Research Article

Dynamics of a Stochastic Functional System for Wastewater Treatment

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The dynamics of a delayed stochastic model simulating wastewater treatment process are studied. We assume that there are stochastic fluctuations in the concentrations of the nutrient and microbes around a steady state, and introduce two distributed delays to the model describing, respectively, the times involved in nutrient recycling and the bacterial reproduction response to nutrient uptake. By constructing Lyapunov functionals, sufficient conditions for the stochastic stability of its positive equilibrium are obtained. The combined effects of the stochastic fluctuations and delays are displayed.

1. Introduction

In the last few years, the use of mathematical models describing wastewater treatment is gaining attention as a promising method [1–6]. A basic chemostat model describing substrate-microbe interaction in an activated sludge process is as follows:

\[
\begin{align*}
\frac{dS}{dt} &= \frac{Q(S_0 - S)}{V} - \frac{kxS}{K_S + S} \frac{D_O}{K_O + D_O}, \\
\frac{dx}{dt} &= x\left(\frac{kYS}{K_S + S} - K_d\right) \frac{D_O}{K_O + D_O} - \frac{Q_w x}{V},
\end{align*}
\]

where \(S(t)\) and \(x(t)\) represent the concentrations of the substrate (biochemical oxygen demand) and microbes in an aeration tank at time \(t\), respectively. \(Q\) is the washout rate, \(S_0\) is the input concentration of the substrate, and \(V\) is the effective volume of the aeration tank; \(k\) is the maximum uptake rate of the substrate; \(K_S\) and \(K_O\) are the half-saturation constants of the substrate and oxygen; respectively, \(K_d\) is the decay rate of microbes and \(Q_w\) is the emission rate of the sludge; \(D_O\) is the concentration of the dissolved oxygen and \(D_O/(K_O + D_O)\) is a switching function describing the effect of \(D_O\) on the uptake rate \(k\) and the decay rate \(K_d\); \(Y \in (0, 1)\) is the ratio of the concentration of mixed liquor suspended solids to the substrate. Some extensions and generalizations of the model have been proposed by many researchers (see [7–27], etc.).

Even though deterministic model (1) has a stable positive equilibrium \((S^*, x^*)\) under certain conditions, oscillations have been observed frequently in the growth of microbes during the experiments [28, 29], which have also been confirmed by many mathematical works for some extended chemostat models incorporating factors such as time delay [15–18, 30–32], periodic nutrient input [19–21, 33–35], feedback control [22–24], and stochastic environmental perturbations [25–27]. For a better understanding of microbial population dynamics in the activated sludge process, we take two steps towards developing model (1).

On the other hand, we take into account time delays that may exist in the process of wastewater treatment. By the death regeneration theory of Dold and Marais [36], the active biomass dies at a certain rate; of the biomass lost, the biodegradable portion adds to the slowly biodegradable organic matter which passes through the various stages to be utilised for active biomass synthesis, which requires some time for the completion of the regeneration. Also there is a time delay that accounts for the time lapse between the uptakes of substrates and the incorporation of these substrates, which has ever been observed from chemostat experiments with microalgae Chlamidomonas Reinhardii even when the limiting nutrient is at undetectable small
concentration (see [37, 38], etc.). In the recent years, chemostat models with such time delays have been given much attention (see, e.g., [9, 14, 16–18, 39], etc.). In this paper, we will use distributed delays to describe the nutrient recycling and the time lapse between the uptakes of nutrient and the incorporation of this nutrient with delay kernels $f(s)$ and $g(s)$, respectively.

On the other hand, in a real process of wastewater treatment there will be fluctuations in concentration of the substrate and microbe population due to stochastic perturbations from external sources such as temperature, light, and the like, or inherent sources in the chemical-physical and biological processes [40]. So we assume that model (1) is exposed by stochastic perturbations which are of white noise type and are proportional to the distances $S(t), x(t)$ from values of the positive equilibrium $S^*, x^*$, influence on the $S(t)$ and $x(t)$, respectively. By this way, model (1) becomes in the following form:

$$
dS = \left[ \frac{Q(S^0 - S)}{V} - kU(S) \frac{D_O}{K_O + D_O} + \mu D_1 \int_0^\infty f(s) x(t - s) ds \right] dt + \sigma_1 (S - S^*) dB_1(t) ,
$$

$$
dx = \left[ (Yk \int_0^\infty g(s) U(S(t - s)) ds - K_d) - \frac{Q_w x}{V} \right] dt + \sigma_2 (x - x^*) dB_2(t) ,
$$

where $B_i(t)$ ($i = 1, 2$) are standard independent Wiener processes and $\sigma_i \geq 0$ ($i = 1, 2$) represent the intensities of the noises, $\mu \in (0, 1)$ is the fraction of the substrate regenerated from the dead biomass; $U(S)$ is a general specific growth function.

Recently, stochastic biological systems and stochastic epidemic models have been studied by many authors; see, for example, Mao et al. [41, 42], Jiang et al. [43, 44], Liu and Wang [45, 46], and the references cited therein. But, as far as we know, there are few works on model (2). In this paper, our main purpose is to study the combined effect of the noises and delays on the dynamics of model (2), that is, whether and how the noises and delays affect the stability of $E^*$. By the construction of appropriate Lyapunov functionals, we will show that the positive equilibrium keeps stochastically stable if the noises and delays are small. Furthermore, the sensitivities of the stability of $E^*$ with respect to the delays and noises are also discussed.

The paper is organized as follows. We first establish some preliminary results in Section 2. By constructing Lyapunov functionals, sufficient conditions for the stochastic stability of the positive equilibrium of the model without and with delays are obtained, respectively, in Sections 3 and 4. Numerical simulations and discussions are finally presented in Section 5.

2. Some Preliminaries

Define $Q/V = D, Q_w/V = D_w, k(D_O/(K_O + D_O)) = m, K_d(D_O/(K_O + D_O)) = D_1$, and $Y = y$. Then model (2) can be simplified as follows:

$$
dS = \left[ D(S^0 - S) - mU(S) x + \mu D_1 \int_0^\infty f(s) x(t - s) ds \right] dt + \sigma_1 (S - S^*) dB_1(t) ,
$$

$$
dx = x \left[ (D_w + D_1) + \gamma m \int_0^\infty g(s) U(S(t - s)) ds \right] dt + \sigma_2 (x - x^*) dB_2(t) ,
$$

with initial value conditions

$$
S(\theta, \omega) = \varphi_1(\theta) \geq 0 , \quad x(\theta, \omega) = \varphi_2(\theta) \geq 0 , \quad \theta \in (-\infty, 0] ,
$$

where $\varphi_1(\theta), \varphi_2(\theta) \in \mathcal{BC}((-\infty, 0], \mathbb{R}_+)$, the families of bounded continuous functions from $(-\infty, 0]$ to $\mathbb{R}_+$.

The corresponding deterministic model of (3) is

$$
\dot{S} = D(S^0 - S) - mU(S)x + \mu D_1 \int_0^\infty f(s) x(t - s) ds ,
$$

$$
\dot{x} = - (D_w + D_1) x + \gamma mx \int_0^\infty g(s) U(S(t - s)) ds ,
$$

the special case of which when $D = D_w$ has ever been investigated by He et al. [18]. It is easy to see that model (5) has a positive equilibrium $E^*(S^*, x^*)$ provided that

$$
D_w + D_1 < \gamma m , \quad S^0 > S^* ,
$$

where

$$
S^* = U^{-1} \left( \frac{D_w + D_1}{\gamma m} \right) , \quad x^* = \frac{D(S^0 - S^*)}{mU(S^*) - \mu D_1} .
$$

$E^*(S^*, x^*)$ is globally asymptotically stable provided that the average delays are sufficiently small. Obviously, $E^*$ is still an equilibrium of stochastic model (3) if condition (6) holds.

We assume that function $U(S)$ is nonnegative satisfying

$$
U(0) = 0 , \quad U'(S) > 0 , \quad U''(S) < 0 \quad \text{for} \quad S > 0 , \quad \lim_{S \to \infty} U(S) = 1 .
$$

And we extend the function $U(S)$ by defining

$$
U(S) = U'(0) S + \frac{1}{2} U''(0) S^2 \quad \text{for} \quad S \leq 0 ,
$$

so that $U$ is well defined in $\mathbb{R}$ and is still of class $\mathcal{C}^2$ in $\mathbb{R}$. Thus one can write

$$
U(S) = a + b(S - S^*) + F(S - S^*) ,
$$
where $F$ represents terms of order $\geq 2$ in $S - S^*$. Noting also that $a = U(S^*)$ and $b = U'(S^*)$, by condition (6), it follows that $ma > \mu D_1$.

