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Adaptive Anti-Disturbance Control of Dissolved Oxygen in Circulating Water Culture Systems

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Abstract: In the three-dimensional culture model, the breeding basket of the culture area is symmetrical and it is important to control the dissolved oxygen in the symmetrical region to improve the culture efficiency. Practical engineering issues, such as the influence of flow rate, pH, water temperature, and biological oxygen consumption on the dissolved oxygen content in the circulating water culture system, must be considered along with the presence of modeling errors in the control model. The authors propose an adaptive anti-disturbance control strategy for dissolved oxygen that combines nonlinear disturbance observation with an adaptive sliding model control. Initially, a dynamic model for controlling dissolved oxygen in a recirculating water aquaculture system was developed. The model considers external disturbances like artificial oxygenation, abrupt changes in system flow, and variations in culture oxygen consumption. Secondly, to enhance the robustness and accuracy of controlling dissolved oxygen concentration, the paper introduces a nonlinear adaptive disturbance observer for real-time estimation and observation of external disturbances and system uncertainties. This is accompanied by a sliding-mode control-based adaptive anti-disturbance strategy. Lastly, the simulation results demonstrate that the control strategy proposed in this paper shows resistance to system uncertainties and unknown external disturbances. Furthermore, it reduces the model accuracy requirements for the controller and proves to be suitable for accurately controlling dissolved oxygen in circulating water systems.

Keywords: recirculating water farming; dissolved oxygen; dissolved oxygen control; nonlinear disturbance observer; slide model control

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1. Introduction

In recent years, with the decline of marine resources, the fishing industry, which has been primarily based on marine fishing, has gradually shifted towards aquaculture. Traditional aquaculture practices are often extensive, resulting in low yields and high pollution, leading to continuous deterioration of the aquaculture environment. These drawbacks cannot meet the goals of sustainable development. In response to these challenges, the concept of "recirculating aquaculture systems" has emerged as a promising solution. Factory recirculating aquaculture is a novel farming model that offers advantages such as high productivity and water conservation [1]. In aquaculture, breeding baskets are symmetrically distributed; the quality of aquaculture water directly affects the survival of farmed organisms [2]. Therefore, real-time monitoring of water quality and regulation of the corresponding water treatment equipment to meet the requirements of aquaculture is a necessary prerequisite for ensuring the recyclability of water. Dissolved oxygen is a fundamental parameter in water quality and imbalances in its concentration can cause sickness or death in aquatic species [3,4]. As a result, accurate control of dissolved oxygen in recirculating water culture is critical. However, achieving such control is challenging due to uncertainties arising from factors like environmental temperature variations, biological activity, human behavior, and changes in system flow during water treatment processes [5].

Furthermore, there are clear nonlinear characteristics between dissolved oxygen content and aeration as well as other disturbances [6–8]. Moreover, because the influencing factors such as biomass and biological respiration rate are continually changing within a particular range, the dissolved oxygen control system has typical time-varying properties in the meantime. At the same time, to assure the quality of the flowing water, the oxygenation equipment generally operates in the continuous load mode for an extended length of time [9]. However, various water treatment loads occur at different periods during the breeding process and the fixed-load operating strategy has resulted in a significant energy burden. According to the literature [10], the intelligent control of the aeration equipment using frequency conversion technology is proposed. The oxygenator operates in a low-power mode when the dissolved oxygen concentration meets the requirements but the power increases when there is a significant deviation from the set value. However, the operating power is increased when the dissolved oxygen concentration deviates significantly from the set value. Compared to traditional control methods, the frequency conversion control method saves more than 42.3% of the power. As a result, variable load accurate regulation of dissolved oxygen concentration is an essential research subject to enhance water quality and save energy.

To achieve accurate regulation of dissolved oxygen, it is necessary to establish a mathematical model for dissolved oxygen. Numerous researchers are now working on dissolved oxygen modeling [11–13]. Huang et al. [14,15] employed a small indoor culture pond as a study object and the dissolved oxygen system was modeled as a transfer function while disregarding temperature and pH variations and the model parameters were obtained experimentally. Zhou et al. [16] created a dynamic model of dissolved oxygen in a recirculating water culture system, assuming constant system flow, culture mass, and biological oxygen consumption rate, and provided model parameters for dissolved oxygen without taking into account changes in internal and external factors via aeration experiments. Based on diffusion theory and material balance, Yin et al. [17] created a dynamic model of the daily change in dissolved oxygen at different depths in a crab pond. The model considers plant photosynthesis, biological respiration, mechanical oxygenation, and other variables that influence dissolved oxygen variations. The experimental findings suggest that the model's average absolute inaccuracy is around 6%. In the model research of dissolved oxygen in the recirculating water culture system, there are limitations to assuming constant parameters like circulating water flow, water temperature, pH, culture mass, and biological oxygen consumption, ignoring system uncertainties like disturbance factors and using a transfer function form as a mathematical model for dissolved oxygen in circulating water culture systems.

The traditional PID control [18,19] is more extensively employed in the dissolved oxygen control and has achieved certain successes but, since its control parameters tend to remain constant, the control performance in the dissolved oxygen system with uncertainty is low [20]. The literature [21–23] brought intelligent control approaches into the classic PID control, such as neural network techniques and fuzzy control methods. The adaptiveness of dissolved oxygen management is increased to some extent by using the neural network's nonlinear function approximation abilities and fuzzy inference rules based on expert knowledge to update PID parameters live. A fuzzy controller was devised for the problem of dissolved oxygen regulation in indoor shrimp growth systems in the literature [24] and the controller output was regulated based on the dissolved oxygen tracking error and the rate of change in the error. Circulating water culture systems are prone to nonlinear disturbances, parameter uncertainty, and other variables and fuzzy control lacks autonomous learning capability, requiring expert knowledge to construct inference rules [25]. A fuzzy neural network internal mode controller was proposed in the literature [26] to enhance dissolved oxygen management by online modification of filter settings using a fuzzy neural network. However, factors such as the network structure and initial value setting influence neural network performance had a significant impact on adaptive performance [27]. As a result, the problem of adaptive immunity regulation of dissolved oxygen system under internal and external disruptions and uncertainty environment requires more investigation.

