Investigation of the Influence of Network-Induced Time Delays on the Activated Sludge Process Behavior in the Networked Wastewater Distributed Systems

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Paper

Investigation of the Influence of Network-Induced Time Delays on the Activated Sludge Process Behavior in the Networked Wastewater Distributed Systems

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This paper examines the effects of networked induced time delays on the dissolved oxygen (DO) concentration in the activated sludge process (ASP) of a networked wastewater treatment plant (WWTP). This is a situation in which the controller and the wastewater plant are separated by wide geographical distance. This is a new type of WWTP control that allows two or more WWTPs to be controlled by a single controller placed in a remote location. The objective is to achieve flexibility of control and to reduce its cost. The communication medium between the controller and the WWTPs introduces communication drawbacks into the control system. The influences of network-induced time delays [controller to actuator delay (τ_{ca}) and the sensor to controller delay (τ_{sc})] over the behavior of the DO process controlled by both nonlinear linearizing and proportional-integral controllers are investigated for constant and random delays. Investigation of the DO process under random delays was also performed with varying linear controller parameters [proportional gain (K_p) and integral time (T_I)]. Simulation results reveal that large network-induced time delays in the closed-loop DO process leads to depletion of the amount of oxygen available for microorganism metabolism, leading to inefficiency of the ASP. The critical delay during which the DO process becomes unstable due to communication drawbacks was also determined for constant and random delays. These values are found to vary depending on the delay type (constant/random), delay magnitude, and the linear controller parameters K_p and T_I. The results of this study would provide useful information for process performance and form the basis for the design of a robust networked control for the DO process capable of mitigating communication drawbacks in a networked wastewater distributed systems.

Keywords: networked wastewater distributed systems, wastewater treatment plant, activated sludge process, networked control systems, robust control

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1. Introduction

The activated sludge process (ASP) is the most popular biological wastewater treatment process [1,2]. In wastewater treatment, wastewater from industrial or municipal sources is processed before it can be released into the environment in line with environmental health and safety regulations [3,4]. A unique feature of the ASP is the control of dissolved oxygen (DO) concentration. Here, oxygen is introduced into wastewater in order to be used up by microorganisms for their metabolic processes. The microorganisms help to break down organic substances in the wastewater to obtain the required effluent quality [2,5]. Optimal control of DO concentration is of utmost importance for economic and process reasons. For instance, very high electrical energy consumption and poor sludge formation could result from too high DO concentration, while too low DO concentration could result in insufficient oxygen for the microorganism that are responsible for breaking down organic matter in the wastewater [2,6,7]. In traditional wastewater treatment, the controller and the wastewater plant being controlled are usually in the same location. This paper considers a case in which the controller and the wastewater treatment plant (WWTP) are not in the same location. As a result, a means of communication is required between the controller and the actuator and between the sensor and the controller.

This is a networked control system (NCS) involving WWTPs and could be referred to as networked wastewater distributed systems (NWDS). It provides flexibility, modularity, ease of maintenance, and economy because a single controller can serve two or more WWTPs [8,9]. It is, however, plagued with communication drawbacks such as network-induced time delay, jitter, and packet dropout [8], which could adversely affect stability of the DO concentration and the efficiency of the ASP.

WWTPs are complex nonlinear systems because of the very high level of disturbances they are exposed to. The treatment processes in WWTPs can be grouped as chemical, biological, and physical. As a result, the ASP, which takes place within the biological reactor of the WWTP, has different variables with varying time constants or response times. For example, while the time constant of the sludge decomposition is in weeks, biological oxygen demand (BOD) is in hours, and DO concentration will respond in minutes [4,9].

The aim of this study is as follows:

- To use controllers designed for the DO process without time delays in the conditions of a networked induced time delays;
- To carry out investigations on the influence of the time delays on the DO process stability and performance under the above controller;

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- To investigate the critical delays for various cases of the controller parameters which could later be used for design of a robust controller capable of overcoming the impact of the time delays.

The rest of the paper is organized as follows. Section 2 considers the plant description and design of a nonlinear linearizing controller for the closed-loop DO process. The NWDS is also introduced in this section, while Section 3 presents the simulation of the WWTP with network-induced time delays (constant and random) as well as with varying controller parameters. Section 4 presents the results and discussion, and the paper concludes with Section 5.

2. Description of the Plant

2.1. COST Benchmark model of DO process The WWTP considered in this study is the benchmark model of the ASP with two anoxic tanks (tank 1 and tank 2) and three aerobic tanks (tank 3, tank 4, and tank 5) [13]. This is shown in Fig. 1 where $Q_o(t), Q_r(t), Q_a(t), Q_e(t)$ and $Q_w(t)$ (mL/day) are the input flow rate, the return flow rate, the internal recycle flow rate, the effluent flow rate, and wasting sludge flow rate respectively. $Q_n(t)$ (mL/day), $n = 1, 5$, are the output flow rates for the corresponding tanks of the structure. The biological model ASM1 was chosen to describe the microorganism activities [10]. Equations (1)–(2) describe the mass balance equations of the dynamics of the DO concentration in the ASP [11]. The developed Simulink model of the DO process can be seen in Fig. 2, while its open-loop response to a step input is shown in Fig. 3.