Introduce new variables $u_1 = S - S^*$, $u_2 = x - x^*$; then model (3) can be rewritten as follows:

\begin{align}
  du_1 & = \left[ - (D + mbx^*) u_1 + \mu D_1 \int_0^\infty f(s) u_2 (t - s) \, ds \\
  & \quad - mau_2 + F_1(u_1, u_2) \right] \, dt + \sigma_1 u_1 \, dB_1, \\
  du_2 & = \left[ g(s) u_1 (t - s) \, ds \\
  & \quad + F_2(u_1, u_2) \right] \, dt + \sigma_2 u_2 \, dB_2,
\end{align}

where

\begin{align}
  F_1 &= -mbu_1 u_2 - mF(u_1) u_2 - mx^* F(u_1), \\
  F_2 &= g(s) u_1 (t - s) \, ds + (u_2 + x^*) ym \int_0^\infty g(s) F(u_1 (t - s)) \, ds.
\end{align}

Note that if $f(s) = g(s) = \delta(0)$, then model (11) has the form

\begin{align}
  du_1 & = \left[ - (D + mbx^*) u_1 + (\mu D_1 - ma) u_2 \\
  & \quad + F_1(u_1, u_2) \right] \, dt + \sigma_1 u_1 \, dB_1, \\
  du_2 & = \left[ g(s) u_1 (t - s) \, ds \\
  & \quad + F_2(u_1, u_2) \right] \, dt + \sigma_2 u_2 \, dB_2,
\end{align}

where

\begin{align}
  F_2 &= gmbu_1 u_2 + (u_2 + x^*) ym F(u_1). \quad (14)
\end{align}

Obviously, model (13) has the same equilibrium $(0, 0)$ as model (11), and the stochastic stability of the positive equilibrium $E^*$ of model (3) is equivalent to the zero solution of model (11). We wonder how the stochastic perturbations and delays affect the dynamics of model (3) or (11).

Before starting our analysis, we first give some basic theories in stochastic differential equations and stochastic functional differential equations [47–49]. Let $(\Omega, \mathcal{F}, \{\mathcal{F}_t\}_{t \geq 0}, P)$ be a complete probability space with a filtration $\{\mathcal{F}_t\}_{t \geq 0}$ satisfying the usual conditions (i.e., it is right continuous and $\mathcal{F}_0$ contains all $P$-null sets). Let $B_t$ ($i = 1, 2, \ldots, n$) be the Brownian motions defined on this probability space. Consider the following $n$-dimensional stochastic differential equation:

\begin{align}
  dx(t) = f(x(t), t) \, dt + g(x(t), t) \, dB(t), \quad t \geq t_0. \quad (15)
\end{align}

**Definition 1.** The trivial solution of system (15) is said to be as follows:

(i) stochastically stable or stable in probability if for every pair of $\varepsilon \in (0, 1)$ and $r > 1$, there exists a $\delta = \delta(\varepsilon, r, t_0) > 0$ such that

\begin{align}
  P \left\{ |x(t; t_0, x_0)| < r \forall t \geq t_0 \right\} \geq 1 - \varepsilon, \quad (16)
\end{align}

whenever $|x_0| < \delta$. Otherwise, it is said to be stochastically unstable,

(ii) stochastically asymptotically stable if it is stochastically stable and, moreover, for every $\varepsilon \in (0, 1)$, there exists a $\delta_0 = \delta_0(\varepsilon, t_0) > 0$ such that

\begin{align}
  P \left\{ \lim_{t \to \infty} x(t; t_0, x_0) = 0 \right\} \geq 1 - \varepsilon, \quad (17)
\end{align}

whenever $|x_0| < \delta_0$.

(iii) globally asymptotically stable in probability if it is stochastically asymptotically stable and, moreover, for all $x_0 \in \mathbb{R}^n$

\begin{align}
  P \left\{ \lim_{t \to \infty} x(t; t_0, x_0) = 0 \right\} = 1. \quad (18)
\end{align}

**Lemma 2.** If there exists a nonnegative function $V(x, t) \in C^{2,1}(\mathbb{R}^n \times [t_0, \infty]; \mathbb{R}_+)$, two continuous functions $\psi_1$, $\psi_2 : \mathbb{R}_+ \to \mathbb{R}_+$, and a positive constant $K$ such that, for $|x| < K$,

\begin{align}
  \psi_1(|x|) \leq V(x, t) \leq \psi_2(|x|) \quad (19)
\end{align}

hold.

(i) If

\begin{align}
  LV \leq 0, \quad \text{for} |x| \in [0, K], \quad (20)
\end{align}

then the trivial solution of system (A.1) is stochastically stable.

(ii) If there exists a continuous function $\psi_3 : \mathbb{R}_+ \to \mathbb{R}_+$ such that

\begin{align}
  LV \leq -\psi_3(|x|) \quad (21)
\end{align}

holds, then the trivial solution of system (15) is stochastically asymptotically stable.

(iii) If (ii) holds and moreover

\begin{align}
  \lim_{r \to \infty} \psi_1(r) = +\infty, \quad (22)
\end{align}

then the trivial solution of system (15) is globally asymptotically stable in probability.

For the stability of the equilibrium of a nonlinear stochastic system, it can be reduced to problems concerning stability of solutions of the linear associated system. The linear form of (15) is defined as follows:

\begin{align}
  dx(t) = F(t) \cdot x(t) \, dt + G(t) \cdot x(t) \, dB(t), \quad t \geq t_0. \quad (23)
\end{align}

**Lemma 3.** If the trivial solution is stochastically stable for the linear system (23) with constant coefficients ($F(t) = F$, $G(t) = G$) and the coefficients of systems (15) and (23) satisfy the following inequality:

\begin{align}
  |f(x, t) - F \cdot x| + |g(x, t) - G \cdot x| < \rho |x| \quad (24)
\end{align}

in a sufficiently small neighborhood of $x = 0$, with a sufficiently small constant $\rho$, then the trivial solution of system (15) is asymptotically stable in probability.
Consider the following $n$-dimensional stochastic functional differential equation
\[ dx = f(t, x_t) \, dt + g(t, x_t) \, dB(t) \]  
with initial condition $x_0 = \varphi \in \mathcal{H}$, where $\mathcal{H}$ is the space of $\mathcal{F}_0$-adapted random variables $\varphi$, with $\varphi(s) \in \mathbb{R}^n$ for $s \leq 0$, and
\[ \|\varphi\| = \sup_{s \leq 0} |\varphi(s)|, \quad \|\varphi\|_1 = \sup E \left( |\varphi(s)|^2 \right). \]  

Definition 4. The trivial solution of system (25) is said to be
(i) mean square stable if, for each $\varepsilon > 0$, there exists $\delta(\varepsilon) > 0$ such that for any initial process $\varphi(\theta)$,
\[ E \left( |x(t, \varphi(\theta))|^2 \right) < \varepsilon, \]  
for any $t \geq 0$ provided that $\sup_{0 \leq \theta < \infty} E(|\varphi(\theta)|^2) < \delta(\varepsilon)$,

(ii) asymptotically mean square stable if it is mean square stable and
\[ \lim_{t \to \infty} E \left( |x(t, \varphi)|^2 \right) = 0, \]  

(iii) stochastically stable if for any $\varepsilon_1 > 0$ and $\varepsilon_2 > 0$, there exists a $\delta > 0$ such that
\[ P \left\{ \sup_{t \geq 0} |x(t, \varphi)| \leq \varepsilon_1 \right\} \geq 1 - \varepsilon_2 \]  
provided that $P(\|\varphi\| \leq \delta) = 1$.

3. Dynamical Behavior of the System without Delays

We first study the stochastic stability of the equilibria $(0, 0)$ of model (13). Throughout the paper, we assume that the basic hypotheses given in the Section 2 are satisfied. The linearized system of model (13) is
\[ du_1 = \left[-(D + mbx^*) u_1 + (\mu D_1 - ma) u_2 \right] dt + \sigma_1 u_1 dB_1, \]  
\[ du_2 = ymbx^* u_1 dt + \sigma_2 u_2 dB_2. \]  

For convenience, let
\[ p = \frac{y \sigma_1}{2 (ma - \mu D_1)}, \quad q = \frac{y \sigma_2}{2 y (ma - \mu D_1) + y D}. \]  

For linearized system (30), we have the following theorem.

Theorem 5. Let condition (6) hold. If
\[ \sigma_1^2 < 2D + 2mbx^*, \quad \sigma_2^2 < \frac{2q}{1 + q} y (ma - \mu D_1), \]  
then the trivial solution of system (30) is globally asymptotically stable in probability.

