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Research Article

Effect of Change in Plant Capacity towards Controllability of Biohydrogen Production Plant from Biomass

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This paper discusses the plant-wide control system of a biohydrogen plant from biomass. The plant's control structure is designed by assessing the use of model predictive control (MPC) and proportional-integral (PI) controllers for each controlled variable. Then, the control structure design is tested by set point and disturbance change tests, and its performance is evaluated by integral square error (ISE). This plant is simulated in two different capacities to understand the effect of change in plant capacity on the plant's controllability. Results show that the plant with capacity A has controllability of +25% and −5%, while the plant with capacity B has controllability of +100% and −5% for the dry biomass molar flow rate change test. Both plants have the same controllability of +100% and −100% for the dry biomass temperature test. Both plants result in a dry biomass conversion rate of 16.52%, where the amount of H_2 produced is 382 kg/h and 2,291 kg/h, respectively.

1. Introduction

Hydrogen is predicted to be the future of clean energy, and it is crucial to produce hydrogen cleanly and sustainably. Hydrogen is very beneficial for human life. In organic chemistry, it is used for hydrogenation reactions such as the Rosenmund chemical reaction [1] and the Friedel–Crafts acylation chemical reaction [2]. Hydrogen is also used in the fertilizer, food, cooking oil, and fuel industries [3]. Its use in fuel cells is also very prominent [4].

There are various ways to produce hydrogen, but there is an increasing interest in utilizing biomass due to its resource diversity, availability, and sustainability [5, 6]. Three routes of producing biohydrogen from biomass are thermochemical, biological, and electrochemical processes [7]. Three types of thermochemical processes are gasification, pyrolysis, and aqueous phase reforming (APR) [5, 7]. Five types of biological processes are direct photolysis, indirect photolysis, biological water gas shift (BWGS) reaction, photofermentation, and dark fermentation [7, 8]. Meanwhile, two types of electrochemical processes are proton exchange membrane electrolysis cell (PEMEC) and microbial electrolysis cell (MEC) [7]. The factors considered in selecting the technology are but are not limited to H_2 yield, technology readiness level (TRL), and economic feasibility [9]. In this work, the gasification process is chosen due to its high energy recovery and efficiency [6, 10], highest H_2 yield [5, 10], best technological maturity [7], and it is the most economically feasible process to implement on an industrial scale [5, 8].

Despite the feasibility of the gasification process to produce biohydrogen, more research needs to be done before implementing it on an industrial scale. One of the urgent issues to be addressed is the scalability and controllability of the biohydrogen production process [10]. Yuan et al. [11] defined controllability as how easy it is to control a plant within an acceptable operating range despite any disturbance in the system. Controllability is a crucial issue to consider when scaling up a pilot scale plant into an industrial scale plant to ensure a smooth production process and stability and reliability of the H_2 supply. Plant controllability analysis is conducted using integral square error (ISE) to evaluate the controllers' performance in controlling the plant, i.e., handling set point and disturbance changes in the system. Currently, no research is conducted on analyzing the effect of change in plant capacity on plant controllability. Therefore, this research will evaluate the controllers' performance in two different plant capacities: capacity A with 2,312 kg/h of dry biomass and capacity B with 13,870 kg/h of dry biomass. The results will be analyzed to see whether the change in plant capacity will affect plant controllability and to what extent the difference in the plant controllability between the plant with capacities A and B.

Before assessing the plant's controllability, the plant-wide control system must be designed first. Previous works have applied process control to the biohydrogen plant from biomass, where each unit operation is controlled and optimized separately. Salma [12] used proportional-integral (PI) controllers for the gasifier, char combustor, and flue gas cooler. Wahid and Nararya [13] improved the control performance by reidentifying the system models and applying model predictive control (MPC) for the gasifier, char combustor, and flue gas cooler. Wahid and Iqbal [14] used PI controllers for the compressor and steam methane reformer (SMR). Wahid and Taqwallah [15] improved the control performance by reidentifying the system models and applying MPC for the compressor and SMR, and Adjisetya and Wahid [16] used multivariable model predictive control (MMPC) for the compressor and steam methane reformer (SMR) control. This research will continue developing the simulation by combining all unit operations into one simulation and assigning each controlled variable with either an MPC or PI controller. Then, the system models are identified, and the controllers are tuned to achieve optimum control performance. Afsi et al. [17] have also researched the use of PI and MPC in bioprocesses, namely, polylactic acid (PLA), as well as using dynamic optimization, and then chose which one is better. In contrast to this research, the research did not choose which was the best of them but chose PI and MPC based on the accuracy of using both in controlling certain variables.