This paper proposes a dissolved oxygen adaptive anti-disturbance control strategy for the problem of dissolved oxygen control in circulating water aquaculture systems with nonlinearity, time variation, and uncertainty which reduces water quality fluctuation while improving dissolved oxygen control accuracy. The following concerns were highlighted:

(1) The effects of temperature fluctuations, changes in circulating water flow, variations in biological respiration rates, modeling errors, and other factors were comprehensively considered to develop a mathematical model for dissolved oxygen in circulating water aquaculture systems that aligns with actual working conditions;
(2) To address the issue of uncertain disturbances in dissolved oxygen control of circulating water aquaculture systems, a nonlinear disturbance observer with a simple structure and real-time capability is introduced. This observer effectively eliminates the influence of disturbances and model uncertainty on dissolved oxygen. Building upon this, an adaptive sliding mode controller is designed to enhance dissolved oxygen control immunity and ensure water quality stability.

The structure of this paper is organized as follows. Section 1 presents a mathematical model for dissolved oxygen in the recirculating aquaculture system. Section 2 shows the problem of uncertain disturbances in dissolved oxygen control within the recirculating aquaculture system, which is addressed herein. This section introduces a nonlinear disturbance observer and designs an adaptive sliding mode controller to regulate the dissolved oxygen levels in the water. Section 3 conducts simulations to validate the performance of the controller.

2. Materials and Methods

2.1. Dissolved Oxygen Control Model

2.1.1. Recirculating Water Farming System

The main process structure of the system is shown in Figure 1, including culture ponds, sand filters, biofilters, and other water treatment systems. The water from the breeding pond undergoes purification through a microfilter which effectively removes fine suspended materials. The protein separator separates most of the organic impurities in the water, the sand filtering pond precipitates and filters the water impurities, and the breeding water then flows through the biofilter equipped with an aeration device and a biological filler to reduce the ammonia and nitrogen content of the breeding water; finally, the breeding water is pumped back into the breeding pond after sterilization and disinfection.

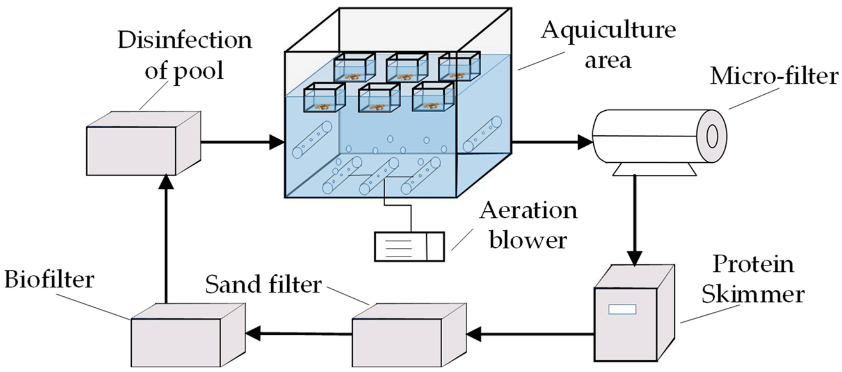

Figure 1. Diagram of circulating water system.

Temperature, pH, biotic and abiotic oxygen consumption, artificial oxygenation, and intake and outflow water flow all influence the concentration of dissolved oxygen in the culture pond in the circulating water culture area. It is difficult to precisely explain its dynamic features due to its usual nonlinear, coupled, and unpredictable qualities. As a result, before modeling dissolved oxygen in circulating water systems, acceptable assumptions must be established. The following assumptions are commonly used in current dissolved oxygen modeling research [14–16]:

Hypothesis 1 (H1). *Over a short period of time, there is a negligible increase in biological mass in the culture system.*

Hypothesis 2 (H2). *Changes in water temperature, pH, and biological respiration rate are negligible.*

Hypothesis 3 (H3). *In the culture region, the microporous aeration process is continuous and stable and the dissolved oxygen content in the water bodies is more equally distributed.*

However, when the culture system is in use, the biological quality, biological respiration rate, and water quality parameters are constantly changing. The model assumptions are decreased here in order to represent dissolved oxygen more accurately to the real circulating water culture conditions.

The hypothesis proposed in this study suggests that the microporous aeration process within the culture area maintains a continuous and stable supply of oxygen, resulting in a uniform distribution of dissolved oxygen content in the water.

Unlike the usual dissolved oxygen control modeling assumptions in aquaculture, in this paper, we consider changes in biomass, temperature, and biological respiration in modeling and treat the effects of these factors on dissolved oxygen as a composite perturbation of the dissolved oxygen model. According to the assumptions of this study, the entire breeding region is regarded as a system. The dynamics of dissolved oxygen in this system is a combination of dissolved oxygen in the water entering and leaving the culture area, artificial oxygenation of the culture area, oxygen consumption by respiratory metabolism of the culture, and dissolved oxygen influenced by other compound disturbances. As seen in Figure 2, this article first develops a notional model of dissolved oxygen including the three primary components of artificial oxygenation, circulating water inflow and output, and oxygen consumption by cultures in a recirculating water culture system. Based on this, the system composite perturbation is introduced to the model to boost its applicability.

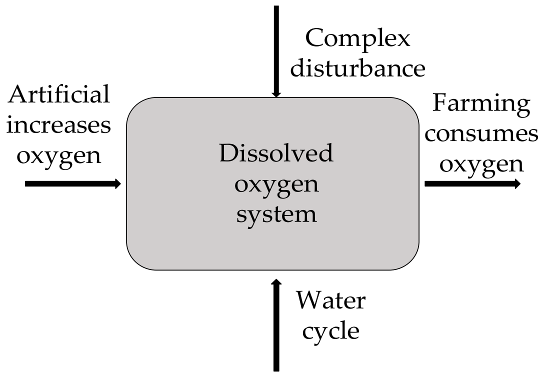

Figure 2. Dynamic of dissolved oxygen system.

