The Biomass Control in a Biochemical Reactor Process Using a Single Neuron PID Controller

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Abstract:

A novel procedure to design a hybrid intelligent Single Neuron PID controller (SNPID) for the continuous biochemical reactor has been proposed in this paper. High levels of nonlinearity are observed in the biochemical reactor process because of the continuous change of the fermentation process parameters. So, in order to attain high steady-state productivity, a strong hybrid PID controller is designed for the biochemical reactor. By regulating the (inlet) dilution rate, the proposed controller effectively controls the biomass concentration in the bioreactor at an unstable steady state. The proposed hybrid intelligent Single Neuron PID controller takes the closed loop error as the input and the dilution rate as its output. The closed loop performance of the SNPID controller is compared with that of a PID controller under disturbance conditions. Simulation results show that the proposed controller outperforms the PID in all cases.

Keywords: PID controller; Single Neuron, Continuous Biochemical reactor.

1. Introduction

A biochemical reactor is a system used to perform biological reactions with the help of microorganisms, enzymes, or mammalian cells. The purpose of a biochemical reactor is to provide optimal conditions for microorganisms or enzymes to carry out their biological functions. The biochemical reactor can be used to produce a variety of products such as antibiotics, enzymes, biopolymers, biofuels, and other useful biomolecules [1–3]. Because bioreactors are so widely used, it is crucial to control and correctly optimise their efficiency, which mostly influences the end product's quality. Regulating microbial growth for the reference input and reducing reactor failure due to internal and external disturbances are the two main ways high efficiency is accomplished.

The nonlinear behaviour of the bioreactor makes biochemical control difficult due to a number of factors, including pH, temperature, dissolved oxygen, needed substrate concentration, etc. The cost of the biochemical reactor should be kept as low as possible while maintaining good product quality and guaranteeing that both biological and industrial requirements are met. Therefore, it is necessary to construct a controller with the right parameters in order to stabilise it.

Numerous control methods have been proposed in the literature for implementing a reliable controller for the biochemical reactor. An input multiplicity bioreactor was studied by Kumar et al. A nonlinear PI controller was put into use for the various steady state working zones through experimental research [4]. A RNN modeling technique for bioreactors has been presented in [5], and a nonlinear model predictive controller has been proposed to achieve good results. A PI controller using genetic algorithm for bioreactor systems running at steady state (stable) has been addressed in [6]. The complexity and instability of the bioreactor at steady state (unstable) were explored [7–9].

PID controllers are still frequently used in industrial systems due to their simple structure, effective disturbance rejection , stability, and ease of implementation, despite the significant advancements in sliding mode, model predictive, and internal model control techniques. The majority of PID tuning methods [10, 11] depends on numerical calculations to determine the controller coefficients. Due to the minimum computation time of soft computing techniques, they have recently gained much attention recently to tune PID controller parameters. Numerous sophisticated intelligent control techniques have evolved greatly as a result of advances in science and technology, including neural networks with exceptional fault tolerance, self-learning adaptability, parallel information processing techniques, and strong nonlinear mapping capabilities [12]. A single neuron, the fundamental building block of a neural network, is highly capable of self-learning and self-adaptation. It has been widely used because the adaptive controller made of it has a straightforward structure, is simple to design, requires little calculation, is able to adjust to changes in the outside environment, and has a high level of resilience[13]. To achieve parameter self-Adapt to setting, this study uses the speed loop control system as the object and integrates the single neuron method with the classical PID algorithm.

In this study, a SNPID controller for a biochemical reactor is presented. The proposed controller's simulation results have been contrasted with those of a conventional PID controller. This paper is further divided into the following sections: The biochemical reactor mathematical model is presented in Section 2. The design of the SNPID controller, as well as their effects on the biochemical reactor system are covered in Section 3. Analysis of simulation results are presented in Section 4 and conclusion is given in the last section.

2. Biochemical Reactor

A biochemical reactor is a device used to carry out biological reactions using microorganisms such as bacteria, fungi, or yeast to produce a desired product. The reactor can be designed and operated in different ways, depending on the specific reaction and product required.

