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A Comparative study between Neural Networks (NN)-based and Adaptive-PID Controllers for the Optimal Bio-Hydrogen Gas Production in Microbial Electrolysis Cell Reactor

M.Y. Azwar[a,b], M.A. Hussain[b] , A.K. Abdul Wahab[c] and M.F. Zanil[d]

[a]*Chemical Engineering Department, Faculty of Engineering, University of Syiah Kuala, 23111 Banda Aceh, Indonesia*
[b]*Chemical Engineering Department, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia.*
[c]*Biomedical Engineering Department, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia.*
[d]*Chemical and Petroleum Engineering, Faculty of Engineering & Built Environment, UCSI University, 56000 Kuala Lumpur, Malaysia.*

Abstract

The main challenge of the hydrogen production study for the MEC reactor is to obtain a good automatic control system due to the nonlinearity and complexity of the microbial interactions. To address this issue an integrated approach involving process modeling, optimization and advanced control has to be implemented. This work focus on the controller's performance in the control system; neural network (NN)-based and Adaptive-PID controllers. The study has been carried out under optimal condition for the production of bio-hydrogen gas wherein the controller output are based on the correlation of the optimal current and voltage to the MEC. A Ziegler–Nichols tuning method and an adaptive gain technique have been used to design the PID controller, while the neural network controller has been designed from the inverse response of the MEC neural network model.

Keywords: **B**io-hydrogen gas, microbial electrolysis cell, neural network-based controller, adaptive-PID controller.

1. Introduction

Microbial electrolysis cells (MEC) is part of the microbial electrochemical cell technology which is one of the renewable energy alternatives today. MEC operation is based on the fundamental of a bio-electrochemical process and is a promising renewable energy technology that produce hydrogen gas. Anodophilic microorganisms in the anaerobic MEC bioreactor is capable of oxidizing substrates containing organic materials in the cell compartment into electrical energy. Anodophilic microorganisms is able to break the organic material and wastewater that has been diluted at low concentrations of organic compounds. In the MEC system, due to the addition of voltage into the cathode of the anaerobic-bioreactor, the reaction between protons and electrons occur leading to the formation of hydrogen gas (Rozendal et al., 2006 and Logan, 2010).

Bio-hydrogen production process in the MEC is a nonlinear and highly complex system due to microbial interaction. Its complexity makes MEC system difficult to operate and control under optimal conditions. However, these problems can be alleviated using an integrated process system engineering approach, which involves process modelling, optimization and control simultaneously. Artificial neural network (ANN) is an effective technique and a powerful tools to be used in modeling of complex processes and unknown systems. ANNs are able to cope with non-linear process between input and output variables without the requirement of explicit mathematical representation. In process control system, ANNs have been widely used when conventional control techniques did not give good performance (Wang and Wan, 2009; Sridevi et al., 2014).

A novel application of using advanced controller including neural network with adaptive PID has been carried out in the MEC bioreactor. This type of controller has not been reported yet in any MEC reactor application especially on control system performance investigation. This study focuses on the performance of the advanced controller in a feedback control system for controlling the MEC reactor. The comparative study including PID, Adaptive-PID, and neural network model-based controller has been discussed. The controller's performance assessment for regulator and servo cases has been investigated. The analysis was conducted in the presence of noise to imitate the real environment in the process system.

2. MEC Model

This section presents a model for the MEC in a fed-batch reactor, which is a modified model from Pinto et al. (2010). The mathematical models presented here aim to simulate the competition of microbial in the MEC. The model represents competition between anodophilic, acetoclastic methanogenic and hydrogenotrophic methanogenic microorganisms for the substrate (Pinto et al., 2011). The dynamic mass balance equations in the reactor system are given below as follows:

$$\frac{dS}{dt} = -q_{max,a}\frac{S}{K_{S,a}+S}\frac{M_{Ox}}{K_M+M_{Ox}}x_a - q_{max,m}\frac{S}{K_{S,m}+S} \tag{1}$$

$$\frac{dx_a}{dt} = \mu_{max,a}\frac{S}{K_{A,a}+S}\frac{M_{Ox}}{K_M+M_{Ox}}x_a - K_{d,a}x_a - \alpha_1 x_a \tag{2}$$

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

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

$$Q_{H_2} = Y_{H_2}\left(\frac{I_{MEC}}{mF}\frac{RT}{P}\right) - Y_h\mu_h x_h V_r \tag{5}$$

$$-E_{applied} = E_{CEF} - \eta_{ohm} - \eta_{conc} - \eta_{act} \tag{6}$$

$$I_{MEC} = \frac{E_{CEF}+E_{applied}-\frac{RT}{mF}ln\left(\frac{M_{Total}}{M_{red}}\right)-\eta_{act,C}(I_{MEC})}{R_{int}} \tag{7}$$

where S is the substrate concentration; x_a, x_m, and x_h are the concentration of the anodophilic, acetoclastic, and hydrogenotrophic microorganisms, respectively; Q_{H_2} is the hydrogen production rate (mL/day); $E_{applied}$ is the electrode potentials (V) and I_{MEC} is the MEC current (A).

