Mathematical Analysis of Noise Induced Social Networking Game Addiction Disease Model

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Abstract

In many countries around the world, the issue of teen addiction to internet gaming is getting worse. The fact that many of them lack parental education, which is a significant issue that must not be disregarded, contributes to their addiction to online games. Environmental noise is unavoidable in the spread of social networking game addiction. A new dynamic model of teens' social networking game addiction is created in order to investigate the impact of noise on the growth of game addiction. First, we analyse the model qualitatively and dynamically. We investigate the presence and stability of equilibria, the non-negativity and boundedness of solutions, and the fundamental reproduction number. Additionally, we used the Fourier Transform to test the impact of white noise on the suggested online addictive game. For a suitable set of qualities with randomised intensities, numerical simulations are compiled.

Keywords: Social networking game addiction, stability, equilibrium, white noise, Fourier transform.

1. Introduction

Online games have emerged as a new form of amusement with the advancement of the times and science and technology. While playing online games might be happy, more and more people are becoming addicted to them, especially teens. The China Internet Network Information Center released its 46th statistical report on the growth of the Chinese Internet on September 29, 2020 [1] in Beijing. By June 2020, there will be 540 million active online game players. Teenagers are in a crucial stage of growth and development, and their capacity for discrimination is insufficient. They might stray from their values as a result of some unfavourable facts in the game, and it might even inspire them to commit crimes like stealing and assault. Playing video games excessively also depletes energy, puts off studying, and causes physical and mental weakness [2]. Online game addiction has been proven to be "internet opium" and "electronic heroin" by American researchers who used medical techniques to discover that internet addicts' brain waves perfectly match those of substance addicts. Online gaming is a teen obsession that is on par with drug use [3].

It has been discovered that the primary cause of teenagers' addiction to internet games is a lack of parental education. Teenagers' excessive reliance on online games can be caused by parents' rudeness, lack of concern, adoration, excessive care, and failure to care for their kids. Additionally, children who are left behind and single-parent households are more prone to play online games [4]. As a result, family education is crucial to the development of teenagers. Online games also have a high contagious quality since they sometimes require teams of players to compete and offer lucrative rewards for bringing in new players [5]. In recent years, it has become increasingly necessary to analyse disease control procedures by simulating infectious diseases using mathematical models [6–9]. Numerous researchers used infectious illness research techniques to study a variety of other infectious issues, including gossip, game addiction, drinking, smoking, and drinking [10–23]. In order to evaluate the dynamics of smoking and its effects on community public health, Sharomi [10] developed a comprehensive mathematical research. A new alcoholism model on networks, presented by Huo et al. [11], classified alcoholism into mild and severe forms. The authors investigated the fundamental reproduction number, the presence and stability of equilibria, and other dynamical aspects of the unweighted network model. In order to reduce the impact of rumour, Zhao et al. [12] proposed an isolation-conversion technique and discussed a new rumor-truth mixed dissemination model. Li and Guo [13] looked at a model of online game addiction that included both positive and negative media coverage. The scientists took into account for the first time that the media can have both positive and negative effects on the spread of games, which is a significant distinction from the transmission of contagious diseases. Based on the reality of teens' addiction in Thailand, Viriyapong et al.[14] developed a deterministic model of online game addiction and investigated its dynamic features. The results of the numerical simulation lead to the conclusion that family education is effective in lowering the reproduction number, which is crucial in lowering the number of Thai children and teenagers who are addicted to online games.

