



Open
Access

Automation of Bio-Hydrogen Gas Production in a Fed-Batch Microbial Electrolysis Cell Reactor by using Internal Model Control of Neural Network

Azwar^{1,*}, A Muslim¹, Mukhlisien¹, Jakfar¹, M. F. Zani²

¹ Chemical Engineering Department, Faculty of Engineering, University of Syiah Kuala, 23111 Banda Aceh, Indonesia

² Chemical and Petroleum Engineering, Faculty of Engineering & Built Environment, UCSI University, 56000 Kuala Lumpur, Malaysia

ARTICLE INFO

ABSTRACT

Article history:

Received 24 December 2019

Received in revised form 3 February 2020

Accepted 5 February 2020

Available online 18 March 2020

Microbial Electrolysis Cell (MEC) is an environmentally friendly technology for hydrogen production in which a bio-electrochemical process occurs with catalysts of microorganisms. The microorganisms oxidize all organic matters in a fed-batch MEC reactor of hydrogen gas production. The production of hydrogen electron exchange occurs continuously by rising the cathode potential. The amount of energy used in hydrogen gas production from organic matter is much less than the one from water by electrolysis. The MEC process is a complex and highly nonlinear because of the microbial interactions, and it makes the system difficult to optimally operate and control. Artificial Neural Networks (ANN) was used to model the MEC process, and it was reliable model with coefficient correlation of validation, R_2 being 0.915. To control the current and voltage of MEC, two controller of Proportional-Integral-Derivative Ziegler-Nichols (PID ZN) and Internal Model Control of Neural Network (IMC NN) were applied. The comparative study on both controllers with the controller output being in an optimal current and voltage to the MEC process was conducted in Matlab software. As the result, the IMC NN controllers provided the best control performance.

Keywords:

Microbial electrolysis cell; internal model control; hydrogen production

Copyright © 2020 PENERBIT AKADEMIA BARU - All rights reserved

1. Introduction

Microbial Electrolysis Cell (MEC) is an environmentally friendly technology for hydrogen production in which a bio-electrochemical process occurs with catalysts of microorganisms. The microorganisms can catalyze the oxidation and reduction reactions at the two electrodes. Process control is required in the MEC plant so that the process can continue to operate consistently, and increase the production rate of hydrogen gas to produce continuously [1-3]. The MEC current and voltage are two important variables that need to control at all times because the two variables are related directly to the production rate of hydrogen gas. The main difficulty encountered in controlling MEC system is how to determine the amount of applied voltage and current IMEC accurately because the condition of the process is very highly uncertain and nonlinear [4-6].

* Corresponding author.

E-mail address: azwar@che.unsyiah.ac.id (Azwar)

Recently, the uses of inverse neural network model in controlling various processes become popular. This is due to the ANN has the ability to accurately model a system, so it is used in designing process control systems using very precise modeling consideration. Direct inverse control is one the simplest form of inverse models acts as a controller to compute the exact output parameters and control the input values obtained can be achieved in accordance with the desired target. In this case, the network inverse model is then used as a control strategy and with a certain set point value is then fed to the network together by using past and outputs the data of a process to predict the desired input current [7-9].

Several studies have been conducted for applying model-based optimization and control techniques of MEC to maximize the hydrogen production. Optimal production of biohydrogen gas was studied in a controlled batch reactor system [2, 6]. A cluster of artificial neural networks was used to model biohydrogen generation in MEC [10,11]. Modeling, optimization and control of the MEC in a fed-batch reactor has been studied [12]. Artificial neural networks (ANN) were used for modeling of biohydrogen production [13,14]. Currently, there is no study reported on Artificial Neural Networks (ANN) by using Internal Model Control of Neural Network (IMC NN) controller for the MEC.

Therefore, the objective of current study was to model the MEC process using the ANN in which the MEC process between input and output variables was solve using the ANN. The MEC process model was validated using training data from previous study to determine the reliability of the MEC models. The MEC process was controlled using Proportional-Integral-Derivative Ziegler-Nichols (PID ZN) and the IMC NN controllers in Matlab software. The PID ZN and IMC NN controller outputs were compared to get a better performance of controller.

