A novel approach to wastewater treatment control: a self-organizing fuzzy sliding mode controller

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Article Info

Article history:

Received Oct 29, 2023
Revised Jan 18, 2024
Accepted Feb 11, 2024

Keywords:

Dissolved oxygen
Effluents
Fuzzy logic
Sliding mode controller
Wastewater treatment

ABSTRACT

This research introduces a novel approach to wastewater treatment management utilizing a self-organizing fuzzy sliding mode controller (SOFSMC). This methodology showcases improved efficiency in wastewater treatment operations by incorporating MATLAB Simulink for simulation. The SOFSMC provides flexible and reliable control, effectively managing important factors such as pH levels, dissolved oxygen levels, and flow rates in the complex and uncertain process of treating wastewater. This novel approach integrates fuzzy logic and sliding mode control (SMC), resulting in a self-learning system that can autonomously adapt to the complexities of wastewater treatment operations. The results are positive, with an integrated absolute error of 0.082 mg/L, an integrated square differential error of 0.091 mg/L, and a response time of 1.85 seconds. This improvement demonstrates the ability of SOFSMC to enhance the effectiveness of treatment, preserve resources, and safeguard the environment. This study makes a significant contribution to sustainable water management and environmental conservation by providing a comprehensive approach to wastewater treatment regulation.

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1. INTRODUCTION

The process of wastewater treatment is of utmost importance because it serves as a crucial component in upholding public health, safeguarding the environment, and promoting the sustainable utilisation of water resources. The process entails the elimination of both organic and inorganic pollutants from wastewater before its discharge into the environment or its utilisation for diverse applications [1]. The implementation of this procedure is crucial in ensuring the preservation of water quality, conservation of ecosystems, and mitigation of transmission of waterborne illnesses. The origins of wastewater treatment can be traced back to ancient civilisations. Historical societies have acknowledged the significance of segregating human waste from unpolluted water sources as a means of averting contamination. It is noteworthy to mention that the Indus Valley Civilization, which stands as one of the earliest urban settlements in the world, exhibited meticulously designed sewage systems dating back to approximately 2500 before common era (BCE). Similarly, the ancient Romans devised intricate aqueducts and drainage systems to effectively regulate the disposal of wastewater. During the mid-20th century, an increasing recognition of environmental concerns and the adverse impacts of pollution on ecosystems and human well-being led governments to implement stringent policies regarding the release of wastewater [2]. The clean water act in the United States, along with analogous legislation implemented globally, establishes stringent criteria for wastewater treatment [3]. Consequently, these regulations have spurred the development of advanced technologies and the widespread implementation of more comprehensive treatment methodologies.

Efficient control in wastewater treatment is of paramount importance due to various crucial factors, including the protection of public health, preservation of the environment, and responsible utilisation of water resources. The principal objective of wastewater treatment is to eliminate harmful pollutants from sewage and industrial effluents. Neglecting to address this issue may lead to the proliferation of waterborne illnesses, thereby presenting significant health hazards to local populations. Efficient management of wastewater discharge is crucial for mitigating ecological consequences, thereby safeguarding the wellbeing of aquatic organisms and preserving the equilibrium of ecosystems. Wastewater treatment facilities must adapt to accommodate dynamic conditions, encompassing fluctuations in influent flow rates, pollutant loads, and meteorological patterns.

Fuzzy logic provides a method for dealing with imprecise and uncertain data and is inspired by the way humans think and make decisions [4]. This mathematical framework permits the representation of nebulous inputs, paving the way for the creation of control systems with the intelligence to make sound judgments in highly uncertain settings. Fuzzy logic is an effective modelling and control tool for wastewater treatment, where influent characteristics can vary widely, and sensor data can be noisy or uncertain [5]. Because it facilitates the creation of adaptive controllers, it is critical to maximising treatment effectiveness.

The ability to steer the system states along a specified sliding surface makes sliding mode controller (SMC) such a robust control strategy. This method is particularly effective for dealing with nonlinear and uncertain systems because it can be used to steer the system's behaviour towards a stable trajectory despite external disturbances and unknowns [6]. Nonlinear dynamics are common in wastewater treatment processes, and influent characteristics are notorious for being highly unpredictable. With its ability to maintain stability and desired performance even despite disturbances, SMC is a promising option for controlling wastewater treatment [7]. Self-organizing fuzzy sliding mode controller (SOFSMCs) are the result of the merging of fuzzy logic and SMC, and they combine the flexibility of the former with the stability of the latter. Together, they offer a promising approach to the complex and ever-changing problems of wastewater treatment.

In this study, we build a SOFSMC that is specifically designed for wastewater treatment processes and then test it. Our objective is to develop an adaptive control system that can optimise treatment performance under different conditions by combining the flexibility of SMC with the precision of fuzzy logic to model the inherent uncertainties of wastewater treatment. We hope to make a significant contribution to the field of control systems in critical domains and demonstrate that this novel approach improves the efficiency, reliability, and compliance of wastewater treatment processes through extensive experimentation and analysis.