Proof. Define a smooth function $V : \mathbb{R}^2 \to \mathbb{R}_+$ by
\[ V(u_1, u_2) = pu_1^2 + u_2^2 + q(yu_1 + u_2)^2. \]  
Then using Itô’s formula, for all $(u_1, u_2) \neq (0, 0)$, we have
\[ dV(u_1, u_2) = 2pu_1 du_1 + p(du_1)^2 + 2u_2 du_2 + (du_2)^2 \]  
\[ + 2q(\gamma yu_1 + u_2) d(\gamma yu_1 + u_2) \]  
\[ + q(\gamma yu_1 + u_2)^2 \]  
\[ = LV(u_1, u_2) dt + 2\sigma_1 u_1^2 dB_1 + 2\sigma_2 u_2^2 dB_2 \]  
\[ + 2q(\gamma yu_1 + u_2)(\gamma yu_1 u_2 + \sigma_2 u_2^2), \]  
where
\[ LV(u_1, u_2) = 2pu_1 \left[ -(D + mbx^*) u_1 + (\mu D_1 - ma) u_2 \right] \]  
\[ + p\sigma_1^2 u_1^2 + 2y mbx^* u_1 u_2 + \sigma_2^2 u_2^2 \]  
\[ + 2q(\gamma yu_1 + u_2) \]  
\[ \times \left[ -\gamma Du_1 + \gamma(\mu D_1 - ma) u_2 \right] \]  
\[ + q\left( y^2 \sigma_1^2 u_1^2 + \sigma_2^2 u_2^2 \right) \]  
\[ = -\left[ 2p(D + mbx^*) - p\sigma_1^2 \right] u_1^2 \]  
\[ + 2qy^2 D - qy^2 \sigma_1^2 \right] u_1^2 \]  
\[ - \left[ 2q(\gamma ma - \mu D_1) - (1 + q) \sigma_2^2 \right] u_2^2 \]  
\[ -2 \left[ p(ma - \mu D_1) - ymbx^* \right] \]  
\[ + qy^2 (ma - \mu D_1) + qyD \right] u_1 u_2. \]  

By (31), we obtain
\[ LV(u_1, u_2) \]  
\[ = -\left[ 2p(D + mbx^*) - p\sigma_1^2 + 2qy^2 D - qy^2 \sigma_1^2 \right] u_1^2 \]  
\[ - \left[ 2qy^2 (ma - \mu D_1) - (1 + q) \sigma_2^2 \right] u_2^2. \]  
We take $\psi_i : \mathbb{R}_+^i \to \mathbb{R}_+^i \ (i = 1, 2, 3)$ by
\[ \psi_1(|u|) = \min \{p, 1, q\} |u|^2, \]  
\[ \psi_2(|u|) = \max \{p, 1, q\} |u|^2, \]  
\[ \psi_3(|u|) = \min \left\{ 2p(D + mbx^*) - p\sigma_1^2 + 2qy^2 D \right\} \right] |u|^2; \]  
thus the thesis follows by Lemma 2. This completes the proof of Theorem 5.
Now, we are in a position to prove the stability of the trivial solution \((0, 0)\) of model (13).

**Theorem 6.** Let condition (6) hold. If the conditions in (32) are satisfied, then the trivial solution of model (13) is stochastically asymptotically stable.

**Proof.** For a sufficiently small constant \(\epsilon > 0\), \((u_1, u_2) \in (-\epsilon, \epsilon) \times (-\epsilon, \epsilon)\), we have

\[
\begin{align*}
|f(t, X) - F \cdot X| + |g(t, X) - G \cdot X| &= \sqrt{F_1^2(u_1, u_2) + F_2^2(u_1, u_2)},
\end{align*}
\]

(38)

Note that \(F_1, F_2\) are the terms of order \(\geq 2\) in \(u_1\) and \(u_2\); then we have

\[
\begin{align*}
\lim_{u_1^2 + u_2^2 \to 0} \frac{F_1^2(u_1, u_2) + F_2^2(u_1, u_2)}{u_1^2 + u_2^2} &= 0.
\end{align*}
\]

(39)

Thus for a sufficiently small constant \(\rho > 0\), we have

\[
F_1^2(u_1, u_2) + F_2^2(u_1, u_2) < \rho^2 (u_1^2 + u_2^2)
\]

(40)

provided \(u_1^2 + u_2^2 < \epsilon^2\). Therefore,

\[
|f(t, X) - F \cdot X| + |g(t, X) - G \cdot X| < \rho |u|.
\]

(41)

Applying Lemma 3 and Theorem 5, we obtain the conclusion. \(\square\)

### 4. Dynamical Behavior of the System with Delays

We now study the stability in probability of the equilibria \((0, 0)\) of system (11). Its corresponding linearized system is

\[
\begin{align*}
du_1 &= \left[- (D + mbx^*) u_1 ight. \\
&\quad + \mu D_1 \int_0^\infty f(s) u_2(t-s)ds - ma u_1 \left. \right] dt \\
&\quad + \sigma_1 u_1 dB_1,
\end{align*}
\]

(42)

\[
\begin{align*}
du_2 &= mbx^* \int_0^\infty g(s) u_1(t-s)dsdt + \sigma_2 u_2 dB_2.
\end{align*}
\]

Define the average time lags as

\[
T_f = \int_0^\infty sf(s)ds, \quad T_g = \int_0^\infty sg(s)ds,
\]

(43)

and let \(q, p\) be defined in (31). For linearized system (42) we have the following theorem.

**Theorem 7.** Let condition (6) hold. If

\[
\begin{align*}
\sigma_1^2 + 2\mu D_1 ymbx^* T_f + \frac{1 + q}{p + qy^2} (D + mbx^*) ymbx^* T_g \\
< 2D + \frac{2ymbx^*}{p + qy^2},
\end{align*}
\]

(44)

\[
\begin{align*}
\sigma_2^2 + (D + mbx^* + 2ma + 2\mu D_1) ymbx^* T_g \\
< \frac{2q}{1 + q} (ma - \mu D_1),
\end{align*}
\]

then the trivial solution of system (42) is asymptotically mean square stable.

**Proof.** Consider the function \(V_1(u_1, u_2)\) defined in (33). It follows from (42) and Itô’s formula that

\[
\begin{align*}
dV_1(u_1, u_2) &= 2pu_1 du_1 + p(du_1)^2 + 2u_2 du_2 \\
+ (du_2)^2 + 2q(yu_1 + u_2) d(yu_1 + u_2) \\
+ q(d(yu_1 + u_2))^2 \\
= \left[2pu_1 \left[- (D + mbx^*) u_1 ight. \\
&\quad + \mu D_1 \int_0^\infty f(s) u_2(t-s)ds \\
&\quad - ma u_1 \left. \right] dt \\
&\quad + p\sigma_1^2 u_1^2 + 2ymbx^* u_2 \int_0^\infty g(s) u_1(t-s)ds \\
&\quad + \sigma_2^2 u_2^2 + 2q(yu_1 + u_2) \\
&\quad \times \left[ - \gamma (D + mbx^*) u_1 ight. \\
&\quad + \gamma \mu D_1 \int_0^\infty f(s) u_2(t-s)ds - \gamma ma u_2 \\
&\quad + ymbx^* \int_0^\infty g(s) u_1(t-s)ds \\
&\quad + q \left(y^2 \sigma_1^2 u_1^2 + \sigma_2^2 u_2^2 \right) \right] dt \\
&\quad + 2\sigma_2^2 u_2 dB_2 + 2q(yu_1 + u_2) \\
&\quad \times (\gamma \sigma_1 u_1 dB_1 + \sigma_2 u_2 dB_2) + 2p\sigma_1 u_1^2 dB_1.
\end{align*}
\]

(45)
Straightforward computations lead to

\[
LV_1(u_1, u_2) = -\left[2p (D + mbx^*) - p\sigma_1^2 + 2qy^2 (D + mbx^*) - qy^2 \sigma_1^2\right] u_1^2 \\
-\left[2q y m a - (1 + q) \sigma_2^2\right] u_2^2 \\
-\left[p ma + q y m a + qy (D + mbx^*)\right] u_1 u_2 \\
+ 2(1 + q) y m b x^* u_2 \int_0^\infty g(s) u_1(t - s) ds \\
+ 2qy^2 m b x^* u_1 \int_0^\infty g(s) u_1(t - s) ds \\
+ 2\left(p + q y^2\right) \mu D_1 u_1 \int_0^\infty f(s) u_2(t - s) ds \\
+ 2q y \mu D_1 u_2 \int_0^\infty f(s) u_2(t - s) ds.
\]

(46)

From the terms of the right-hand side of (46), we have

\[
u_1 \int_0^\infty g(s) u_1(t - s) ds \leq \frac{1}{2} \left(u_1^2 + \int_0^\infty g(s) u_1^2(t - s) ds\right),
\]

\[
u_2 \int_0^\infty f(s) u_2(t - s) ds \leq \frac{1}{2} \left(u_2^2 + \int_0^\infty f(s) u_2^2(t - s) ds\right).
\]

(47)

For the term \(u_1 \int_0^\infty f(s) u_2(t - s) ds\), it is clear that

\[
u_1 \int_0^t f(s) u_2(t - s) ds = u_1 u_2 - u_1 \int_0^t f(s) d\int_{t-s}^t u_2(\tau) d\tau + h_1(t)
\]

\[
= u_1 u_2 - y m b x^* H_1(u_1, u_2) + h_1(t)
\]

\[
- u_1 \int_0^t f(s) \int_{t-s}^t \sigma_2 u_2(\tau) dB_2(\tau) d\tau,
\]

where

\[
h_1(t) = -u_1 \int_t^\infty f(s)(u_2(t) - u_2(t - s)) ds,
\]