2. Method

2.1 The MEC Model Development

The MEC models in the previous study [8] were used in the current study with some modifications. The interesting phenomena in the MEC model are competition between anodophilic (x_a), acetoclastic (x_m) and hydrogenotrophic (x_h) microorganisms to consume the substrate (S) in the anode compartment. Competition among the microbial population will have an effect on the performance of MEC reactor. Some of the data parameters [15] were used for the current simulation study. The dynamic mass balance equations in the MEC reactor system were given as follows:

$$\frac{dS}{dt} = -q_{max,a} \frac{S}{K_{S,a}+S} \frac{M_{ox}}{K_M+M_{ox}} x_a - q_{max,m} \frac{S}{K_{S,m}+S} \quad (1)$$

$$\frac{dx_a}{dt} = \mu_{max,a} \frac{S}{K_{S,a}+S} \frac{M_{ox}}{K_M+M_{ox}} x_a - K_{d,a} x_a - \alpha_1 x_a \quad (2)$$

$$\frac{dx_m}{dt} = \mu_{max,m} \frac{S}{K_{S,m}+S} - K_{d,m} x_m - \alpha_1 x_m \quad (3)$$

$$\frac{dx_h}{dt} = \mu_{max,h} \frac{H_2}{K_h+H_2} - K_{d,h} x_h - \alpha_2 x_h \quad (4)$$

$$\frac{dM_{ox}}{dt} = \frac{\gamma}{V_r x_a} \frac{I_{MEC}}{mF} - Y_M q_{max,a} \frac{S}{K_{A,a}+S} \frac{M_{ox}}{K_M+M_{ox}} \quad (5)$$

$$Q_{H_2} = Y_{H_2} \left(\frac{I_{MEC} RT}{mF P} \right) - Y_h \mu_h x_h V_r \quad (6)$$

where S is the concentration of substrate; x_a , x_h and x_m , are the concentration of the anodophilic, hydrogenotrophic and acetoclastic microorganisms, respectively; M_{ox} is the oxidized mediator fraction per electricigenic microorganism; and Q_{H_2} is the production rate of hydrogen (mL/day). The detailed operation and parameter constants, characterization used in the current study are listed in Table 1.

Table 1
 The values of operation and parameter constants, characterization

Symbols	Description	Value
$\mu_{max,m}$	The maximum acetoclastic methanogenic microorganism growth rate	0.3 d^{-1}
$\mu_{max,a}$	The maximum anodophilic microorganism growth rate	1.97 d^{-1}
$\mu_{max,h}$	The maximum hydrogenotrophic microorganism growth rate	0.5 d^{-1}
$q_{max,a}$	The maximum anodophilic microorganism reaction rate	$13.14 \text{ mg-A mg}^{-1} \text{ d}^{-1}$
$q_{max,m}$	The maximum acetoclastic methanogenic reaction rate	$14.12 \text{ mg-A mg}^{-1} \text{ d}^{-1}$
$K_{S,a}$	The half-rate (Monod) constant of the anodophilic	20 mg-A L^{-1} or mg-M L^{-1}
$K_{S,m}$	The half-rate (Monod) constant of the acetoclastic methanogenic microorganism	80 mg-A L^{-1} or mg-M L^{-1}
K_M	Mediator half-rate constant	0.01 mg-M L^{-1}
K_h	Half-rate constant	0.001 mg L^{-1}
Y_{H_2}	The dimensionless cathode efficiency	0.9 [dimensionless]
Y_h	The yield rate of hydrogen consumption by methanogenic	$0.05 \text{ [ml-H}_2 \text{ mg-x}^{-1} \text{ d}^{-1}]$
m	The electrons transferred/mol of H_2 number	$2 \text{ mol-e}^- \text{ mol-H}_2^{-1}$
P	The pressure of anode compartment	1 atm
M_{ox}	The fraction of oxidized mediator	$800 \text{ mg-M mg-x}^{-1}$
β	The transfer coefficient of reduction, or oxidation	0.5 [dimensionless]
$A_{sur,A}$	The anode surface area	0.01 m^2
i_0	The exchange current density in reference conditions	0.005 A m^{-2}
E_{CEF}	The counter-electromotive force for the MEC	-0.35 V
$E_{applied}$	The electrode potentials	0.80 V
$K_{d,a}$	The anodophilic microorganism decay rate	0.04 d^{-1}
$K_{d,m}$	The acetoclastic methanogenic microorganism decay rate	0.01 d^{-1}
$K_{d,h}$	The hydrogenotrophic microorganism decay rate	0.01 d^{-1}
Y_M	The oxidized mediator yield	$34.85 \text{ mg-M mg-A}^{-1}$
γ	The molar mass of mediator	$663400 \text{ mg-M mol}_{med}^{-1}$
V_r	The volume of anodic compartment	10 l

