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Fuzzy integral fault-tolerant control of an activated sludge process

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ABSTRACT

This paper presents a fuzzy integral fault-tolerant controller (FIFTC) for robust regulation of substrate and dissolved oxygen in activated sludge processes (ASP). The nonlinear dynamics of the process are represented using an augmented Takagi–Sugeno (TS) fuzzy model, which includes an additional vector representing the integral state to improve tracking accuracy. A fuzzy proportional-integral (PI) observer is employed to estimate states and detect actuator faults, particularly in the aeration system. Controller and observer gains are computed by solving linear matrix inequalities (LMIs), while an H_∞ performance criterion, defined by the parameter, ensures effective disturbance attenuation and bounds the error energy. In the simulation, we considered actuator faults of the loss of effectiveness (LOE) type. Simulation results demonstrate that FIFTC significantly outperforms classical linear quadratic regulator (LQR) in terms of tracking accuracy, robustness, and fault tolerance, even under partial actuator failures and external disturbances. The proposed FIFTC control strategy, which leverages fuzzy modeling, robust observers, and LMI-based optimization, provides significant benefits, primarily by improving efficiency, reducing energy consumption, and enhancing robustness.

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1. INTRODUCTION

Wastewater treatment facilities (WWTPs) are sophisticated systems characterized by complex nonlinearities and external disturbances, which encompass all uncontrollable factors impacting the process. The activated sludge process (ASP) is the most intricate and demanding among the associated chemical, mechanical, and biological processes [1]. Managing and overseeing wastewater treatment facilities (WWTPs) [2], [3] is difficult due to the intricacy of the operations, system uncertainties, and inadequate measuring tools [4].

A fuzzy fault-tolerant control (FTC) technique [5], [6] offers an efficient solution for preserving the stability and performance of an activated sludge process, notwithstanding disturbances or actuator malfunctions. This method employs fuzzy logic [7] to manage nonlinearities and uncertainties, hence guaranteeing dependable performance. The activated sludge process is a great case study due to the direct impact of important factors, such as dilution rate and aeration flow, on reactor stability and treatment efficiency.

Nonetheless, partial actuator failures, such as a defective feed valve or variations in the air compressor, might influence these parameters, resulting in imbalances in dissolved oxygen levels and substrate concentration, both essential for the biological processes that decompose contaminants. It facilitates the dynamic reconfiguration of the control strategy to effectively address anomalies when integrated with fuzzy fault-tolerant control.

The integration of fuzzy control [8] and fuzzy observer [9] ensures enhanced system resilience and maintains the continuity and quality of wastewater treatment. Recent studies on fuzzy fault-tolerant control underscore the efficacy of Takagi–Sugeno (TS) fuzzy models in conjunction with fuzzy or adaptive observers for the estimation of internal states and the identification of actuator and sensor faults [10]. These methodologies aim to maintain system performance and stability despite disruptions, measurement noise, or partial component failures. To ensure strong closed-loop performance, control laws are typically formulated by resolving linear matrix inequalities (LMIs) [11].

Various strategies have been developed to enhance estimation accuracy and facilitate active fault compensation, including sliding mode observers, disturbance observers, and adaptive fuzzy controllers [12], [13]. Findings on diverse nonlinear systems (including manipulators, time-delay processes, and noise-affected systems) indicate that these techniques can attain robust trajectory tracking [14], [15] and reduce fault sensitivity. They also enhance energy performance, rendering them particularly suitable for dissolved oxygen control in activated sludge processes.

This study seeks to develop a Takagi–Sugeno (TS) model representation [16], [17] of the ASP [18], integrating actuator malfunctions and external disturbances that may affect system performance. An enhanced system incorporating both process states and the integral of the tracking error is presented to reframe the issue as a trajectory tracking challenge [19]. The objective of this technique is to implement the proposed fuzzy fault-tolerant controller in real systems [20]. Furthermore, stability conditions articulated via LMIs can be integrated utilizing optimization tools. This guarantees comprehensive evaluation of disruptions and actuator malfunctions while maintaining the overall resilience and stability of the process.

This presents a notable benefit over parallel distributed compensation control (PDC) [21] and linear quadratic integral control (LQI) [22], which neglect disturbances and actuator failures in their LMI formulations. Furthermore, numerous research have compared the fuzzy proportional-integral (PI) controller [23] with the fuzzy PID controller [24]. We focus the inquiry on the regulation of dissolved oxygen and substrate to illustrate the originality and effectiveness of our methods. A fuzzy integral fault-tolerant controller (FIFTC) is designed to ensure that the system reliably follows the desired nominal behavior despite faults and disturbances. The H_∞ performance criterion, which mitigates the effects of uncertainties and constrains error energy through an attenuation limit specified by the parameter γ, is employed in the design of this controller. Additionally, an integrated fuzzy observer is designed to concurrently estimate the system's internal states and faults, facilitating accurate and dynamic fault compensation. The achieved performance is subsequently compared with that of a LQR controller, illustrating that the proposed technique exhibits significantly enhanced behavior under fault situations, superior robustness, and improved disturbance attenuation.

This paper advances the domain of intelligent control for bioprocesses by: i) creating an enhanced TS fuzzy model that incorporates integral action for superior tracking precision in ASP; ii) introducing an innovative FIFTC strategy that enables concurrent state and fault estimation through a fuzzy PI observer; iii) establishing LMI-based stability criteria with H_∞ performance assurances; and iv) illustrating through comparative simulations the enhanced efficacy of FIFTC relative to traditional LQR in the presence of actuator faults.