The safe disposal or reuse of polluted water relies on wastewater treatment. It's crucial for ensuring people's wellbeing, keeping the environment safe, and keeping water supplies secure. However, wastewater treatment plants (WWTPs) that use conventional control methods often face difficulties in terms of efficiency, adaptability, and robustness. The dynamic and variable nature of influent wastewater can cause suboptimal performance and resource wastage in traditional treatment systems, making it one of the primary challenges. In addition, strict environmental regulations require highly effective pollutant removal and disinfection, which in turn calls for cutting-edge approaches to pollution management.

The problem statement focuses on the pursuit of a novel and adaptive control strategy to improve wastewater treatment process efficiency. Managing the complex and nonlinear dynamics of WWTPs can be difficult for traditional proportional integral derivative (PID) controllers and fixed-parameter control systems. This study's overarching objective is to test how well a SOFSMC can handle the complexities of wastewater treatment.

The study of controlling wastewater treatment with a SOFSMC is significant in many ways. Its primary function is to provide a novel and flexible solution to the difficult problems that have long plagued wastewater treatment systems. Research into improving the efficiency and dependability of WWTPs benefits ecosystems kerbs the spread of waterborne diseases and reduces pollution in receiving water bodies. There are far-reaching implications for sustainable water resource management from being able to maximise resource utilisation and facilitate water reuse through cutting-edge control strategies, especially in this era of growing water scarcity. From a financial standpoint, the proposed controller can make wastewater treatment processes more economically viable by reducing energy consumption, chemical usage, and the need for operational interventions.

The SOFSMC was chosen because of its inherent capacity to adapt to the nonlinear dynamics of wastewater treatment processes. In contrast to traditional control approaches, the SOFSMC excels at dealing with the complexities of these systems, ensuring robust and steady operation. Fuzzy logic, which is included in the SOFSMC, adds a level of uncertainty management that is critical for wastewater treatment. Traditional control approaches struggle with the unpredictability of influent features, whereas fuzzy logic allows the controller to make judgements based on imperfect information, increasing flexibility. In addition, this study contributes to the development of control systems by providing an example of the use of SOFSMC in a practical and crucial setting. This research is significant because it can improve wastewater treatment in terms of efficiency, reliability, and sustainability, all while addressing critical issues of water quality, resource scarcity, and environmental protection that affect people all over the world.

The subsequent sections of this paper are structured as follows: section 2 delves into recent works related to the topic, while section 3 outlines the methodology of the proposed approach. In section 4, a comprehensive analysis of results is provided, including a comparison with peer methods. The concluding remarks and a discussion on future work are presented in section 5.

2. RELATED WORKS

In this literature review, we explore the current body of knowledge and research on methods for controlling wastewater treatment, with specific emphasis on the use of fuzzy logic and SMC strategies. The introductory section establishes the context for a thorough analysis of previous research, emphasising significant findings, progress, and areas that require further investigation within the discipline. Through a comprehensive examination of the existing body of knowledge, our objective is to establish a robust framework for comprehending the importance of SOFSMC in the context of wastewater treatment, as well as its potential advancements in this vital field.

It must be emphasised that the construction of WWTPs does not solve all environmental problems; instead, constant monitoring of treatment plant performance is required to ensure that the intended environmental standards are met [8]. Complex biological, chemical, and physical processes are involved in wastewater treatment, and their nonlinear, and at times, time-varying dynamics can have a direct impact on the ability of the treatment plant to function [9]. The biochemical oxygen demand (BOD), chemical oxygen demand (COD), level of suspended and soluble solids, and pH of the effluent from this treatment plant are all common parameters used to evaluate the performance of WWTPs [10] proposed a learning control approach that does not rely on a specific model. This approach was developed to address the challenges posed by nonlinearity and environmental uncertainties in WWTPs. Furthermore, a nonlinear model-based predictive controller (NMPC) was developed to meet the effluent quality regulations of a WWTP while also considering economic feasibility [11]. Additional control strategies based on data analysis have also been examined in [12]. The development of control strategies based on data analysis can significantly enhance the identification of nonlinearity in WWTPs, thereby leading to improved control performance. However, a genuine WWTP frequently encounters significant disturbances linked to uncertainties, resulting in frequent and unpredictable variations in operational procedures.The efficacy of such control methods based on data may be compromised because of uncertainties and disturbances encountered in WWTPs [13]. In broad terms, the analysis of chattering is deemed advantageous for engineering applications because ofits ability to enhance the understanding of its impact on the stability of closed-loop control systems [14].

SMC is an advanced and diverse control methodology that operates discontinuous and modifies the components of a nonlinear system. The rule of state-investigation control is an abstract concept that imposes a consistent temporal constraint. In contrast, the transition can vary from one stable configuration to the next, depending on the current state within the state space [15]. The use of fuzzy-based sliding mode control (FSMC) has been suggested as a potential alternative for mitigating chattering. In past decades, scholarly literature has primarily concentrated on the introduction of "logic decision" in sliding systems [16]. The integration of both algorithms effectively addresses two significant issues: the mitigation of chattering attenuation and the minimisation of rules in dynamic fuzzy controllers. This is achieved by utilising a singular fuzzy variable, known as the sliding surface function, which encompasses all aspects of the dynamic process [17]. The predominant approach involves modifying the primary parameters of the SMC, including robust gain, sliding surface gradient, and switching control, in accordance with the plant's characteristics. One primary benefit of these schemes is that there is no requirement to possess knowledge of the upper bound of uncertainty and disturbance [18]. Ahmed *et al.* [19] present adaptive techniques for estimating uncertainties and disturbances using variable structure controllers. However, the uncertainties and disturbances inherent in the dynamical system may have bounded characteristics but are not known in terms of their specific parameters in real-world experimental scenarios.