Real-world factors like alterations in nutrition levels, temperature, or interactions between forces, among others, can cause random variations in the human cells and chemical compounds involved. Not all behaviours are the same, even when taking into account one social networking game addiction and one game quitter of a specific individual. The system's equilibrium is impacted by these variances, which cause changes in the game addiction populations. Using stochastic differential equations is one method for incorporating and researching these variances and uncertainties into a mathematical model [15, 16, and 17]. A deterministic differential equation model may be converted into a stochastic differential equation model using a variety of methods. One method is to multiply each differential equation by a constant-magnitude white noise term, while another method multiplies each differential equation by a white noise term whose intensity is relative to the dimension of the population whose rate of growth is being mimicked [18]. These methods of introducing noise, nevertheless, raise concerns since they might not be biologically sound. The parameter perturbation methodology, which is closely connected to such techniques, is developed by taking into consideration the ambient variations that have an impact on the dynamics of the investigated phenomena. This approach, which is more realistic than the alternatives, incorporates ecological randomness by perturbing variables in the deterministic equations with a white noise component [16, 19, 20, and 21]. The Allen's method [24,25], which determines the asset of the random noise duration of the SDE by contrast with a discrete stochastic equation obtained by taking into account random impacts in the physical sensation, and another one that uses the Random Variable Revolution method on model parameters as an alternative are other methods that are biologically consistent.

The following describes the organisational structure of this rest work. Section 2 displays the formulation of noise induced social networking game addiction model and its fundamental attributes. Section 3 contains the existence and the basic reproduction number. Section 4 discusses the stability study of the addiction-free equilibrium and. Section 5 presents the impact of noise on social networking game addictions. Section 6 provides numerical simulation with a thorough discussion. In section 7, the findings are described together with any recommendations.

2. Social networking game addiction model with noise

In this section, we built noise model for social networking games that has four compartments: those who play for less than five hours per day, those who play for more than five hours per day but don't have a job, those who play for more than five hours per day but do have a job, and those who quit playing altogether.

$$\left.\begin{aligned}
S^1(t) &= \Delta - \alpha SI - \mu S + \eta_1\psi_1(t)\\
I^1(t) &= \alpha SI - \sigma\alpha SI - (V_1 + V_2 + \mu)I + \eta_2\psi_2(t)\\
P^1(t) &= \sigma\alpha SI + V_1 I - (\delta + \mu)P + \eta_3\psi_3(t)\\
Q^1(t) &= V_2 I + \delta P - \mu Q + \eta_4\psi_4(t)
\end{aligned}\right\} \tag{1}$$

Table1: Physical description of the parameters in social networking game addiction disease model

Parameter	Description of the parameters	Values
$S(t)$	Less than 5 hours a day are spent playing games.	580
$I(t)$	who play video games for longer than five hours each day and who are unemployed	98
$P(t)$	Gaming time is greater than five hours per day for those with legitimate jobs.	40
$Q(t)$	The players that stopped participating in games	71
Δ	Natural birth rate	0.05
α	The contact transmission rate	0.2
σ	The likelihood of someone entering the workforce without delay and becoming a professional	0.2
V_1	The likelihood that Infected warehouse residents work as professionals as a result of their game-related activities	0.05
V_2	The likelihood that people in the Infected warehouse play video games for a living, becoming professionals as a result	0.2
δ	The percentage of employees who withdraw permanently as a	0.5

	result of evolving physical conditions or environmental changes	
μ	Natural death rate	0.05
$\eta_i; i=1,2,3,4$	Intensities of each individual population	Variable
$\psi_i; i=1,2,3,4$	Gaussian white Noise of each individual population	Variable

3. Basic reproduction number and steady states of the social networking game addiction

The system (1) has social networking game addiction free equilibrium point (G_0). The next generation matrix approach will be used to determine the fundamental reproduction number of system (1) in the sections that follow. System (1)'s fundamental reproduction number is provided by

$$R_0 = \frac{(1-\sigma)\alpha}{(\mu+V_1+V_2)}$$

There are two stable equilibrium points in the system (1). The requirements for their stability and existence are as follows.

(i) Social networking game addiction free equilibrium point $(G_0) = (1,0,0,0)$

(ii) Social networking game addiction equilibrium point $(G^*) = (S^*, I^*, P^*, Q^*)$

Where

$$S^* = \frac{1}{R_0}; I^* = \frac{\mu}{\alpha}(R_0 - 1); P^* = \frac{[\sigma(V_2+\mu)+V_1]I^*}{(\delta+\mu)(1-\sigma)}; Q^* = \left[V_2 + \frac{\sigma(V_2+\mu)+V_1}{(\delta+\mu)(1-\sigma)}\right]I^*$$

4. Stability analysis of social networking game addiction disease

In the section (4), we study the stability of the system (1) at Social networking game addiction free equilibrium point and Social networking game addiction equilibrium point.