Based on the explanation above, the discussion in this paper will be arranged as follows. Section 2 discusses the steady-state simulation of the plant, consisting of the process description and process flowsheet in UniSim Design R491. Section 3 discusses the dynamic simulation of the plant, consisting of the plant's control structure design, system identification, controller tuning, controller testing, performance, and plant controllability. Section 4 discusses the conclusion and future directions of this research.

2. Materials and Methods

2.1. Steady State Simulation. Figure 1 shows the steady-state simulation of the biohydrogen plant from biomass. The plant design is based on the work by Budianta et al. [9] with modifications. The feed to the biohydrogen plant is assumed to be dry biomass containing 92.77% carbon and 7.23% water (i.e., the biomass has been pretreated, so there is no pretreatment equipment in this simulation). Dry biomass enters directly into the gasifier together with steam, where it is converted into gases such as CO, CO_2, H_2O, H_2, and CH_4. The amount of steam used is based on the steam to biomass ratio of 0.75 [18]. The gasifier is simulated as a conversion reactor in UniSim, with reactions occurring shown in equations (1)–(4) [19]. The outlet streams of the gasifier are divided into two; the "gas" stream flows to the SMR, while the "char" stream flows to the char combustor.

$$C + H_2O \longrightarrow CO + H_2 \tag{1}$$

$$C + 2H_2 \longrightarrow CH_4 \tag{2}$$

$$C + CO_2 \longrightarrow 2CO \tag{3}$$

$$CO + H_2O \longrightarrow H_2 + CO_2 \tag{4}$$

The "char" stream flows to the char combustor, where it is reacted with air to produce heat for the gasification process. The char combustor is simulated as a conversion reactor in UniSim, with reactions occurring shown in equations (5) and (6). The outlet streams of the char combustor are divided into two; the "flue gas" stream flows to the flue gas cooler before being discarded, while the "ash" stream is discarded.

$$C + \frac{1}{2}O_2 \longrightarrow CO \tag{5}$$

$$C + O_2 \longrightarrow CO_2 \tag{6}$$

The "gas" stream flows to the SMR, where it is reacted with steam to convert CH_4 into CO and more H_2. The SMR is simulated as a plug flow reactor in UniSim, with the reaction occurring shown in equation (7). The outlet stream, namely, "gas out SMR," flows to the cooler to lower the temperature before entering the water gas shift (WGS) reactor together with more steam to convert CO into CO_2 and more H_2. The WGS reactor is simulated as a conversion reactor in UniSim with reactions occurring shown in equation (8). The outlet stream of the WGS reactor is the final product, namely, "H_2 gas," which contains 61.95% H_2, 30.96% CO_2, and traces amount of CO and H_2O.

$$CH_4 + H_2O \longrightarrow CO + 3\ H_2 \tag{7}$$

$$CO + H_2O \leftrightarrow CO_2 + H_2 \tag{8}$$

This plant is simulated in two capacities, capacity A with 2,312 kg/h of dry biomass and capacity B with 13,870 kg/h of dry biomass, which aims to mimic the pilot scale and industrial scale plant. The amount of H_2 produced in capacity A is 382 kg/h, while in capacity B is 2,291 kg/h. Both plants with capacities A and B result in a dry biomass conversion rate of 16.52%. This capacity is calculated based on Indonesia's estimated hydrogen imports in 2040, which amount to 908.5 kg/h. Therefore, capacity A accounts for 42% of the total hydrogen imports, while capacity B is planned to substitute all hydrogen imports and the remainder will be for export.