According to Lin *et al*. [20], a novel SMC technique was proposed for regulating the dissolved oxygen (DO) concentration within a WWTPs integrated nitrogen removal process. The findings from the laboratory-scale reactor experiment demonstrated that the SMC method exhibited a commendable ability to reject disturbances and delivered satisfactory performance across a broad spectrum of operating conditions. In addition, various strategies have been implemented to mitigate uncertainties and disturbances in WWTPs [21],

[22]. Nevertheless, the strategies for SMC necessitate a comprehensive understanding of the nonlinearity exhibited by WWTPs todevelop an appropriate sliding surface design. The design of SMCs for WWTPs remains a challenging task [23]–[25]. A novel adaptive FSMC was proposed for multivariable control in a WWTP [26]. The adaptive FSMC employed a fuzzy method to approximate the unknown process while utilising SMC to guarantee the asymptotic stability of the closed-loop system. The simulation results demonstrated that the proposed method exhibited effective disturbance rejection and robustness. Despite the significant achievements of the methods mentioned in section 1 in WWTPs, chattering remains a persistent and significant challenge that has yet to be fully resolved. Based on the review and analysis presented earlier, this paper proposes the use of a SOFSMC to attain satisfactory and consistent control performance for WWTP.

3. METHOD

Fuzzy logic within a control system can incorporate prior knowledge to address uncertainties, the absence of adequate models, and disruptions in operational processes. The occurrence of chattering phenomena represents a significant drawback of SMCs, which arises from the use of the sign function during their design process. The proposed SOFSMC approach does not require the inclusion of a robust term to account for the inherent uncertainty in the mathematical model of the system. Consequently, it can mitigate the occurrence of chattering phenomena commonly observed in traditional sliding mode control systems. The control system model for a WWTP based on self-organizing sliding mode controller (SOSMC) is depicted in Figure 1. This model serves as the foundational framework for this study.

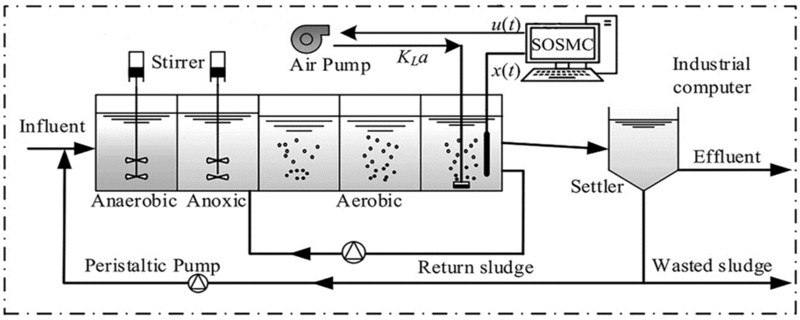

Figure 1. Control system model for WWTP based on SOSMC [27]

3.1. Self-organizing SOFSMC

The use of an SOSMC in the context of WWTPs signifies a novel approach to control that integrates the flexible nature of self-organizing systems with the resilience of sliding mode control. The use of this advanced controller holds promise in greatly improving the efficiency, reliability, and adherence to regulations in WTTPS procedures. To reduce the impact of uncertainties and nonlinearities, the SMC technique is applied. Rejecting disturbances caused by varying inflow loads due to environmental conditions is the task of the counting controller. Combining the adaptability of neural networks with the linguistic, rule-based approach of fuzzy logic, self-organizing fuzzy neural network (SOFNN) is a hybrid computational model. This sophisticated programme can adjust, learn, and make choices despiteambiguity. Its ability to model and process information in a way that closely resembles human reasoning and decision-making makes it particularly useful for tasks involving pattern recognition, classification and control.

No standard SMC methodology isdeveloped in the direct sliding-mode fuzzy controller design approaches. Instead, a fuzzy controller is developed according to the SMC theory concepts. To attain the desired objective, the fuzzy rule basis is adjusted such that $s\dot{s} \leq 0$. If $s\dot{s} < 0$, the control signal's prior alteration is preserved, while if $s\dot{s} > 0$, the control signal's previous alteration is reversed.To prevent any instances of chattering, the rules are considered. Presented in (1) is an illustrative instance of a second-order nonlinear dynamic system:

$$\ddot{x}_1 = f(x) + g(x)u \tag{1}$$

where $g(x) > 0$ and $f(x)$ are two scalar functions of the states of the system that are not known $x \in R^2$. Where $s = \dot{x} + \lambda x$is sliding manifold. The derivative in time of the sliding surface may be expressed as in (2).