3. Controller Design

3.1 Adaptive-PID controllers

Adaptive-PID controller is able to control the system dynamics in the event of a non-nominal process condition. Consider the MEC process model given by:

$$y(k) = A_1x(k-1) + A_2x(k-2) + [B_1u(k-1) + B_2u(k-2)]u(k) \tag{8}$$

For the case at nominal condition, A_i and B_i for i = 1, 2, and 3 are known through least-square regression technique. The control action is derived as:

$$u(k) = \frac{K_P\left[e(k)+\frac{1}{\tau_I}\int_0^t e(k)dt+\tau_D\frac{d}{dt}e(k)\right]- A_1x(k-1)+ A_2x(k-2)}{B_1u(k-1)+ B_2u(k-2)} \tag{9}$$

The block diagrams show the method of adaptive PID as in Figure 1.

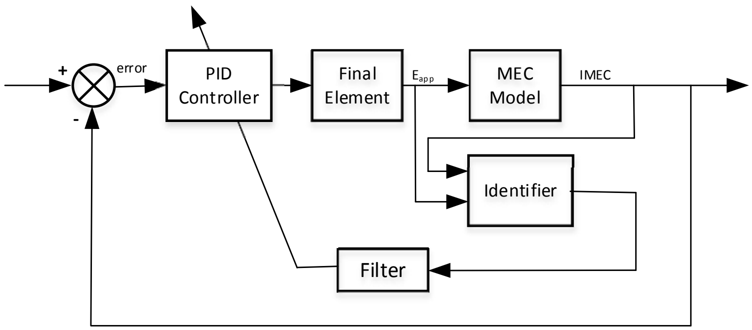

Figure 1. Block diagram of PID-Adaptive gain closed loop design

3.2 Neural network controllers

The NNs controller concept refers to the inverse response of the open loop MEC process. The diagram of the controller and control strategy are shown in Figure 2. In this case, the neural network model is trained to predict the required manipulated variable, Electrode potential $(E_{applied})$ with the given desire of set-point, MEC current (I_{MEC}) .

3.3 Training and Forward Modelling

The forward NNs modeling refers to the open loop response of the MEC process. The networks have been trained to obtain the weights of every node and map the dynamic response of the input-output open loop dataset. The dataset is collected through a moving window approach. The model is made of 14 input nodes; the input nodes consist of data for substrate (S), anodophilic microorganisms (x_a), acetoclastic microorganism (x_m), ammonium nitrogen (x_h), oxidized mediator fraction (M_{ox}), MEC current (I_{MEC}) and the single output node is electrode potentials ($E_{applied}$).

3.4 Inverse modelling and NNs Controller

However, inverse NNs modelling are the opposite of open loop response which can be used as an ideal controller inside the control system. Inverse model is designed similar to the forward modeling approach. The 14 inputs node and single manipulated output variable has been selected; $S_{(t)}$, $S_{(t-1)}$; x_a i.e. $x_{a(t)}$, $x_{a(t-1)}$; x_m i.e. $x_{m(t)}$, $x_{m(t-1)}$; x_h i.e. $x_{h(t)}$, $x_{h(t-1)}$; M_{ox} i.e. $M_{ox(t)}$, $M_{ox(t-1)}$; I_{MEC} i.e. $I_{MEC(t)}$, $I_{MEC(t+1)}$, $I_{MEC(t-1)}$ and output node is the electrode potentials ($E_{applied}$) respectively. The detail network architecture for NNs controller development can refer to Hussain and Mujtaba, 2001.

4. Neural Network Controller Scheme

4.1 Multiple set-point tracking study

In this work, we perform multiple set-point tracking study when the I_{MEC} current has been maintained at the optimal operation value of 0.16 A. Figure 2 shows the comparison of conventional PID, adaptive-PID, and neural networks model-based controllers. Figure 2 shows good tracking performance for neural network controllers. The controlled variable follows the given set points and the result show reasonable control performance. Neural networks controller gives no overshoot compare to the others controller. However, PID controller shows the largest overshoot and longest settling time which indicates the conventional controller is not suitable to be applied in the MEC process. Meanwhile, adaptive-PID controller shows an adaptation progress which the overshoot and settling time performance are improving over time.

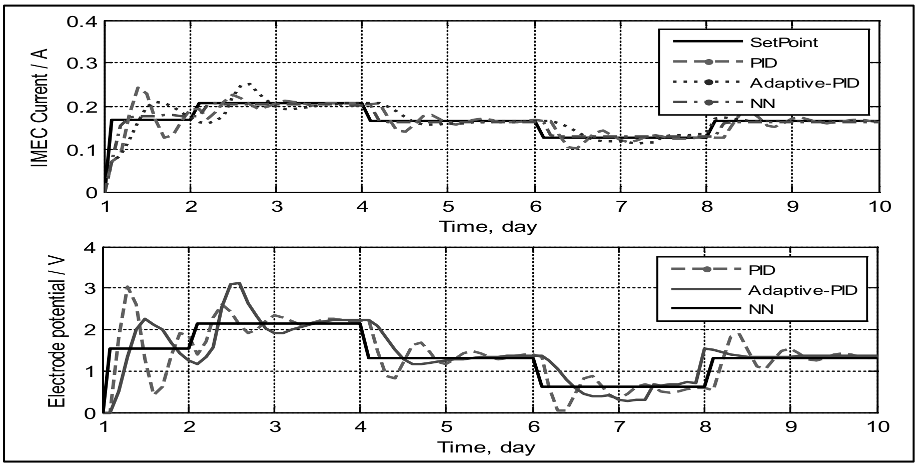

Figure 2. Comparison of controlling for set point tracking

The neural network model-based controller can provide better control for the MEC system compared with the conventional PID and adaptive-PID controller.