Some of the control strategy has been applied to control the reactor MEC as adaptive PID controller [16]. However, the conventional control methods cannot provide good damping performance, so that the necessary design Internal Model Control (IMC) as one of the control strategies. Development of control strategy is expected to provide satisfactory performance in the MEC system. IMC design is very suitable for the conditions of the linear process model and nonlinear. IMC control models can be applied in bioprocess systems because it has high durability and performance is satisfactory. However, the performance of the IMC controller will be less stable when applied to nonlinear processes with various operating conditions. IMC-Neural network is an alternative solution and controller design for the open-loop system and is one of the advanced control systems based tuning method that has a high programming. Although in practice this method is still very rarely applied among industry.

3. Results and Discussion

3.1 Training Data and The MEC Model Validation

One alternative approach is to develop black-box models (neural network) from either the data collection process of industrial or experimental work. Data nonlinear dynamics of the process of training the NN results were used as models of IMC, while the other NN training outcome data are used to study the dynamics of the process upside down and used as a nonlinear IMC controller [17]. IMC algorithm when combined with neural network control method is able to adapt and improve the performance of the IMC, so this idea has been widely used in a variety of disciplines. In this study, the application of neural network neural network controller was adopted in the design of IMC NN controller.

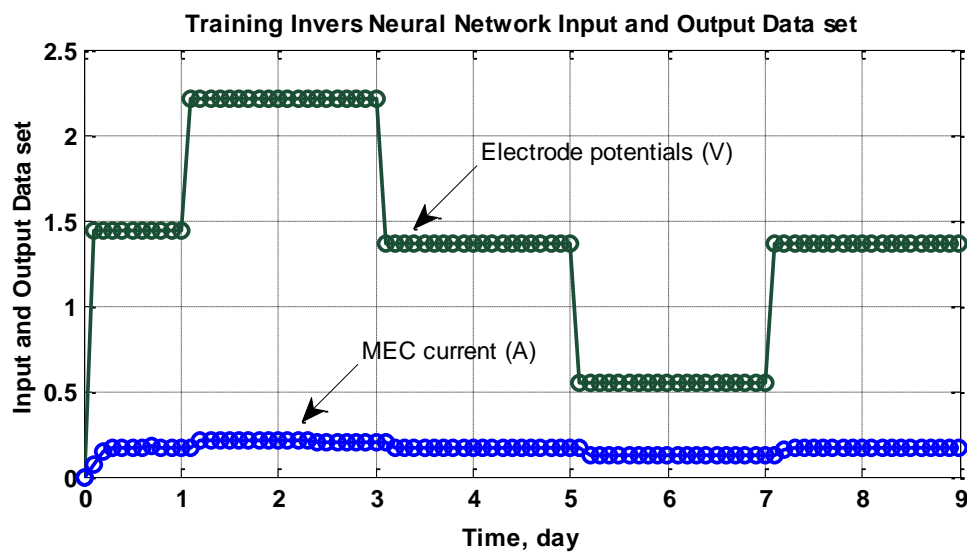


Fig. 1. Training data for the neural network in the simulation model

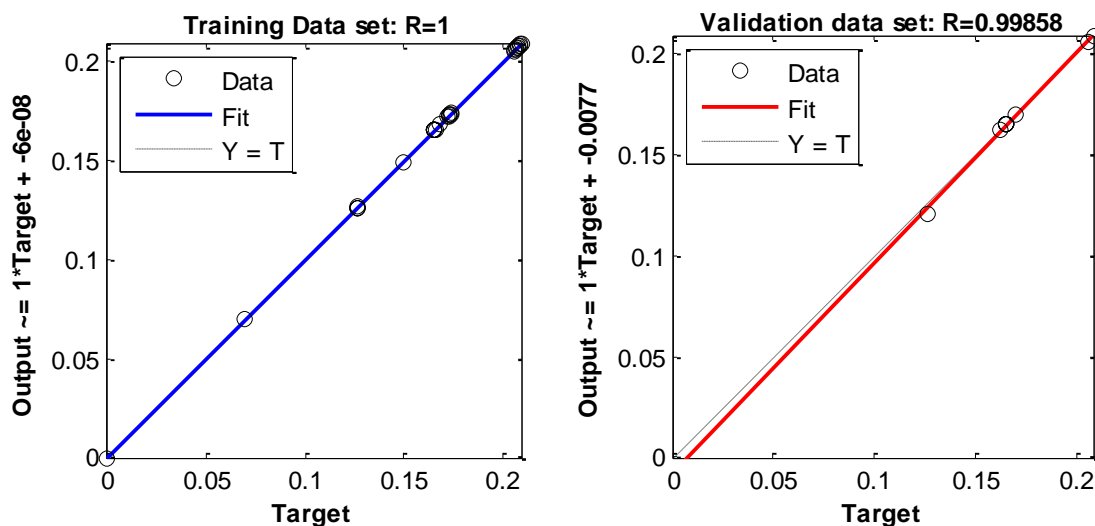