$$\dot{s} = f(x) + g(x)u + \lambda\dot{x} \quad (2)$$

Choosing a Lyapunov function, it is necessary, according to Lyapunov theory, that $s\dot{s} < 0$. A fuzzy rule-based system is proposed to determine changes in the control signal Δu.The control system proposed in this study is illustrated in Figure 2. In this system, the control input $u(t)$ is determined by the fuzzy logic controller (FLC) component, which considers the values of s and $\dot{s}$at each sampling interval. The proposed algorithm is a self-organizing mechanism that considersdynamic reactions to effectively update the knowledge base of fuzzy rules.

$$\bar{u}_i(k+1) = \bar{u}_i(k) + \Delta\bar{u}_i(k) \quad (3)$$

$$= \bar{u}_i(k) + \omega_{e_i}\omega_{ec_i}\frac{\gamma}{M} \times [(1-\varsigma)s(k) + \varsigma\Delta s(k)]' \quad (4)$$

In this context, the symbol $\bar{u}_i$ represents the variation in control input for the ith rule, while $\Delta\bar{u}_i$ denotes the correction amount associated with each rule. Additionally, ω_{e_i} and ω_{ec_i} represent the excitation strength of each fuzzy rule, γ corresponds to the learning rate, ς signifies the weighting distribution, and M denotes the direct forward system gain, which is commonly assigned a value of 1. In this context, $s(k)$ and $\Delta s(k)$ represent the sliding surface and the change in the sliding surface over the k-step sample period, respectively. This methodology facilitates the establishment of a control loop in the absence of any initial guidelines. Once the rules are updated by a self-organizing algorithm, it is necessary to defuzzify the output of fuzzy inference.

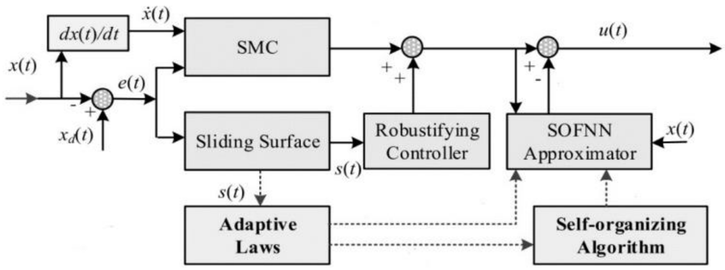

Figure 2. Proposed control system model

In a SOFSMC, fuzzy logic is used to dynamically adjust the parameters of the SMC based on the current state of the system. This allows the controller to adapt to changing conditions and maintain precise control even in the presence of uncertainties and disturbances. To address the occurrence of chattering phenomenon, a self-organizing mechanism has been developed to facilitate the construction of the structure of an fuzzy neural network (FNN). The self-organizing mechanism establishes a comprehensive assessment of the structural risks associated with FNN.

$$r(t_g) = \rho_1(t_g) + \rho_2(t_g) \quad (5)$$

In this context, the variable "t_g" represents the number of sampling intervals at a given time "t". The variable "$r(t_g)$" denotes the structural risk value, while "$\rho_1(t_g)$" represents the empirical error derived from the tracking error on the "t_gth" sampling interval and "$\rho_2(t_g)$" is the estimation error.

$$\rho_1(t_g) = \frac{1}{2}e(t)^T e(t) \quad (6)$$

$$\rho_2(t_g) = \frac{\sqrt{K(t_g)N\log T_g} - 2\log K(t_g)}{\sqrt{T_g}} \quad (7)$$

Let T_g represent the ratio of Tt_g to t, where T is the periodof the control process and $K(t_g)$ denotes the number of fuzzy rules during the t_gth sampling interval. Structural risk is said to be low when both empirical risk and structural complexity are small. If the condition $r(t_g) < \alpha 1$ holds, the structural risk value is acceptable.

If the self-organizing algorithm under consideration is capable of dynamically determining an appropriate size for the structure in realtime, it must strike a balance between minimising tracking error and minimising the complexity of the structure. The proposed SOFNN demonstrates the capability to accurately estimate and compensate for uncertain dynamics and disturbances, effectively mitigating the occurrence of the chattering phenomenon in SOSMC.

3.2. Dissolved oxygen dynamics

DO monitoring and control in WWTPs is of critical importance because it has a direct bearing on the success of biological treatment. Because aerobic conditions are required for the activity of beneficial microorganisms that break down organic pollutants, DO is a crucial indicator of the health of the microbial ecosystem. By accurately measuring DO levels, treatment effectiveness can be maximised, leading to timely organic matter degradation and decreased energy consumption. Furthermore, protecting environmental quality and meeting strict regulatory standards require maintaining adequate DO levels to prevent the release of inadequately treated effluents into natural water bodies. DO monitoring and control be essential for reducing water pollution and protecting ecosystem health because it improves the efficiency, cost-effectiveness, and regulatory compliance of wastewater treatment.The amount of oxygen required by an organism to decompose organic matter over a given time is known as its BOD. Concentrations of BOD in water that are too high (for example, 5 mg O2/L) reduce the amount of oxygen in the water, harm ecosystem biodiversity, lower water quality, and pollute freshwater supplies [28], [29]. The measurement of BOD necessitates the acquisition of at least two measurements. The first measurement, denoted as DO0, is taken immediately, whereas the second measurement is obtained after incubating water samples for a few days. The purpose of the incubation is to allow for the subsequent assessment of the remaining quantity of dissolved oxygen, referred to as DO1.