$$\frac{dS_{o,n}(t)}{dt} = \frac{1}{V_n}Q_n(t)(S_{o,n-1}(t) - S_{o,n}(t)) + K_{La,n}(t)(S_{o,sat} - S_{o,n}(t)) + r_{s0,n}(t) \quad (1)$$

where $S_{o,n}(t)$ (mg/L) is the DO concentration in the nth tank, $K_{La}(t)$ is the oxygen transmission coefficient, $S_{o,sat}$ (mg/L) is the DO concentration at saturation point, $r_{so,n}(t)$(mg/L·d) is the oxygen uptake rate, V_n (m^3) is the tank volume, and n is the current number of the aerobic tank (n = 3,4,5). The oxygen transmission coefficient depends on the flow rate of the air sent to the aerobic tank. This variable is used to control the concentration of the DO in the wastewater [5]. There are different mathematical

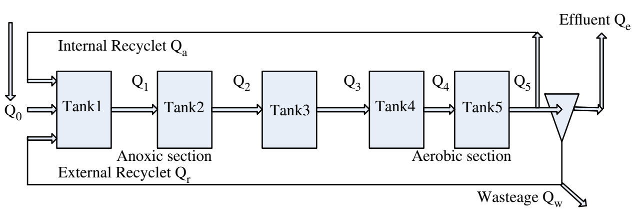

Fig. 1. The COST benchmark structure of ASP [13]

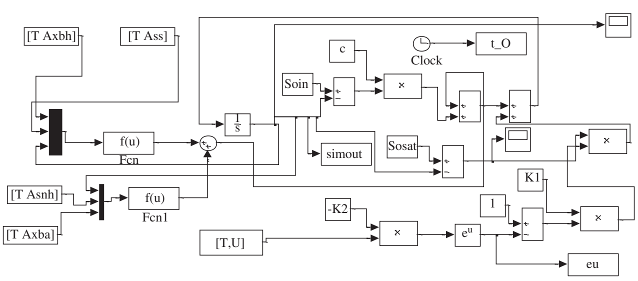

Fig. 2. Developed Simulink model of the DO process

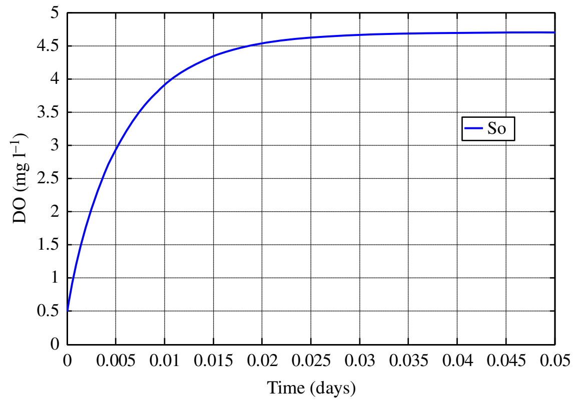

Fig. 3. Open-loop response of the DO process

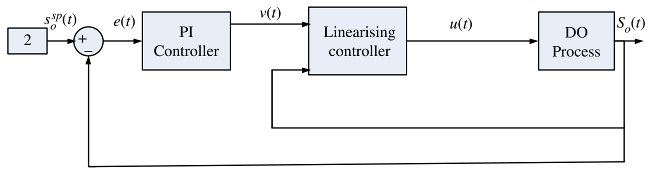

Fig. 4. Nonlinear linearizing closed-loop control of DO process without network time delays

expressions of the dependences $K_{La}(t)[u(t)]$, but the most used one is by the exponential function [11] shown in (3).

$$K_{La}(t) = K_1[1 - e^{-K_2 u(t)}] \quad (2)$$

where the coefficients K_1 and K_2 are determined for $k_{La}(t) = 240d^{-1}$, $u(t)$ (m^3/d) represents the air flow rate, which is the control action. The oxygen uptake rate is represented as a nonlinear function of the air flow rate [11].

$$r_{So}(t) = -\hat{\mu}_H\left(\frac{1 - Y_H}{Y_H}\right)\left(\frac{s_{S,n}(t)}{K_S + s_{S,n}(t)}\right)\left(\frac{s_{O,n}(t)}{K_{OH} + s_{O,n}(t)}\right) x_{BH}(t) - - \hat{\mu}_A\left(\frac{4.57 - Y_A}{Y_A}\right)\left(\frac{s_{NH,n}(t)}{K_{NH} + s_{NH,n}(t)}\right)\left(\frac{s_{O,n}(t)}{K_{OA} + s_{O,n}(t)}\right) x_{BA}(t) \quad (3)$$

where μ_H is the maximum heterotrophic growth rate, Y_H is the heterotrophic yield, μ_A is the maximum autotrophic growth rate, Y_A is the autotrophic yield, $S_{S,n}(t)$ is the readily biodegradable substrate, $S_{NH,n}(t)$ is the $NH_4^+ + NH_3$ nitrogen, and $K_s, K_{NH}, K_{OH}, K_{OA}$ are the half-saturation coefficients for heterotrophic growth, autotrophic growth, heterotrophic and autotrophic oxygen respectively.

2.2. Linear and nonlinear linearizing closed-loop control of the DO process Investigations are done for the closed-loop control system of the DO process developed in Ref. [12] and shown in Fig. 4. The closed loop has two components.

- Input/output linearizing nonlinear control $u(t)$, leading the nonlinear DO process closed-loop behavior to be equivalent to a stable one with desired behavior of a linear system: $S_o(t) = aS_o(t) + bv(t)$, where a and b are the state and control coefficients, and $v(t)$ is the linear control input to the linearized closed-loop system.
- Linear control $v(t)$ leads the linearized closed-loop behavior of the DO process to follow some desired trajectory (set point).