Theorem 1: The system (1) is locally asymptotically stable at social networking game addiction free equilibrium point (G_0) if $\mu+V_1+V_2 > (1-\sigma)\alpha$ $(R_0 < 1)$

Proof: The characteristic equation of the system (1) at social networking game addiction free equilibrium point (G_0)

$$(\lambda+\mu)(\lambda+\delta+\mu)(\lambda+\mu)\left(\lambda+(V_1+V_2+\mu)-(1-\sigma)\alpha\right)=0 \quad (2)$$

$$\lambda_1 = -\mu; \lambda_2 = -(\delta+\mu); \lambda_3 = -\mu; \lambda_4 = (V_1+V_2+\mu)(R_0-1);$$

If $\mu + V_1 + V_2 > (1-\sigma)\alpha\ (R_0 < 1)$ then all the Eigen values of the system (1) are negative at social networking game addiction free equilibrium point (G_0). By the Routh Hurwitz criteria, the system (1) is locally asymptotically stable at G_0. Hence the proof is completed.

Theorem 2: The system (1) is locally asymptotically stable at social networking game addiction equilibrium point (G^*) if $D_i > 0$ where i-1, 2, 3, 4.

Proof: The characteristic equation of the system (1) at social networking game addiction equilibrium point (G^*) is

$$\lambda^4 + \mathrm{M}_1\lambda^3 + \mathrm{M}_2\lambda^2 + \mathrm{M}_3\lambda + \mathrm{M}_4 = 0 \qquad (3)$$

where $\mathrm{M}_1 = 2\mu + \delta + V_1 + V_2 + \mu - (1-\sigma)\alpha S^* + \mu + \alpha I^*$;

$$\mathrm{M}_2 = \mu(\mu+\delta) + (2\mu+\delta)(\mu+\alpha I^*) + \left((V_1+V_2+\mu) - (1-\sigma)\alpha S^*\right)\left(2\mu+\delta+\mu+\alpha I^*\right) + \alpha^2 S^* I^* (1-\sigma);$$

$$\mathrm{M}_3 = \mu(\mu+\delta)\left((V_1+V_2+\mu) - (1-\sigma)\alpha S^* + \mu + \alpha I^*\right) + (2\mu+\delta)(\mu+\alpha I^*)\left((V_1+V_2+\mu) - (1-\sigma)\alpha S^*\right) + \alpha^2 S^* I^* (1-\sigma)(2\mu+\delta);$$

$$\mathrm{M}_4 = \mu(\mu+\delta)(\mu+\alpha I^*)\left((V_1+V_2+\mu) - (1-\sigma)\alpha S^*\right) + \alpha^2 S^* I^* (1-\sigma)(2\mu+\delta).$$

According to Routh- Hurwitz criterion, if the conditions (4-7) holds the the system (1) is asymptotically stable at social networking game addiction equilibrium point (G_1)

$$D_1 = \mathrm{M}_1 > 0 \qquad (4)$$

$$D_2 = \begin{vmatrix} \mathrm{M}_1 & 1 \\ \mathrm{M}_3 & \mathrm{M}_2 \end{vmatrix} > 0$$

$$D_3 = \begin{vmatrix} \mathrm{M}_1 & 1 & 0 \\ \mathrm{M}_3 & \mathrm{M}_2 & \mathrm{M}_1 \\ 0 & \mathrm{M}_4 & \mathrm{M}_3 \end{vmatrix} > 0 \qquad (6)$$

$$D_4 = \begin{vmatrix} \mathrm{M}_1 & 1 & 0 & 0 \\ \mathrm{M}_3 & \mathrm{M}_2 & \mathrm{M}_1 & 1 \\ 0 & \mathrm{M}_4 & \mathrm{M}_3 & \mathrm{M}_2 \\ 0 & 0 & 0 & \mathrm{M}_4 \end{vmatrix} > 0 \qquad (7)$$

5. Analysis of noise on social networking game addiction disease

Noise may be brought on by random fluctuations in one or more model parameters around known mean values or by stochastic variations in population densities around fixed values. In this article, we analyse the effect of the environmental randomness in the social networking game addiction model (1) presented by the parameter perturbation technique. The stochastic social networking game addiction model is obtained by perturbing each individual of the population with a white noise. The population intensities of white noise-induced fluctuations and variations near the positive equilibrium are also identified.