In an activated sludge process, the DO concentration shouldbe high enough so that the microorganisms can obtain the oxygen they should perform their metabolic processes. However, a high concentration of DO can be harmful to sludge quality and lead to excessive energy consumption. A proportional controller can be used to maintain the average DO level at a steady, user-specified value. Pulse width modulation (PWM) is used to modify the aeration rate, also known as the oxygen transfer rate.

$$u(k) = K_m(k)(C_{sat} - \hat{c}(k)) \quad (8)$$

The variable $\hat{c}(k)$ represents the estimated DO concentration as determined by the Kalman filter. The utilisation of this value in lieu of the measured value is attributed to its reduced noise, thereby leading to improved estimation outcomes. The aeration rate of the proportional controller can be calculated as (9).

$$u(k) = k_p.(c_{ref} - \hat{c}(k) \quad (9)$$

The reference value for the dissolved oxygen concentration is denoted as c_{ref}, while the gain of the proportional controller is represented by k_p. Figure 3 depicts the architecture of the DO concentration control system, which includes critical components such as PWM, the reactor, and the Kalman filter. The PWM block controls the reactor's input, while the Kalman filter improves accuracy in calculating DO concentrations. The interconnected blocks demonstrate the incorporation of sophisticated control techniques, highlighting the importance of the suggested methodology. This diagram depicts the complicated, yet choreographed processes required to establish exact control over DO concentrations, which is critical in wastewater treatment optimisation.

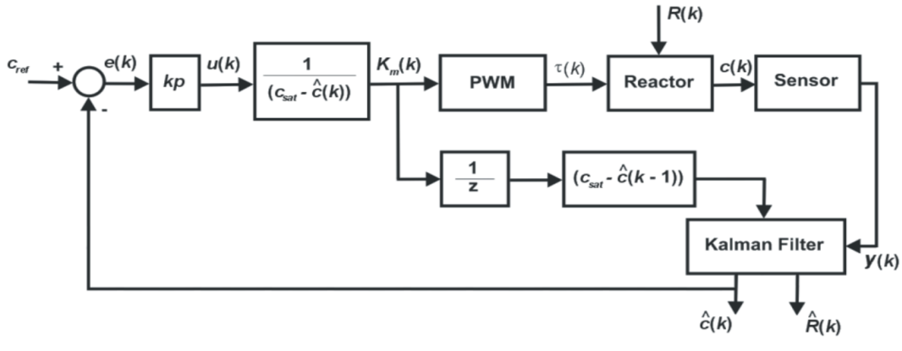

Figure 3. Estimation of DO concentration control

4. SIMULATION RESULTS AND ANALYSIS

The simulation setup in MATLAB 2023a Simulink was used to construct a model of a wastewater treatment process. The objective of this study was to evaluate the effectiveness of a self-organizing fuzzy SMC in regulating DO levels and other relevant parameters. The equations employed for this purpose are described in the preceding section. The experimental setup comprised a continuous flow activated sludge reactor, where the primary variables were configured as follows: influent DO concentration of 4.0 mg/L, biomass concentration of 2000 mg/L, flow rate of 1000 L/day, and desired DO setpoint of 6.0 mg/L. The Simulink environment enabled the execution of dynamic simulations, which enabled the assessment of the controller's efficacy in regulating DO levels within specified ranges among fluctuating influent conditions. The difference in Figure 4 between the set value and the measured value has significant ramifications for the DO concentration control. The observed disparity underscores the difficulties in establishing exact control of DO levels in real time. A notable gap indicates that, while the control system is functional, it may have delays or restrictions in reacting to dynamic changes in wastewater conditions. This discrepancy may result in inferior treatment efficiency, which may have an influence on the overall quality of treated water. Addressing and minimising this disparity is critical for fine-tuning the control approach and ensuring that DO concentrations are near the target setpoints. The knowledge acquired from analysing this difference is useful for fine-tuning control settings and optimising the effectiveness of the WWTP. The disparity noticed between the set value and the measured value can be attributed to the use of a closed loop configuration. The reduction of this error can be achieved by boosting the value of the proportional gain or by incorporating an integrator into the system.