(49)

\[
H_1(u_1, u_2) = u_1 \int_0^t f(s) \int_{t-s}^t \int_{t-s}^\infty g(v) u_1(\tau - v) dv d\tau ds
\]

\[
\leq \frac{1}{2} \int_0^\infty f(s) x \int_{t-s}^t \int_{t-s}^\infty g(v) x \left(u_1^2(t) + u_1^2(\tau - v)\right) dv d\tau ds
\]

Substituting (47)–(48) together with (51) into (46), we obtain

\[
LV_1(u_1, u_2) \leq \frac{1}{2} T_j u_1^2 + \frac{1}{2} T_j u_2^2 \\
+ 2qy^2 (D + mbx^*) - qy^2 \sigma_1^2 - qy^2 mbx^* \\
- \left(p + q y^2\right) \mu D_1 y m b x^* T_j u_1^2 \\
- \left[2q y m a - (1 + q) \sigma_2^2\right] u_2^2 + h_1(t).
\]

(50)

For the term \(u_2 \int_0^\infty g(s) u_1(t - s) ds\), we have that

\[
u_2 \int_0^\infty g(s) u_1(t - s) ds
\]

\[
= u_1 u_2 - u_2 \int_0^t g(s) \int_{t-s}^t u_1(\tau) d\tau ds + h_2(t)
\]

\[
+ ma H_3(u_1, u_2) - \mu D_2 H_4(u_1, u_2)
\]

\[
+ u_2 \int_0^\infty g(s) \int_{t-s}^t \sigma_2 u_2(\tau) dB_2(\tau) d\tau ds + h_2(t),
\]

where

\[
h_2(t) = -u_2 \int_t^\infty g(s)(u_1(t) - u_1(t - s)) ds,
\]

(52)

\[
H_2(u_1, u_2) = u_2 \int_0^t g(s) \int_{t-s}^t u_1(\tau) d\tau ds
\]

\[
\leq \frac{1}{2} T_j u_2^2 + \frac{1}{2} T_j \int_{t-s}^\infty g(s) \int_{t-s}^t u_1^2(\tau) d\tau ds,
\]

(51)

\[
H_3(u_1, u_2) = u_2 \int_0^t g(s) \int_{t-s}^t \int_{t-s}^\infty f(v) u_2(\tau - v) dv d\tau ds
\]

\[
\leq \frac{1}{2} T_j u_2^2 + \frac{1}{2} T_j \int_{t-s}^\infty g(s) \int_{t-s}^t \int_{t-s}^\infty f(v) u_2^2(\tau - v) dv d\tau ds,
\]

\[
H_4(u_1, u_2) = u_2 \int_0^t g(s) \int_{t-s}^t \int_{t-s}^\infty f(v) u_2(\tau - v) dv d\tau ds
\]

\[
\leq \frac{1}{2} T_j u_2^2 + \frac{1}{2} T_j \int_{t-s}^\infty g(s) \int_{t-s}^t \int_{t-s}^\infty f(v) u_2^2(\tau - v) dv d\tau ds.
\]

(53)
\begin{align*}
&\times (D + mbx^* + ma + \mu D_1) ymbx^* T_g \\
&- qy \mu D_1 u_2^1 \\
&- 2 \left[ pma + qy^2 ma + qy (D + mbx^*) \right] u_1 u_2 \\
&- (1 + q) ymbx^* - \left( p + qy^2 \right) \mu D_1 u_1 u_2 \\
&+ (1 + q) ymbx^* \\
&\times \left[ \mu D_1 \int_0^\infty g(s) \\
&\times \int_0^t \int_0^t f(v) u_2^1 (\tau - v) dv d\tau ds \\
&+ (D + mbx^*) \int_0^\infty g(s) \int_0^t u_2^1 (\tau) d\tau ds \\
&+ ma \int_0^\infty g(s) \int_0^t u_2^1 (\tau) d\tau ds \\
&+ qy^2 mbx^* \int_0^\infty g(s) \int_0^t u_2^1 (\tau) d\tau ds \\
&+ (p + qy^2) \mu D_1 ymbx^* \\
&\times \int_0^\infty f(s) \\
&\times \int_0^t \int_0^t g(v) u_2^1 (\tau - v) dv d\tau ds \\
&+ 2 (1 + q) ymbx^* h_2 (t) \\
&+ 2 (p + qy^2) \mu D_1 h_1 (t) .
\end{align*}

\text{(54)}

is well defined. Using Itô's formula, we have

\begin{align*}
L(V_1 + V_2) &\leq - \left[ 2 p (D + mbx^*) - p \sigma_1^2 \right] \\
&+ 2qy^2 (D + mbx^*) - qy^2 \sigma_1^2 - 2qy^3 mbx^* \\
&- \left( p + qy^2 \right) \mu D_1 ymbx^* T_f \\
&- (1 + q) (D + mbx^*) ymbx^* T_g \] u_2^1 \\
&- 2qy ma - (1 + q) \sigma_2^2 - (1 + q) \\
&\times (D + mbx^* + 2ma + \mu D_1) ymbx^* T_g \\
&- 2qy \mu D_1 u_2^2 \\
&- 2 \left[ pma + qy^2 ma + qy (D + mbx^* \right] u_1 u_2 \\
&- (1 + q) ymbx^* - \left( p + qy^2 \right) \mu D_1 u_1 u_2 \\
&+ (1 + q) ymbx^* \mu D_1 T_g \\
&\times \int_0^\infty f(s) u_2^1 (t - s) ds \\
&+ \left( p + qy^2 \right) \mu D_1 ymbx^* T_f \\
&\times \int_0^\infty g(s) u_2^1 (t - s) ds \\
&+ 2 (1 + q) ymbx^* h_2 (t) \\
&+ 2 (p + qy^2) \mu D_1 h_1 (t) .
\end{align*}

\text{(55)}

For technical reasons, we assume that \( \int_0^\infty s^2 f(s) ds < \infty \) and \( \int_0^\infty s^2 g(s) ds < \infty \). Then the function

\begin{align*}
V_2(u_1, u_2) &= (1 + q) ymbx^* \\
&\times \left[ \mu D_1 \int_0^\infty g(s) \\
&\times \int_0^t \int_0^t f(v) u_2^1 (\tau - v) dv d\tau ds \\
&+ (D + mbx^*) \\
&\times \int_0^\infty g(s) \int_0^t u_2^1 (\tau) d\tau ds \\
&+ ma \int_0^\infty g(s) \int_0^t u_2^1 (\tau) d\tau ds \\
&\right]
\end{align*}

\text{(56)}

We now consider the function

\begin{align*}
V_3(u_1, u_2) &= (1 + q) ymbx^* \mu D_1 T_g \\
&\times \int_0^\infty f(s) \int_0^t u_2^1 (\tau) d\tau ds \\
&+ \left( p + qy^2 \right) \mu D_1 ymbx^* T_f \\
&\times \int_0^\infty g(s) \int_0^t u_2^1 (\tau) d\tau ds .
\end{align*}

\text{(57)}
It follows from (56) and (57) that
\[ L(V_1 + V_2 + V_3) \leq -2p(D + mbx^*) - p\sigma_i^2 + 2qy^2(D + mbx^*) - qy^2\sigma_i^2 - 2qy^2mbx^* - 2 \left( p + qy^2 \right) \mu D_1 ymbx^* T_f - (1 + q)(D + mbx^*) ymbx^* T_g - 2 \left( p + qy^2 \right) \mu D_1 \int_t^\infty f(s) ds - (1 + q) ymbx^* \int_t^\infty g(s) ds \] u_i^2

Therefore, for the function
\[ V(u_1, u_2) = V_1(u_1, u_2) + V_2(u_1, u_2) + V_3(u_1, u_2), \] we have
\[ LV \leq -2p(D + mbx^*) - p\sigma_i^2 + 2qy^2(D + mbx^*) - qy^2\sigma_i^2 - 2qy^2mbx^* - 2 \left( p + qy^2 \right) \mu D_1 ymbx^* T_f - (1 + q)(D + mbx^*) ymbx^* T_g - 2 \left( p + qy^2 \right) \mu D_1 \int_t^\infty f(s) ds - (1 + q) ymbx^* \int_t^\infty g(s) ds \] u_i^2

By (44), we choose \( \varepsilon > 0 \) such that
\[ 2p(D + mbx^*) + 2qy^2D > \left( p + qy^2 \right) \sigma_i^2 + 2 \left( p + qy^2 \right) \mu D_1 ymbx^* T_f + (1 + q)(D + mbx^*) ymbx^* T_g + 2 \left( p + qy^2 \right) \mu D_1 \varepsilon + (1 + q) ymbx^* \varepsilon, \] (61)