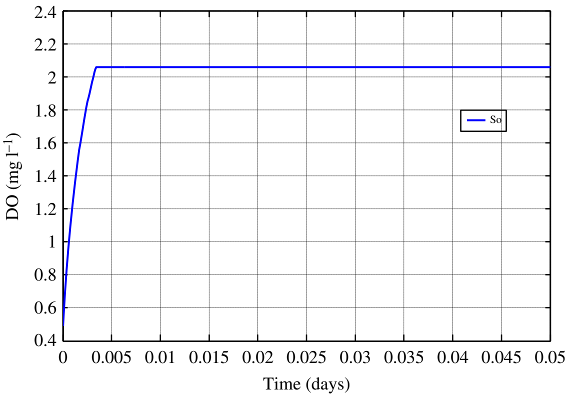

Fig. 5. Closed-loop response of the DO process without network-induced time delays

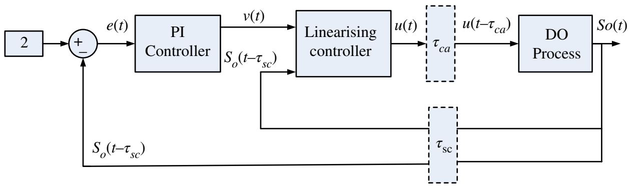

Fig. 6. Nonlinear linearizing closed-loop control of DO process including network time delays

The linear control is selected to be proportional integral (PI), described by the equation

$$V(t) = K_p\left[e(t) + \frac{1}{T_I}\int e(t)dt\right] \tag{4}$$

where the coefficients K_p and T_I are designed for the desired linear system using the pole placement method, and $e(t)$ is the error between the set point and the closed-loop DO process output. The nonlinear controller including the linear one for the nth tank (where n is omitted) is designed to be

$$u(t) = -\frac{1}{k_2}\ln\left\{\frac{\begin{array}{c}\left(a+\frac{Q}{V}-k_1\right)s_O(t)+bK_p\left[e(t)+\frac{1}{T_i}\int e(t)dt\right]\\ +k_1 s_{O,sat}-\frac{Q}{V}s_{O,in}(t)-r_{SO}(t)\end{array}}{-k_1(s_{O,sat}-s_O(t))}\right\} \tag{5}$$

MATLAB/Simulink model of the closed-loop system using the linear control and the nonlinear linearizing one as presented by (5) is developed in this paper and used as a basis for investigations of the impact of the network induced time delays. The closed-loop response of the DO process according to the structure in Fig. 4 is given in Fig. 5, for $S_o^{sp}(t) = 2$ mg/L, where $S_o^{sp}(t)$ is the set point for the DO process output.

The remote control of the DO process would bring about communication drawbacks into the traditional DO concentration closed-loop control system. Only communication delays between the controller and actuator and between the sensor and controller are considered, as shown in Fig. 6.

The induced time delays lead to a situation where at moment t the actuator will receive a control signal from the moment $t - \tau_{ca}$, and the sensor data received by the controller will be from the moment $t - \tau_{sc}$. Network-induced time delays can be constant or random, but for the purpose of the analysis in this paper both constant and random time delays are investigated.

3. Simulation Results

In order to investigate the effect of the network-induced time delays on the closed loop DO behavior, simulations are carried out using transport delay functions in the MATLAB/Simulink environment. The closed-loop DO process is simulated first with only controller to the actuator delay (τ_{ca}). This is placed in the forward path of the closed-loop system. After this, simulation is carried out only with the sensor to controller delay (τ_{sc}) placed in the feedback path. The DO process closed-loop behavior is then simulated with a combined delay τ_{tot} (the sum of τ_{ca} and τ_{sc}). The values of the delays used for the simulation are chosen from one given minimum value and increased until sustained oscillation is achieved (critical delay) and even beyond the critical value. This is to observe the DO process behavior in the cases of: below the critical delay, at the critical delay, and above the critical delay for both constant and random delays. The Simulink block in Fig. 7 shows this arrangement for constant time delays and Fig. 13 for random time delays. Figures 8–10 show the comparison of the simulation results of the closed-loop DO process under the influence of the constant delays, and Figs. 14–16 show similar results under the random delays (τ_{ca} only), (τ_{sc} only), and a combined delay (τ_{tot}).

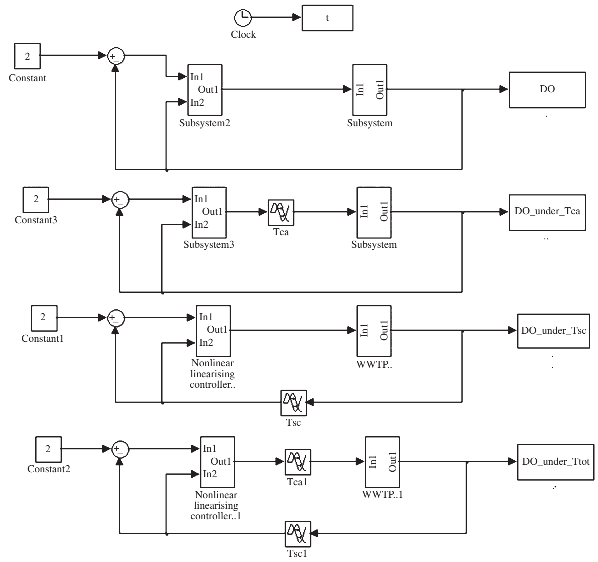

Fig. 7. Simulink block showing the closed-loop DO process with constant network-induced time delays

3.1. Investigation of the DO process under constant delays

It could be observed that, as the value of the network-induced time delays increases, there is an overshoot in the system response. This is shown in Figs. 8 and 9. In Fig. 8, the closed-loop DO process was able to regain its stability and return to the steady state despite the presence of network-induced time delays. In Fig. 9, the system experienced a sustained oscillation when a total delay (τ_{tot}) of 0.000614 days was induced. This could be referred to as the *critical delay* (τ_c). From this point, any additional delay would make the system unstable. Figure 10 shows the unstable DO process when a total delay (τ_{tot}) of 0.000615 days was induced in the system. The performance indices for the different types and values of the considered above delays are shown in Table I.