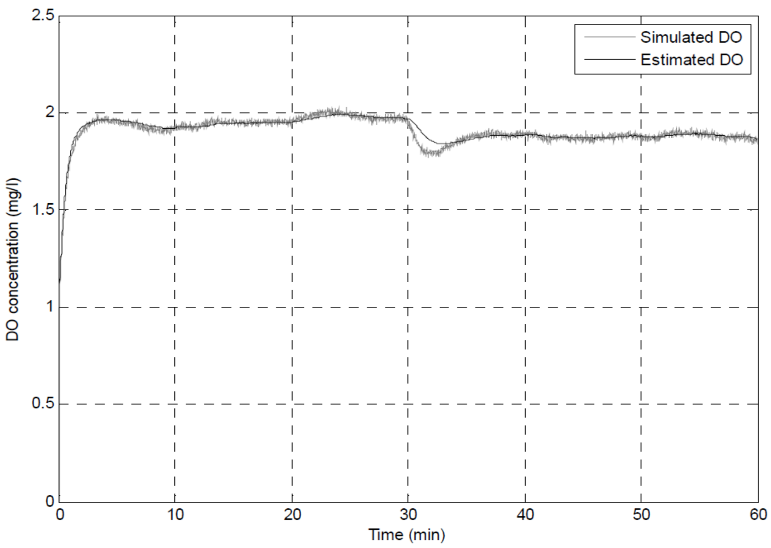

Figure 4. Curves representing the simulated and estimated DO concentrations

There are two primary options for dealing with this discrepancy and boosting the controller's efficiency. One way to decrease the discrepancy between the target and actual DO levels is to increase the controller's proportional gain, which speeds up the response to deviations from the setpoint and slows down the time it takes for the system to stabilise after an adjustment. Second, the control loop can be further optimised by including an integrator component. Incorporating this integral action improves the system's capability to keep DO concentrations within the specified range over extended periods of time by systematically correcting any long-term cumulative errors. Monitoring and regulating pH values and flow rates are crucial aspects of wastewater treatment that have a direct bearing on the efficacy and performance of the treatment process. Insight into how these critical parameters respond to the influence of the control system can be gleaned from the time-series data that are likely to be included in the simulation result analysis chart, as shown in Figures 5 and 6.

The study's results—a pH of 13.40 and a flow rate of 2.87—point to a wastewater treatment system that has been fine-tuned. Achieving a pH of 13.40 indicates that the control system manages and regulateschemical dosing effectively, which keeps the treatment process operating within the desired pH range. With a rate of 2.87, the influent flow into the treatment system is consistent. To avoid either overusing or underusing the treatment infrastructure, it is crucial to maintain a constant flow rate throughout the treatment process. Indicating that the control strategy is effectively performing its task, this finding points to increased pollutant removal efficiency, decreased operational costs, reduced environmental impact and enhanced reliability in treatment process. Optimisation yields a best performance of 0.031 seconds. The superiority of the control system and the treatment process is demonstrated by a performance measure of 0.031. This indicates that the system is performing at its optimum level, providing excellent care at a reasonable cost while also satisfying the most exacting regulatory requirements. This result demonstrates the value of sophisticated control strategies in improving wastewater treatment and preserving natural resources. Figure 7 shows the observed pH curve with respect to the set value.