Let \( T = T(\varepsilon) \) such that \( \int_t^\infty f(s) ds < \varepsilon \) and \( \int_t^\infty g(s) ds < \varepsilon \) for all \( t \geq T \). Then for all \( t \geq T \), one has
\[ LV \leq -2p(D + mbx^*) - p\sigma_i^2 + 2qy^2(D + mbx^*) - qy^2\sigma_i^2 - 2qy^2mbx^* - 2 \left( p + qy^2 \right) \mu D_1 ymbx^* T_f - (1 + q)(D + mbx^*) ymbx^* T_g - 2 \left( p + qy^2 \right) \mu D_1 \varepsilon - (1 + q) ymbx^* \varepsilon \] u_i^2

Therefore, for the function
\[ V(u_1, u_2) = V_1(u_1, u_2) + V_2(u_1, u_2) + V_3(u_1, u_2), \] we have
\[ LV \leq -2p(D + mbx^*) - p\sigma_i^2 + 2qy^2(D + mbx^*) - qy^2\sigma_i^2 - 2qy^2mbx^* - 2 \left( p + qy^2 \right) \mu D_1 ymbx^* T_f - (1 + q)(D + mbx^*) ymbx^* T_g - 2 \left( p + qy^2 \right) \mu D_1 \varepsilon - (1 + q) ymbx^* \varepsilon \] u_i^2

(62)
For convenience, let

\[ Q = \min \left\{ 2p \left( D + mbx^* \right) - po_1^2 \right\} \]

\[ + 2qy^2 \left( D + mbx^* \right) - qy^2 \sigma_1^2 - 2qy^2 mbx^* \]

\[ - 2 \left( p + qy^2 \right) \mu D_1 ymbx^* T_f - \left( 1 + q \right) \]

\[ \times \left( D + mbx^* \right) ymbx^* T_g \]

\[ - 2 \left( p + qy^2 \right) \mu D_1 e - \left( 1 + q \right) ymbx^* e, \] (63)

\[ 2qy\sigma_2 - \left( 1 + q \right) \sigma_2^2 - \left( 1 + q \right) \]

\[ \times \left( D + mbx^* + 2ma + 2 \mu D_1 \right) ymbx^* T_g \]

\[ - 2qy\mu D_1 - \left( p + qy^2 \right) \mu D_1 e \]

\[ - 2 \left( 1 + q \right) ymbx^* e \right\} . \]

Integrating both sides of (62) from \( T \) to \( t \geq T \), we have

\[ E \left( V \left( t \right) \right) + Q \int_T^t E \left( u_1^2 \left( s \right) + u_2^2 \left( s \right) \right) ds \]

\[ \leq V \left( T \right) \left( p + qy^2 \right) \mu D_1 \left\| \varphi_2 \right\|^2 \int_T^t \int_0^\infty f \left( u \right) du ds \]

\[ + \left( 1 + q \right) ymbx^* \left\| \varphi_1 \right\|^2 \int_T^t \int_0^\infty g \left( u \right) du ds \]

\[ \leq V \left( T \right) \left( p + qy^2 \right) \mu D_1 \left\| \varphi_2 \right\|^2 \int_0^\infty sf \left( s \right) ds \]

\[ + \left( 1 + q \right) ymbx^* \left\| \varphi_1 \right\|^2 \int_0^\infty sg \left( s \right) ds \]

\[ = V \left( T \right) \left( p + qy^2 \right) \mu D_1 \left\| \varphi_2 \right\|^2 T_f \]

\[ + \left( 1 + q \right) ymbx^* \left\| \varphi_1 \right\|^2 T_g < \infty. \] (64)

Discussing as that in He et al. [18], by the Barbâlat lemma, we conclude \( E(u_1^2(t) + u_2^2(t)) \to 0 \) as \( t \to \infty \). Applying Definition 4, we obtain the conclusion. \( \square \)

Now, we are in a position to prove the stability of the trivial solution \((0,0)\) of nonlinear system (II) using the Lyapunov functionals constructed above.

**Theorem 8.** Let condition (6) hold. If conditions (44) are satisfied, then the trivial solution \((0,0)\) of the system (II) or the equilibrium \((S^*, x^*)\) of system (6) is stochastically stable.

**Proof.** Consider the Lyapunov function \( V_1(u_1, u_2) \) defined in (33). It follows from (II) and Itô’s formula that

\[ dV_1 \left( u_1, u_2 \right) = 2pu_1 du_1 + p \left( du_1 \right)^2 + 2u_2 du_2 \]

\[ + \left( du_2 \right)^2 + 2q \left( yu_1 + u_2 \right) d \left( yu_1 + u_2 \right) \]

\[ + q \left( d \left( yu_1 + u_2 \right) \right)^2 \]

\[ = 2pu_1 \left[ - \left( D + mbx^* \right) u_1 \right. \]

\[ + \mu D_1 \int_0^\infty f \left( s \right) u_2 \left( t - s \right) ds \]

\[ - ma u_2 + F_1 + po_1^2 u_1 \]

\[ + 2ymbx^* u_2 \int_0^\infty g \left( s \right) u_1 \left( t - s \right) ds \]

\[ + 2u_2 F_2 + \sigma_2^2 u_2^2 + 2q \left( yu_1 + u_2 \right) \]

\[ \times \left[ - y \left( D + mbx^* \right) u_1 \right. \]

\[ \left. + \gamma D_1 \int_0^\infty f \left( s \right) u_2 \left( t - s \right) ds \right. \]

\[ - yma u_2 + \gamma F_1 \]

\[ + \gamma mbx^* \int_0^\infty g \left( s \right) u_1 \left( t - s \right) ds + F_2 \]

\[ + q \left( y^2 \sigma_1^2 u_1^2 + \sigma_2^2 u_2^2 \right) \right\} dt \]

\[ + 2\sigma_2^2 u_2^2 d B_2 \]

\[ + 2q \left( yu_1 + u_2 \right) \left( y\sigma_1 u_1 d B_1 + \sigma_2 u_2 d B_2 \right) \]

\[ + 2p\sigma_1^2 u_1 d B_1 = LV_1 \left( u_1, u_2 \right) dt + 2\sigma_2^2 u_2^2 d B_2 \]

\[ + 2q \left( yu_1 + u_2 \right) \left( y\sigma_1 u_1 d B_1 + \sigma_2 u_2 d B_2 \right) \]

\[ + 2p\sigma_1^2 u_1 d B_1, \] (65)

where

\[ LV_1 \left( u_1, u_2 \right) = - \left[ 2p \left( D + mbx^* \right) - po_1^2 \right] \]

\[ - 2qy^2 \left( D + mbx^* \right) - qy^2 \sigma_1^2 \] \( u_1^2 \]

\[ - 2qy \sigma_2 - \left( 1 + q \right) \sigma_2^2 \] \( u_2^2 \]

\[ - 2 \left[ pma + qy^2 ma + qy \left( D + mbx^* \right) \right] u_1 u_2 \]

\[ + \left( 1 + q \right) ymbx^* u_2 \int_0^\infty g \left( s \right) u_1 \left( t - s \right) ds \]

\[ + 2qy^2 mbx^* u_1 \int_0^\infty g \left( s \right) u_1 \left( t - s \right) ds \]

\[ + 2 \left( p + qy^2 \right) \mu D_1 u_1 \int_0^\infty f \left( s \right) u_2 \left( t - s \right) ds \]

\[ + \left[ 2p \left( D + mbx^* \right) - po_1^2 \right] \]

\[ + 2qy^2 \left( D + mbx^* \right) - qy^2 \sigma_1^2 \] \( u_1^2 \]

\[ - 2qy \sigma_2 - \left( 1 + q \right) \sigma_2^2 \] \( u_2^2 \]

\[ - 2 \left[ pma + qy^2 ma + qy \left( D + mbx^* \right) \right] u_1 u_2 \]

\[ + 2 \left( p + qy^2 \right) \mu D_1 u_1 \int_0^\infty f \left( s \right) u_2 \left( t - s \right) ds \]

\[ + 2qy \mu D_1 u_2 \int_0^\infty f \left( s \right) u_2 \left( t - s \right) ds \]
\[
+ 2p u_1 F_1 + 2u_2 \bar{F}_2 \\
+ 2q (\gamma u_1 + u_2) (\gamma F_1 + \bar{F}_2).
\]