2.1.2. Dissolved Oxygen Control Model with Uncertainty

(1) Circulating water in and out process

The aquaculture water is filtered and returned to the aquaculture area by sedimentation, biological filtration, sterilization, and other activities in the circulating water aquaculture system. Since there is no dissolved oxygen consumption throughout the disinfection process, the dissolved oxygen concentration of the biofilter effluent may be assumed to represent the dissolved oxygen concentration of the influent water in the breeding region. Based on the assumptions in this paper, the dissolved oxygen concentration value of the water outflowing from the breeding area can be used as the dissolved oxygen concentration in the breeding area, thus,

$$E_{io} = \frac{Q}{V}(C_{in} - y) \quad (1)$$

where E_{io}—dissolved oxygen change rate in a circulating water process (mg $\cdot$L^{-1} $\cdot$ h^{-1}); V—volume of water in the breeding area (m^3); Q—circulating water system flow (m^3 $\cdot$ h^{-1}); C_{in}—dissolved oxygen concentration in the influent water of the breeding area (mg $\cdot$L^{-1}); and y—dissolved oxygen concentration in the breeding area (mg $\cdot$L^{-1}).

To guarantee that the biochemical reaction of the biofilter runs normally, the dissolved oxygen content of the biofilter effluent should be more than 2.0 mg $\cdot$L^{-1} [28]; C_{in} is taken as 3.0 mg $\cdot$L^{-1} in this article.

(2) Aeration process

Microporous aeration and oxygenation are one of the most common oxygenation technologies used in the recirculating water culture process. Microporous devices are evenly arranged at the bottom of the breeding area and the wall of the breeding pool. Aeration equipment, such as blowers, are linked to microporous air stones or microporous tubes to deliver oxygen straight into the breeding region for oxygen. Dissolved oxygen transfer processes for the aeration process [29,30].

$$A_m = K_{La} \cdot (C_{sat} - y) \quad (2)$$

where A_m—dissolved oxygen change rate during aeration (mg $\cdot$L^{-1} $\cdot$ h^{-1}); C_{sat}—saturated dissolved oxygen concentration in the water bodies (mg $\cdot$L^{-1}); K_{La}—total oxygen transfer coefficient which is mostly related to water temperature and aeration, as described by the following equation [31]:

$$K_{La} = (c_1 + c_2 \cdot u(t)^{c_3}) \cdot \beta^{(T-20)} \quad (3)$$

In Equation (3), c_1—atmospheric reoxygenation factor, c_2—oxygen transfer rate of artificial aeration process, u—aeration volume (m^3 $\cdot$ h^{-1}), and β—temperature correction factor. In recirculating water culture, c_3 is close to 1.0 [17] and the aeration of the artificial aeration component is roughly linear with the oxygen transfer coefficient [30–32]; hence, $c_3 = 1.0$ is used in this research.

(3) Oxygen consumption by respiration of cultures

The primary cause of the reduction in dissolved oxygen concentration in the culture region is the culture's respiratory metabolism. The respiration rate of cultures is influenced by a variety of internal and external factors. The relationship between the respiration rate, temperature, and body weight of farmed crabs is generally described by the following equation [33,34]:

$$R = \frac{A}{1 + e^{(2.351 - 0.138 \cdot T)}} \times M^{-0.5} \quad (4)$$

In Equation (4), R—oxygen consumption rate per unit mass of crab (mg $\cdot$h^{-1} $\cdot$ kg^{-1}); A—upper limit of the biological respiration rate (mg $\cdot$h^{-1}); and M—biological quality (kg).

When the temperature and biological mass do not fluctuate much, the respiration rate per unit mass of culture may be regarded a constant using Equation (4). In this article, the culture's respiration rate is utilized as a constant to build a notional model of the system and the culture's oxygen consumption [35] is taken as

$$R_s = \frac{M \cdot R}{V} \quad (5)$$

where R_s—oxygen consumption rate of all cultures (mg $\cdot$L^{-1} $\cdot$ h^{-1}) and V—volume of water in the breeding area (m^3).

In summary, the dynamic model of dissolved oxygen without considering other factors can be described as

$$\frac{dy}{dt} = E_{io} + A_m - R_s \tag{6}$$

Substituting into Equations (1)–(5) yields:

$$\frac{dy(t)}{dt} = \frac{Q}{V} \cdot (C_{in} - y(t)) + (c_1 + c_2 \cdot u(t)) \cdot \beta^{(T-20)}(C_{sat} - y(t)) - \frac{M \cdot R}{V} \tag{7}$$

The dissolved oxygen model (7) is defined as follows:

$$y(t) = x(t) \tag{8}$$

$$f_0(x(t)) = \frac{Q}{V} \cdot (C_{in} - x(t)) - \frac{M \cdot R}{V} + c_1 \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \tag{9}$$

$$g_0(x(t)) = c_2 \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \tag{10}$$

Then, the dissolved oxygen control state space model is:

$$\begin{cases} \dot{x}(t) = f_0(x(t)) + g_0(x(t))u(t) \\ y(t) = x(t) \end{cases} \tag{11}$$

The system flow rate Q, biological respiration rate R, and biological mass parameters M, and c_1 and c_2 in the dissolved oxygen equation obtained from the above analysis are nominal values. In the actual operation of the system, changes in water components, temperature, system flow, biological growth, and many other factors will lead to parameter uptake and external disturbances, introducing model parameter errors ΔQ, ΔR, ΔM, Δc_1 Δc_2 and ΔC_{in}. Substituting them into Equations (9) and (10) yields

$$\begin{aligned} f(x(t)) = \ & \tfrac{Q+\Delta Q}{V} \cdot ((C_{in} + \Delta C_{in}) - x(t)) - \tfrac{(M+\Delta M)\cdot(R+\Delta R)}{V} \\ & +(c_1 + \Delta c_1) \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \\ & = \tfrac{Q}{V} \cdot (C_{in} - x(t)) - \tfrac{M \cdot R}{V} + c_1 \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \\ & + \tfrac{\Delta Q}{V} \cdot (C_{in} - x(t) + \Delta C_{in}) + \tfrac{Q \cdot \Delta C_{in}}{V} - \tfrac{\Delta M \cdot R + M \cdot \Delta R + \Delta M \cdot \Delta R}{V} \\ & + \Delta c_1 \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \end{aligned} \tag{12}$$

$$\begin{aligned} g(x(t)) & = (c_2 + \Delta c_2) \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \\ & = c_2 \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) + \Delta c_2 \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \end{aligned} \tag{13}$$