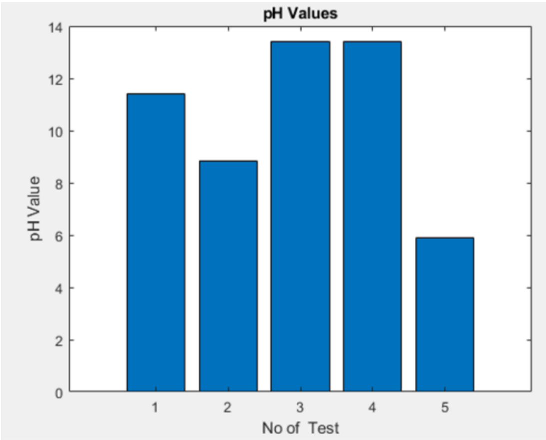

Figure 5. pH values at different number of tests performed

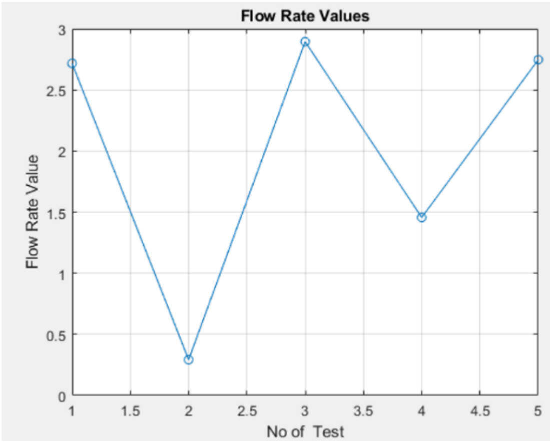

Figure 6. Flowrate value curve

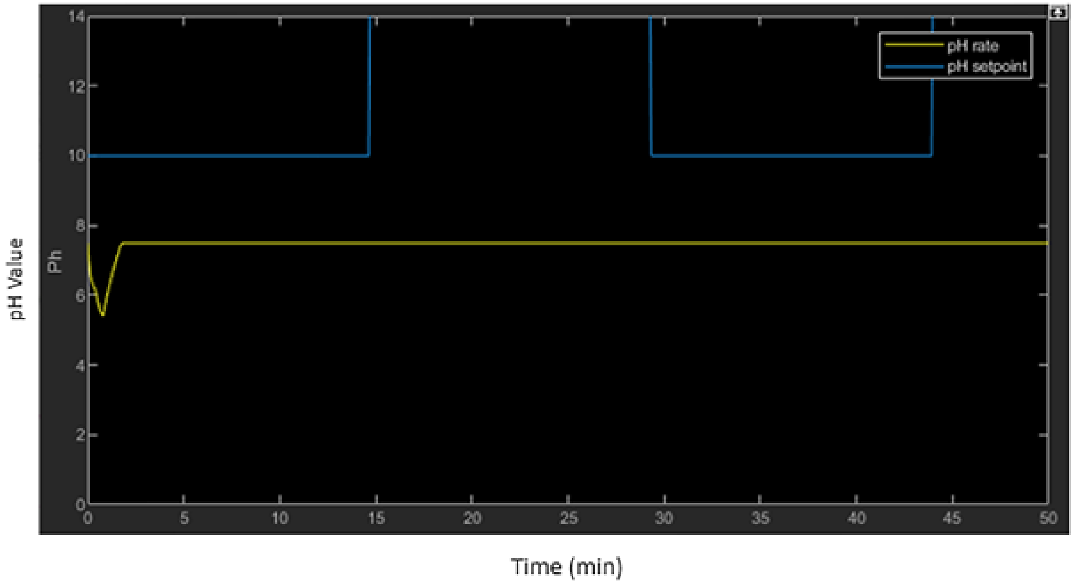

Figure 7. pH rate values

Graph depicting pollutant removal efficiency (%) vs. time (sec) provides (see Figure 8) valuable insights into the dynamic performance of a wastewater treatment process. As time progresses, the pollutant removal efficiency is tracked, showing how effectively the treatment system is cleansing the wastewater. The trends in this graph reveal crucial information about the treatment's response to varying influent conditions and its overall stability (in Figure 9). Steep initial increases in efficiency may indicate the prompt removal of readily biodegradable pollutants, whereas plateauing or fluctuations might signify the presence of complex or slowly degradable contaminants. The speed with which a controller can respond to deviations from the desired setpoint is a crucial parameter in the dynamics of control systems.

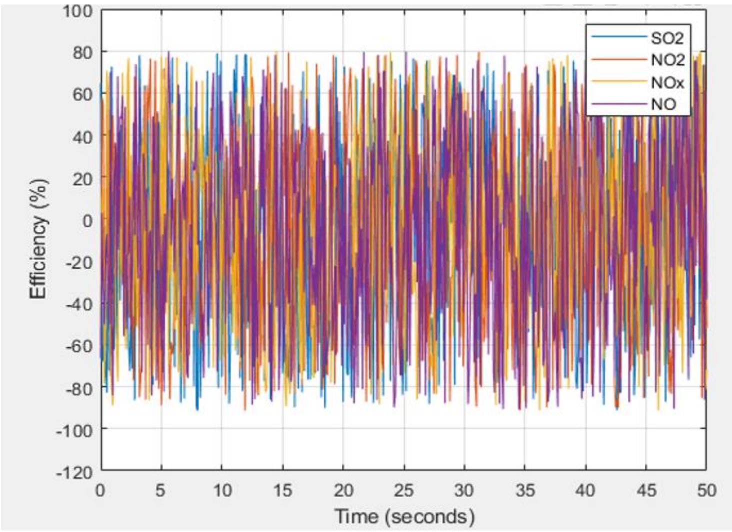

Figure 8. Pollutant removal efficiency

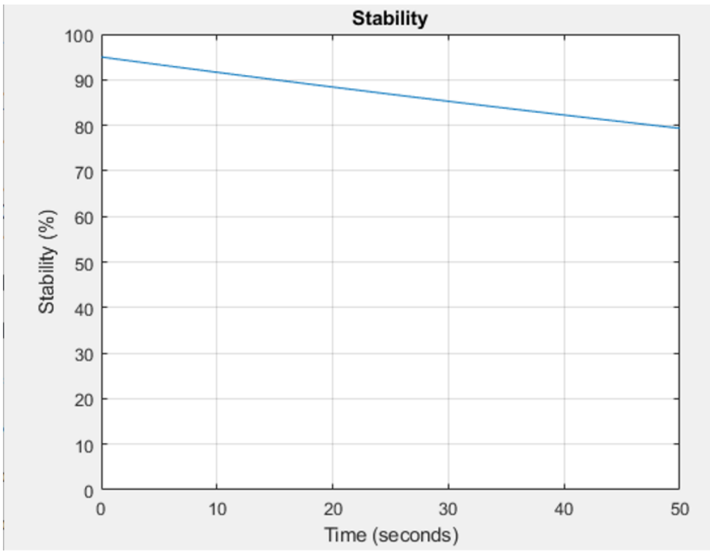

Figure 9. Controller stability

If we look at a graph of response times, in Figure 10, notice that once the time reaches 1.85 seconds, the graph saturates, indicating that the controller has reached its maximum possible response speed. At this point, the controller quickly responds to disturbances or changes in the setpoint, reducing the controlled variable's overshoot and deviation while stabilising it in record time. Saturation is reached in 1.85 seconds, demonstrating the controller's rapid and effective maintenance of the desired process conditions, an essential feature in many control applications. The relevance of attaining saturation within 1.85 seconds resides in the controller's quick reaction, which indicates its ability to rapidly reach and maintain optimal control inputs. Saturation at this stage indicates that the controller has successfully and efficiently managed essential parameters of the wastewater treatment system, such as DO levels, in an unusually short period of time. This quick reaction is critical for maintaining optimal process conditions, avoiding overshooting, and minimising deviations from setpoints. The controller's saturation at 1.85 seconds indicates a quick adaptability to shifting dynamics, which is critical for efficiently stabilising the treatment process. Such quick and accurate management has far-reaching ramifications for overall system performance, ensuring that the wastewater treatment system constantly functions at peak efficiency, satisfying demanding regulatory criteria, and improving pollutant removal efficiency.