From the terms of the right-hand side of (66), we observe that

\[
\begin{align*}
\quad & u_1 \int_0^\infty g(s) u_2(t - s) ds \\
& = u_1 u_2 - u_1 \int_0^t f(s) \int_{t-s}^t du_2(\tau) ds + h_1(t) \\
& = u_1 u_2 - \gamma mbx^* H_1(u_1, u_2) - u_1 \int_0^t f(s) \int_{t-s}^t \bar{F}_2 d\tau ds \\
& - u_1 \int_0^t f(s) \int_{t-s}^t \sigma_2 u_2(\tau) d\sigma_2(\tau) ds + h_1(t),
\end{align*}
\]

where \( h_1(t) \) is defined in (49), and

\[
\begin{align*}
\quad & u_2 \int_0^\infty g(s) u_1(t - s) ds \\
& = u_1 u_2 - u_2 \int_0^t g(s) \int_{t-s}^t du_1(\tau) ds + h_2(t) \\
& = u_1 u_2 + (D + mbx^*) H_2(u_1, u_2) \\
& \quad + ma H_3(u_1, u_2) - \mu D_1 H_4(u_1, u_2) \\
& - u_2 \int_0^t g(s) \int_{t-s}^t F_1 d\tau ds \\
& + u_2 \int_0^t g(s) \int_{t-s}^t \sigma_2 u_2(\tau) d\sigma_2(\tau) ds + h_2(t),
\end{align*}
\]

where \( h_2(t) \) is defined in (52). Substituting (67) and (68) into (46), we get

\[
LV_1(u_1, u_2)
\leq -2p(D + mbx^*) - p\sigma_1^2 \\
+ 2q(\gamma mbx^*) - q\gamma^2 \sigma_1^2 - q\gamma^2 mbx^* \\
- \left( p + q\gamma^2 \right) \mu D_1 mbx^* T_f u_1^2 \\
- \left[ 2q\gamma ma - (1 + q) \sigma_2^2 -(1 + q) \right] \\
\times (D + mbx^* + ma + \mu D_1) mbx^* T_g \\
- q\gamma \mu D_1 u_2^2 \\
- 2 \left[ p ma + q\gamma^2 ma \right] \\
+ q(\gamma mbx^*) - (1 + q) \gamma mbx^* \\
- \left( p + q\gamma^2 \right) \mu D_1 u_1 u_2 + (1 + q) \gamma mbx^* \\
\times \left[ \mu D_1 \int_0^\infty g(s) \int_{t-s}^t \int_0^\infty f(v) u_1^2 (\tau - v) dv d\tau ds \\
+ (D + mbx^*) \int_0^\infty g(s) \int_{t-s}^t u_2^2 (\tau) d\tau ds \\
+ ma \int_0^\infty g(s) \int_{t-s}^t \bar{F}_2 d\tau ds \right] \\
+ q\gamma^2 mbx^* \int_0^\infty g(s) u_1^2 (t - s) ds \\
+ q\gamma \mu D_1 \int_0^\infty f(s) u_2^2 (t - s) ds \\
+ \left( p + q\gamma^2 \right) \mu D_1 \gamma mbx^* \\
\times \int_0^\infty f(s) \int_{t-s}^t \int_0^\infty g(v) u_2^2 (\tau - v) dv d\tau ds \\
+ 2p u_1 F_1 + 2u_2 \bar{F}_2 + 2q(\gamma u_1 + u_2) (\gamma F_1 + \bar{F}_2) \\
- 2 \left( p + q\gamma^2 \right) \mu D_1 u_1 \int_0^\infty f(s) \int_{t-s}^t \bar{F}_2 d\tau ds \\
+ 2 \left( p + q\gamma^2 \right) \mu D_1 h_1(t) \\
- 2(1 + q) \gamma mbx^* u_2 \int_0^\infty \int_{t-s}^t F_1 d\tau ds \\
+ 2(1 + q) \gamma mbx^* h_2(t).
\]

For the functions \( V_2(u_1, u_2) \) and \( V_3(u_1, u_2) \) defined in (55) and (57), one has

\[
L(V_1 + V_2 + V_3)
\leq -2p(D + mbx^*) - p\sigma_1^2 + 2q\gamma^2 (D + mbx^*) \\
- q\gamma^2 \sigma_1^2 - q\gamma^2 mbx^* \\
- 2 \left( p + q\gamma^2 \right) \mu D_1 \gamma mbx^* T_f - (1 + q) \\
\times (D + mbx^* + 2ma + 2\mu D_1) mbx^* T_g \\
- 2q\gamma ma - (1 + q) \sigma_2^2 -(1 + q) \\
\times (D + mbx^* + ma + \mu D_1) mbx^* T_g \\
- 2q\gamma \mu D_1 u_2^2 \\
- 2 \left[ p ma + q\gamma^2 ma + q\gamma (D + mbx^*) \right] \\
- (1 + q) \gamma mbx^* - \left( p + q\gamma^2 \right) \mu D_1 u_1 u_2 \\
+ 2p u_1 F_1 + 2u_2 \bar{F}_2 + 2q(\gamma u_1 + u_2) (\gamma F_1 + \bar{F}_2) \\
- 2 \left( p + q\gamma^2 \right) \mu D_1 u_1 \int_0^\infty f(s) \int_{t-s}^t \bar{F}_2 d\tau ds \\
+ 2 \left( p + q\gamma^2 \right) \mu D_1 h_1(t) \\
- 2(1 + q) \gamma mbx^* u_2 \int_0^\infty \int_{t-s}^t F_1 d\tau ds \\
+ 2(1 + q) \gamma mbx^* h_2(t).
\]
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For 

\[ h_1(t) \leq 2u_1^2 \int_0^\infty f(s) ds + (u_2^2 + \|\varphi_2\|^2) \int_0^\infty g(s) ds, \]

\[ h_2(t) \leq 2u_2^2 \int_0^\infty g(s) ds + (u_1^2 + \|\varphi_1\|^2) \int_0^\infty g(s) ds. \]

For \( V(u_1, u_2) = V_1(u_1, u_2) + V_2(u_1, u_2) + V_3(u_1, u_2), \) one has

\[ LV(u_1, u_2) \leq - \left[ 2p (D + mbx^*) - po_1^2 \right. \]

\[ + 2qy^2 (D + mbx^*) - qy^2 o_2^2 - 2qy^2 mbx^* \]

\[ - 2 \left( p + qy^2 \right) \mu D_1 ymbx^* T_g - \left( 1 + q \right) \]

\[ \times (D + mbx^*) ymbx^* T_g \]

\[ - 2 \left( p + qy^2 \right) \mu D_1 \int_t^\infty f(s) ds \]

\[ - \left( 1 + q \right) \gamma ymbx^* \int_t^\infty g(s) ds \] \( u_1^2 \]

\[ + \left( p + qy^2 \right) \mu D_1 \|\varphi_2\|^2 \int_t^\infty f(s) ds \]

\[ + (1 + q) \gamma ymbx^* \|\varphi_1\|^2 \int_t^\infty g(s) ds \]

\[ + 2pu_1 F_1 + 2u_2 F_2 + 2q (y u_1 + u_2) \left( \gamma F_1 + F_2 \right) \]

\[ - 2 \left( 1 + q \right) \gamma ymbx^* u_2 \int_0^t f(s) ds \int_{s-t}^t F_1 d\tau ds \]

\[ - 2 \left( p + qy^2 \right) \mu D_1 u_1 \int_0^t f(s) ds \int_{s-t}^t F_2 d\tau ds. \]

Since \( F_1 \) and \( F_2 \) are terms of order \( \geq 2 \) in \( u_1, u_2, \) then we have

\[ \lim_{u_1, u_2 \to 0} \frac{F_1(u_1, u_2)}{u_1^2 + u_2^2} = \lim_{u_1, u_2 \to 0} \frac{F_2(u_1, u_2)}{u_1^2 + u_2^2} = 0. \]

For \( \varepsilon > 0, \) we can find a constant \( \zeta \in (0, 1) \) such that

\[ F_1(u_1, u_2) \leq \frac{\varepsilon}{\sqrt{2}} \sqrt{u_1^2 + u_2^2}, \]

\[ F_2(u_1, u_2) \leq \frac{\varepsilon}{\sqrt{2}} \sqrt{u_1^2 + u_2^2}. \]

provided that \( u_1^2 + u_2^2 \leq 2\zeta^2. \) Now consider the class of processes

\[ \Psi = \left\{ \varphi \in \mathcal{H} | P \left\{ \sup_{t \geq 0} |\varphi(t)| < \zeta \right\} = 1 \right\}. \]