Fig. 2. Comparison of the training and validation data set of neural network model

Training data for the neural network in the simulation model was determined by solving the ordinary differential equations (ODE). It governs the sequencing batch reactor as discussed in the

previous chapter. Two sets of other training data were used for validation of neural network models. To improve system identification, the three training data sets [17] were switched between the two sets of other training data. The training data for the neural network in the simulation model is shown in Figure 1 whereas the unit for electrode potential and MEC current is V (Volt) and A (Ampere), respectively. Meanwhile, the validation of neural network model of the MEC using the five sets of training data is shown in Figure 2, whereas the neural network model was reliable to present the MEC process with correlation coefficient being 0.915.

3.2 The PID ZN and IMC NN Controllers' Performance for Setpoint Change

A comparison of the PID ZN and IMC NN controllers' performance for multiple setpoint tracking of electrode potential and MEC current is shown in Figure 3. Both controllers performed well, and managing the MEC process to track the given set point changes was successful. The MEC process output controlled at around approximately 0.11, 0.16 and 0.20 A. As can be seen in Figure 3, the IMC NN controller's performance was better in tracking the set-point change compared to the PID ZN. The IMC NN controller's response was faster than the PID ZN controller's response in tracking the set-point for the five set point changes. The IMC NN controller's response was also more stable than the PID ZN controller's response. Moreover, the IMC NN controller was able to give offset free response.

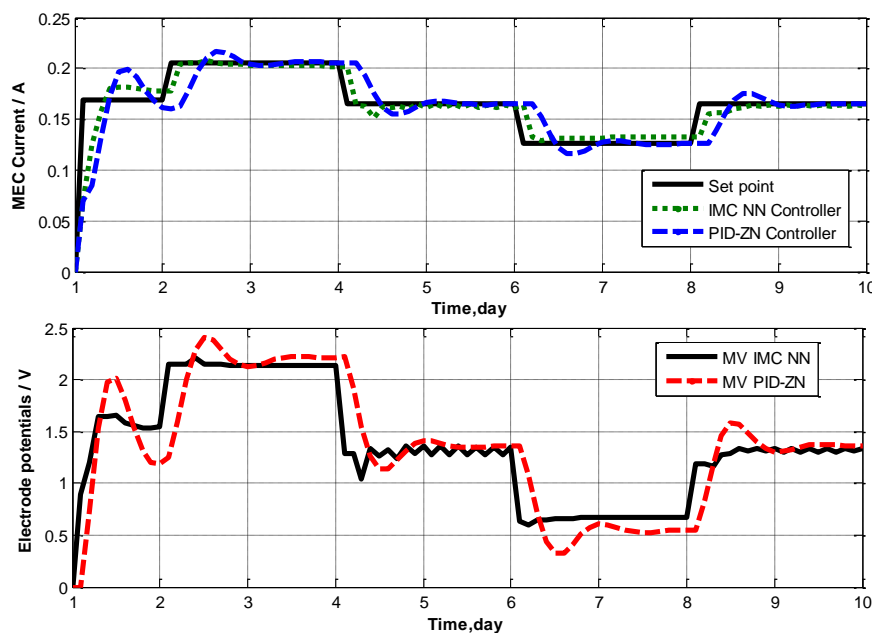


Fig. 3. Comparison of the PID ZN and IMC NN controllers performance for setpoint change