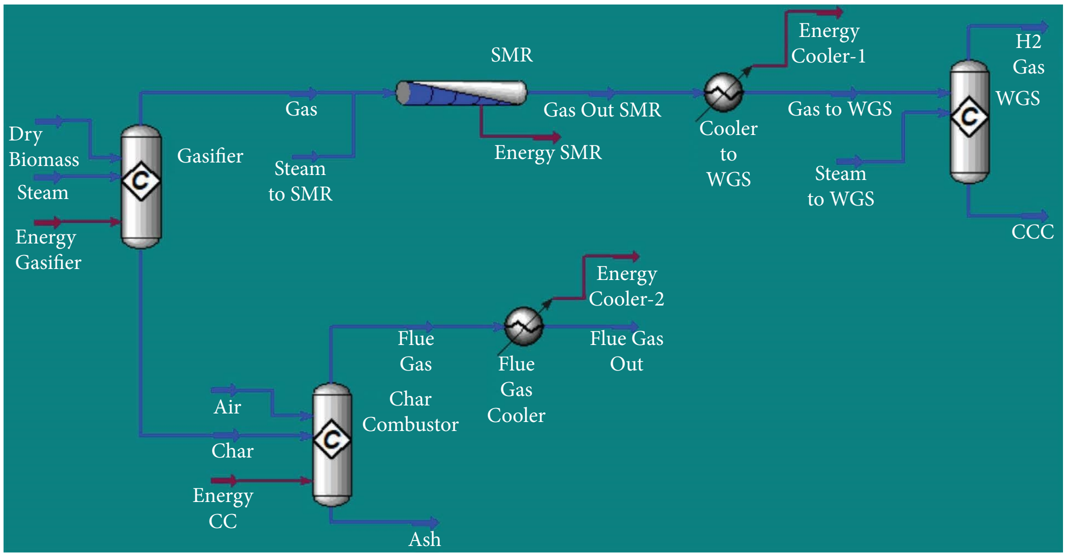


Figure 1: Steady-state simulation of the biohydrogen plant from biomass.

2.2. Dynamic Simulation

2.2.1. Control Structure Design. Figure 2 shows the dynamic simulation of the biohydrogen plant from biomass with controllers. There are five pairs of controlled and manipulated variables, as shown in Table 1. Temperature is the control focus of this plant because the temperature in each unit operation needs to be controlled to achieve the maximum reaction conversion, which correlates to the final amount of H_2 produced.

In this simulation, we consider using both MPC and PI controllers, and therefore, an assessment is conducted to determine the controller used for each controlled variable. The two factors considered in this assessment are (1) the controller's performance in controlling the system and (2) the urgency to apply a more complex controller to achieve the control objective. According to Kano and Ogawa [20], MPC outperforms the PI controller in almost every controller type (i.e., temperature, flow, pressure, and concentration) except for the level controller. However, not all unit operations directly affect the final amount of H_2 produced, e.g., char combustor and flue gas cooler, and therefore, a PI controller is sufficient for these unit operations. Table 2 concludes the chosen controller type for each controlled variable.

2.2.2. System Identification and Controller Tuning. All systems in this plant are assumed to follow a first-order linear plus dead time (FOPDT) model, not a nonlinear model. This is intended to simplify the optimization problem. This low-level model captures the important dynamics of the system while reducing computational complexity. The mathematical formulation of predictive control is essentially based on linear models [21]. Linear models simplify optimization problems and enable the use of efficient numerical optimization techniques, such as quadratic programming, to solve optimization problems at any control interval. System identification is conducted to obtain the FOPDT models, as shown in Tables 3 and 4.

In MPC, the prediction (P) and control (M) horizons and sampling time (T) in MPC determine how far in the future the system is predicted and optimized. Longer horizons generally produce more accurate predictions but also increase computational complexity. This tuning is based on specific applications and system dynamics to find a balance between accuracy and computational efficiency. To tune the MPC parameters, the Shridhar and Cooper method [22] was first used and then continued with fine tuning to enhance the robustness of the MPC controller so that it can handle mismatches between the model and reality. Meanwhile, for the PI controller, the Ziegler–Nichols method [23] is used. This method is known for producing settings that tend to minimize oscillations and stabilize the system. The method aims to strike a balance between responsiveness and stability, making it a good starting point for many control systems. Although this method was basically developed to tune a PI controller to achieve the desired balance between responsiveness and stability when there is a setpoint change and does not have specific guidelines for tuning a PI controller to handle disturbances, however, integral action in the calculated PI parameters can help reduce errors in a steady state caused by disturbances over time. The integral term allows the controller to continuously adjust the control output to eliminate long-term offsets.