3.2. Investigation of the DO process under random delays

Communication delays (τ_{ca} and τ_{sc}) in this case are assumed to be random variables which are uniformly distributed. The DO process is sampled at a sampling rate of $T = 0.0001$ days (0.864 s) using the zero-order hold (ZOH) technique. A uniform random number is introduced into the system to generate random delays with the signal-to-noise ratio of 90% [14,15]. Figure 11

Table I. Performance indices of the closed loop DO process under constant time delays

Measurement conditions	Time delay values (days)	K_p	T_I	Rise time (days)	Settling time (days)	Percentage overshoot (%)	Steady-state error (mg/L)	Oscillation amplitude (mg/L) Min; max.	Delay in response (days)
					τ_{ca} only				
$\tau_{ca} = 0$	0	3.2	8000	0.002000	0.003050	1.50	−0.030000	2.030	0
$\tau_{ca} < \tau_c$	0.000033	3.2	8000	0.002033	0.004083	3.20	−0.054000	2.044, 2.064	0.000033
$\tau_{ca} = \tau_c$	0.000307	3.2	8000	0.002308	0.004357	6.00	0.021000	1.460, 2.120	0.000307
$\tau_{ca} > \tau_c$	0.000308	3.2	8000	0.002308	0.004357	6.00	0.024000	1.420, 2.100	0.000308
					τ_{sc} only				
$\tau_{sc} = 0$	0	3.2	8000	0.002000	0.003050	1.50	−0.030000	2.030	0
$\tau_{sc} < \tau_c$	0.000033	3.2	8000	0.002000	0.004017	2.90	−0.054000	2.050, 2.058	0
$\tau_{sc} = \tau_c$	0.000307	3.2	8000	0.002000	0.004017	5.50	0.200000	1.490, 2.110	0
$\tau_{sc} > \tau_c$	0.000307	3.2	8000	0.002000	0.004017	5.00	0.205000	1.490, 2.100	0
					τ_{tot}				
$\tau_{tot} = 0$	0	3.2	8000	0.002000	0.003050	1.50	−0.030000	2.030	0
$\tau_{tot} < \tau_c$	0.00066	3.2	8000	0.002033	0.008133	3.20	−0.040000	2.016, 2.064	0.000033
$\tau_{tot} = \tau_c$	0.000614	3.2	8000	0.002307	0.008407	8.00	0.985000	-0.130, 2.16	0.000307
$\tau_{tot} > \tau_c$	0.000615	3.2	8000	0.002308	0.008408	9.00	1.010000	-0.20, 2.180	0.000308

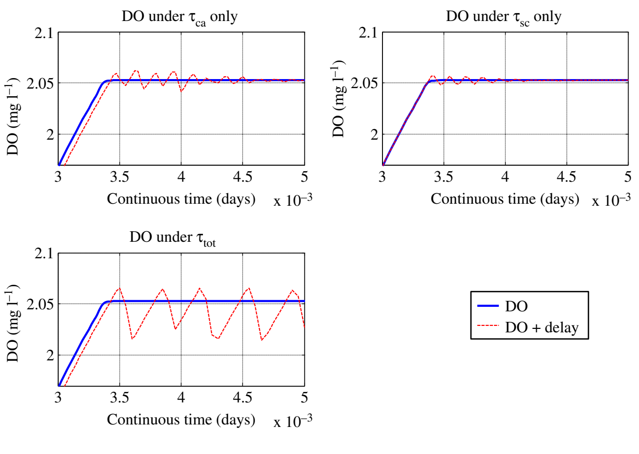

Fig. 8. Simulation of the DO process closed-loop behavior under network delays when $\tau_{ca} = \tau_{sc} = 0.000033$ days and $\tau_{tot} < \tau_c = 0.00066$ days. Note: Simulation time is altered to enlarge it for the purpose of clarity

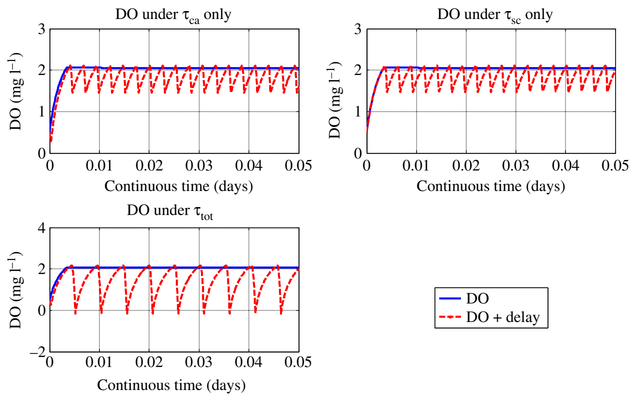

Fig. 9. Simulation of the DO process closed-loop behavior under network delays when $\tau_{ca} = \tau_{sc} = 0.000307$ days, $\tau_{tot} = \tau_c = 0.000614$ days

shows the Simulink block of how the uniform random delays used for simulation is generated, while Fig. 12 shows the time distribution of the random delay generated at a time delay of 0.000027 days.

