with (POME) as the feedstock. This model is built based on several assumptions: Effective mixing occurs within each PBR, there is minimal water evaporation within each PBR, there is negligible heat generation or loss within each PBR, meaning that it operates isothermally (constant temperature) with a constant liquid volume, the presence of species depends on the activities of microalgae, and factors such as substrate and gases are not limiting, the presence of species relies on microalgae activities, and factors such as substrate and gases are not limiting, Other nutrients like phosphorus or micronutrients do not act as limiting factors in this context.

Note that in deriving the algal cultivation model, only the conservation of mass is applied because the PBR are isothermal, i.e., the implication of third assumption. Because of first assumption, lumped parameter modelling is adopted which shall result in the system described by a set of Ordinary Differential Equations (ODEs).

For PBR 1, the i^{th} species mass balance equation is given as follows:

$$\frac{dx_{i,1}}{dt} = \frac{F_P\left(x_{i,in} - x_{i,1}\right)}{V_{pb}} + R_{i,1}, \qquad i = 1, 2, \dots, \text{n} \tag{10}$$

Here, $x_{i,1} \in X_{sA,1}$ is a state variable, e.g., $x_1 = X_{alg}$, $x_2 = X_d$, etc., as in Equation while $x_{i,in}$ the inlet concentration corresponding to the state variable $x_{i,1}$, Note that the inlet concentrations of the viable algal and dead algal cells to the PBR 1 are zero, i.e., $x_{1,in} = 0$ and $x_{2,in} = 0$. Meanwhile, the inlet concentrations corresponding to the rest of the state variables are as in **Equation (9)**, e.g., $x_{3,in} = S_{nh3i}$, $x_{4,in} = S_{nh4i}$, etc. In Equation (10), V_{pb} and $R_{i,1}$ denote the liquid hold-up volume and overall reaction rate associated with the i^{th} species in the PBR 1, respectively.

For the subsequent PBR in the serial configuration shown in Fig. 3, the ith species mass balance is given as follows equation (11):

$$\frac{dx_{i,j}}{dt} = \frac{F_P\left(x_{i,j,in} - x_{i,j}\right)}{V_{pb}} + R_{i,j}, \qquad i = 1, 2, \dots, 9 \quad \text{j} = 2, 3, \dots, n \tag{11}$$

where$x_{i,j}$, $R_{i,j}$ and $x_{i,j,in}$ denote the i^{th} state variable (or concentration of i^{th} species), overall reaction associated with the i^{th} species, and inlet concentration of i^{th} species entering the j^{th} PBR, respectively. The vector of species concentrations in the liquid stream going into the j^{th} PBR is given by equation (2):

$$X_{j,in} = X_{out,j-1} = X_{sA,j-1}, \quad j = 2, 3, \dots, n \tag{12}$$

3. Results and Discussion

3.1 Three-PBR configuration control strategy

The exploration of diverse control strategies during controller design enables engineers and control system designers to make well-informed choices, taking into account the unique attributes, objectives, and limitations of the system in question. This, in turn, leads to the development of control solutions that are not only more effective but also more efficient. There are several compelling reasons why it is crucial to contemplate various control strategies in controller design analyses such as system variability, adaptation, robustness, optimization, trade-offs, testing and simulation etc. In this study, we devised five distinct control strategies to evaluate their effectiveness and identify the most suitable one for proficiently managing the system. For a detailed overview of the various control structures designed, outlining the manipulated variables employed to regulate the process variable and attain the desired target value. In this study a multi-loop controller structure is presented with three PBR each in a single module with each control structure connected to sensor (AT), controller (AC) and actuator (U), as illustrated in **Fig. 4.** The multi-loop controller considered the first PBR to control carbon capture (CO_2), while the second PBR to control algae concentrations (Calg1) as control variables respectively. The manipulating variables in all the PBRs were the flowrates of POME and inlet flue gas.