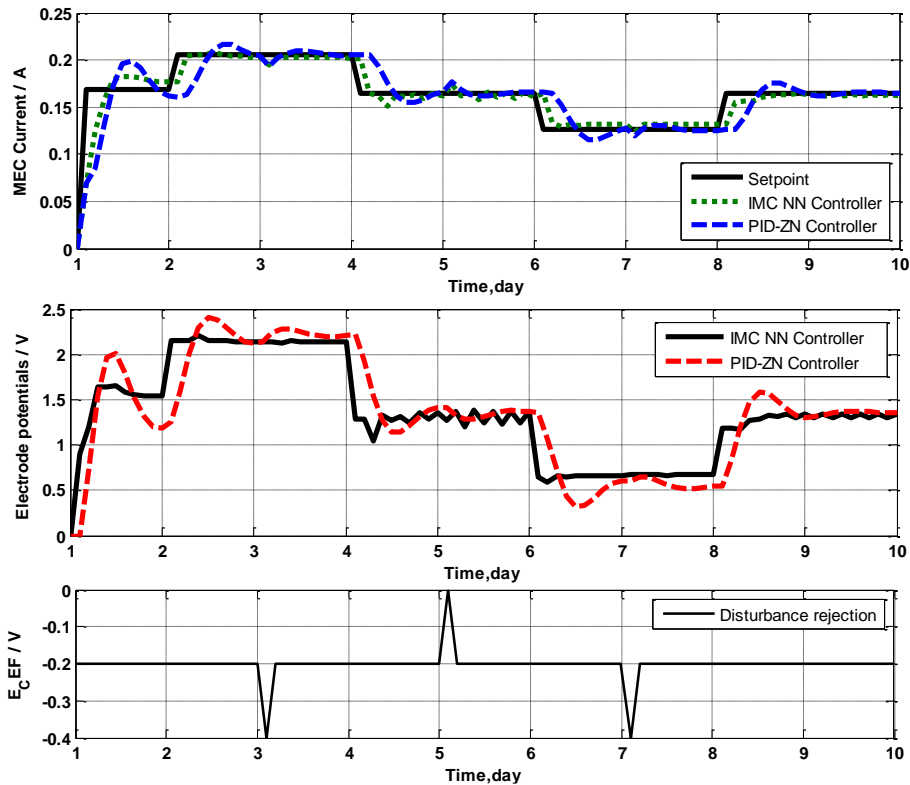


Fig. 4. Comparison of the PID ZN and IMC NN controllers performance for disturbance rejection

3.3 The PID ZN and IMC NN Controllers' Performance for Disturbance Rejection

Figure 4 shows the PID ZN and IMC NN controllers' performance for tracking set-point changes with the injected disturbances in the system. The disturbances rejection test was intended to determine the effect of disturbances given to the system and to see the controller's ability to reject it. In this test, the disturbance to the system which included the change of the counter-electromotive force (V) by range -0.2 V to 0.0 V and -0.2 V to -0.4 V from the initial nominal operating condition of the plant. The results show that the controller was able to bring back the MEC current to the set-point in a short time with minimal overshoot and fluctuations. Overall, the IMC NN controller's performance was better in tracking the set-point changes with the injected disturbances compared to the PID ZN.

3.4 The PID ZN and IMC NN Controllers' Performance for Measurement Noise

The random noisy ($u(k) \neq 0$) which was added to nonlinear system given by the equation added to the MEC system. The noise level of a process can be calculated by the equation Signal-to-Noise Ratio (SNR) as follows:

$$SNR = \frac{\sum_{k=1}^N (y(k) - \bar{y})^2}{\sum_{k=1}^N (v(k) - \bar{v})^2} \quad (7)$$

Where \bar{y} and \bar{v} are respectively the output average value and noise value. Figure 5 shows the performance of the PID ZN and IMC NN controllers under nominal operating conditions when the measurement of the MEC process output was corrupted by noise. In this test, the MEC process output

was corrupted by 10% noises and the controller action is able to handle the noises although the process is very fluctuating.