In general, a biochemical reactor consists of a vessel or container where the microorganisms are placed along with a nutrient medium to support their growth and metabolism. The reactor may be aerated or agitated to maintain optimal conditions for the microorganisms, and temperature and pH may also be controlled.

The types of biochemical reactions that can be carried out in a reactor are diverse, including fermentation, biodegradation, and biotransformation. Fermentation reactions involve the conversion of sugars into alcohol or organic acids, while biodegradation reactions involve the breakdown of organic compounds by microorganisms. Biotransformation reactions involve the conversion of one compound into another using enzymes produced by microorganisms.

Biochemical reactors have many applications in various industries, including the production of food, pharmaceuticals, and chemicals. They can be used to produce antibiotics, enzymes, and biofuels, among other products. The design and operation of the reactor depend on the specific reaction and product being produced, as well as economic and environmental factors.

Biochemical reactors are used to carry out various biochemical processes such as fermentation, enzyme catalysis, and cell culture. The biochemical reactions that occur in these reactors can be described using various types of equations, including mass balance equations, kinetic equations, and thermodynamic equations. Here are some common types of equations used in biochemical reactor modelling:

Mass balance equations: These equations describe the conservation of mass in a biochemical reactor. They are used to calculate the concentrations of various components in the reactor as a function of time.

Kinetic equations: These equations describe the rate at which a biochemical reaction occurs as a function of the concentrations of the reactants and the reaction conditions (e.g., temperature, pH). The most common type of kinetic equation used in biochemical reactor modelling is the Michaelis-Menten equation, which describes the rate of an enzyme-catalysed reaction.

Thermodynamic equations: These equations describe the thermodynamic properties of the reactants and products in a biochemical reaction. The most common thermodynamic equation used in biochemical reactor modelling is the Van't Hoff equation.

Overall, these equations are used to model the behaviour of biochemical reactors and optimise the process parameters to achieve the desired outcomes.

To optimise the process for producing important chemical and biochemical compounds from the agricultural, medicinal, and other sectors, various biochemical reactor models have been developed recently. The bioreactor plays a vital role in transforming the microorganisms into commercial consumables, including drinks, antibiotics, medicines, vaccinations, and industrial solvents. The schematic diagram of the biochemical reactor process is shown in figure 1

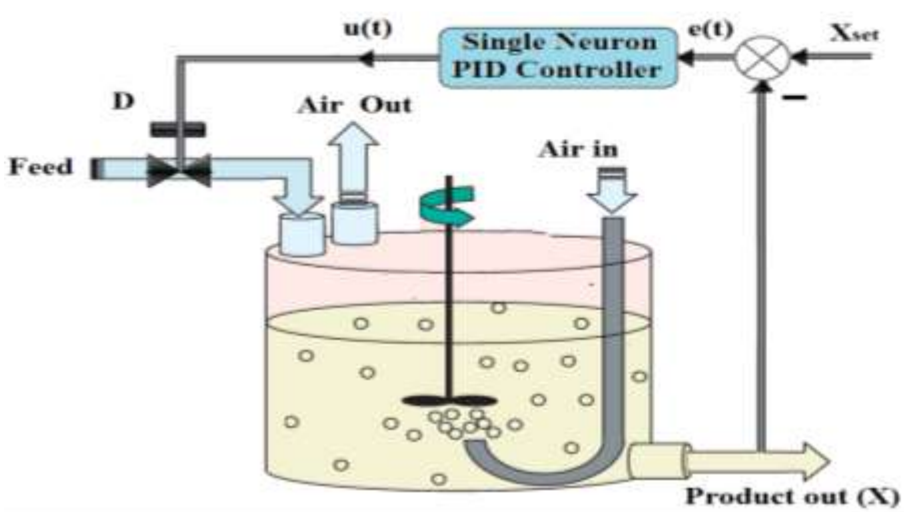

Fig.1 The Schematic diagram of bioreactor

The mathematical model is developed using the material balances on the biomass (cells) and the substrate (feed source for the cells), which are expressed as

Biomass Material balance:

$$\frac{dV_X}{dt} = F\,X_f - F\,X + V\,r_1 \tag{1}$$

Where, X_f is Biomass concentration in feed, F is volumetric flow rate and r_1 is rate of cell generation

Substrate Material balance:

$$\frac{dV_S}{dt} = F\,S_f - F\,S - V\,r_2 \tag{2}$$

Where, S_f is feed substrate concentration and r_2 is rate of Substrate consumption.