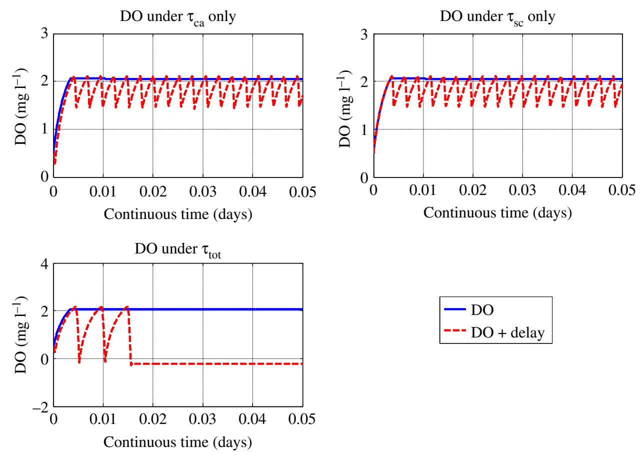

Fig. 10. Simulation of the DO process closed-loop behavior under network delays when $\tau_{ca} = 0.000308$, $\tau_{sc} = 0.000307$ days, $\tau_{tot} > \tau_c = 0.000615$ days

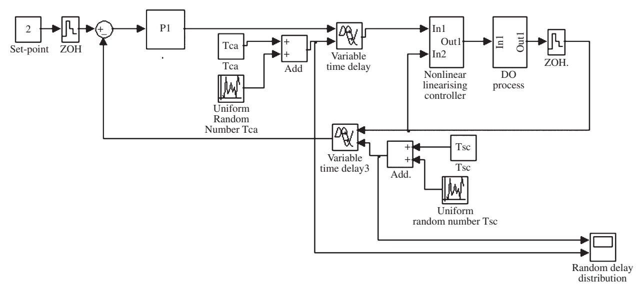

Fig. 11. Simulink block diagram showing the generation of uniform random delays.

Communication drawbacks (constant or random) in the control system affect the stability of the DO process and the ASP. In the both investigations, the DO process is seen to exhibit similar behaviors under constant and random delays. For example, the higher the value of time delays, the more the rise time, percentage overshoot, and steady-state error. This is shown in Tables I and II. The network-induced time delays (τ_{ca}, τ_{sc}, and τ_{tot}) have varying influences on the control system depending on which of the time delays is in operation at a particular time. The DO process is

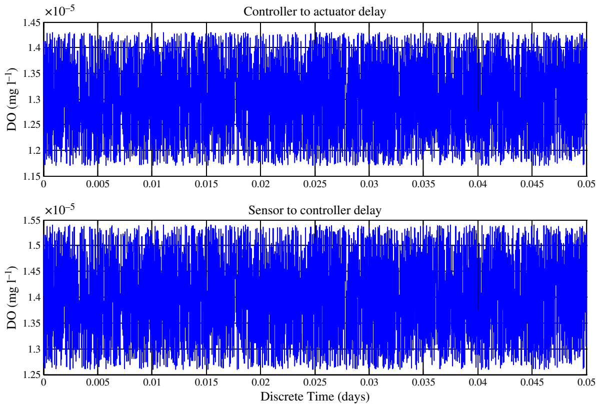

Fig. 12. Time distribution of random delays ($\tau_{ca} + \tau_{sc} = \tau_{tot}$) = 0.000027 days. (a) Controller to actuator delay $\tau_{ca} =$ 0.000014 days under interval (−0.0000014 days, 0.0000014 days). (b) Sensor to controller delay $\tau_{sc} = 0.000013$ days under interval (−0.0000013 days, 0.0000013 days)

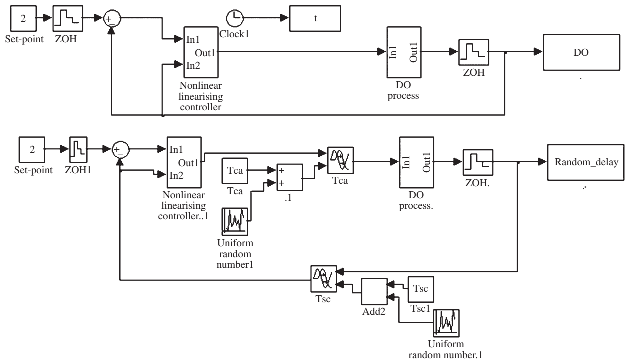

Fig. 13. Simulink block diagram showing simulation of DO process with random time delays

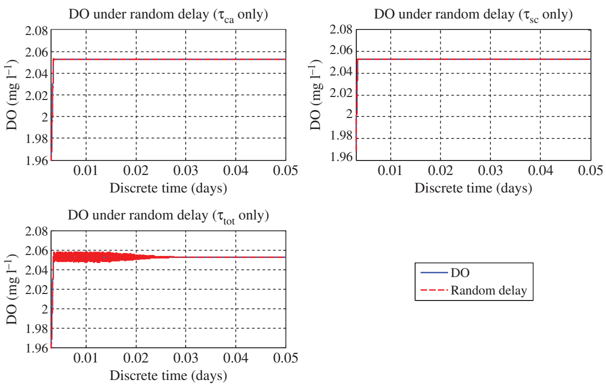

Fig. 14. Simulation of the DO process closed-loop behavior under random delays when $\tau_{ca} = 0.000013$ days, $\tau_{sc} = 0.000013$ days, $\tau_{tot} < \tau_c = 0.000026$ days

delayed by the value of τ_{ca} when it is under the influence of τ_{ca} and τ_{tot}, while no delay is experienced in system response when it is under τ_{sc} only. It could also be observed from both cases of constant and random delays that the DO process under τ_{ca} performed poorer than under τ_{sc} in terms of the percentage overshoot, but when it is under τ_{ca}, it results in better steady-state error than τ_{sc}. It could be noted that τ_{ca} seems to have a greater influence on the system than τ_{sc}, which could be due to the fact that τ_{ca} is in the forward path of the control loop and τ_{sc} is in the feedback loop. However, the main feature of the