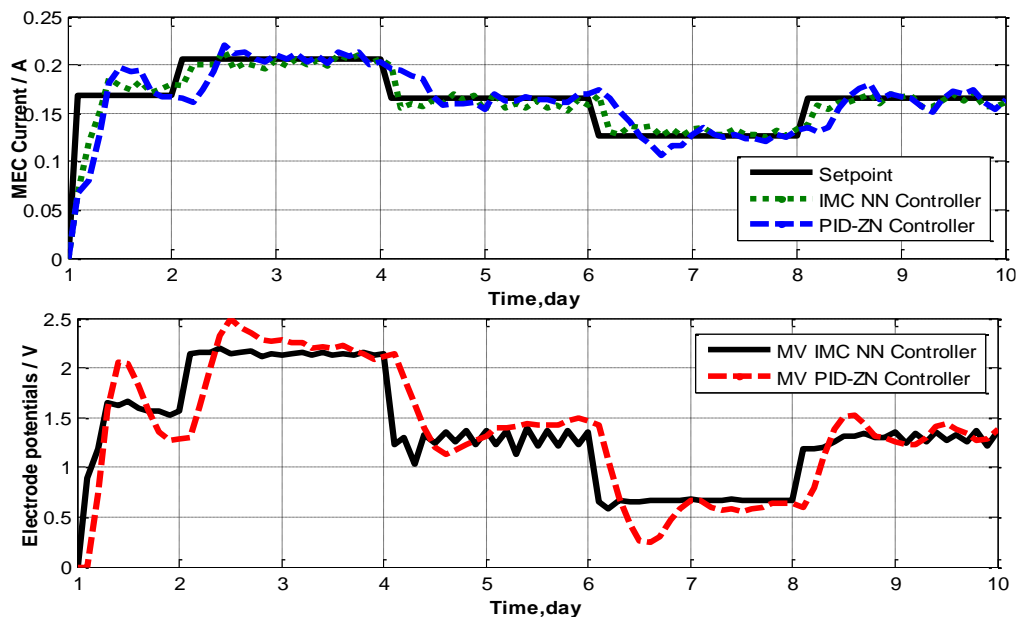


Fig. 5. Comparison of the PID ZN and IMC NN controllers performance for measurement noise

A comparison of the PID ZN and IMC NN controllers' performance for measurement noise is shown in Figure 5. The disturbance and noise introduced in the system simultaneously throughout the process to observe the performance of the controller and phenomenon of the process. If observed carefully there were some shortcomings obtained from the controller such action adaptation worked slowly, the rise time or settling time of the process response was rather long. Generally, although the disturbance or noise was given to the process, the controller was able to track the set-point changes and the controller was able to follow the time varying characteristic of the process response

4. Conclusions

In this work, the ANN was used to model the MEC process in a fed-batch MEC reactor for hydrogen gas production. The ANN model was reliable to present the MEC process with correlation coefficient of validation being 0.915. Two schemes including the ANN were investigated to control the current and voltage of the MEC process, which were the PID ZN and IMC NN controllers. A comparative study has been conducted for the production of hydrogen gas under optimal condition. The MEC process output was based on optimal voltage and current to the MEC system. Various simulation studies involving set-point tracking for set-point change, disturbance rejection and measurement noise had been evaluated using the PID ZN and IMC NN controllers. The comparison of control performance between showed that the IMC NN controllers provided the best control performance.

Acknowledgement

This research was funded by Syiah Kuala University, Ministry of Research, Technology and Higher Education (Scopus H-Index Based Research, No. 523 / UN11 / SPK / PNPB / 2019).