If μ is the Specific growth rate coefficient, and Y is the yield then,

$$Y = \frac{r_1}{r_2}\ \&\ r_1 = \mu\,X \quad \Longrightarrow \quad Y = \frac{\mu\,X}{r_2} \tag{3}$$

Assuming a constant volume reactor, we get:

$$\frac{dX}{dt} = \frac{F}{V}\,X_f - \frac{F}{V}\,X + r_1 \quad \& \quad \frac{dS}{dt} = \frac{F}{V}\,S_f - \frac{F}{V}\,S - r_2 \tag{4}$$

Defining, $\frac{F}{V} = D$ the dilution rate, we find

Assuming a constant volume reactor, we get:

$$\frac{dX}{dt} = D\,X_f - D\,X + r_1 = D\,X_f - D\,X + \mu\,X \tag{5}$$

$$\frac{dS}{dt} = D\,S_f - D\,S - r_2 = D\,S_f - D\,S - \frac{\mu\,X}{Y} \tag{6}$$

In general, $X_f = 0$ since there is no biomass in the feed stream.

The simplified model of bio chemical reactor is given as

$$\frac{dX}{dt} = -D\,X + \mu\,X = (\mu - D)X \tag{7}$$

$$\frac{dS}{dt} = D\left(S_f - S\right) - \frac{\mu\,X}{Y} \tag{8}$$

Growth Rate Equations

Table 1. Nominal parameters of biochemical Reactor

Operating Variable	Nominal Value
Cell (biomass) concentration, X	$6\ g/L$
Substrate concentration, S	$5\ g/L$
Substrate concentration in feed, S_f	$20\ g/L$
Dilution rate, D	0.202 □r^{-1}
Cell mass yield Y	$0.4\ g/g$

The transfer function of the biomass concentration (X) with respect to the dilution rate (D) is given as:

$$G_X(s) = \frac{X(s)}{D(s)} = \frac{5.8604}{-5.8893\ s + 1} \tag{9}$$

The pole of $G_X(s)$ is $s = 0.1690$, so the transfer function, represent unstable processes.

3. Single neuron adaptive PID control

A SNPID controller is a type of artificial neural network (ANN) that is used for control applications. It is based on the PID control algorithm, which is a commonly used feedback control method in engineering. In this controller, the input is the error between the desired output and the actual output of the system being controlled. The single neuron then computes the control signal based on the error signal, as well as the P, I, and D gains.

The proportional gain is a parameter that determines the proportion of the error signal that is used to calculate the control signal. The integral gain is a parameter that determines the effect of the accumulated error signal over time on the control signal. The derivative gain is a parameter that determines the effect of the rate of change of the error signal on the control signal. The output of the SN PID controller is the control signal, which is used to adjust the input to the system being controlled. The controller can be trained using supervised learning algorithms such as backpropagation to optimize the values of the proportional, integral, and derivative gains for a given control application.

Single neuron PID controllers have been used in a wide range of applications, including robotics, industrial process control, and automotive control systems. They offer advantages over traditional PID controllers, such as the ability to handle nonlinear systems and adapt to changing operating conditions. However, they require careful tuning of the network parameters to ensure stable and effective control. Figure 2 depicts the system with a single neuron PID controller .