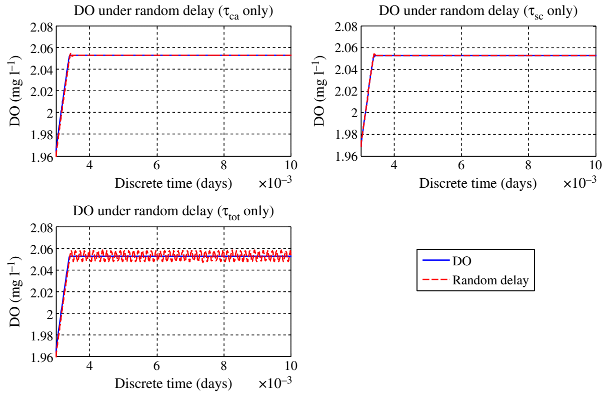

Fig. 15. Simulation of the DO process closed-loop behavior under random delays when $\tau_{ca} = 0.000014$ days, $\tau_{sc} = 0.000013$ days, $\tau_{tot} = \tau_c = 0.000027$ days

investigation with random time delays as compared with constant delays is that with the random time delays it could be observed that the DO process attained sustained oscillation (critical delay) in 0.000027 days (2.3328 s), which is earlier when compared to the case of the constant delays in 0.000614 days (53.0496 s). This is shown in Figs. 9 and 15. It could also be noticed that the larger the probability distribution, the more the instability experienced by the DO process. This is due to the fact that the probability distribution depicts the amount of noise in the communication medium which constitutes a disturbance in the control system. For the purpose of this investigation, a ±10% of τ_{tot} (90% signal-to-noise ratio) is assumed and used for simulation. In other words, the DO process under random delays becomes more sensitive to disturbances (noise) than under constant delay and so could become unstable (oscillate) with any small change in the system dynamics. This confirms why the random time delays are more difficult to handle compared to the constant delays.

3.3. Investigation of the DO process under random delays with varying controller parameters (K_p and T_I)

The results obtained with the closed-loop DO process in Tables I and II are based on fixed values of the controller parameters (K_p and T_I). In order to obtain more information to aid process performance, an investigation with varying values of K_p and T_I is performed. The purpose is to investigate the effects of the linear controller parameters (K_p and T_I) on the value of the process performance characteristics and the critical delay obtained under the random delays investigations shown in Table II. The fixed values of $K_p = 3.2$ and $T_I = 8000$ used for investigation in Tables I and II are considered as reference. Three cases are considered:

Case 1: K_p is varied from 2.2 to 5.2 while T_I is kept constant at 8000.

Case 2: K_p is constant at 3.2 while T_I varies from 2000 to 14 000.

Case 3: Both K_p and T_I are increased from a minimum value to maximum (from 2.2 to 5.2 for K_p and from 2000 to 14 000 for T_I). For each case, the performance indices are analyzed, as shown in Table III. Figures 17–19 show the simulation results. For all examinations, the value of the critical delay is kept constant at $\tau_{tot} = 0.000027$ days.

In case 1, K_p is increased to be (2.2, 2.7, 3.2, 3.7, 5.2) while T_I is kept constant at 8000. It could be observed that with increase in K_p, the DO process experiences a decrease in percentage overshoot, steady-state error, and oscillation amplitude. However, the delay in

Table II. Performance indices of the closed-loop DO process under random time delays

Measurement Conditions	Time delay Values (days)	K_p	T_I	Rise time (days)	Settling time (days)	Percentage overshoot (%)	Steady-state error (mg/L)	Oscillation amplitude (mg/L) Min; max.	Delay in response (days)
					τ_{ca} only				
$\tau_{ca} = 0$	0	3.2	8000	0.002000	0.003050	2.63	−0.052600	2.0526	0
$\tau_{ca} < \tau_c$	0.000013	3.2	8000	0.002013	0.003400	2.73	−0.05460	2.0520, 2.0546	0.000013
$\tau_{ca} = \tau_c$	0.000014	3.2	8000	0.002014	0.003400	2.73	−0.05460	2.0518, 2.0546	0.000014
$\tau_{ca} > \tau_c$	0.000400	3.2	8000	0.002400	0.003400	6.55	0.42200	1.025, 2.131	0.000400
					τ_{sc} only				
$\tau_{sc} = 0$	0	3.2	8000	0.002000	0.003050	2.63	−0.052600	2.0526	0
$\tau_{sc} < \tau_c$	0.000013	3.2	8000	0.002000	0.003400	2.73	−0.05460	2.0520, 2.0546	0
$\tau_{sc} = \tau_c$	0.000013	3.2	8000	0.002000	0.003400	2.73	−0.05460	2.0520, 2.0546	0
$\tau_{sc} > \tau_c$	0.000400	3.2	8000	0.002000	0.003400	6.40	0.42100	1.030, 2.1280	0
					τ_{tot}				
$\tau_{tot} = 0$	0	3.2	8000	0.002000	0.003050	2.63	−0.052600	2.0526	0
$\tau_{tot} < \tau_c$	0.000026	3.2	8000	0.002013	0.003413	2.87	−0.052600	2.0477, 2.0575	0.000013
$\tau_{tot} = \tau_c$	0.000027	3.2	8000	0.002014	0.003414	2.90	−0.05250	2.047, 2.058	0.000014
$\tau_{tot} > \tau_c$	0.000800	3.2	8000	0.002400	0.003400	9.70	1.08500	-0.364, 2.194	0.000400