The tuning parameters used for both MPC and PI controllers are shown in Tables 3 and 4, respectively. Both plants with capacities A and B have the same controller type and tuning parameters.

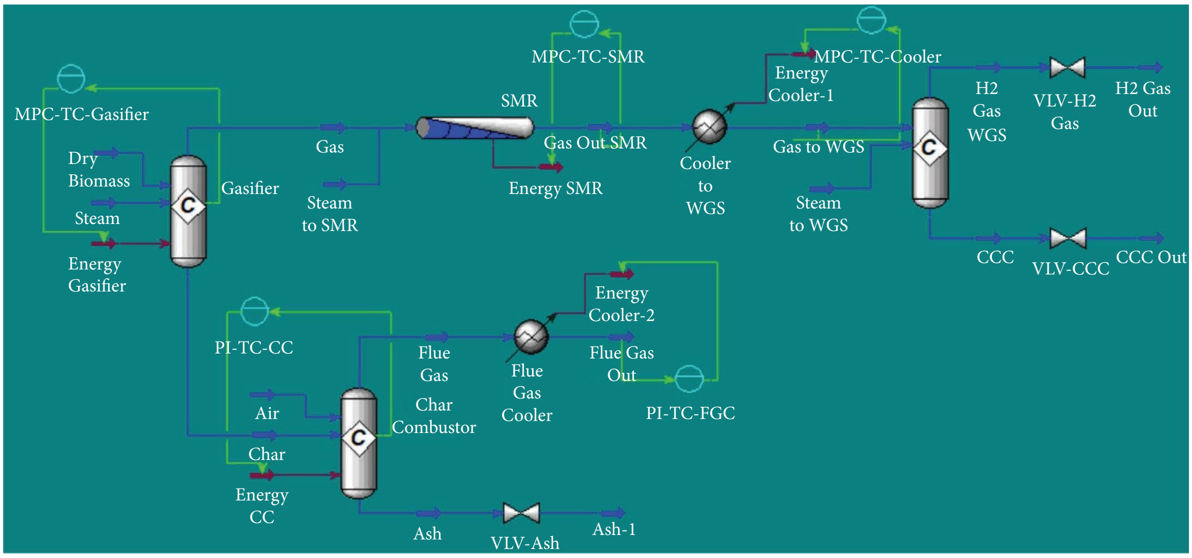


Figure 2: Dynamic simulation of the biohydrogen plant from biomass with controllers.

Table 1: List of controlled and manipulated variables.

Controlled variables	Manipulated variables
Temperature inside gasifier	Heat duty of the gasifier
Temperature inside char combustor	Heat duty of the char combustor
Temperature of "flue gas out" stream	Heat duty of the flue gas cooler
Temperature of "gas out SMR" stream	Heat duty of the SMR
Temperature of "gas to WGS" stream	Heat duty of the cooler before WGS reactor

Table 2: List of controlled variables and the chosen controller type.

Controlled variables	Controller types	Reasons
Temperature inside gasifier	MPC	Energy conversion and maximizing reaction inside the gasifier
Temperature inside char combustor	PI	This process does not directly affect the amount of H_2 produced
Temperature of "flue gas out" stream	PI	This process is simple and does not directly affect the amount of H_2 produced
Temperature of "gas out SMR" stream	MPC	Energy conversion and maximizing reaction inside the SMR
Temperature of "gas to WGS" stream	MPC	Energy conversion and maximizing reaction inside the WGS reactor

3. Results and Discussion

Controller testing is conducted to evaluate the controllers' performance in handling set point and disturbance changes. In the set point change test, the initial set point of each controlled variable is increased with a determined increment, as shown in Table 5. The test's objective is to see whether the controller can adjust the manipulated variable to the new set point, therefore minimizing the difference between the new value of the set point and the controlled variable.

In the disturbance change test, the value of the chosen disturbance is changed from its initial value with a determined percentage. The two disturbances in this test are dry biomass molar flow rate and dry biomass temperature. The percentage change of the dry biomass molar flow rate ranges from +5% to +100% and −5% to −10%. Meanwhile, the percentage change of the dry biomass temperature ranges from +50% to +100% and −50% to −100%. The test's objective is to see whether the controller can adjust the manipulated variable so that the controlled variable can return to its initial value, therefore minimizing the difference between the unchanged value of the set point and the controlled variable.