Organizing the above equation makes

$$\begin{aligned} f_n(x(t)) & = \tfrac{\Delta Q}{V} \cdot (C_{in} - x(t) + \Delta C_{in}) + \tfrac{Q \cdot \Delta C_{in}}{V} - \tfrac{\Delta M \cdot R + M \cdot \Delta R + \Delta M \cdot \Delta R}{V} \\ & + \Delta c_1 \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \end{aligned} \tag{14}$$

$$g_n(x(t)) = \Delta c_2 \cdot \beta^{(T-20)} \cdot (C_{sat} - x(t)) \tag{15}$$

Then, the original dissolved oxygen state space equation is

$$\begin{cases} \dot{x}(t) & = f(x(t)) + g(x(t))u(t) + \xi(t) \\ & = f_0(x(t)) + f_n(x(t)) + [g_0(x(t)) + g_n(x(t))] \cdot u(t) + \xi(t) \\ & = f_0(x(t)) + g_0(x(t)) \cdot u(t) + d \\ y(t) & = x(t) \end{cases} \tag{16}$$

where $d = f_n(x(t)) + g_n(x(t)) \cdot u(t) + \xi(t)$ and $f_n(x(t)) + g_n(x(t)) \cdot u(t)$ are internal perturbations due to parameter uptake and $\xi(t)$ are external perturbations due to time-varying and unmodeled parts of the system.

2.2. Dissolved Oxygen Controller Design

The dissolved oxygen adaptive immunity controller is proposed in this study for the dissolved oxygen state space Equation (16). The controller, as illustrated in Figure 3, is made up of a nonlinear disturbance observer and an adaptive sliding film controller. The nonlinear disturbance observer continuously estimates the real-time system disturbance and uncertainty while the adaptive law is designed to compensate for the disturbance before the convergence of the disturbance observation error. This approach enhances the speed and accuracy of the disturbance convergence. Finally, the sliding film controller is intended to improve the system's capacity to suppress disturbances and guarantee that the dissolved oxygen system maintains a consistent track of the set value. Therefore, the dissolved oxygen controller design objectives are summarized as follows:

① The nonlinear interference-based observer makes the observation error converge while the input gain design compensates for the control u_d.

② Based on ①, the adaptive law $\dot{\hat{f}}$ and the sliding film control law u_s are designed to make the system track the dissolved oxygen setting value asymptotically in a limited time.

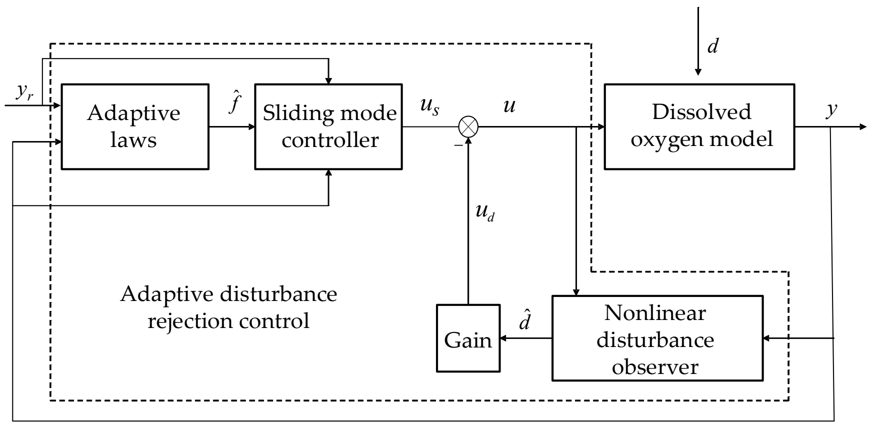

Figure 3. Dissolved oxygen control structure.

2.2.1. Nonlinear Interference Observer Design

d is a complicated system perturbation consisting of unmodeled dissolved oxygen system dynamics as well as internal and external disturbances; d is bounded. The structural nonlinear interference observer [36] is designed.

$$\begin{cases} \hat{d} = z + p(x) \\ \dot{z} = -L(x) \cdot z - L(x) \cdot [f_0(x) + g_0(x) \cdot u + p(x)] \end{cases} \tag{17}$$

In Equation (17), $\hat{d}$—observer estimation of compound disturbances; z—auxiliary Variables; $p(x)$—the function to be designed; and $L(x)$—the nonlinear interference observer's gain as defined by Equation (18):

$$L(x) \cdot \dot{x} = \frac{dp(x)}{dt} \tag{18}$$

Since the prior information of the perturbation differential is unknown, it is assumed that the disturbance evolves slowly in relation to the observer's dynamic attributes, i.e., $\dot{d} \approx 0$. By defining the observation error f,

$$f = d - \hat{d} \tag{19}$$

From Equation (19), the dynamic characteristics of the observation error can be obtained as follows:

$$\begin{aligned} \dot{f} &= \dot{d} - \dot{\hat{d}} = -\dot{z} - L(x) \cdot \dot{x} \\ &= L(x) \cdot \hat{d} + L(x) \cdot (f_0(x) + g_0(x) \cdot u) - L(x) \cdot x \\ &= L(x) \cdot \hat{d} - L(x) \cdot d \\ &= -L(x) \cdot f \end{aligned} \tag{20}$$

Construct the Lyapunov function for Equation (17).

$$V_1 = \frac{1}{2} f^2 \tag{21}$$

Differentiating the two sides of (21) with respect to t:

$$\dot{V}_1 = f \cdot \dot{f} = -L(x) \cdot f^2 \tag{22}$$

Obviously, when the interference observer gains $L(x) > 0$, $\dot{V}_1 \leq 0$, the observer estimation error converges exponentially, taking $p(x) = L(x) \cdot x$.