Table III. Performance indices of the closed-loop DO process under random time delays with varying controller parameters (K_p and T_I)

Measurement Conditions	Time delay Values (days)	K_p	T_I	Rise time (days)	Settling time (days)	Percentage overshoot (%)	Steady-state error (mg/L)	Oscillation amplitude (mg/L) Min; max.	Delay in Response (days)
Case 1									
	0.000027	2.2	8000	0.002014	0.003400	4.01	−0.0801	2.0738, 2.0801	0.000014
	0.000027	2.7	8000	0.002014	0.003414	3.35	−0.0627	2.0583, 2.0671	0.000014
$\tau_{tot} = \tau_c$	0.000027	3.2	8000	0.002014	0.003414	2.90	−0.0525	2.047, 2.058	0.000014
	0.000027	3.7	8000	0.002014	0.003414	2.57	−0.0449	2.038, 2.0515	0.000014
	0.000027	5.2	8000	0.002014	0.003414	1.97	−0.0296	2.0202, 2.0394	0.000014
Case 2									
	0.000027	3.2	2000	0.002014	0.003400	2.90	−0.0525	2.047, 2.058	0.000014
	0.000027	3.2	5000	0.002014	0.003414	2.90	−0.0525	2.047, 2.058	0.000014
$\tau_{tot} = \tau_c$	0.000027	3.2	8000	0.002014	0.003414	2.90	−0.0525	2.047, 2.058	0.000014
	0.000027	3.2	11000	0.002014	0.003414	2.90	−0.0525	2.047, 2.058	0.000014
	0.000027	3.2	14000	0.002014	0.003414	2.90	−0.0525	2.047, 2.058	0.000014
Case 3									
	0.000027	2.2	2000	0.002014	0.003400	4.01	−0.0801	2.0738, 2.0801	0.000014
	0.000027	2.7	5000	0.002014	0.003414	3.35	−0.0627	2.0583, 2.0671	0.000014
$\tau_{tot} = \tau_c$	0.000027	3.2	8000	0.002014	0.003414	2.90	−0.0525	2.047, 2.058	0.000014
	0.000027	3.7	11000	0.002014	0.003414	2.58	−0.0449	2.0383, 2.0515	0.000014
	0.000027	5.2	14000	0.002014	0.003414	1.95	−0.0296	2.0203, 2.0389	0.000014

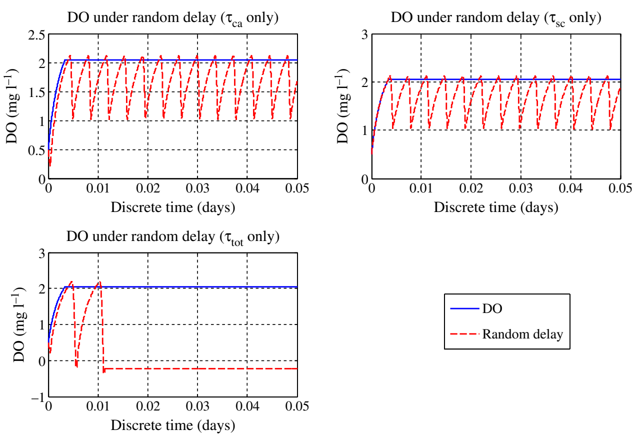

Fig. 16. Simulation of the DO process closed-loop behavior under random delays when $\tau_{ca} = 0.0004$ days, $\tau_{sc} = 0.0004$ days, $\tau_{tot} > \tau_c = 0.0008$ days

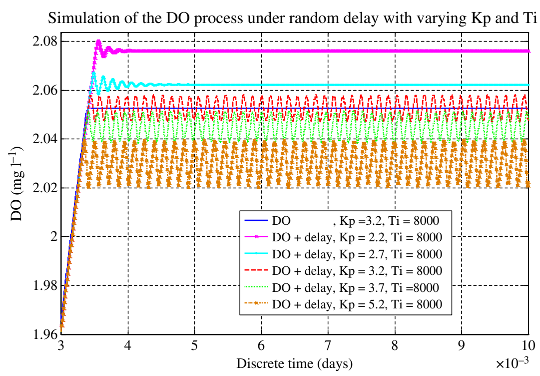

Fig. 17. Case 1. $\tau_{ca} = 0.000014$ days, $\tau_{sc} = 0.000013$ days

system response and the rise time remain constant. This is shown in Fig. 17 and Table III. It could also be seen that with values of the K_p less than 3.2, the DO process did not experience a