2. TAKAGI-SUGENO FUZZY MODEL WITH ACTUATOR FAULTS

The ASP system is described using a nonlinear state model that captures how the actuator, the process, and the sensors interact. Equation (1) defines how the process evolves over time, while the sensor output reflects the internal state through measurable quantities. This model clearly shows how actuator faults and external disturbances directly influence the system's behavior. It provides a solid basis for designing fault observers and fault-tolerant control strategies.

$$\begin{cases} \dot{x} = h(x, u + f, d) \\ y = g(x) \end{cases} \tag{1}$$

Let $x \in \mathbb{R}^n$ represent the state and $u \in \mathbb{R}^m$ denote the control; $f \in \mathbb{R}^m$ signifies the actuator fault, while the output $y \in \mathbb{R}^p$ is defined by the nonlinear functions h and g. Additionally, $d \in \mathbb{R}^q$ corresponds to the external disturbances. We examine the Takagi-Sugeno representation (2), wherein the i-th rule in a fuzzy rule base is:

RULE i: IF z_1 is A_1^i and ... and z_r is A_r^i

$$\text{THEN} \begin{cases} \dot{x}(t) = A_i x(t) + B_i\big(u(t) + f(t)\big) + R_i d(t) \\ y(t) = C_i x(t) \end{cases} \tag{2}$$

The premise variable vector $z \in \mathbb{R}^r$ is a subset of x, u, θ, and y. A_j^i is a fuzzy subset characterized by the membership function $\mu_{A_j^i} : \mathbb{R} \to [0, 1]$. The membership function $\mu_{A_j^i}(z_j)$ is delineated in the i-th rule pertaining to the j-th premise variable.

$$A_i = \frac{\partial h}{\partial x}\mid_{(x_i,u_i)}, B_i = \frac{\partial h}{\partial u}\mid_{(x_i,u_i)}, C_i = \frac{\partial g}{\partial x}\mid_{(x_i)}, R_i = \frac{\partial h}{\partial d}\mid_{(x_i,u_i)} \tag{3}$$

where : $d = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} DO_{in} \\ S_{in} \end{bmatrix}, f = \begin{bmatrix} f_1 \\ f_2 \end{bmatrix}$ represents the vector of actuator faults in dilution and aeration systems.

The depiction of the TS system is provided as follows:

$$\begin{aligned} \dot{x}(t) &= \sum_{i=1}^{r} h_i\big(z(t)\big)\Big(A_i x(t) + B_i\big(u(t) + f(t)\big) + R_i d(t)\Big) \\ y(t) &= \sum_{i=1}^{r} h_i\big(z(t)\big) C_i x(t) \end{aligned} \tag{4}$$

$$h_i(z) = \frac{\mu^i(z)}{\sum_{k=1}^{r} \mu^k(z)} \quad ; \quad \mu^i(z) = \prod_{j=1}^{r} \mu_j^i(z_j) \tag{5}$$

Given that $\sum_{i=1}^{r} h_i(z) = 1$, where r denotes the number of rules, $u(t)$ signifies the fault-tolerant control law, $f(t)$ denotes the actuator fault, $d(t)$ represents the disturbance signal, and $h_i(z(t))$ constitutes the validity model of the Takagi-Sugeno model. It is assumed that the time derivative of the fault is bounded.

3. METHOD

Our goal is to develop an intelligent control strategy that maintains system performance even in the presence of faults and external disturbances.

3.1. Fuzzy integral fault-tolerant control (FIFTC)

The novel fuzzy integral fault-tolerant control strategy is built on three key components. At its core, the controller uses a control law that combines integral action to ensure reference tracking, proportional action on the system states, and active compensation of estimated faults. The addition of an integral state forms an augmented system $\widetilde{x}(t) = [x(t), x_y(t)]^T$, enhancing stability and accuracy. The diagram of fuzzy integral fault-tolerant control of ASP is given in Figure 1.

The local state feedback controller with fault compensation is designed as:

$$u(t) = k_{1i} x(t) + k_{2i} x_y(t) - \widehat{f}(t) \tag{6}$$

where $k_{1i} \in \mathbb{R}^{m \times n}$, $k_{2i} \in \mathbb{R}^{m \times p}$ are the control gains and $\widehat{f}(t) \in \mathbb{R}^m$ is the estimated actuator fault.

$$\dot{x}_y(t) = y_{ref} - y(t) \tag{7}$$

where $x_{y(t)} \in \mathbb{R}^p$ represents an integral state variable. The fuzzy feedback controller with fault tolerance is presented as follows:

$$u(t) = \sum_{i=1}^{r} h_i(z(t)) \left[k_{1i} x(t) + k_{2i} x_y(t) - \widehat{f}(t)\right] \tag{8}$$

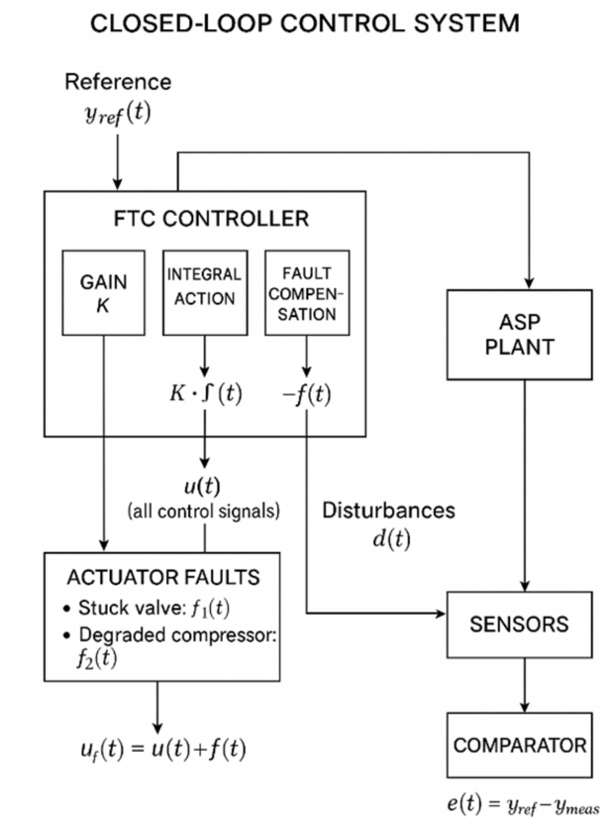

Figure 1. Diagram of fuzzy integral fault-tolerant control of activated sludge process