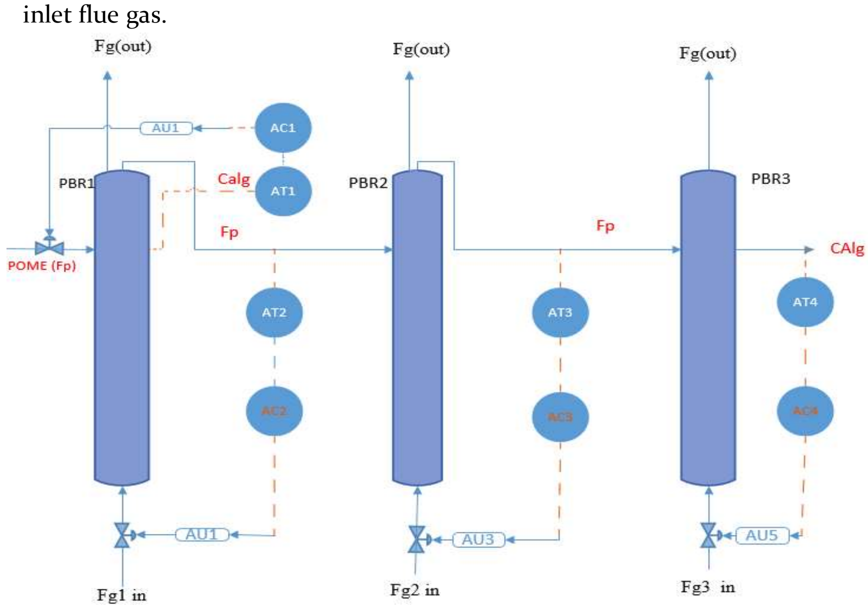


Fig 4. Multi-loop control strategy for 3-PBR system (1 module).

3.2 Pereformance of multi-loop controller performance

In this section, a feedback diagram for the multi-variable control system as illustrated in **Fig. 5.** Meanwhile, a multi-loop controller structure designed to control two process variables, for algae concentration, CO_2 capture and DO results are presented in **Figs. 6a to 6c.** Multi-loop controller design is an approach that involves using multiple control loops to regulate different variables within a dynamic system. Each control loop is responsible for controlling a specific variable, and the loops work together in a coordinated manner to achieve the desired overall system behavior. This approach was commonly used due to the complex system process in this study where different variables need to be controlled independently to maintain stability and optimal performance. The advantages of using a multi-loop controller design include increased flexibility, improved robustness, and the ability to handle complex interactions between different variables. The main idea behind a multi-loop controller is that the control actions for different variables are coordinated based on their interdependencies and interactions containing the inner loop and outer loop as shown in **Fig. 5**. By considering these interactions, a multi-loop controller can achieve better control performance and stability compared to individual single-loop controller.

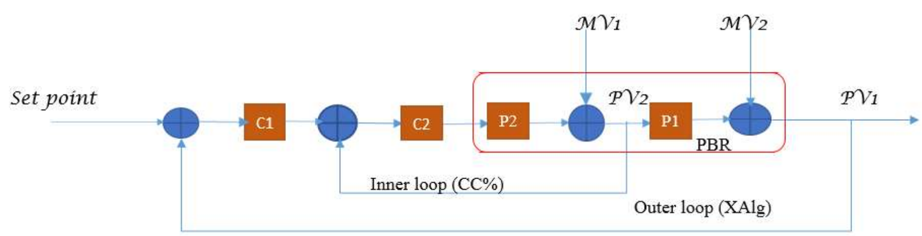
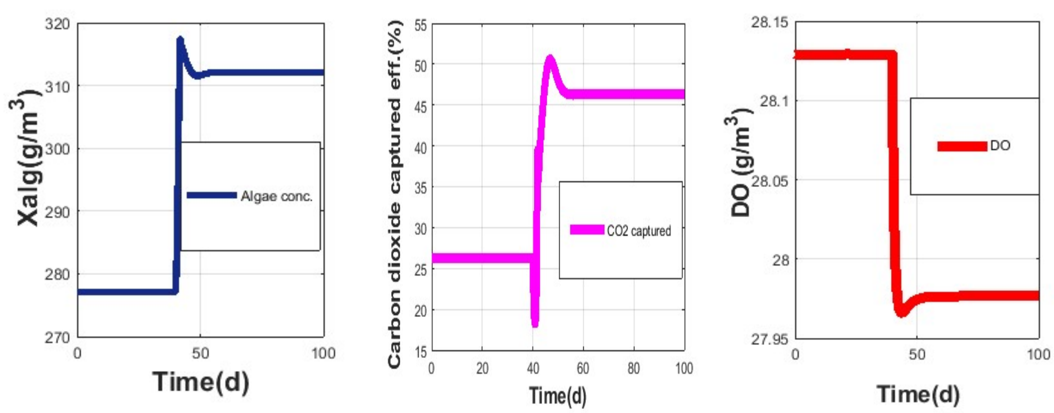


Fig 5. Feedbackdiagram for the multi-variable control system.



(a) **(b)** **(c)**

Fig. 6. Present the results for the efficiency of multi-variable controller design for algae concentration, CO_2 captured efficiency and DO as process variable, the concentration of the flowrate (Fp1) and the flue gas concentration (Fg1) were considered as as manipulating variables.

The results preasented in **Fig 6a and 6c** showed that the concentration of microalgae growth could increase to about 318 g/m^3 from 275.5 g/m^3 concerning the time constant when the flue gas concentration was appropriately controlled. The principle behind using the flow rate as a manipulating variable for microalgae growth was that at high flow rates, viable microalgae cells could be swept away, leading to less photosynthesis and an increase in respiration. This, in turn, caused more CO_2 to accumulate in the system, making it available for capture. On the other hand, lower flow rates provided a more advantageous environment for microalgae growth. At this point, more CO_2 was utilized during photosynthesis, resulting in efficient microalgae growth with less CO_2 remaining in the system. This controller design aimed to optimize both the efficiency of CO_2 captured and the growth of microalgae by carefully manipulating the flow rate of POME and the concentration of flue gas. By controlling these variables, the system could achieve better microalgae growth and CO_2 utilization, leading to more sustainable and efficient CC and utilization in the PBR.