4.2 Disturbance rejection

Figure 3 shows the control performance comparison of the conventional PID, adaptive-PID and neural network model-based controllers for servo and regulator cases. The disturbance has been generated by changing the counter-electromotive force from the nominal value (from 0.15 V to 0.35 V). Based on Figure 3, all controllers show good performance but the neural network model-based controller is better compare to the rest. However, small offset has been observed from NNs controller and this offset can be compensated by introducing integral effect inside the NNs structure.

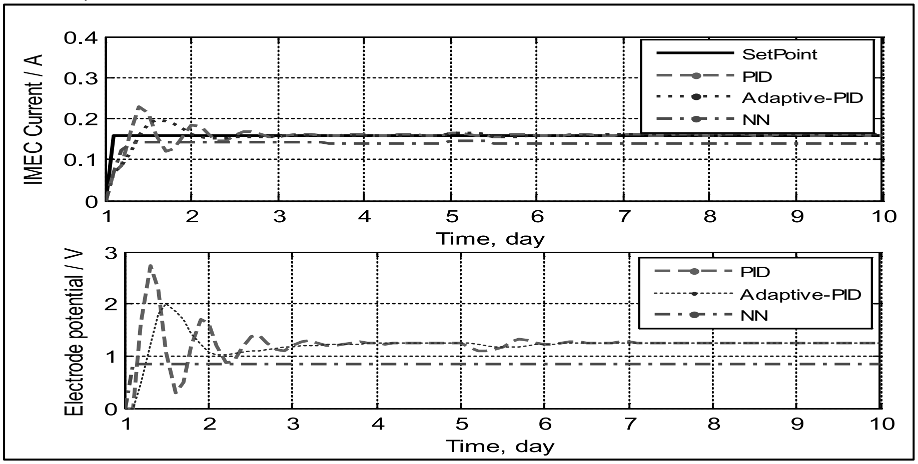

Figure 3. Control performance under disturnabce rejection

4.3 Measurement noise

Figure 4 shows the controller performance with the presence of noise under nominal operating conditions. The noises source are assumed from measurement element inside MEC system. NNs controller responses are more stable with less oscillations compared to the conventional PID and adaptive-PID gain controllers.

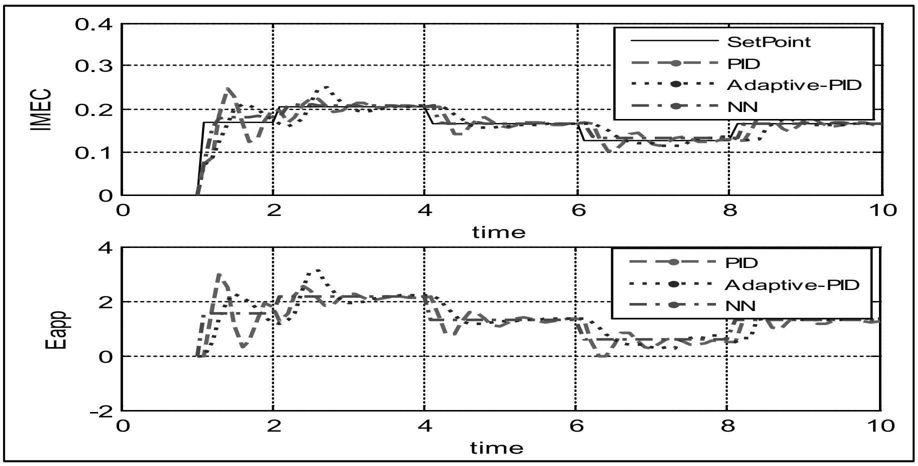

Figure 4. Control performance with measurement noise

In summary, the MEC reactor can be controlled to give an optimum current set-point (simultaneously an optimal hydrogen production rate) using the conventional PID, adaptive-PID and neural network model-based controller. However, the NNs model-based controller is able to give more robust performance compared to this PID and adaptive-PID gain controllers.

5. Conclusions

In this paper, a novel approach for implementing an advanced (NNs) controller for MEC system has been carried out. A comparative study for MEC with various simulation cases involving multiple set-point, disturbance rejection and noise measurement has been achieved. The NNs controller gives fast settling time response, less overshoots, and minimal offset. Thus, NNs controller performances surpass the other types of controller and performs better in all the simulation cases.

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