ISE is used to evaluate the controllers' performance quantitatively. A low ISE value is desired, meaning that the error between the values of the set point and the controlled variable is minimum, and the controller can adjust quickly to the changes. The percentage determines the plant's controllability, meaning to what extent the controllers can handle disturbance changes in the plant.

Table 5 shows the ISE values for the set point change test in both plants with capacities A and B. Figure 3 shows the graph results of the set point change test in both plants with capacities A and B. Overall, the controllers in both plants perform well. However, the ISE values of the plant with

Table 3: FOPDT models and tuning parameters for MPC.

Control system	FOPDT model	MPC tuning parameters			
		Step response length (SRL)	Prediction horizon (P)	Model horizon (M)	Sampling time (T)
Gasifier	$(2.97e^{-4.89s}/104.805s+1)$	20	20	2	5
SMR	$(0.041e^{-0.1s}/s+1)$	50	30	3	10
Cooler before WGS reactor	$(2.268e^{-2.858s}/14.505s+1)$	20	20	2	5

Table 4: FOPDT models and tuning parameters for the PI controller.

Control system	FOPDT model	PI controller tuning parameters	
		Controller gain (Kc)	Integral time (Ti)
Char combustor	$(1.84e^{-5.365s}/142.791s+1)$	5.200	0.745
Flue gas cooler	$(5.71e^{-2.645s}/13.431s+1)$	0.800	0.147

Table 5: ISE values for the set point change test in both plants with capacities A and B.

Controlled variables	Initial set point (°C)	Increment (°C)	New set point (°C)	ISE values	
				Capacity A	Capacity B
Temperature inside gasifier	800	+50	850	1,062.43	4,202.27
Temperature inside char combustor	850	+50	900	429.19	2,776.15
Temperature of "flue gas out" stream	100	+20	120	83.15	136.10
Temperature of "gas out SMR" stream	800	+50	850	2,087.61	2,799.45
Temperature of "gas to WGS" stream	150	+20	170	189.22	620.80

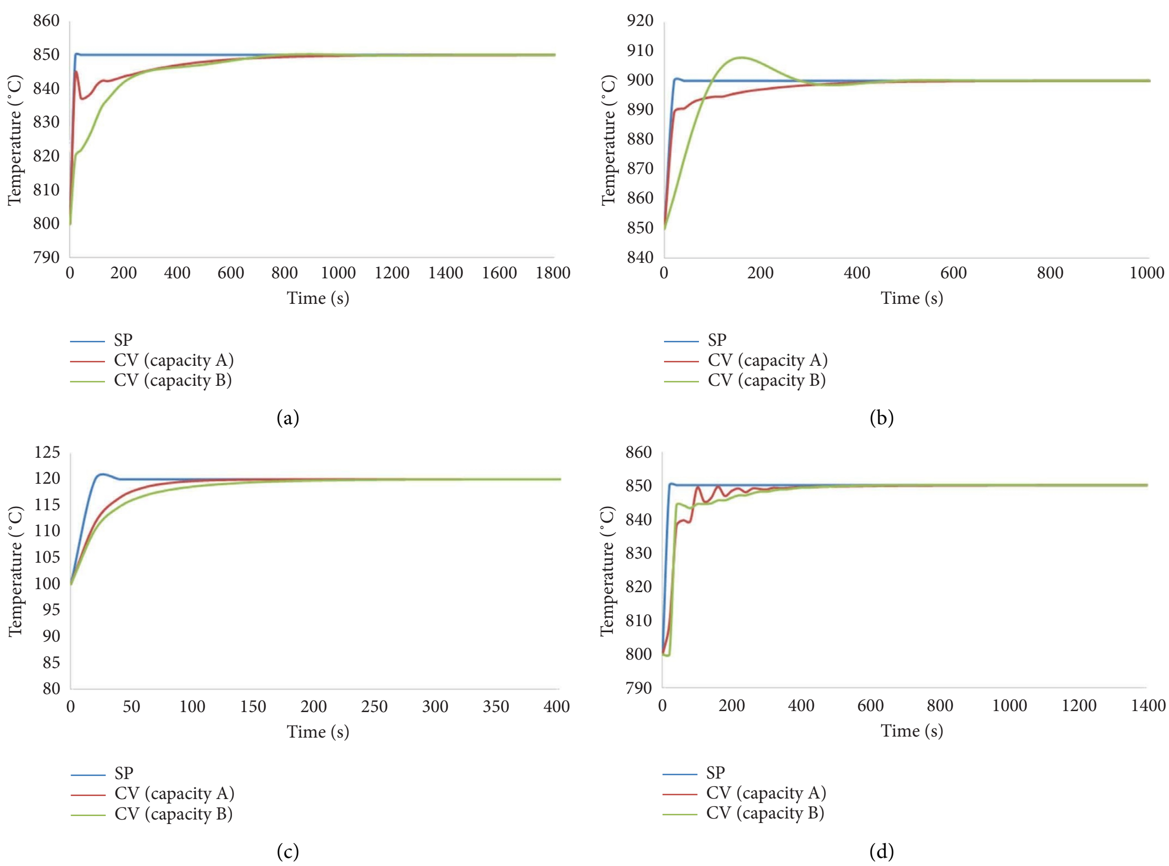
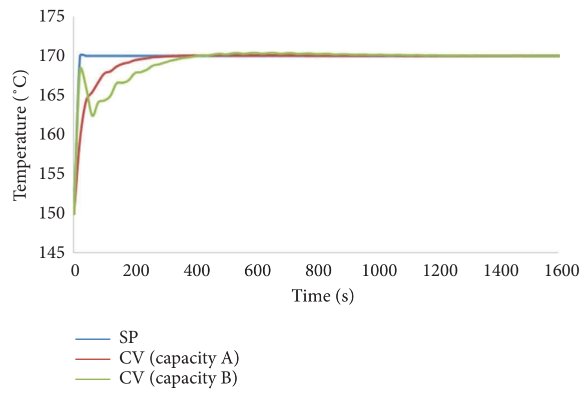