However, designing and tuning multi-loop control systems can be more challenging than single-loop control systems, as it requires careful consideration of loop interactions and coordination. Nevertheless, when properly implemented, multi-loop control systems can provide significant benefits in terms of system performance, stability, and efficiency. This controller was designed in this study to investigate the dynamics and the efficiency of CO_2 captured and the growth of microalgae. The manipulating variables used in this controller design were the flow rate of POME and the concentration of flue gas. In this multi-loop controller design, PBR1 was used to control both the rate of CO_2 and microalgae concentration. The results showed that the flow rate of POME had a significant impact on CO_2 emissions. Even a slight increase in the flow rate resulted in a significant rise in CO_2 levels, which could become concerning. On the other hand, at lower flow rates, the system performed better, especially in terms of microalgae growth. To address this, the flow rate was chosen as the manipulating variable to control the rate of microalgae growth. The concentration of flue gas, on the other hand, was used to control the rate of CO_2 efficiency. By properly manipulating the flue gas concentration, the CO_2 captured efficiency could be raised to 51% as illustrated in **Fig 6b** with respect to the time. Overall, the utilization of flue gas as a source of CO_2 in the microalgae PBR demonstrates a synergistic approach that addresses CC, sustainable biomass production, and environmental preservation. It represents a promising and innovative solution to the global challenges of climate change and environmental sustainability. It helps reduce the concentration of CO_2 in the atmosphere, mitigating greenhouse gas emissions and their impact on climate change.

Furthermore, DO plays a crucial role in the growth and productivity of microalgae in a PBR, as illustrated in **Fig 6c**. This study achieved the maximum dropped off of saturated DO by 16%. The concentration of DO affects various biological processes, including photosynthesis, respiration, and overall cellular metabolism. Here are some effects of DO on microalgae in a PBR. Microalgae depend on O_2 for photosynthesis, the crucial process through which they convert CO_2 and light energy into O_2 and biomass. Adequate levels of DO are essential for ensuring efficient photosynthesis in microalgae. When DO is insufficient, it can limit the photosynthetic activity of microalgae, leading to decreased growth rates and reduced biomass production.

The availability of DO directly impacts the energy production and metabolic processes involved in photosynthesis. If O_2 levels are too low, microalgae may not have the necessary resources to carry out photosynthesis effectively. As a result, their growth can be stunted, and they may not produce as much biomass as they would under optimal conditions. Maintaining proper DO levels in the PBR is crucial to support the health and productivity of microalgae. Adequate O_2 supply ensures that microalgae can efficiently convert CO_2 and light energy into O_2 and biomass, enabling them to thrive and contribute to various applications, such as biofuels, bioplastics, and other valuable products. Regular monitoring and control of DO levels are essential to optimize microalgae growth and maximize biomass production in the PBR. In addition to that, to control microalgae growth in a PBR, it is important to maintain appropriate DO levels. The specific DO concentration required for optimal growth varies depending on the microalgae species and environmental conditions. Monitoring and controlling DO levels through aeration or oxygenation systems can help ensure favorable growth conditions and maximize biomass production in the PBR. Hence, in microalgae PBR, CO_2 is an essential component for the growth and photosynthetic activity of microalgae. Microalgae uses CO_2 as a carbon source for photosynthesis, converting it into organic compounds and releasing O_2 in the process. The presence of CO_2 in the PBR has a significant effect on the overall productivity and efficiency of microalgae cultivation. Given how these process variables are interrelated to each other in the building of effective PBR, this study constructs a controller design structure to tackle this dynamic behavior happening in the system.

4. Conclusion

In conclusion, the multi-loop controller design studies to test the capability of how the growth of microalgae, CO_2 capture efficiency, and saturated DO can be processed by manipulating flue gas concentration and the concentrations of POME flowrate was conducted. However, the findings from this study entail that, all the control structures performed significantly most especially for two process parameters enhancing CO_2 capture efficiency and microalgae concentration and this was achieved as a result 16% dropped off DO. In addition to that, the CO_2 capture efficiency was up to 51% and a molar fraction of CO_2 and the concentration of microalgae growth could increase to about 318 g/m^3 from 275.5 g/m^3. Moreover, there are some indications to suppose that aqua cultural and aquatic applications will be a profitable field for microalgae in the next 10 years. Both ecological applications in the sense of wastewater treatment and the agricultural use of microalgae for nitrogen fixation or as soil conditioners have promising economic potential [20]. In fact, this indicate that more research are still required in this area.

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