Notice that for \( \varphi \in \Psi, \)

\[ \left\| \int_0^t g(s) \int_{s-t}^t F_1(\tau) d\tau ds \right\| \leq \varepsilon T_y \zeta, \]

\[ \left\| \int_0^t f(s) \int_{s-t}^t F_2(\tau) d\tau ds \right\| \leq \varepsilon T_\zeta \]

are valid. Substituting (74)-(76) into (72), we obtain

\[ LV(u_1, u_2) \leq - \left[ 2p (D + mbx^*) - po_1^2 \right. \]

\[ + 2qy^2 (D + mbx^*) - qy^2 o_2^2 - 2qy^2 mbx^* \]

\[ - 2 \left( p + qy^2 \right) \mu D_1 ymbx^* T_g \]

\[ - 2 \left( p + qy^2 \right) \mu D_1 \int_t^\infty f(s) ds \]

\[ - \left( 1 + q \right) \gamma ymbx^* \int_t^\infty g(s) ds \] \( u_1^2 \]

\[ + \left( p + qy^2 \right) \mu D_1 \|\varphi_2\|^2 \int_t^\infty f(s) ds \]

\[ + (1 + q) \gamma ymbx^* \|\varphi_1\|^2 \int_t^\infty g(s) ds \]

\[ + 2pu_1 F_1 + 2u_2 F_2 + 2q (y u_1 + u_2) \left( \gamma F_1 + F_2 \right) \]

\[ - 2 \left( 1 + q \right) \gamma ymbx^* u_2 \int_0^t f(s) ds \int_{s-t}^t F_1 d\tau ds \]

\[ - 2 \left( p + qy^2 \right) \mu D_1 u_1 \int_0^t f(s) ds \int_{s-t}^t F_2 d\tau ds. \]

\[ + \left( p + qy^2 \right) \mu D_1 \|\varphi_2\|^2 \int_t^\infty f(s) ds \]

\[ + (1 + q) \gamma ymbx^* \|\varphi_1\|^2 \int_t^\infty g(s) ds \]

\[ + 2e \left[ p + 1 + q(y + 1)^2 + (1 + q) ymbx^* T_g \right. \]

\[ + \left( p + qy^2 \right) \mu D_1 T_y \right\} \zeta^2. \]
Integrating both sides of the above formula from \( T \) to \( t \wedge T_{e_i} \) yields

\[
E \left( V \left( t \wedge T_{e_i} \right) \right) \leq V \left( T \right) + \left( p + qy^2 \right) \mu D_1 \| \phi_2 \|^2 \times \int_{0}^{t \wedge T_{e_i}} \int_{s}^{\infty} f \left( \tau \right) d\tau \ ds \\
+ \left( 1 + q \right) \gamma mbx^* \| \phi_1 \|^2 \times \int_{0}^{t \wedge T_{e_i}} \int_{s}^{\infty} g \left( \tau \right) d\tau \ ds + 2ek_1 \zeta^2 \\
\leq V \left( T \right) + \left( p + qy^2 \right) \mu D_1 \| \phi_2 \|^2 \int_{0}^{\infty} sf \left( s \right) \ ds \\
+ \left( 1 + q \right) \gamma mbx^* \| \phi_1 \|^2 \times \int_{0}^{\infty} sg \left( s \right) \ ds + 2ek_1 \zeta^2,
\]

where

\[
k_1 = p + 1 + q(y^2 + 1) + \left( 1 + q \right) \gamma mbx^* T_g \\
+ \left( p + qy^2 \right) \mu D_1 T_f.
\]

By the definition of function \( V(u_1, u_2) \), we can find a constant \( k_2 > 0 \) such that

\[
V \left( T \right) \leq k_2 \left( \| \phi_1 \|^2 + \| \phi_2 \|^2 \right).
\]

Obviously,

\[
E \left( V \left( t \wedge T_{e_i} \right) \right) \leq k_3 \left( \| \phi_1 \|^2 + \| \phi_2 \|^2 \right) + 2ek_1 \zeta^2,
\]

where \( k_3 = \max\{k_2 + \left( 1 + q \right) \gamma mbx^*, k_2 + \left( p + qy^2 \right) \mu D_1 \} \).

Now for \( \varepsilon_1, \varepsilon_2 \in (0, 1) \), let

\[
\delta = \min \left\{ \left( \frac{1 + p}{2ek_1 + k_3} \varepsilon_2 \right)^{1/2}, \varepsilon_1, 2, 2 \right\}
\]

and \( \| \phi_1 \|^2 + \| \phi_2 \|^2 < \delta^2 \). Then it follows that

\[
E \left( V \left( t \wedge T_{e_i} \right) \right) \leq \left( 2ek_1 + k_3 \right) \delta^2 \leq \left( 1 + p \right) \varepsilon_1^2 \varepsilon_2.
\]

On the other hand, we have

\[
E \left( V \left( t \wedge T_{e_i} \right) \right) \geq E \left[ \int_{[T_{e_i}, \infty]} V \left( t \wedge T_{e_i} \right) \right] \\
= E \left[ \int_{[T_{e_i}, \infty]} V \left( T_{e_i} \right) \right] \\
= p \left( T_{e_i} \leq t \right) V \left( T_{e_i} \right) \\
\geq \left( 1 + p \right) \varepsilon_1^2 \varepsilon_2 \left( T_{e_i} \leq t \right).
\]

Hence, we have \( P\{T_{e_i} \leq t \} \leq \varepsilon_2 \). Let \( t \to \infty \), then

\[
P \left\{ T_{e_i} < \infty \right\} \leq \varepsilon_2.
\]

Equivalently,

\[
P \left\{ u_1^2 + u_2^2 < \varepsilon_1^2 \right\} \geq 1 - \varepsilon_2.
\]

Applying Definition 4, we obtain the conclusion.

5. Simulations and Discussions

In this paper, we have considered a stochastic chemostat model simulating the process of wastewater treatment. The model incorporates a general nutrient uptake function and two distributed delays. The first delay models the fact that nutrient is partially recycled after the death of the biomass by bacterial decomposition and the second indicates that the growth of the species depends on the past concentration of the nutrient. Furthermore, we consider the stochastic perturbations which are of white noise type and are proportional to the distances of \( S(t), x(t) \) from the values of the positive equilibrium \( S^*, x^* \). By constructing appropriate Liapunov-like functionals, some sufficient conditions for the stochastic stability of the positive equilibrium have been obtained.

For model (3), we have first analyzed the stochastic stability of the positive equilibrium \( E^* \) in the case when the delays are ignored, that is, the average delays \( T_f = T_g = 0 \). Our findings in Theorem 6 reveal that \( E^* \) is stochastically stable provided that the intensities of noises are small. When at least one of the average delays \( T_f \) and \( T_g \) is not equal to zero, our results in Theorem 8 reveal that \( E^* \) is stochastically stable provided that the average delays \( T_f \) and \( T_g \) are both small. Obviously, Theorem 8 reduces to Theorem 6 when \( T_f = T_g = 0 \), which indicates that if the average delays are sufficiently small, \( E^* \) is still stochastically stable; and in the case of \( \sigma_1 = 0 \) \( (i = 1, 2) \), Theorem 8 reduces to He et al. [18, Theorem 3.1]; that is to say, the equilibrium \( E^* \) of model (3) is still stable if \( \sigma_2 \) and \( \sigma_2 \) are sufficient small, which preserves the dynamics of its corresponding deterministic counterpart (5).

To illustrate the results obtained above, some numerical simulations are carried out by using Milstein scheme [50]. Here we assume that the specific growth function \( U(S) \) is of Michaelis-Menten type

\[
U \left( S \right) = \frac{S}{a_1 + S},
\]

where \( a_1 \) is the half-saturation constant. For the kernel functions \( f(s) \) and \( g(s) \), we consider two special cases: (1) \( f(s) = g(s) = \delta(0) \); (2) \( f(s) = ae^{-as} \) and \( g(s) = \beta e^{-bs} \). For case (1), the discretization of model (3) for \( t = 0, \Delta t, 2\Delta t, \ldots, n\Delta t \) takes the form

\[
S_{i+1} = S_i + \left[ D \left( S^0 - S_i \right) - mU \left( S_i \right) x_i + \mu D_1 x_i \right] \Delta t \\
+ \sigma_1 \left( S_i - S^* \right) \sqrt{\Delta \xi}.
\]

\[
x_{i+1} = x_i + x_i \left[ - \left( D_w + D_1 \right) + \gamma mU \left( S_i \right) \right] \Delta t \\
+ \sigma_2 \left( x_i - x^* \right) \sqrt{\Delta \xi},
\]

where time increment \( \Delta t > 0 \) and \( \xi \) is \( N(0, 1) \)-distributed independent random variables which can be generated
Figure 1: The dynamics of stochastic model compared with deterministic model with $\sigma_1 = 0.1$ and $\sigma_2 = 0.08$. Here $S(0) = 0.3$, $x(0) = 0.5$.

Figure 2: The dynamics of stochastic model with different values of $\sigma_1$ and $\sigma_2$. Here $S(0) = 0.3$, $x(0) = 0.5$.

Numerically by pseudorandom number generators. For case (2), define

$$y(t) = \int_0^\infty ax(t-s) ds,$$
$$z(t) = \int_0^\infty \beta e^{-\beta s} U(S(s)) ds,$$

then the discretization of model (3) for $t = 0, \Delta t, 2\Delta t, \ldots, n\Delta t$ takes the form

$$S_{i+1} = S_i + \left[D (S^0 - S_i) - m U(S_i) x_i + \mu D_1 y_i\right] \Delta t$$
$$+ \sigma_1 (S_i - S^*) \sqrt{\Delta t} \xi_i,$$

$$x_{i+1} = x_i + x_i \left[ - (D_w + D_1) + \gamma mz_i \right] \Delta t$$
$$+ \sigma_2 (x_i - x^*) \sqrt{\Delta t} \xi_i,$$

$$y_{i+1} = y_i + (-\alpha y_i + \alpha x_i) \Delta t,$$
$$z_{i+1} = z_i + (-\beta z_i + \beta U(S_i)) \Delta t.$$

Let in model (3) $D = D_w = 0.3, D_1 = 0.1, S^0 = 5, m = 0.7, a_1 = 0.4, \mu = 0.3, \gamma = 0.8$. It is easy to compute that $a \approx 0.7143, b \approx 0.2041, p \approx 0.3100, q \approx 0.2694$, and $E^* = (1, 2.55)$.