Let us consider, $S(t)=u_1(t)+S^*$; $I(t)=u_2(t)+I^*$; $P(t)=u_3(t)+P^*$; $Q=u_4(t)+Q^*$; then the respective linear system of (1) will changes as

$$\begin{cases} u_1'(t)=-\alpha u_2(t)S^*+\eta_1\psi_1(t) \\ u_2'(t)=(\alpha-\sigma\alpha)u_1(t)I^*+\eta_2\psi_2(t) \\ u_3'(t)=\eta_3\psi_3(t) \\ u_4'(t)=\eta_4\psi_4(t) \end{cases} \tag{8}$$

When we apply the Fourier transform to (8), we obtain

$$M(\omega)\tilde{u}(\omega)=\tilde{\psi}(\omega) \tag{9}$$

where

$$M(\omega)=\begin{pmatrix} i\omega & \alpha S^* & 0 & 0 \\ (\sigma\alpha-\alpha)I^* & i\omega & 0 & 0 \\ 0 & 0 & i\omega & 0 \\ 0 & 0 & 0 & i\omega \end{pmatrix};\ \tilde{u}(\omega)=\begin{bmatrix} \tilde{u}_1(\omega) \\ \tilde{u}_2(\omega) \\ \tilde{u}_3(\omega) \\ \tilde{u}_4(\omega) \end{bmatrix};\ \tilde{\psi}(\omega)=\begin{bmatrix} \eta_1\tilde{\psi}_1(\omega) \\ \eta_2\tilde{\psi}_2(\omega) \\ \eta_3\tilde{\psi}_3(\omega) \\ \eta_4\tilde{\psi}_4(\omega) \end{bmatrix};$$

From (10), we have $\tilde{u}(\omega)=K(\omega)\tilde{\psi}(\omega)$ (10)

where $K(\omega)=\left[M(\omega)\right]^{-1}=\dfrac{Adj\,M(\omega)}{\left|M(\omega)\right|}$

Now we will give some preliminary information about population function $Y(t)$. If it has a zero mean value then the intensities/variances of its components in $[\omega,\omega+d\omega]$ will be $S_Y(\omega)d\omega$, where $S_Y(\omega)$ is the density of Y and is given by

$$S_Y(\omega)=\lim_{\tilde{T}\to\infty}\frac{\left|\tilde{Y}(\omega)\right|^2}{\tilde{T}} \tag{11}$$

and the inverse transform of $S_Y(\omega)$ is as follows

$$C_Y(\tau)=\frac{1}{2\pi}\int_{-\infty}^{\infty}S_Y(\omega)e^{i\omega\tau}d\omega \tag{12}$$

and its normalized function is $P_Y(\tau)=\dfrac{C_Y(\tau)}{C_Y(0)}$

The corresponding variance in $Y(t)$ is given by

$$\sigma_Y{}^2 = C_Y(0) = \frac{1}{2\pi}\int_{-\infty}^{\infty} S_Y(\omega) d\omega \tag{13}$$

It will be for a Gaussian white noise process if

$$S_{\xi_i\xi_j}(\omega) = \lim_{\hat{T}\to+\infty} \frac{E\left[\tilde{\xi}_i(\omega)\tilde{\xi}_j(\omega)\right]}{\hat{T}} = \lim_{\hat{T}\to+\infty} \frac{1}{\hat{T}} \int_{-\frac{\hat{T}}{2}}^{\frac{\hat{T}}{2}} \int_{-\frac{\hat{T}}{2}}^{\frac{\hat{T}}{2}} E\left[\tilde{\psi}_i(t)\tilde{\psi}_j(t')\right] e^{-i\omega(t-t')} dt\, dt' = \delta_{ij} \tag{14}$$