Figure 3: Continued.



(e)

Figure 3: Set point change test for plants with capacities A and B in (a) gasifier, (b) char combustor, (c) flue gas cooler, (d) SMR, and (e) cooler before WGS reactor.

Table 6: ISE values for the dry biomass molar flow rate change test for plant with capacity A.

Control systems	ISE values						
	+5%	+10%	+20%	+25%	+30%	−5%	−10%
Gasifier	13,251	16,899	21,474	38,061	-(Failed)	17,801	97,941
Char combustor	3,289	5,903	22,735	180,272	-(Failed)	3,734	-(Failed)
Flue gas cooler	1,174	1,806	6,912	607,827	-(Failed)	1,173	-(Failed)
SMR	7,405	11,487	34,866	104,564	-(Failed)	6,680	20,011
Cooler before WGS reactor	1,384	2,234	7,855	44,963	-(Failed)	1,366	3,721

Table 7: ISE values for the dry biomass molar flow rate change test for plant with capacity B.

Control systems	ISE values				
	+5%	+50%	+100%	−5%	−10%
Gasifier	3,424	148,432	532,494	3,668	-(Failed)
Char combustor	27.59	2,615	6,163	28,278	-(Failed)
Flue gas cooler	0.76	397.58	486	0.50	2.21
SMR	1,662	117,163	316,761	1,182	6,159
Cooler before WGS reactor	674.48	20,782	105,017	187.89	2,590

Table 8: ISE values for the dry biomass temperature change test for plant with capacity A.

Control systems	ISE values			
	+50%	+100%	−50%	−100%
Gasifier	5.72	22.80	5.26	19.83
Char combustor	0.24	1.10	0.44	0.93
Flue gas cooler	0.87	4.05	0.60	4.80
SMR	2.73	18.37	3.36	11.49
Cooler before WGS reactor	0.86	2.49	0.85	2.15

capacity B are larger than those of capacity A. This result means that a larger plant capacity is more challenging to control with the current controllers' tuning parameters.