3.1.1. Augmented system formulation

The fuzzy controller is subsequently incorporated into the state equation of the closed-loop system:

$$\dot{x}(t) = \sum_{i=1}^{r} h_i(z(t))\Big(A_i x(t) + B_i\Big[\sum_{j=1}^{r} h_j(z(t))\big(k_{1j}x(t) + k_{2j}x_y(t) - \widehat{f}(t)\big) + f(t)\Big] + R_i d(t)\Big) \quad (9)$$

$$\dot{x}(t) = \sum_{i=1}^{r}\sum_{j=1}^{\Omega} h_i(z(t))\, h_j(z(t))[A_i x(t) + B_i\, k_{1j}x(t) + B_i k_{2j} x_y(t)\,) + B_i(f(t) - \widehat{f}(t)) + R_i d(t)]\,) \quad (10)$$

$$\dot{x}_y(t) = \sum_{i=1}^{r} h_i\,(z(t))\,(y_{ref} - C_i x(t)) \quad (11)$$

we define an augmented system such as:

$$\widetilde{x}(t) = \begin{bmatrix} x(t) \\ x_y(t) \end{bmatrix} \quad (12)$$

the augmented system is expressed as:

$$\dot{x}(t) = \sum_{i=1}^{r}\sum_{j=1}^{\Omega} h_i(z(t))\, h_j(z(t))[\widetilde{A}_i\, \widetilde{x}(t) + \widetilde{B}_i\, w(t) + \widetilde{R}_i\, d(t)]] \quad (13)$$

where

$$\widetilde{A}_{ij} = \begin{bmatrix} A_i + B_i k_{1j} & B_i k_{2j} \\ -C_i & 0 \end{bmatrix}, \widetilde{B}_i = \begin{bmatrix} B_i & 0 \\ 0 & -I \end{bmatrix}, \widetilde{R}_i = \begin{bmatrix} R_i & 0 \\ 0 & 0 \end{bmatrix},\; w(t) = \begin{bmatrix} f(t) - \widehat{f}(t) \\ y_{ref}(t) \end{bmatrix} \quad (14)$$

In the augmented system, the state vector $\widetilde{x}(t) \in \mathbb{R}^{n+p}$ combines the original system state and the integral state, thus accounting for both the system dynamics and the integral action for control. The augmented state matrices $\widetilde{A}_{ij} \in \mathbb{R}^{(n+p)\times(n+p)}$ describe the system dynamics for each pair of rules i and j, while the augmented input matrices $\widetilde{B}_i \in \mathbb{R}^{(n+p)\times(m+p)}$ incorporate not only the control inputs but also the effects of faults and references. The augmented disturbance matrix $\widetilde{R}_i \in \mathbb{R}^{(n+p)\times l}$ preserves the contributions of the disturbance $R_i d(t)$ in the extended system. The external input vector $w(t) \in \mathbb{R}^{m+p}$ groups the actuator fault estimation error $f(t) - \widehat{f}(t) \in \mathbb{R}^m$, the output reference $y_{\text{ref}}(t) \in \mathbb{R}^p$, and the external disturbances $d(t) \in \mathbb{R}^q$, which are treated separately, enabling better management of uncertainties and discrepancies between the model and the real system.

3.1.2. Fundamental Lemmas for stability analysis

Lemma 1 (Young's Inequality): For any matrices X, Y of appropriate dimensions and for any positive scalar η, the following inequality holds:

$$X^T Y + Y^T X \leq \eta X^T X + \eta^{-1} Y^T Y \tag{15}$$

Lemma 2 (Schur complement): for a symmetric matrix: $\begin{bmatrix} A & B \\ B^T & C \end{bmatrix}$ with $C > 0$,

$$\begin{bmatrix} A & B \\ B^T & C \end{bmatrix} < 0 \iff A - BC^{-1}B^T < 0 \tag{16}$$

3.2. LMI problem formulation

We begin by defining the Lyapunov function:

$$V(\widetilde{x}(t)) = \widetilde{x}(t)^T P \widetilde{x}(t), \;\; P = P^T > 0 \tag{17}$$

then, the derivative of this function along the trajectories of the system is:

$$\dot{V}(\widetilde{x}(t)) = \dot{\widetilde{x}}(t)^T P \widetilde{x}(t) + \widetilde{x}^T P \dot{\widetilde{x}}(t) \tag{18}$$

substituting the augmented system dynamics:

$$\dot{V} = \sum_{i=1}^{r} \sum_{j=1}^{\Omega} h_i \, h_j [\; \widetilde{x}^T (\widetilde{A}_{ij}^T P + P\, \widetilde{A}_{ij})\widetilde{x} + w^T \widetilde{B}_i^T P \widetilde{x} + \widetilde{x}^T P \widetilde{B}_i w + d^T \widetilde{R}_i^T P d \widetilde{x} + \widetilde{x}^T P \widetilde{R}_i d] \tag{19}$$

applying the H_∞ performance criterion to ensure disturbance and fault attenuation:

$$\dot{V}(\widetilde{x}(t)) + \widetilde{x}(t)^T Q \widetilde{x}(t) - \gamma^2 (w(t)^T w(t) + d(t)^T d(t)) < 0 \tag{20}$$

where
$Q = Q^T > 0 \in \mathbb{R}^{(n+p)\times(n+p)}$: Positive definite weighting matrix for state performance.
$\gamma > 0$: H_∞ performance level (attenuation level from disturbances to outputs).
$w(t)^T w(t) + d(t)^T d(t)$: Combined energy of fault estimation errors and disturbances.
According to Lemma 1, the following inequalities are obtained for the cross terms:

$$\begin{aligned} w^T \widetilde{B}_i^T P \widetilde{x} + \widetilde{x}^T P \widetilde{B}_i w &\leq \eta_1 \widetilde{x}^T P \widetilde{B}_i \widetilde{B}_i^T P \widetilde{x} + \eta_1^{-1} w^T w \\ d^T \widetilde{R}_i^T P \widetilde{x} + \widetilde{x}^T P \widetilde{R}_i d &\leq \eta_2 \widetilde{x}^T P \widetilde{R}_i \widetilde{R}_i^T P \widetilde{x} + \eta_2^{-1} d^T d \end{aligned} \tag{21}$$