The first two examples given below concern case (1) when the delays are ignored; that is to say, it is assumed that the
process of nutrient recycling and the growth response of the species are immediate and, therefore, $T_f = T_g = 0$. Example 1 verifies the results obtained in Theorem 6.

**Example 1.** Let $\sigma_1 = 0.1$ and $\sigma_2 = 0.08$, then by straightforward computations, we have that $0.01 = \sigma_1^2 < 2D + 2mbx^* = 1.3285$, $0.0064 = \sigma_2^2 < (2q/(1 + q))\gamma(ma - \mu D_1) = 0.1596$. In view of Theorem 6, the equilibrium $E^*$ of (3) is stochastically asymptotically stable, which is consistent with the simulation results as shown in Figure 1.

To further study the combined effects of $\sigma_i$, $i = 1, 2$ when $T_f = T_g = 0$, we need to consider four situations: (a) $\sigma_1$ increases, $\sigma_2$ increases; (b) $\sigma_1$ increases, $\sigma_2$ decreases; (c) $\sigma_1$ decreases, $\sigma_2$ increases; (d) $\sigma_1$ decreases, $\sigma_2$ decreases. Here we only give one example about situation (a); other situations can be considered similarly.

**Example 2.** Let the intensities $\sigma_i$, $i = 1, 2$ increase from $\sigma_1 = 0.1$, $\sigma_2 = 0.08$ to $\sigma_1 = 1$, $\sigma_2 = 0.12$, respectively. Simulations show that the trajectories of model (3) still approach ultimately to the positive equilibrium $E^*$, but they need to go through more oscillations and more time to return to $E^*$ (see Figure 2).

The next two examples concern case (2) when $f(s)$ and $g(s)$ take weak kernels; that is, $f(s) = ae^{-\alpha s}$ and $g(s) = \beta e^{-\beta s}$,
Figure 5: The positive equilibrium $E^*$ is stochastically stable provided that $(\sigma_1, T_f) \in \Omega_{\sigma_1, T_f}$. Here $\sigma_2 = 0.08$ and $T_g = 0.2$.

Figure 6: The positive equilibrium $E^*$ is stochastically stable provided that $(\sigma_2, T_f) \in \Omega_{\sigma_2, T_f}$. Here $\sigma_1 = 0.1$ and $T_g = 0.2$.

Figure 7: The positive equilibrium $E^*$ is stochastically stable provided that $(T_f, T_g) \in \Omega_{T_f, T_g}$. Here $\sigma_1 = 0.1$ and $\sigma_2 = 0.08$. 
which means that $T_f = 1/\alpha$ and $T_g = 1/\beta$. Example 3 verifies the results obtained in Theorem 8.

**Example 3.** Let $\sigma_1 = 0.1, \sigma_2 = 0.08, \alpha = 1$ and $\beta = 5$. It is easy to compute that $(p + qy^2)\sigma_1^2 + 2(p + qy^2)\mu D_1 ymbx^*T_f + (1 + q)(D + mbx^*)ymbx^*T_g = 0.0624, 2p(D + mbx^*) + 2qy^2D = 0.5154$ and $(\sigma_2^2 + (D + mbx^* + 2ma + 2\mu D_1))ymbx^*T_g = 0.1069, (2q/(1 + q))\gamma (ma - \mu D_1) = 0.1596; thus conditions (44) are satisfied. By Theorem 8, the equilibrium $E^*$ of model (3) is stochastically stable. Our simulation supports this result as shown in Figure 3.

To examine the combined effects of the noise intensities and the delays on the dynamics of model (3), we first consider the case when the values of $\sigma_i, i = 1, 2$ in Example 3 are fixed and the values of $\alpha$ and $\beta$ are reduced from 1 to 0.1 and 0.1, respectively. That is to say, the average delays $T_f$ and $T_g$ increase from 1 and 0.2 to 10 and 10, respectively. Simulation results show that the solution of (3) will suffer more oscillations and more time to approach the equilibrium $E^*$ when delays increase (see Figure 3). When both the values of the noise intensities and the delays vary, the dynamics of model (3) may become more complicated. Here we only consider the case when $\sigma_i (i = 1, 2), T_f$ and $T_g$ (i.e., $1/\alpha$ and $1/\beta$) all increase. See the following Example.

**Example 4.** Let $\sigma_i (i = 1, 2), T_f$ and $T_g$ (i.e., $1/\alpha$ and $1/\beta$) increase from 0.1, 0.08, 1 and 0.2 (i.e., $\alpha = 1$ and $\beta = 5$) to 1, 0.8, 10 and 10 (i.e., $\alpha = 0.1$ and $\beta = 0.1$), respectively. It is found that the trajectories of model (3) fluctuate wildly and suffer more oscillations and need more time to approach the equilibrium $E^*$; please see Figure 4.

Notice also that conditions (44) in Theorem 8 are only sufficient conditions to insure the stochastic stability of $E^*$, which are dependent on parameters $\sigma_1, \sigma_2, T_f$, and $T_g$. Define

$$M_0 = \left( (p + qy^2)\sigma_1^2 + 2(p + qy^2)\mu D_1 ymbx^*T_f + (1 + q)(D + mbx^*)ymbx^*T_g \right) \times (2p(D + mbx^*) + 2qy^2D)^{-1},$$

$$M_1 = \frac{\sigma_2^2 + (D + mbx^* + 2ma + 2\mu D_1))ymbx^*T_g}{(2q/(1 + q))\gamma (ma - \mu D_1)}.$$

Thus, conditions (44) are equivalent to those when parameters $\sigma_1, \sigma_2, T_f$, and $T_g$ are seated in the following parameter set:

$$\Omega = \left\{ \left( \sigma_1, \sigma_2, T_f, T_g \right) \mid \max \{M_0, M_1\} < 1, \sigma_i \geq 0, T_f \geq 0, T_g \geq 0 \right\},$$

from which we can further perform some approximate sensitivity analysis of the stochastic stability of $E^*$ with respect to these parameters. To do this, we can let two of the parameters (e.g., $\sigma_1$ and $T_f$) vary and the other two ($\sigma_2$ and $T_g$) be fixed, which have six cases in all.

Let us first consider the case when $\sigma_2 = 0.08$ and $T_g = 0.2$; then $M_0$ and $M_1$ are both functions of $\sigma_1$ and $T_f$. Then $\Omega$ defined in (92) is equivalent to

$$\Omega_{\sigma_2,T_g} = \left\{ \left( \sigma_1, T_f \right) \mid \left( \sigma_1, 0.08, T_f, 0.2 \right) \in \Omega \right\},$$

which is the projection of surfaces $M_0 = M_0(\sigma_1, T_f)$ and $M_1 = M_1(\sigma_1, T_f)$ in the first octant such that $\max\{M_0, M_1\} < 1$ (see Figure 3). The positive equilibrium $E^*$ is stochastically stable provided that $(\sigma_1, T_f) \in \Omega_{\sigma_2,T_g}$.

To better observe the dependence of the stochastic stability of $E^*$ on all parameters, we further consider another two cases when $\sigma_1 = 0.1$ and $T_f = 0.2$ are fixed and $\sigma_2 = 0.1$ and $\sigma_2 = 0.08$ are fixed. Accordingly, $\Omega$ defined in (92) is equivalent, respectively, to

$$\Omega_{\sigma_1,T_f} = \left\{ \left( \sigma_2, T_f \right) \mid \left( 0.1, \sigma_2, T_f, 0.2 \right) \in \Omega \right\},$$

$$\Omega_{T_f,T_g} = \left\{ \left( T_f, T_g \right) \mid \left( 0.1, 0.08, T_f, T_g \right) \in \Omega \right\},$$

which are plotted, respectively, in Figures 6 and 7 (other three cases can be considered similarly). From Figures 5–7, we find that the stochastic stability of $E^*$ is greatly affected by $\sigma_1, \sigma_2$, and $T_g$ and less affected by $T_f$ (which is consistent with the results observed in [13, 17]). We would like to point out here that $E^*$ may also be stable when the parameters are seated outside of the set $\Omega$, since (44) are only sufficient conditions ensuring the stochastic stability of $E^*$.

In conclusion, this paper presents an investigation on the combined effect of the noises and delays on a bottom–microbe model. Our findings are useful for better understanding of the dynamics of microbial population in the activated sludge process. We should point out that there are still some other interesting topics about the wastewater treatment deserving further investigation, for example, membrane reactor, and so forth. We leave these for future considerations.

**Conflicts of Interests**

The authors declare that there is no conflict of interests regarding the publication of this paper.

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