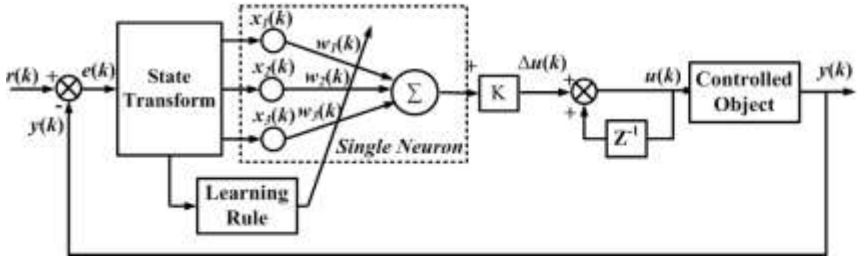

Fig.2. Block diagram of single neuron PID control system

The three input variables of the single neuron are given as

$$\begin{aligned} x_1(k) &= e(k) = r(k) - y(k) \\ x_2(k) &= \Delta e(k) = e(k) - e(k-1) \\ x_3(k) &= \Delta^2 e(k) = e(k) - 2e(k-1) + e(k-2) \end{aligned} \tag{10}$$

The incremental output of the single neuron is expressed as

$$\Delta u(k) = u(k) - u(k-1) = K\left(\frac{x_1(k)w_1(k) + x_2(k)w_2(k) + x_3(k)w_3(k)}{|w_1(k)| + |w_2(k)| + |w_3(k)|}\right) \tag{11}$$

Where K is the positive constant. The self-learning of the single neuron is achieved by adjusting weights $w_i(k)$, i=1,2,3 using supervised Hebb's learning.

The updated weights are given as.

$$\begin{aligned} w_1(k+1) &= w_1(k) + \eta_I\, K\, z(k+1)u(k)x_1(k) \\ w_2(k+1) &= w_2(k) + \eta_P\, K\, z(k+1)u(k)x_2(k) \\ w_3(k+1) &= w_3(k) + \eta_D\, K\, z(k+1)u(k)x_3(k) \end{aligned} \tag{12}$$

where $z(k+1) = e(k+1)$ and η_P , η_I and η_D are learning constants of I, P and D parts respectively.

Designed parameters of SNPID controller are $= 1$; Learning constants: $\eta_I = 0.6$, $\eta_P = 0.2$, and $\eta_D = 0.45$, and initial weights: $w_{x_1}(0) = w_{x_2}(0) = w_{x_3}(0) = 0.4$

4. Results and Discussions

The designed SNPID controller's performance is compared with that of a PID controller with the help of simulations carried out using MATLAB software. Figure 3 displays the biochemical reactor response when the positive step change in biomass concentration from 6 g/L to 7 g/L and an impulse disturbance is applied at time t = 80 hrs. Figure 4 displays the biochemical reactor response when the negative step change in biomass concentration from 6 g/L to 5 g/L.

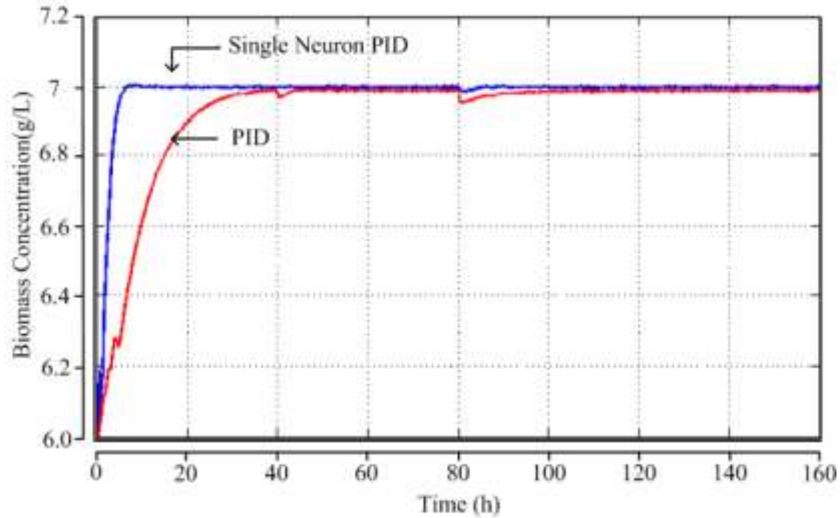

Fig3. Response of biomass concentration to a sudden level change from 6 g/L to 7 g/L