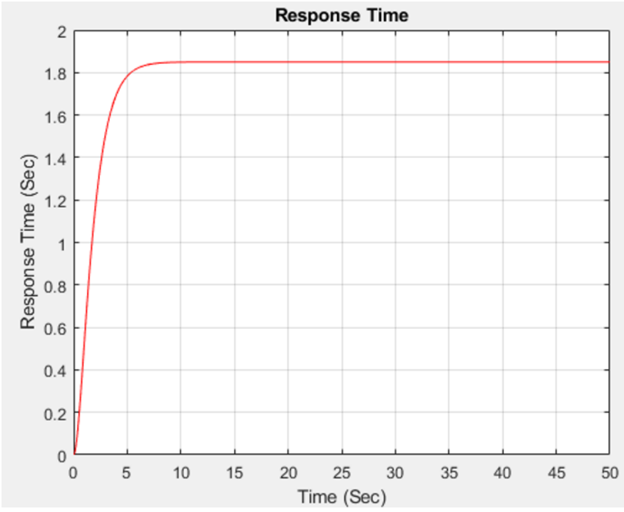

Figure 10. Response curve of the controller under consideration

4.1. Comparative analysis

The examination of the average control accuracy between the SOFSMC and the PID controller offers significant insights into the effectiveness of these control strategies within the WWTP framework. The study on SOFSMC exhibited a mean control accuracy of 0.23. This value signifies that, on average, the controller effectively regulates crucial parameters (such as dissolved oxygen, pH, and flow rate) within a deviation of 0.23 units from the target setpoint. The PID controller demonstrates a mean control accuracy of 0.194 [30], indicating its ability to sustain control within a deviation of 0.194 units from the desired setpoint. The comparison of the SOFSMC and the PID controller demonstrates the efficacy of both control strategies in ensuring precise control within the context of wastewater treatment. The marginally elevated mean precision of the SOFSMC (0.23) can be ascribed to its adaptability and proficiency in managing intricate, nonlinear dynamics, rendering it highly suitable for demanding WWTPs.

Table 1 provides a comparative analysis of alternative control systems for the management of DO in a system. The performance of these strategies is assessed using various metrics. The reference methodologies encompass NMPC, FSMC, and SOSMC. The performance measures that were evaluated include integrated absolute error and integrated square differential error, with the measurement of reaction times expressed in seconds. The method SOFSMC, as described, exhibits commendable outcomes, with a DO error of 0.082 mg/L, an integrated absolute error of 0.091 mg/L, and a response time of 1.85 seconds. The results of this study show that the use of the SOFSMC technique may have some benefits in terms of DO control when compared to the methods mentioned in the literature, as evidenced by the observed decrease in error values.

Table 1. Comparative analysis of the performance of control methods

Reference	Method	Dissolved oxygen		Response time (s)
		Integrated absolute error (mg/L)	Integrated square differential error (mg/L)	
[5]	Fuzzy logic control	0.21	-	1.3
[11]	NMPC	0.11	-	2.9
[27]	SOSMC	0.09	0.075	1.140
Ours	SOF-SMC	0.082	0.091	1.85

5. CONCLUSION

The use of SOFSMC in wastewater treatment control presents a novel and noteworthy advancement in enhancing the effectiveness, dependability, and ecological viability of WWTPs. The research presented in this study highlights the potential of SOFSMC as a viable approach to address the intricate difficulties associated with wastewater treatment. The thorough examination and assessment of this novel control strategy has yielded compelling findings, bolstered by statistical evidence, which demonstrate its versatility, resilience, and precise control capabilities. This novel methodology exhibits significant promise in augmenting the efficiency of pollutant removal, diminishing operational expenditures, and guaranteeing adherence to rigorous environmental regulations. The findings illustrate the significant importance of employing sophisticated control systems to effectively tackle pressing concerns related to water quality, resource management, and environmental preservation. The selection of control strategies should be determined by the distinct requirements and obstacles encountered by the WWTP system being evaluated. The enhanced adaptability and superior performance exhibited by SOFSMC render it a highly appealing choice for systems characterised by dynamic and nonlinear dynamics. Conversely, the PID controller presents a well-established and efficient methodology suitable for a broad spectrum of applications.

ACKNOWLEDGEMENTS

This work was supported by JAIN (Deemed-to-be-University) and Management, Staff and Principal of Moodlakatte Institute of Technology, Kundapura, India.

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