Theorem 1 (Fault-tolerant control stability): There exist positive definite matrices $P \in \mathbb{R}^{(n+p)\times(n+p)}$ and $Q \in \mathbb{R}^{(n+p)\times(n+p)}$ such that the system (10) is asymptotically stable with H_∞ performance level γ if:

$$\widetilde{A}_{ij}^T P + P\widetilde{A}_{ij} + Q + \eta_1 P \widetilde{B}_i \widetilde{B}_i^T P + \eta_2 P \widetilde{R}_i \widetilde{R}_i^T P + \left(\eta_1^{-1} + \eta_2^{-1} - \gamma^2\right) I \leq 0 \tag{22}$$

Applying Lemma 2 (Schur complement), we obtain the LMI formulation:

$$\begin{bmatrix} \widetilde{A}_{ij}^T P + P\widetilde{A}_{ij} + Q & P\widetilde{B}_i & P\widetilde{R}_i \\ \widetilde{B}_i^T P & -\gamma^2 I & 0 \\ \widetilde{R}_i^T P & 0 & -\gamma^2 I \end{bmatrix} < 0 \tag{23}$$

for $Q = Q^T > 0$, we can verify that

$$\dot{V}\left(\widetilde{x}(t)\right) \leq -\widetilde{x}^T(t) Q \widetilde{x}(t) + \gamma^2 \left(w^T(t) w(t) + d^T(t) d(t) \right)$$

the existence of the minimum eigenvalue $\lambda_{\min}$ which verifies

$$-\lambda_{\min} \| \widetilde{x}(t) \|^2 \geq \gamma^2 \left(\| w(t) \|^2 + \| d(t) \|^2 \right) \qquad \dot{V}(\widetilde{x}(t)) \leq 0 \tag{24}$$

then the system is stable.

3.2.1. LMI solution procedure

To derive the LMIs form, we consider the subsequent variable transformation:

$$\begin{aligned} X &= P^{-1} > 0 \\ Y &= XQX > 0 \\ M_{1i} &= k_{1i} X \\ M_{2i} &= k_{2i} X \end{aligned} \tag{25}$$

where $X \in \mathbb{R}^{(n+p)\times(n+p)}$: Inverse of Lyapunov matrix P, $Y \in \mathbb{R}^{(n+p)\times(n+p)}$: Transformed weighting matrix for LMI formulation, $M_{1i} \in \mathbb{R}^{m\times(n+p)}$: Transformed state feedback gain matrix for rule *I*, $M_{2i} \in \mathbb{R}^{m\times(n+p)}$: Transformed integral gain matrix for rule *i*. We obtain the following stability conditions:

for $i = j$:

$$\begin{bmatrix} \Psi_{ii} & \widetilde{B}_i & \widetilde{R}_i & X \\ \widetilde{B}_i^T & -\gamma^2 I & 0 & 0 \\ \widetilde{R}_i^T & 0 & -\gamma^2 I & 0 \\ X & 0 & 0 & -Y^{-1} \end{bmatrix} < 0 \tag{26}$$

for $i \neq j$:

$$\begin{bmatrix} \Psi_{ij} + \Psi_{ji} & \widetilde{B}_i + \widetilde{B}_j & \widetilde{R}_i + \widetilde{R}_j & X \\ (\widetilde{B}_i + \widetilde{B}_j)^T & -2\gamma^2 I & 0 & 0 \\ (\widetilde{R}_i + \widetilde{R}_j)^T & 0 & -2\gamma^2 I & 0 \\ X & 0 & 0 & -Y^{-1} \end{bmatrix} < 0 \tag{27}$$

where

$$\Psi_{ij} = \widetilde{A}_i X + \widetilde{B}_i M_j + (\widetilde{A}_i X + \widetilde{B}_i M_j)^T + Y \tag{28}$$

$\Psi_{ij} \in \mathbb{R}^{(n+p)\times(n+p)}$: LMI matrix term for rules *i* and *j* combination. $\widetilde{A}_i X + \widetilde{B}_i M_j$: Transformed closed-loop system matrix. $M_j = [M_{1j} \quad M_{2j}]$: Combined gain matrix for rule *j*.

$$Y = \begin{bmatrix} Y_{11} & \cdots & Y_{1r} \\ \vdots & \ddots & \vdots \\ Y_{r1} & \cdots & Y_{rr} \end{bmatrix} > 0 \tag{29}$$

therefore, if the aforementioned conditions are met, the closed-loop system exhibits asymptotic stability with fault tolerance capabilities.

4. FUZZY PI OBSERVER

The goal is to design a PI observer that can simultaneously estimate the system's internal states and actuator faults while guaranteeing a H_∞ performance level in the presence of modeling uncertainties and external disturbances. This is important to remember before presenting the stability conditions of the fuzzy observer.

4.1. Fuzzy PI observer structure

Consider the estimated state of the faulty system $\widehat{x}_f \in \mathbb{R}^n$, the estimated actuator fault $f(t) \in \mathbb{R}^m$ and the external disturbances $d(t) \in \mathbb{R}^q$. In this study, $L_i \in \mathbb{R}^{n\times p}$ represents the state observer gains, $K_I \in \mathbb{R}^{m\times p}$ and $K_P \in \mathbb{R}^{m\times p}$ denote respectively the integral and proportional gains of the fault estimator, whil $\widehat{Z}_f(t)$ corresponds to the estimated premise variables. The proportional-integral fuzzy observer is designed for simultaneous state and fault estimation:

$$\begin{array}{c} \dot{\widehat{x}}_f(t) = \sum_{i=1}^r h_i\left(\widehat{z}_f(t)\right)\Big(\ A_i\widehat{x}_f(t) + B_i\left(u(t)+\widehat{f}(t)\right) + L_i\left(y_f(t)-\widehat{y}_f(t)\right)\ \Big) \\ \dot{\widehat{f}}(t) = K_I\left(y_f(t)-\widehat{y}_f(t)\right) + K_P\int_0^t\left(y_f(\tau)-\widehat{y}_f(\tau)\right)d\tau \\ \widehat{y}_f(t) = \sum_{i=1}^r h_i\left(\widehat{z}_f(t)\right)C_i\widehat{x}_f(t) \end{array} \tag{30}$$

consider system (4) and (30), we define the estimation errors:

$$\begin{array}{c} e_x(t) = x_f(t) - \widehat{x}_f(t)(\text{state error}) \\ e_f(t) = f(t) - \widehat{f}(t)(\text{fault error}) \end{array} \tag{31}$$