References

- [1] Azwara, Yahya, Ahmad Khairi Abdul-Wahabb, and Mohamed Azlan Hussaina. "Optimal production of biohydrogen gas via Microbial Electrolysis cells (MEC) in a controlled batch reactor system." *CHEMICAL ENGINEERING* 32 (2013): 727-732.
- [2] Azwar, M. Y., M. A. Hussain, and A. K. Abdul-Wahab. "Development of biohydrogen production by photobiological, fermentation and electrochemical processes: a review." *Renewable and Sustainable Energy Reviews* 31 (2014): 158-173.
- [3] Chen, Jingwei, Wenwen Xu, Xiaomin Wu, E. Jiaqiang, Na Lu, Taosheng Wang, and Hongyan Zuo. "System development and environmental performance analysis of a pilot scale microbial electrolysis cell for hydrogen production using urban wastewater." *Energy Conversion and Management* 193 (2019): 52-63.
- [4] Zhang, Lei, Yong-Zhong Wang, Tiantao Zhao, and Tengfei Xu. "Hydrogen production from simultaneous saccharification and fermentation of lignocellulosic materials in a dual-chamber microbial electrolysis cell." *International Journal of Hydrogen Energy* 44, no. 57 (2019): 30024-30030.
- [5] Paz-Mireles, Claudia L., Elías Razo-Flores, Gabriel Trejo, and Bibiana Cercado. "Inhibitory effect of ethanol on the experimental electrical charge and hydrogen production in microbial electrolysis cells (MECs)." *Journal of Electroanalytical Chemistry* 835 (2019): 106-113.
- [6] Lewis, Alex J., and Abhijeet P. Borole. "Microbial electrolysis cells using complex substrates achieve high performance via continuous feeding-based control of reactor concentrations and community structure." *Applied energy* 240 (2019): 608-616.
- [7] Kumar, Munna, Durga Prasad, Balendu Shekher Giri, and Ram Sharan Singh. "Temperature control of fermentation bioreactor for ethanol production using IMC-PID controller." *Biotechnology Reports* 22 (2019): e00319.
- [8] Pachauri, Nikhil, Asha Rani, and Vijander Singh. "Bioreactor temperature control using modified fractional order IMC-PID for ethanol production." *Chemical engineering research and design* 122 (2017): 97-112.
- [9] Ramli, Nasser Mohamed, Mohd Azlan Hussain, and Badrul Mohamed Jan. "Multivariable control of a debutanizer column using equation based artificial neural network model inverse control strategies." *Neurocomputing* 194 (2016): 135-150.
- [10] Abdul-Wahab, A. K., M. A. Hussain, and R. Omar. "Development of PARS-EX pilot plant to study control strategies." *Control Engineering Practice* 17, no. 10 (2009): 1220-1233.
- [11] Hussain, M. A., Jarinah Mohd Ali, and M. J. H. Khan. "Neural network inverse model control strategy: discrete-time stability analysis for relative order two systems." In *Abstract and Applied Analysis*, vol. 2014. Hindawi, 2014: 1-11.
- [12] Sewsynker, Yeshona, Evariste Bosco Gueguim Kana, and Agbaje Lateef. "Modelling of biohydrogen generation in microbial electrolysis cells (MECs) using a committee of artificial neural networks (ANNs)." *Biotechnology & Biotechnological Equipment* 29, no. 6 (2015): 1208-1215.
- [13] Yahya, Azwar Muhammad, Mohd Azlan Hussain, and Ahmad Khairi Abdul Wahab. "Modeling, optimization, and control of microbial electrolysis cells in a fed-batch reactor for production of renewable biohydrogen gas." *International Journal of Energy Research* 39, no. 4 (2015): 557-572.
- [14] Nasr, Noha, Hisham Hafez, M. Hesham El Naggar, and George Nakhla. "Application of artificial neural networks for modeling of biohydrogen production." *International Journal of Hydrogen Energy* 38, no. 8 (2013): 3189-3195.
- [15] Pinto, R. P., B. Srinivasan, A. Escapa, and B. Tartakovsky. "Multi-population model of a microbial electrolysis cell." *Environmental science & technology* 45, no. 11 (2011): 5039-5046.
- [16] Kansha, Yasuki, Li Jia, and Min-Sen Chiu. "Adaptive IMC controller design using linear multiple models." *Journal of the Taiwan Institute of Chemical Engineers* 41, no. 4 (2010): 446-452.
- [17] Mujtaba, Iqbal M. Application of neural networks and other learning technologies in process engineering. World Scientific, 2001.