In this paper, we design the compensation control amount according to the model of dissolved oxygen system as

$$u_d = \frac{\hat{d}}{g_0(x)} \tag{23}$$

2.2.2. Adaptive Sliding Film Controller Design Based on Disturbance Estimation

Before convergence of the nonlinear disturbance observation error, the dissolved oxygen system can be expressed as $\dot{x} = f_0(x) + g_0(x) \cdot u_s + f$ where $f = d - \hat{d}$. This paper designs an adaptive sliding film controller for the existing dissolved oxygen system (16) based on a sliding film control to accelerate error convergence and improve system immunity. The control aim is to accomplish an accurate dissolved oxygen control in circulating water systems by reducing the error between system output and the fixed value of dissolved oxygen to zero. Let x_d be the dissolved oxygen set value in the circulating water culture system and define the system control output error vector $e = x - x_d$. The control task is to create the control law so that the $\lim_{t \to \infty} e(t) = 0$ holds. Defining the slide surface:

$$s = e \tag{24}$$

Differentiating (24) yields the sliding mode dynamic equation as follows:

$$\dot{s} = \dot{x} - \dot{x}_d \tag{25}$$

Consider the synovial surface convergence law $\dot{s} = -\varepsilon \cdot \mathrm{sgn}(s) - k \cdot s$, $\varepsilon > 0$, and $k > 0$, where $-k \cdot s$ is the exponential convergence term which speeds up the convergence speed and $-\varepsilon \cdot \mathrm{sgn}(s)$ makes certain that the system status reaches the synovial surface in a limited time.

Define and differentiate the Lyapunov function $V_2 = \frac{1}{2} s^2$ as follows:

$$\dot{V}_2 = s \cdot \dot{s} = s \cdot (f_0(x) + g_0(x) \cdot u_s + f - \dot{x}_d) \tag{26}$$

In actual water cycle aquaculture systems, external disturbance signals contain multiple uncertainties. An adaptive compensator is designed using an adaptive strategy to compensate for the unobserved disturbance of the dissolved oxygen system and the disturbance signal before the convergence of the disturbance observation error to speed up the convergence of the disturbance observation error and improve the robustness of the dissolved oxygen control.

$\hat{f}$ is the estimated value of the perturbed signal f. Define the estimation error $\widetilde{f} = f - \hat{f}$. Define the Lyapunov function:

$$V_3 = V_2 + \frac{1}{2\gamma}\widetilde{f}^2 \tag{27}$$

where γ is a normal number. Differentiate (27):

$$\begin{aligned} \dot{V}_3 &= \dot{V}_2 - \tfrac{1}{\gamma}\widetilde{f} \cdot \dot{\hat{f}} \\ &= s \cdot (f_0(x) + g_0(x) \cdot u_s + f - \dot{x}_d) - \tfrac{1}{\gamma}\widetilde{f} \cdot \dot{\hat{f}} \\ &= s \cdot (f_0(x) + g_0(x) \cdot u_s + \hat{f} + \widetilde{f} - \dot{x}_d) - \tfrac{1}{\gamma}\widetilde{f} \cdot \dot{\hat{f}} \\ &= s \cdot (f_0(x) + g_0(x) \cdot u_s + \hat{f} - \dot{x}_d) - \tfrac{1}{\gamma}\widetilde{f} \cdot (\dot{\hat{f}} - \gamma \cdot s) \end{aligned} \tag{28}$$

Design a control law based on an Equation (28):

$$u_{eq} = -\frac{f_0(x) + \hat{f} - \dot{x}_d}{g_0(x)} \tag{29}$$

$$u_{vss} = -\frac{\varepsilon \cdot \mathrm{sgn}(s) + k \cdot s}{g_0(x)} \tag{30}$$

$$u_s = u_{eq} + u_{vss} \tag{31}$$

In Equation (31), u_s is the sliding film control law, u_{eq} is the equivalent control, and u_{vss} is the switching control to compensate for system uncertainty and disturbances.

The adaptive law s

$$\dot{\hat{f}} = \gamma \cdot s \tag{32}$$

2.2.3. Stability Analysis

Conclusion 1. *When the sliding film convergence law parameter $\varepsilon > e^*$, the compensatory control law (23), the sliding film control law (31), and the adaptive law (32) are used such that the dissolved oxygen closed-loop system (16) asymptotically follows the dissolved oxygen setting for a short duration. The tracking time meets the following:*

$$t \le \frac{\sqrt{2} \cdot \sqrt{V_2(0)}}{\varepsilon - e^*}$$

Proof of Conclusion 1. Design a Lyapunov function for the closed-loop system Equation (16).

$$V_4 = \frac{1}{2}s^2 + \frac{1}{2}f^2 + \frac{1}{2\gamma}\widetilde{f}^2 \tag{33}$$

According to Equation (33),

$$\dot{V}_4 = s \cdot (f_0(x) + g_0(x) \cdot u_s + \hat{f} - \dot{x}_d) - \frac{1}{\gamma} \cdot \widetilde{f} \cdot (\dot{\hat{f}} - \gamma \cdot s) + f \cdot \dot{f} \tag{34}$$

From (29)–(32), (34)

$$\dot{V}_4 = -\varepsilon \cdot |s| - k \cdot |s|^2 - L(x) \cdot f^2 \tag{35}$$

Clearly, there exists k,ε and interference observer gain $L(x)$ make $\dot{V}_4(x) \le 0$.

In addition, the system output tracks the set value along the sliding die surface for a finite time, for $\dot{V}_2$:

$$\dot{V}_2 = s \cdot \dot{s} = s \cdot (f_0(x) + g_0(x) \cdot u_s + f - \dot{x}_d) \tag{36}$$

It follows from (22) that the presence of the disturbance observer gain $L(x)$, which converges the system disturbance estimation error, with $\left|f-\widetilde{f}\right| \leq e^* = \sup\limits_{t>0}\left|f-\widetilde{f}\right|$, holds. Substituting the control law (31) into Equation (36) yields the following:

$$\begin{aligned}\dot{V}_2 &= s \cdot \dot{s} \\ &= s \cdot (-\varepsilon \cdot \operatorname{sgn}(s) - k \cdot s + f - \widetilde{f}) \\ &\leq |s| \cdot (-\varepsilon + e^*) = -\sqrt{2}(\varepsilon - e^*) \cdot \sqrt{V_2}\end{aligned} \tag{37}$$