the state error dynamics are given by:

$$\dot{e}_x(t) \ = \sum_{j=1}^r h_i\left(\widehat{z}_f(t)\right)[(A_i - L\,C_i)e_x(t)\ +\ B_i\,e_f(t) + \Delta_h(t)\ +\ R_i d(t)] \tag{32}$$

where $\Delta_h(t)$ represents the uncertainty due to membership function differences:

$$\Delta_h(t) \ = \sum_{j=1}^r (h_i(z_f(t) - h_i(\widehat{z}_f(t))\ \ (A_{\,i}x_f(t) + B_i(u(t)\ + f(t))) \tag{33}$$

consider the augmented state vector:

$$\eta(t) = \begin{bmatrix} e_x(t) \\ e_f(t) \end{bmatrix} \in \mathbb{R}^{n+m} \tag{34}$$

the augmented system dynamics become:

$$\dot{\eta}(t) = \sum_{i=1}^r \left(h_i\left(\widehat{z}_f(t)\right)\left(\overline{A}\eta(t) + \overline{E}\xi(t)\right)\right) \tag{35}$$

with:

$$\begin{array}{c} \overline{A}_i = \begin{bmatrix} A_i - L_iC_i & B_i \\ -K_PC_i & -K_IC_iB_i \end{bmatrix} \\ \overline{E} = \begin{bmatrix} I & 0 & R_i \\ -K^P & I & -K^IC_iR_i \end{bmatrix} \\ \xi(t) = \begin{bmatrix} \Delta_h(t) \\ \dot{f}(t) \\ d(t) \end{bmatrix} \end{array}$$

4.2. Stability analysis through Lyapunov method

The stability conditions of the fuzzy observer are given in the following theorem.

Theorem 2: The system (33) with fuzzy PI observer is asymptotically stable if there exist symmetric positive definite matrices $P_1 \in \mathbb{R}^{n\times n}$, $P_2 \in \mathbb{R}^{m\times m}$, matrices $J_i \in \mathbb{R}^{n\times p}$, $Y_1 \in \mathbb{R}^{m\times p}$, $\varphi_i \in \mathbb{R}^{m\times p}$, and a scalar $\gamma > 0$ such that the following LMIs are satisfied for $i = 1, \ldots, r$:

$$\begin{bmatrix} \Phi_{11} & \Phi_{12} & P_1 & 0 & P_1 R_i \\ \Phi_{12}^T & \Phi_{22} & -Y_1 C_i & P_2 & -Y_1 C_i R_i \\ P_1 & -C_i^T Y_1^T & -\gamma I & 0 & 0 \\ 0 & P_2 & 0 & -\gamma I & 0 \\ R_i^T P_1 & -R_i^T C_i^T Y_1^T & 0 & 0 & -\gamma I \end{bmatrix} < 0 \tag{36}$$

with:

$$\begin{aligned} \Phi_{11} &= P_1 A_i - J_i C_i + (P_1 A_i - J_i C_i)^T + Q_1, \\ \Phi_{12} &= P_1 B_i + \left(\varphi_i^T C_i - Y_1 C_i A_i\right)^T, \\ \Phi_{22} &= -Y_1 C_i B_i + (-Y_1 C_i B_i)^T + Q_2. \end{aligned} \tag{37}$$

Proof: Consider the Lyapunov function candidate:

$$V(\eta(t)) = \eta(t)^T P \eta(t) \qquad , \; P = \begin{bmatrix} P_1 & 0 \\ 0 & P_2 \end{bmatrix} > 0 \tag{38}$$

the time derivative along the system trajectories gives:

$$\dot{V}(\eta(t)) = \dot{\eta}(t)^T P \eta(t) + \eta(t)^T P \dot{\eta}(t) \tag{39}$$

applying the H_∞ performance criterion

$$\int_0^\infty \eta(t)^T Q \eta(t) dt < \gamma^2 \int_0^\infty \xi(t)^T dt + V(\eta(0))$$

Which guarantees the robustness of the observer with respect to uncertainties and disturbances.

$$\dot{V}(\eta(t)) + \eta(t)^T Q \eta(t) - \gamma^2 \xi(t)^T \xi(t) < 0 \tag{40}$$

$$\sum_{i=1}^r h_i(\widehat{z}_f(t)) \left[\begin{array}{r} \eta(t)^T \left(\overline{A}_i^T P + P\overline{A}_i + Q\right) \eta(t) + \xi(t)^T \overline{E}^T P \eta(t) + \eta(t)^T P \overline{E} \xi(t) - \\ \gamma^2 \xi(t)^T \xi(t) \end{array} \right] < 0 \tag{41}$$

This inequality can be written in matrix form:

$$\sum_{i=1}^r h_i(z(t)) \begin{bmatrix} \eta(t) \\ \xi(t) \end{bmatrix}^T \begin{bmatrix} \overline{A}_i^T P + P\overline{A}_i + Q & P\overline{E} \\ \overline{E}^T P & \gamma^2 I \end{bmatrix} \begin{bmatrix} \eta(t) \\ \xi(t) \end{bmatrix} < 0 \tag{42}$$

Using Lemma 2 (Schur Complement) and the variable changes:

$$\begin{aligned} J_i &= P_1 L_i \\ Y_1 &= P_2 K_I \\ \varphi_i &= P_2 (K_I C_i L_i - K_P) \end{aligned} \tag{43}$$

then, we obtain LMI's conditions given in Theorem 2. By solving these LMIs, we then obtain the observer gains in the following form (44):

$$\begin{aligned} L_i &= P_1^{-1} J_i \;,\; i = 1, \ldots, r \\ K_I &= P_2^{-1} Y_1 \\ K_P &= \frac{1}{r} \sum_{i=1}^r \left(K_I C_i L_i - P_2^{-1} \varphi_i\right) \end{aligned} \tag{44}$$

where L_i: State observer gains for each fuzzy rule, K_I : Integral gain of the fault estimator, K_P: Proportional gain of the fault estimator, γ is the H_∞ performance level for the observer.