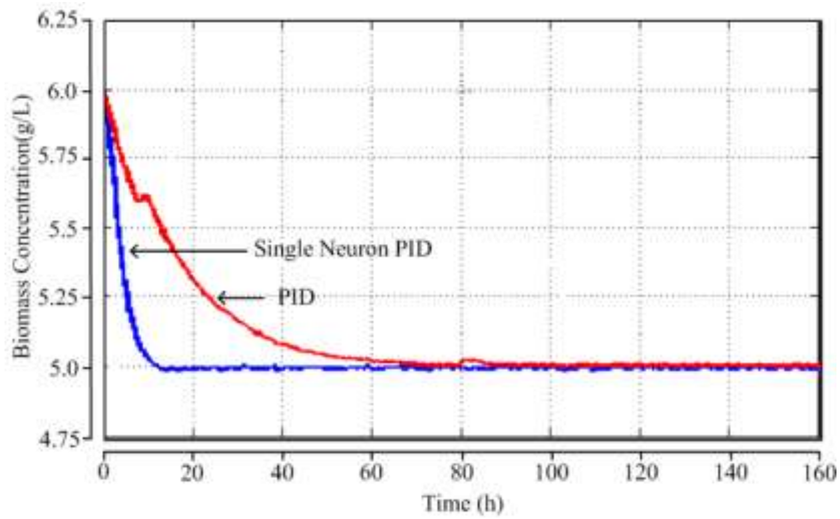

Fig4. Response of biomass concentration to a sudden level change from 6 g/L to 5 g/L

Figures 3 and 4 demonstrate that the biomass concentration settles quickly to the set value with the proposed SNPID controller compared to the PID controller. It also shows that the proposed controller rejects the effect of disturbances without any delay.

Figure 5 displays the biochemical reactor response when the biomass concentration is suddenly changed from 6 g/L to 7 g/L. at time t = 0 hrs and also further increased from 7 g/L to 8 g/L. at time t = 80 hrs. It can be observed from fig that the proposed controller has a shorter settling time and a shorter rising time when compared to the PID controller.

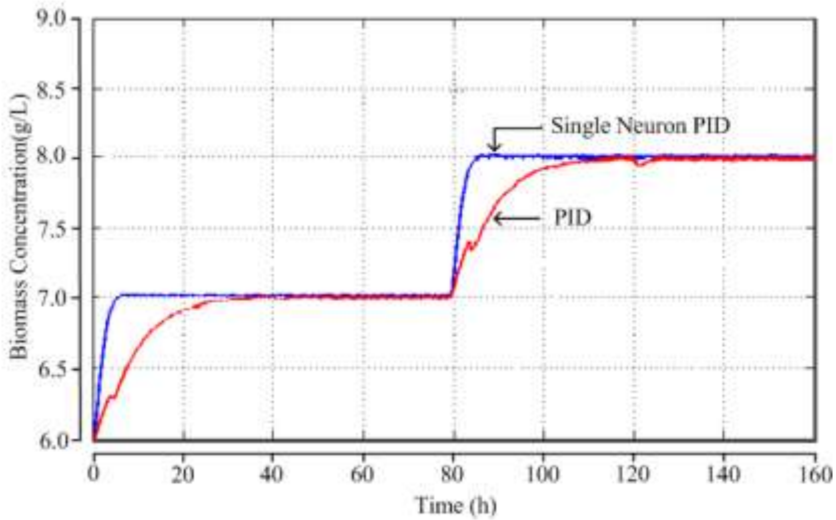

Fig4. Response of biomass concentration to changes in levels at different times

5. Conclusion

The presence of nonlinearities in the biochemical reactor process makes it difficult to model accurately, and it is quite challenging to design a controller that produces desirable outputs without a reliable model. For open loop stable systems, the traditional PID controller may be effective, but for the biochemical reactor which is an open loop unstable system, combined control of Single Neuron and PID is preferable. It can be observed from the biochemical reactor's closed loop response that the dynamics of the system are quick enough to guarantee effective control at the unstable steady state. The simulation results indicate that when the process parameters vary, the Single Neuron PID controller performs better than the PID controller.

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