When $\varepsilon > e^*$,

$$\dot{V}_2 = -\sqrt{2}(\varepsilon - e^*) \cdot \sqrt{V_2} \leq 0 \tag{38}$$

Integration of Equation (38),

$$\sqrt{V_2(t)} \leq -\frac{\sqrt{2}}{2}(\varepsilon - e^*) \cdot t + \sqrt{V_2(0)} \tag{39}$$

From Equation (39),

$$t \leq \frac{\sqrt{2} \cdot \sqrt{V_2(0)}}{\varepsilon - e^*}$$

In summary, through the design of the dissolved oxygen adaptive immunity controller, the system satisfies the Lyapunov stability theory condition and can track the dissolved oxygen setting asymptotically for a limited period of time. Proof complete. □

3. Results

Dissolved Oxygen Control Simulation

To validate the efficiency of the dissolved oxygen adaptive anti-disturbance control approach presented in this study, simulation experiments with varying dissolved oxygen model parameters and uncertainty disturbances in the circulating water system are conducted. The effective volume of the breeding area of this circulating water system is 1.5 m^3. The total mass of farmed crab is about 3.25 kg. The dissolved oxygen concentration setting value is 6 $mg \cdot L^{-1}$. Based on data from relevant culture systems [16,37], the nominal model parameters of dissolved oxygen are shown in Table 1.

Table 1. Model parameters.

Parameters	Numerical Value
Circulating water flow/($m^3 \cdot h^{-1}$)	0.34
Water volume of aquaculture area/m^{-3}	1.5
Total quality of aquatic products/kg	3.25
Oxygen consumption rate/($mg \cdot h^{-1} \cdot kg^{-1}$)	110.2
Saturated dissolved oxygen/($mg \cdot L^{-1}$)	8.89
c_1	0.08046
c_2	1.129
β	1.014
T	19.89
k_p	1.1
k_i	0.92
k_d	0.71

To evaluate the stability and anti-interference performance of the controller, this paper compares and simulates the PID controller and the sliding mode controller designed in this study. The parameters of the sliding mode controller are typically determined based on the system's dynamic characteristics and control performance requirements. Considering that the controller's design objective in this paper is to achieve system stability and robustness while maintaining the desired response time and disturbance estimation speed, the initial values for the sliding mode controller's gain and the parameters of the nonlinear interference observer are set. Following several testing and changes, the controller parameters $k = 15$, $\varepsilon = 0.1$, $\gamma = 0.1$, and the gain of nonlinear disturbance observer $L(x) = 28$ are established with the goal of assuring system reaction speed and disturbance estimation speed. As indicated in Table 1, the PID controller parameters are first substantially modified using the PID Tuner toolbox in MATLAB and then fine-tuned in the order of first k_p, then k_i, and lastly k_d.

Changes in system parameters can be caused by variable flow rate management of circulating water [38] and weight increases in the aquaculture item during recirculating aquaculture. To test the durability of the control approach to changes in the dissolved oxygen model parameters, the circulating water flow rate was doubled at 180 min. The mass of the culture is doubled, all other simulation data are left alone, and the control simulation results are given in Figure 4. As shown in Figure 4, when the system parameters change, the controller overshoots by 0.3% and may be corrected to the set value within 10 min. The overrun of the PID control is 2%, the adjustment time is 180 min, and the adaptive capacity is low. In comparison, the controller in this study has minor overshoot, quick correction, and great self-adaptive capacity and the system's dissolved oxygen content can follow the set value stably under parameter uncertainty.

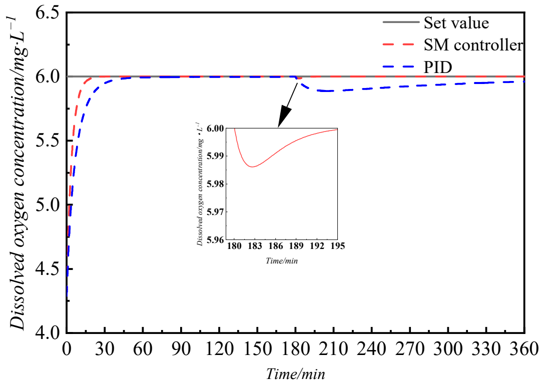

Figure 4. Parameter perturbation.

The environment of a circulating water aquaculture system is complicated and varied; temperature, pH, residual bait deposition, and other variables can all cause significant fluctuations in system dissolved oxygen content. A slow time-varying disturbance $d_1 = (0.1 \cdot \sin(t) - 2)\ \mathrm{mg} \cdot \mathrm{L}^{-1} \cdot \mathrm{h}^{-1}$ is added to the system to further assess the controller's control performance under unknown disturbances; Figure 5 depicts the simulation results with Figure 5a displaying the perturbation estimation results, Figure 5b displaying the estimation error, Figure 5c displaying the tracking control effect, and Figure 5d displaying the tracking control error. Figure 5a,b shows that the estimation accuracy is great, the absolute estimation error is less than ± 0.002, and the interference estimation converges rapidly. It is clear from the study of Figure 5c,d that the PID control of dissolved oxygen concentration struggles to maintain the set value while disturbances are present; at 360 min, the error between the dissolved oxygen concentration and set value is around $-0.04\ \mathrm{mg} \cdot \mathrm{L}^{-1}$. The controller designed in this paper can track the set value in 20 min in the presence of disturbance and the tracking error is kept within $\pm 0.001\ \mathrm{mg} \cdot \mathrm{L}^{-1}$, which has high control accuracy, and the dissolved oxygen concentration in the water body can maintain a stable state.