5. RESULTS AND DISCUSSION

5.1. Process discreption

The ASP presented in Figure 2 is a biological wastewater treatment system based on aeration and the activity of microorganisms responsible for degrading organic matter. The chosen model in the simulation is the model of [25]. It ensures effective purification through the continuous mixing of the substrate, dissolved oxygen, and biomass.

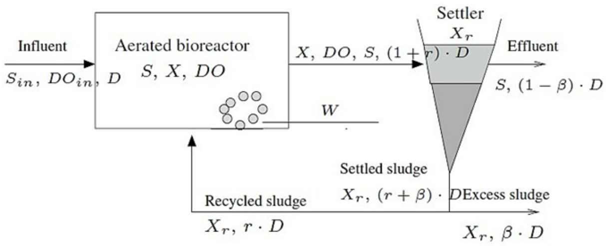

Figure 2. Aerobic wastewater treatment process: ASP

X represents the biomass, S denotes the substrate, while DO and X_r signify the dissolved oxygen and the recycled biomass, respectively, as the state variables. The comprehensive exposition of the state equations and parameter values of the process was delineated in our prior study [14]. The control vector is specified as $u = [D \quad W]$, where D signifies the dilution rate and W indicates the aeration rate.

The biomass X and recycled biomass X_r variables are not directly accessible for real-time measurement because of the sensors' excessively slow response times and technological limitations. As a result, the control of the substrate and the dissolved oxygen, which are quantifiable and pertinent factors for controlling the ASP process, is the sole focus of our investigation.

The occurrence of actuator faults that may affect the system dynamics is considered in this study. In particular, a progressive loss fault can lead to a gradual decrease in the effectiveness of the dilution rate, resulting in a flow lower than the commanded value. Similarly, a gradual degradation of the compressor can impact the aeration rate, causing the air supply to become increasingly lower than the desired setpoint. Equation (4) defines the state-space representation that is used to model these flawed behaviors.

In order to construct the fuzzy model, we consider that the vector of permise variables is composed of $D(t)$ diluion rate and $S_{in}(t)$ Substrate in the influent: $z(t) = \begin{bmatrix} D(t) & S_{in}(t) \end{bmatrix}^T$ which leads to $r = 2^2 = 4$ sub-models corresponding to the minimum and maximum values of the premise variables. The resulting Takagi-Sugeno (TS) representation is therefore defined by $r = 4$ rules, yielding:

$$A_1 = \begin{bmatrix} -0.0432 & 0.0011 & 0.0003 & 0.0455 \\ -0.1202 & -0.1230 & -0.0005 & 0 \\ -0.0601 & -0.0008 & -0.6205 & 0 \\ 0.1214 & 0 & 0 & -0.0607 \end{bmatrix}$$

$$A_2 = \begin{bmatrix} 0.0192 & 0.0006 & 0.0002 & 0.0214 \\ -0.1171 & -0.0579 & -0.0003 & 0 \\ -0.0585 & -0.0005 & -0.3007 & 0 \\ 0.0569 & 0 & 0 & -0.0285 \end{bmatrix}$$

$$A_3 = \begin{bmatrix} 0.0068 & 0.0009 & 0.0339 & 0.0127 \\ 0.0127 & -0.0352 & -0.0522 & 0 \\ -0.0312 & -0.0007 & -0.1210 & 0 \\ -0.0007 & 0 & 0 & -0.0169 \end{bmatrix}$$

$$A_4 = \begin{bmatrix} -0.0012 & 0.0009 & 0.1196 & 0.0074 \\ -0.0286 & -0.0212 & -0.1841 & 0 \\ -0.0143 & -0.0007 & -0.1706 & 0 \\ 0.0198 & 0 & 0 & -0.0099 \end{bmatrix}$$

$$B_1 = \begin{bmatrix} 0 & 140.7595 \\ 0 & -192.6664 \\ -0.5592 & -65.7072 \\ 0 & -189.6118 \end{bmatrix} \quad B_2 = \begin{bmatrix} 0 & 140.7359 \\ 0 & -182.1245 \\ -0.5532 & -65.1720 \\ 0 & -188.7495 \end{bmatrix}$$

$$B_3 = \begin{bmatrix} 0 & 126.6169 \\ 0 & -159.6921 \\ 0.1375 & -3.7803 \\ 0 & -171.1206 \end{bmatrix} \quad B_4 = \begin{bmatrix} 0 & 101.1574 \\ 0 & -127.8967 \\ 0.1661 & -1.2369 \\ 0 & -138.5586 \end{bmatrix}$$

$$R_1 = \begin{bmatrix} 0 & 0 \\ 0.0758 & 0 \\ 0 & 0.0758 \\ 0 & 0 \end{bmatrix} \quad R_2 = \begin{bmatrix} 0 & 0 \\ 0.0356 & 0 \\ 0 & 0.0356 \\ 0 & 0 \end{bmatrix}$$

$$R_3 = \begin{bmatrix} 0 & 0 \\ 0.0211 & 0 \\ 0 & 0.0211 \\ 0 & 0 \end{bmatrix} \quad R_4 = \begin{bmatrix} 0 & 0 \\ 0.0124 & 0 \\ 0 & 0.0124 \\ 0 & 0 \end{bmatrix}$$

The PI observer gains K_I and K_P respectively are given by:

$$K_I = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \quad K_P = \begin{bmatrix} 0.05 & 0 \\ 0 & 0.05 \end{bmatrix}$$

The inputs of the system with actuator faults is given in Figure 3 and 4:

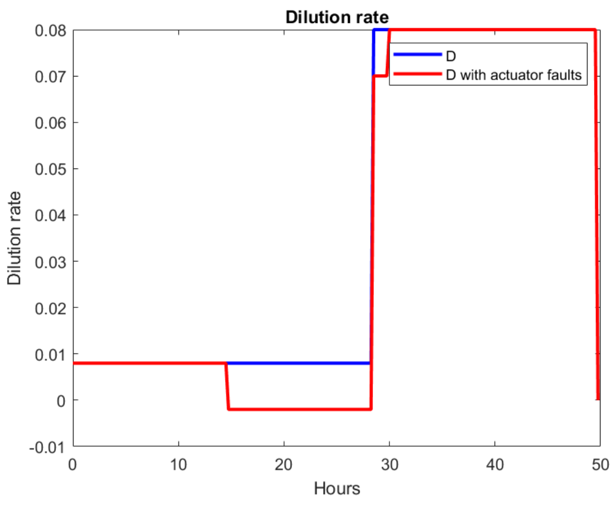

Figure 3. Input signal (Dilution rate) with actuator fault

5.2. Fuzzy integral fault-tolerant control

The following controller gains were derived from the resolution of the LMIs associated with Theorem 1:

$$K_{1i_1} = \begin{bmatrix} -926.263 & -13.673 & -0.324 & -673.121 \\ 0.1576 & 0.0762 & -0.00006 & 0.0339 \end{bmatrix}$$

$$K_{1i_2} = \begin{bmatrix} -1268.587 & 49.687 & -0.897 & -993.657 \\ 0.367 & 0.244 & -0.00001 & 0.031 \end{bmatrix}$$

$$K_{1i_3} = \begin{bmatrix} 1081.672 & 645.085 & 7.067 & 194.496 \\ 0.223 & 0.133 & 0.0007 & 0.035 \end{bmatrix}$$

$$K_{1i_4} = \begin{bmatrix} 685.529 & 492.128 & 6.553 & 104.900 \\ -0.101 & -0.070 & 0.0009 & -0.015 \end{bmatrix}$$

$$K_{2i_1} = \begin{bmatrix} -37.854 & 0.765 \\ -0.020 & -0.009 \end{bmatrix} \quad K_{2i_2} = \begin{bmatrix} -89.015 & -4.064 \\ -0.034 & -0.015 \end{bmatrix}$$

$$K_{2i_3} = \begin{bmatrix} -17.269 & -33.465 \\ -0.005 & -0.007 \end{bmatrix} \quad K_{2i_4} = \begin{bmatrix} -24.579 & -15.176 \\ 0.003 & 0.003 \end{bmatrix}$$

The following are the gains of the synthesized observer obtained from the resolution of the LMIs in Theorem 2:

$$L_1 = \begin{bmatrix} 5.813 & 0.765 \\ 0.241 & 3.339 \\ -1215.788 & -2065.996 \\ 174.738 & 60.899 \end{bmatrix} \quad L_2 = \begin{bmatrix} 5.947 & 1.147 \\ 0.653 & 4.134 \\ -5453.892 & -9782.172 \\ 368.220 & 239.210 \end{bmatrix}$$

$$L_3 = \begin{bmatrix} 5.231 & -0.954 \\ -0.907 & 4.602 \\ 41.539 & -82.839 \\ 358.669 & 44.367 \end{bmatrix} \quad L_4 = \begin{bmatrix} 4.996 & -0.979 \\ -0.907 & 4.800 \\ 11.490 & -25.154 \\ 543.994 & 104.668 \end{bmatrix}$$

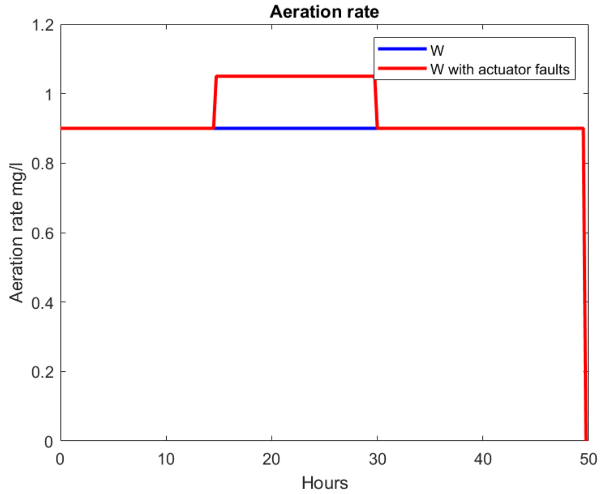

Figure 4. Input signal (Aeration rate) with actuator fault

The evolution of the system outputs is shown in Figure 5 and Figure 6. The comparison in Figure 4 between the conventional LQR controller and the proposed FIFTC shows a clear advantage for the FIFTC in regulating the ASP. The LQR behaves correctly when the system is not affected by faults, but its performance drops as soon as an actuator starts to deviate from its expected behavior. With the FIFTC, the integral action helps to better compensate for disturbances, and the fuzzy structure deals more naturally with the nonlinear behavior of the process.

The controller is designed using LMIs together with an H_∞ performance requirement ($\gamma = 10$), which strengthens stability and reduces the influence of faults acting on the aeration rate. The results confirm this improvement: the FIFTC achieves a lower RMSE (1.3352 mg/L compared with 1.7506 mg/L for the LQR) and reduces tracking errors, with an IAE of 55.0411 instead of 73.0742 for the LQR. The comparison results are presented in Table 1.

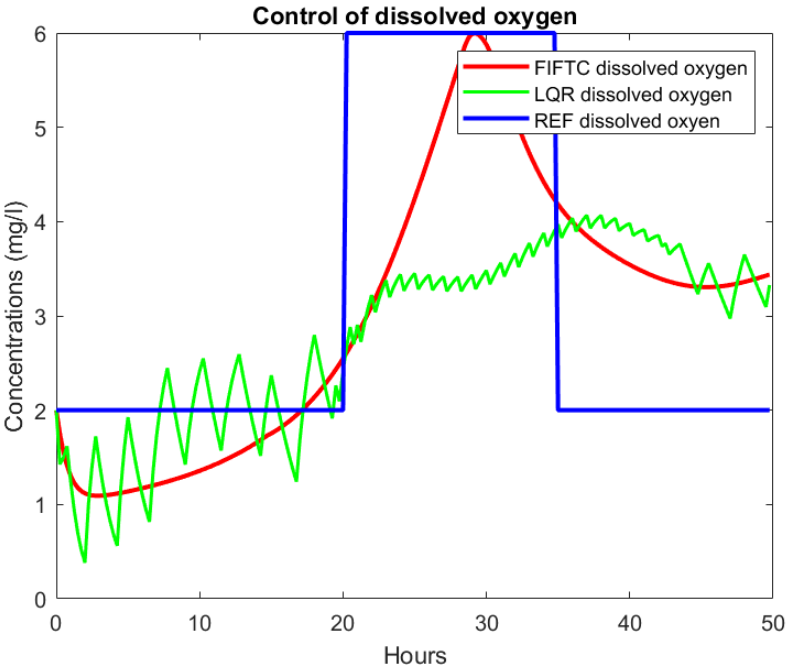

Figure 5. Evolution of dissolved oxygen concentration under FIFTC and LQR control