Tables 6 and 7 show the ISE values for the dry biomass molar flow rate change test in plants with capacities A and B, respectively. The controllers in the plant with capacity A can handle disturbance only up to +25% and −5% from its initial value. Meanwhile, the controllers in the plant with capacity B can handle disturbance up to +100% and −5% from its initial value. Although the controllers can handle disturbance in the plant with capacity B, the ISE values are larger than those of capacity A. This is due to the ISE equation, where the difference between the set point and the controlled variable is squared. With the same disturbance percentage, the disturbance value in the plant with capacity B is larger than that of capacity A. A larger disturbance means that the error is larger, and the error is also squared, therefore increasing the ISE value. Based on these results, increasing factory

Table 9: ISE values for the dry biomass temperature change test for plant with capacity B.

Control systems	ISE values			
	+50%	+100%	−50%	−100%
Gasifier	26.21	104.56	22.40	75.50
Char combustor	0.26	0.95	0.17	0.68
Flue gas cooler	0.01	0.02	0.03	0.15
SMR	12.38	141.07	6.63	45.17
Cooler before WGS reactor	0.85	32.46	3.30	1.37

capacity must be accompanied by reidentifying the system because different capacities will affect the behavior of the processes within it. Next, the MPC and PI controller parameters must be readjusted so that they match the changed process behavior.

Tables 8 and 9 show the ISE values for the dry biomass temperature change test in plants with capacities A and B. Overall, the controllers in both plants perform well, where they can handle disturbance up to +100% and −100% from their initial value. The ISE values in both plants are also relatively smaller than those of the dry biomass molar flow rate change test, showing that the dry biomass temperature does not affect the system as much as the dry biomass molar flow rate.

4. Conclusion

This work proposed a plant-wide control structure design of a biohydrogen plant from biomass using a combination of MPC and PI controllers. MPC is used in the gasifier, SMR, and cooler before the WGS reactor, while the PI controller is used in the char combustor and flue gas cooler. Results show that with the same controller type and tuning parameters for both plants with capacities A and B, the controllers performed relatively well in handling set point and disturbance changes. In terms of the disturbance, the dry biomass molar flow rate affects the plant's controllability more significantly compared to the dry biomass temperature. However, with higher ISE values of the plant with capacity B, it is advisable to reidentify the system and retune the controllers if the plant capacity changes to optimize their performance. Further work can be done to improve steady-state simulations by adding more detailed unit operations and improving controller performance by applying multivariable model predictive control (MMPC) to account for interactions between variables in the plant or using a hybrid approach that combines the strengths of MPC and PI controllers as has been researched by the author himself [24, 25].

Data Availability

The data used to support the findings of this study are available from the authors on the following link: https://bit.ly/3uzlZGd.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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References

[1] T. Shinada, A. Nakayama, H. Okamura, and Y. Yasuno, "Recent progress in the synthesis of deuterated aldehyde," *Bulletin of the Chemical Society of Japan*, vol. 95, no. 10, pp. 1461–1473, 2022.

[2] A. Sumita and T. Ohwada, "Friedel-crafts-type acylation and amidation reactions in strong brønsted acid: taming superelectrophiles," *Molecules*, vol. 27, no. 18, p. 5984, 2022.

[3] J. Pelemo, F. L. Inambao, and E. I. Onuh, "Potential of used cooking oil as feedstock for hydroprocessing into hydrogenation derived renewable diesel: a review," *International Journal of Engineering Research and Technology*, vol. 13, no. 3, pp. 500–519, 2020.

[4] L. Yin, Q. Li, T. Wang, L. Liu, and W. Chen, "Real-time thermal Management of Open-Cathode PEMFC system based on maximum efficiency control strategy," *Asian Journal of Control*, vol. 21, no. 4, pp. 1796–1810, 2019.

[5] R. Kaur, P. Gera, M. K. Jha, and T. Bhaskar, "Thermochemical route for biohydrogen production," in *Biohydrogen*, pp. 187–218, Elsevier, Amsterdam, Netherlands, 2019.

[6] Ö. Tezer, N. Karabağ, A. Öngen, C. Ö. Çolpan, and A. Ayol, "Biomass gasification for sustainable energy production: a review," *International Journal of Hydrogen Energy*, vol. 47, no. 34, pp. 15419–15433, 2022.

[7] T. Lepage, M. Kammoun, Q. Schmetz, and A. Richel, "Biomass-to-hydrogen: a review of main routes production, processes evaluation and techno-economical assessment," *Biomass and Bioenergy*, vol. 144, Article ID 105920, 2021.