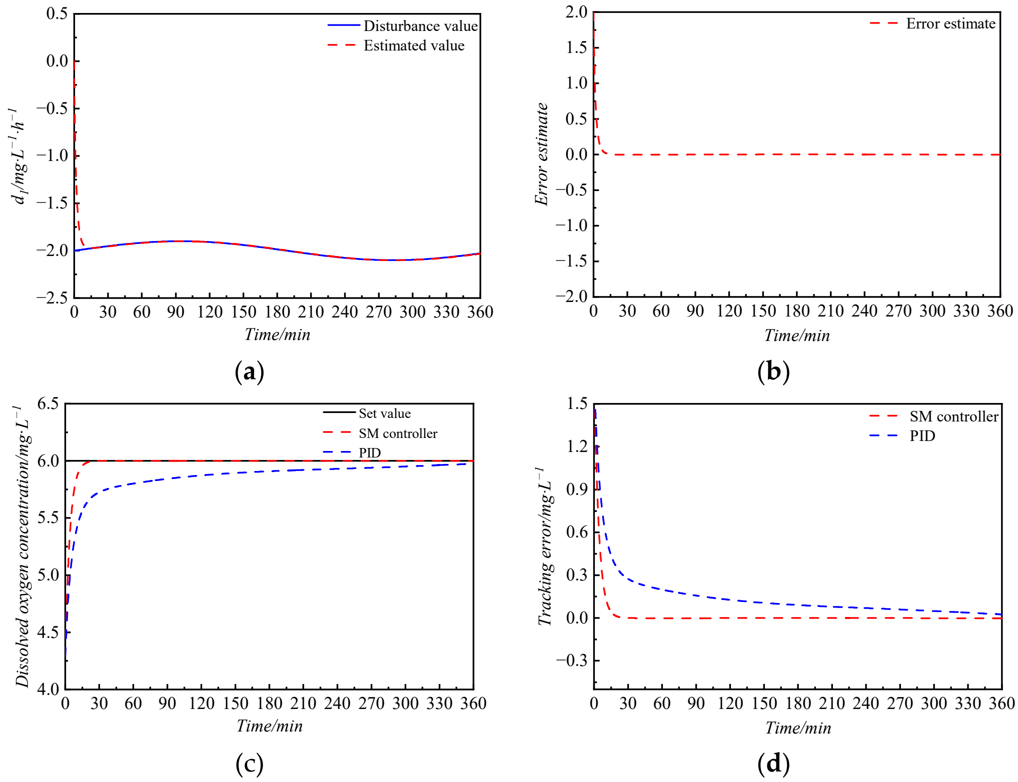

Figure 5. Control simulation under d_1 disturbance. (**a**) Disturbance estimation; (**b**) Disturbance estimation error; (**c**) Control under disturbance; (**d**) Control error under disturbance.

The amount of dissolved oxygen will rapidly decrease if there are too many microorganisms in the water body and they are actively consuming oxygen. In this regard, other simulation parameters are kept constant and a step disturbance d_2 is applied to the dissolved oxygen system. For d_2 at 0–120 min amplitude is $-0.2\ \mathrm{mg \cdot L^{-1} \cdot h^{-1}}$, 120–240 min at amplitude is $-1.88\ \mathrm{mg \cdot L^{-1} \cdot h^{-1}}$, and 240–360 min at amplitude is $-0.37\ \mathrm{mg \cdot L^{-1} \cdot h^{-1}}$, the control simulation results under this perturbation are shown in Figure 6. Figure 6a shows the results of the perturbation estimation, Figure 6b shows the estimation error, Figure 6c shows the results of the tracking control, and Figure 6d shows the results of the tracking error. The analysis of Figure 6a,b demonstrates that the estimation accuracy is high, the nonlinear observer perturbation estimation absolute error is within ± 0.01, and the disturbance estimation response is quick. It can be seen from Figure 6c,d that the water quality fluctuates significantly under PID control. At 135 min, the dissolved oxygen concentration decreased to roughly 5.75 $\mathrm{mg \cdot L^{-1}}$ at which point the overshoot was 4.1%. After 120 min, the overshoot was reduced to be close to the set value but the tracking effect once more departed from the set value when the perturbation changed. Under the action of the controller designed in this paper, the tracking error of dissolved oxygen concentration is within $\pm 0.095\ \mathrm{mg \cdot L^{-1}}$, and the tracking accuracy is high. The system's maximum overshoot is 0.28% at 135 min and the regulation time is 12 min. In the presence of perturbation steps, the set value is still steadily monitored. From the aforementioned simulation, it can be seen that the disturbance observer used in this paper also has a good step disturbance observation effect. The dissolved oxygen control based on the disturbance observer can successfully overcome system uncertainty and the controller has strong anti-disturbance ability.

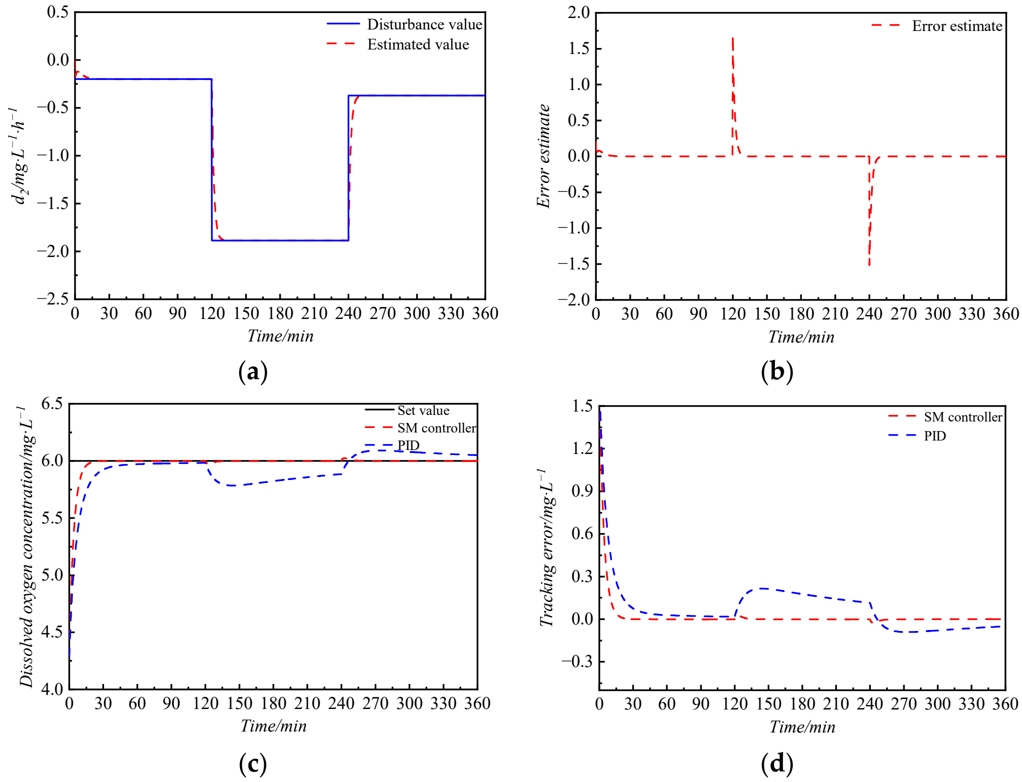

Figure 6. Control simulation under d_2 disturbance. (**a**) Disturbance estimation; (**b**) Disturbance estimation error; (**c**) Control under disturbance; (**d**) Control error under disturbance.