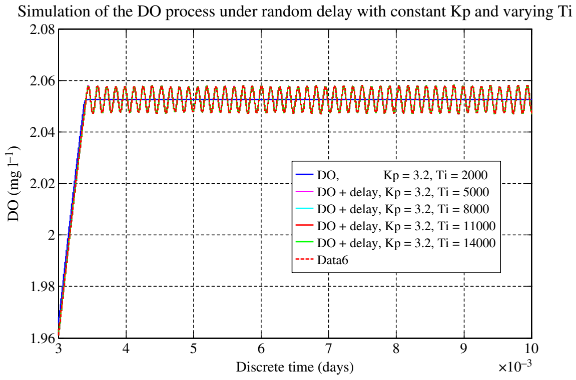

Fig. 18. Case 2. $\tau_{ca} = 0.000014$ days, $\tau_{sc} = 0.000013$ days

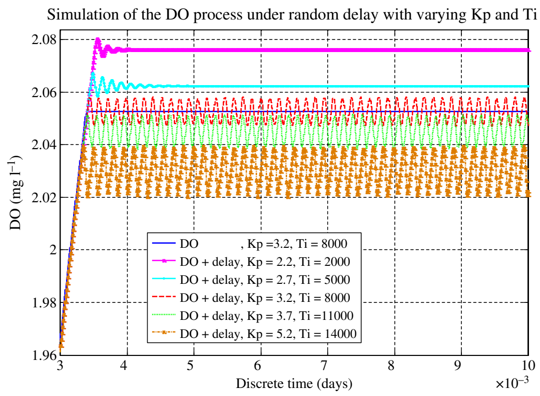

Fig. 19. Case 3. $\tau_{ca} = 0.000014$ days, $\tau_{sc} = 0.000013$ days, $\tau_{tot} = 0.000027$ days, $T_I = (2000, 5000, 8000, 11\,000, 14\,000)$

sustained oscillation. This suggests that the critical delay for values of K_p less than 3.2 must be more than 0.000027 days, as shown in Table II.

In case 2, K_p is kept constant at 3.2 while T_I is increased to be (2000, 5000, 8000, 11 000, 14 000). Despite the increase in T_I, the system response remains the same, as shown in Fig. 18 and Table III. This suggests that the constant K_p must have made the DO process response the same despite the variation in T_I.

In case 3, both K_p and T_I are varied. K_p is increased to be (2.2, 2.7, 3.2, 3.7, 5.2) while T_I is also is increased to be (2000, 5000, 8000, 11 000, 14 000). The DO process system performance in case 3 is consistent with case 1, as shown in Figs. 17 and 19 and Table III in terms of percentage overshoot, steady-state error, delayed system response, and rise time. The only noticeable difference is in the oscillation amplitude and steady-state error. In case 3, the system experienced 1.95% overshoot as compared to 1.97% in case 1. This occurred when T_I in case 3 is 14 000 as compared to 8000 in case 1. Possible explanation could be that the higher value of T_I of 14 000 has helped improve the system performance by reducing percentage overshoot in case 3 when compared to case 1 with a lower value of $T_I = 8000$. Just like in cases 1 and 2, the system's delayed response and rise time are not affected with increased K_p and T_I.

From this investigation, one can therefore conclude that the value of the critical delay is dependent on not only on the magnitude of the random delay introduced into the control system but also on the choice of the controller parameters K_p and T_I, as seen in Table III, case 1. This dependence is found to be more on K_p than T_I. Increasing the value of K_p for the DO process from 2.2 to 5.2 showed some initial improvement in system performance as seen in cases 1 and 3 by reducing percentage overshoot, steady-state error, and oscillation amplitude, but at $K_p = 3.2$, a sustained oscillation is experienced from where the DO process becomes unstable. There would necessary to design a new controller that will take cognizance of the random time delays in its design in order to be able to provide robustness and stability for the DO process under the influence of random time delays.

4. Discussion

The DO concentration with a time constant delay in the range of minutes [4] would reach a sustained oscillation (critical delay) in 0.000614 days (53.0496 s or 0.88 min) delay, while the same system would attain critical delay in 0.000027 days (2.3328 s) with random delays. This means that the critical random time delay is 26.5 times less than the constant one. The presence of large network time delays in the DO process causes large oscillations and deviation from the desired set point of 2 mg/L, as shown in Figs. 10 and 16. From Tables I and II, it can be seen that the DO oscillation amplitude goes to—0.2 mg/L. This could mean that at this point the oxygen supply is completely cut off for the microorganism in the ASP. Although this phenomenon can result in minimal electrical energy usage in the ASP, it can also hinder the removal of organic substances in the wastewater [2,6]. The overall effect would be inefficiency in the performance of the ASP.

5. Conclusion

In this paper, the effects of network-induced time delays on the DO process behavior in the ASP were investigated. Simulation results reveal that network-induced time delays have an adverse effect on the stability and performance of the closed-loop DO process by reducing or even depleting the amount of oxygen available for microorganism's metabolism, resulting in the wastewater not adequately cleaned up and eventual inefficiency of the ASP. The network-induced time delays (τ_{ca}, τ_{sc}, and the combined delay τ_{tot}) have varying influences on the control system (ranging from delayed system response to system overshoot) depending on which of the time delays is in operation at a particular time. The value of the critical delay was also found to vary depending on the type of delay (constant or random delay), magnitude of delay, and choice of controller parameters (K_p and T_I). Good choice of K_p for the DO process was found to improve system stability and performance to a certain degree by delaying sustained oscillation, while T_I slightly improved the steady-state error. To effectively mitigate the presence of network time delays in the networked DO process, there is therefore the need to use the information given in this study to develop a robust nonlinear networked controller that incorporates network-induced time delays in its design. This networked controller would be able to compensate for network-induced time delays and improve the stability and performance for the DO process behavior in a networked WWTP control.

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