[8] P. Sampath, K. R. Reddy, K. R. Reddy et al., "Biohydrogen production from organic waste–a review," *Chemical Engineering and Technology*, vol. 43, no. 7, pp. 1240–1248, 2020.

[9] I. A. Budianta, F. Abqari, A. Cicilia, and Gerry, "Biohydrogen plant design from biomass," Plant Design Report, University of Indonesia, Depok, Indonesia, 2011.

[10] L. Cao, I. K. Yu, X. Xiong et al., "Biorenewable hydrogen production through biomass gasification: a review and future prospects," *Environmental Research*, vol. 186, Article ID 109547, 2020.

[11] Z. Yuan, B. Chen, and J. Zhao, "An overview on controllability analysis of chemical processes," *American Institute of Chemical Engineers Journal*, vol. 57, no. 5, pp. 1185–1201, 2011.

[12] F. Salma, "PI controller tuning of gasifier and char combustor in biohydrogen from biomass plant design," Bachelor's Thesis, University of Indonesia, Depok, Indonesia, 2013.

[13] A. Wahid and R. N. Nararya, “Optimization of control of gasification units and char combustor at biohydrogen plants from biomass using reidentification of predictive control models (in bahasa),” in *Proceedings of the Indonesian Chemical Engineering National Seminar V*, Yogyakarta, Indonesia, October 2015.
[14] A. Wahid and M. Iqbal, “Control of compressor and steam reformer in the design of a biohydrogen factory from biomass with PI controller (in bahasa),” *Sinergi*, vol. 20, no. 2, pp. 81–90, 2016.
[15] A. Wahid and H. Taqwallah, “Model predictive control based on system re-identification (MPC-SRI) to control bio-H2 production from biomass,” in *IOP Conference Series: Materials Science and Engineering*, Bali, Indonesia, July 2018.
[16] M. Adjisetya and A. Wahid, “Multivariable model predictive control to control bio-H_2 production from biomass,” *Chemical Engineering*, vol. 7, no. 1, p. 7, 2023.
[17] N. Afsi, S. Othman, T. Bakir, L. I. Costa, A. Sakly, and N. Sheibat-Othman, “Model predictive control for continuous lactide ring-opening polymerization processes,” *Asian Journal of Control*, vol. 23, no. 1, pp. 92–104, 2020.
[18] W. Doherty, A. Reynolds, and D. Kennedy, “Aspen plus simulation of biomass gasification in a steam blown dual fluidised bed,” in *Materials and Processes for Energy: Communicating Current Research and Technological Developments*, A. Méndez-Vilas, Ed., Formatex Research Centre, Norristown, PA, USA, 2013.
[19] A. Inayat, M. M. Ahmad, M. Mutalib, and M. K. Yunus, “Kinetic modeling of biomass steam gasification system for hydrogen production with CO2 adsorption,” in *Proceedings of International Conference for Technical Postgraduates*, Kula Lumpur, Malaysia, December 2009.
[20] M. Kano and M. Ogawa, “The state of the art in chemical process control in Japan: good practice and questionnaire survey,” *Journal of Process Control*, vol. 20, no. 9, pp. 969–982, 2010.
[21] E. F. Camacho and C. Bordons, *Model Predictive Control*, Springer Science and Business Media, Berlin, Germany, 2013.
[22] R. Shridhar and D. J. Cooper, “A tuning strategy for unconstrained multivariable model predictive control,” *Industrial and Engineering Chemistry Research*, vol. 37, no. 10, pp. 4003–4016, 1998.
[23] C. A. Smith and A. B. Corripio, *Principles and Practice of Automatic Process Control*, John Wiley and Sons, Inc, New York, NY, USA, 2nd edition, 1997.
[24] A. Wahid and A. Ahmad, “Min-max controller output configuration to improve multi-model predictive control when dealing with disturbance rejection,” *International Journal of Technology*, vol. 6, no. 3, pp. 504–515, 2015.
[25] A. Wahid and A. Ahmad, “Improved multi-model predictive control to reject very large disturbances on a distillation column,” *International Journal of Technology*, vol. 7, pp. 962–971, 2016.