In aquaculture, the required level of dissolved oxygen concentration required by cultured organisms varies in different growth states [39]. The controller is simulated for this purpose using variable setpoint tracking. The dissolved oxygen is set to fluctuate in the range of $4.5 \sim 6.5 \text{ mg} \cdot L^{-1}$. Figure 7 shows that when the dissolved oxygen set value changes, the controller described in this study has a quick reaction time, a small tracking error, and strong tracking capabilities for various set values.

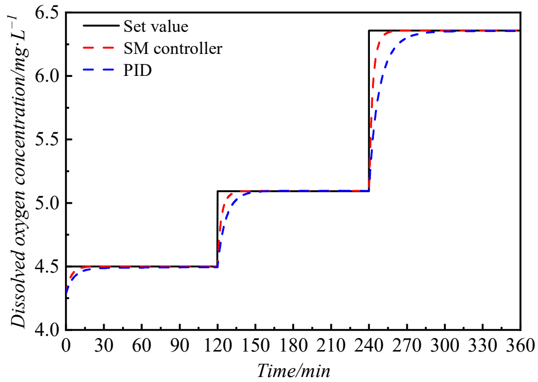

Figure 7. Variable set point control simulation.

In a complicated breeding environment, the controller can keep the concentration of dissolved oxygen at a steady level while reducing the need for the precision of the system model to accomplish exact control of dissolved oxygen. Two indicators, the integral of absolute value of error (IAE) and integral of squared error (ISE), were utilized to objectively monitor and evaluate the performance of the controller in order to manage the concentration of dissolved oxygen in recirculating water cultures.

$$IAE = \int_0^t |y - y_r| dt \tag{40}$$

$$ISE = \int_0^t (y - y_r)^2 dt \tag{41}$$

where y is the dissolved oxygen concentration and y_r is the set value. The controller performance index is calculated from Equations (40) and (41).

According to the performance indicators listed in Table 2, under the effect of d_1 disturbance, the IAE of this controller is 0.121, which is 85.76% lower than the IAE index of PID control, and the ISE index is 0.102, which is 66.88% lower. The IAE index of the PID controller is 0.727 and the ISE index is 0.243 under d_2 perturbation while the IAE index of the controller in this paper is 0.124, which is 82.9% lower, and the ISE index is 0.097, which is 60% lower. The controller in this research has lower IAE and ISE metrics under d_3 perturbation compared to the PID controller. In the dissolved oxygen variable setpoint tracking control, this controller has an ISE performance index of 0.049 and an IAE performance index of 0.112, both of which are 62.87% and 62.66% poorer than the PID control, respectively. In conclusion, the controller in this study can match the demands for aquaculture dissolved oxygen management and has good control precision and tracking capabilities in complicated aquaculture environments.

Table 2. Controller effect data comparison.

	This Strategy			PID		
	Under d_1	**Under d_2**	**Tracking Setpoint**	**Under d_1**	**Under d_2**	**Tracking Setpoint**
IAE	0.121	0.124	0.112	0.85	0.727	0.3
ISE	0.102	0.097	0.049	0.308	0.243	0.132

4. Conclusions

(1) In this paper, we conducted an analysis of the influencing factors of dissolved oxygen from the characteristics of a circulating water aquaculture system, established a dynamic model of dissolved oxygen in a circulating water aquaculture system and improved the model's applicability by taking into account the influence of various disturbing factors such as temperature, pH, and circulating water flow. On the basis of this, a disturbance observer-based adaptive sliding film control method is proposed. Through disturbance observation and adaptive compensation, this approach controls the concentration of dissolved oxygen under unpredictable disturbances without relying on an exact mathematical model of the system. Theory and simulation are used to show that dissolved oxygen control is stable in the presence of unknown disturbances;

(2) When the system circulating water flow and biological quality parameters are modified, the controller overshoot in this study is 0.3% with a 10 min adjustment time but the PID control overshoot is 2% with a 180 min adjustment time. The controller has good anti-interference performance;

(3) The disturbance observer can estimate the unknown disturbance caused by the uncertainty of the circulating water culture system in real time while the adaptive slide film controller assures the stability of the closed-loop system and increases the immunity of dissolved oxygen concentration management. When applying a slow time-varying disturbance d_1 and a step disturbance d_2 to the system, this controller reduces the absolute error integral (IAE) index by 85.76% and 82.9% and the error squared integral (ISE) index by 66.88% and 60%, respectively, compared to the PID controller;

(4) This control technique efficiently overcomes the effects of model uncertainty, random interference, and other variables on dissolved oxygen precision control as well as the problem of water quality fluctuations caused by traditional controllers. The controller designed in this study can estimate compensating interference in real time, ensuring the stability of dissolved oxygen concentrations in circulating water culture systems and improving water quality.

In future work, we will delve into the following areas: (1) the implementation of the nonlinear disturbance observers and adaptive sliding mode control methods discussed in this article may introduce increased complexity to the control system which could potentially pose challenges during algorithm implementation. (2) To achieve optimal performance, the adaptive sliding mode control method necessitates the adjustment of controller parameters which may require expertise in order to attain desired outcomes. (3) This strategy heavily relies on real-time online estimation and observation of external disturbances which places stringent demands on computational power and real-time capabilities.

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