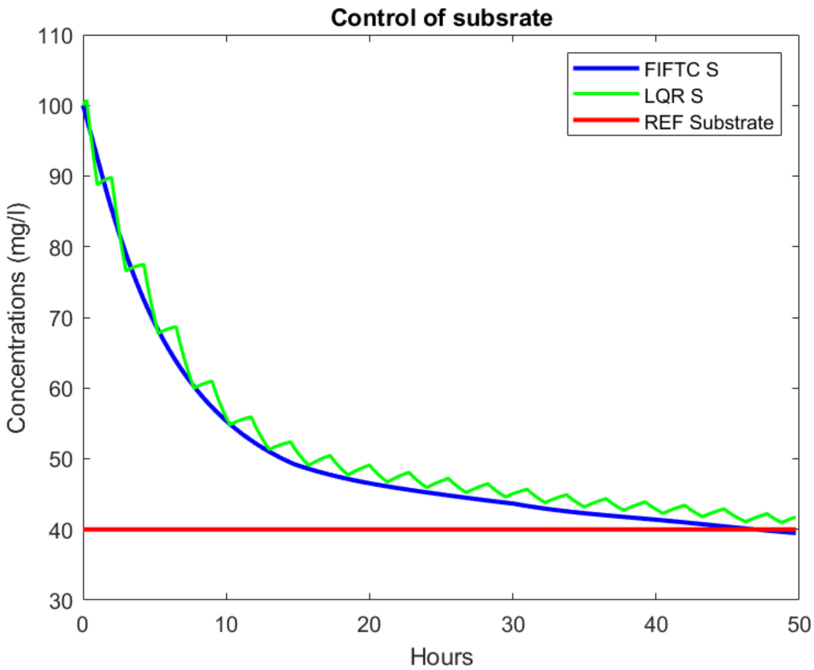

Figure 6. Evolution of substrate concentration under FIFTC and LQR control

Table 1. Evaluation results of the control of the disolved oxygen.

Controller	RMSE	IAE
FIFTC	1.3352 mg/l	55.04
LQR	1.7506 mg/l	73.07

The comparison in Figure 5 between the fault-tolerant fuzzy integral controller (FTIFC) and the classical LQR controller clearly shows how effective the proposed approach is for regulating the substrate in the ASP process. When an actuator begins to fail such as the substrate injection valve no longer responding correctly and reaching only about 70% of the commanded opening the behavior of the system quickly deteriorates. This type of situation remains difficult for linear controllers like the LQR to handle.

In the presence of such a fault, the LQR struggles to reject disturbances, which is reflected by an IAE of 3393.0077 and an RMSE of 70.3104 mg/L. With the FTIFC, the combination of fuzzy reasoning and an integral action improves the controller's ability to compensate for both the fault and the nonlinear nature of the process. As a result, the IAE decreases to 1974.2180 and the RMSE to 39.8242 mg/L, an improvement of roughly 42% and 43%. The comparison results are presented in Table 2.

In practice: In a real wastewater treatment plant, this control system runs on a standard industrial programmable logic controller (PLC). It uses the sensors already in place (dissolved oxygen, substrate). The originality lies in the fact that a fuzzy PI observer continuously estimates actuator faults of the loss of effectiveness (LOE) type — for example, an aerator compressor that has lost 30% of its efficiency or a dilution valve that opens less than requested. Rather than overreacting, the control law compensates gradually and intelligently for this loss. Thanks to the H_∞ tuning, the system remains robust against measurement noise and external disturbances. Most importantly, by avoiding sudden spikes and unnecessary overreactions (unlike a conventional controller), energy consumption is significantly reduced: only the necessary aeration is provided, even when an actuator is worn. The result is a more energy-efficient, more resilient plant that continues to treat water effectively even with slightly faulty equipment.

Table 2. Evaluation results of the control of substrate

Controller	RMSE	IAE
FIFTC	39.8242 mg/l	1974.2180
LQR	70.3104 mg/l	3393.0077

6. CONCLUSION

This study examines a fuzzy-integral fault-tolerant control strategy for Takagi-Sugeno (TS) fuzzy systems facing disturbances and actuator failures. The main idea is to steer the faulty system to follow a healthy nominal model, ensuring it stays robust and accurate even in the presence of faults. To deal with actuator malfunctions and external disturbances, the control strategy introduces an integral correction term on top of the original control law. With this added term, the faulty system is driven to follow the behavior of the ideal nominal model. The controller structure requires information about the fault, which is estimated using a fuzzy PI-type observer.

An H_∞ performance criterion is also used to limit the influence of disturbances and faults. The gains of the fuzzy integral controller (FTIFC) and the observer are computed using LMIs, which offer a solid and reliable framework for designing robust controllers for nonlinear systems like the ASP.

In controlling dissolved oxygen and substrate concentration, a comparison between FTIFC and the linear quadratic regulator (LQR) highlights significant differences. Although LQR performs well under ideal conditions, it is sensitive to modeling errors and external disturbances, which limits its reliability in complex biological systems like the ASP. In contrast, FTIFC maintains more stable and accurate regulation because fuzzy logic is well suited for handling nonlinearities and uncertainties. Compared to LQR, the proposed FIFTC improves RMSE by 24% for dissolved oxygen and 43% for substrate, with corresponding IAE reductions of 25% and 42% under progressive 30% actuator faults.

Looking ahead, future research could focus on strengthening fault detection and tolerance. A promising direction is the development of a fuzzy sliding-mode observer, which could speed up fault detection, improve resilience to unmodeled uncertainties, and offer complete tolerance to both actuator and sensor faults. Such improvements would further reinforce the robustness and reliability of the control system.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
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Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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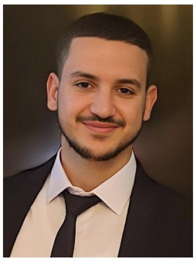

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