Now $\tilde{u}_i(\omega) = \sum_{j=1}^{4} K_{ij}(\omega)\tilde{\psi}_j(\omega); i = 1,2,3,4$ (15)

$$S_{u_i}(\omega) = \sum_{j=1}^{4} \eta_j \left|K_{ij}(\omega)\right|^2 \; ; \; i = 1,2,3,4 \tag{16}$$

As a result, the intensity of variations in the variable u_i; $i = 1,2,3,4$ is determined by

$$\sigma_{u_i}{}^2 = \frac{1}{2\pi}\sum_{j=1}^{3}\int_{-\infty}^{\infty} \eta_j \left|K_{ij}(\omega)\right|^2 d\omega; \; i = 1,2,3,4 \tag{17}$$

and by (13), we obtain.

$$\sigma_{u_1}{}^2 = \frac{1}{2\pi}\left\{\int_{-\infty}^{\infty}\eta_1\left|\frac{Adj(1)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_2\left|\frac{Adj(2)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_3\left|\frac{Adj(3)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_4\left|\frac{Adj(4)}{|M(\omega)|}\right|^2 d\omega\right\}$$

$$\sigma_{u_2}{}^2 = \frac{1}{2\pi}\left\{\int_{-\infty}^{\infty}\eta_1\left|\frac{Adj(5)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_2\left|\frac{Adj(6)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_3\left|\frac{Adj(7)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_4\left|\frac{Adj(8)}{|M(\omega)|}\right|^2 d\omega\right\}$$

$$\sigma_{u_3}{}^2 = \frac{1}{2\pi}\left\{\int_{-\infty}^{\infty}\eta_1\left|\frac{Adj(9)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_2\left|\frac{Adj(10)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_3\left|\frac{Adj(11)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_4\left|\frac{Adj(12)}{|M(\omega)|}\right|^2 d\omega\right\}$$

$$\sigma_{u_4}{}^2 = \frac{1}{2\pi}\left\{\int_{-\infty}^{\infty}\eta_1\left|\frac{Adj(13)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_2\left|\frac{Adj(14)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_3\left|\frac{Adj(15)}{|M(\omega)|}\right|^2 d\omega + \int_{-\infty}^{\infty}\eta_4\left|\frac{Adj(16)}{|M(\omega)|}\right|^2 d\omega\right\}$$

where $|M(\omega)| = |R(\omega)| + i|I(\omega)|$

Now, real part of $|M(\omega)| = R(\omega) = \omega^4 + \omega^2\left[\alpha^2(\sigma-1)S^*I^*\right]$

and imaginary part of $|M(\omega)| = I(\omega) = 0$

So, $\left|Adj(i)\right|^2 = X_i^{\,2} + Y_i^2, i = 1, 2, \ldots 16$

Where

$$X_1 = 0;\ Y_1 = -\omega^3;\ X_2 = -\omega^2\alpha S^*;\ Y_2 = 0;\ X_3 = 0;\ Y_3 = 0;\ X_4 = 0;\ Y_4 = 0;\ X_5 = \omega^2\alpha I^*(\sigma - 1);$$
$$Y_5 = 0;\ X_6 = 0;\ Y_6 = -\omega^3;\ X_7 = 0;\ Y_7 = 0;\ X_8 = 0;\ Y_8 = 0;\ X_9 = 0;\ Y_9 = 0;\ X_{10} = 0;\ Y_{10} = 0;$$
$$X_{11} = 0;\ Y_{11} = -\left(\omega^3 + \alpha\omega(\sigma - 1)S^* I^*\right);\ X_{12} = 0;\ Y_{12} = 0;\ X_{13} = 0;\ Y_{13} = 0;\ X_{14} = 0;\ Y_{14} = 0;$$
$$X_{15} = 0;\ Y_{15} = 0;\ X_{16} = 0;\ Y_{16} = -\left(\omega^3 + \alpha\omega(\sigma - 1)S^* I^*\right).$$

The population variances are so provided by

$$\sigma_{u_1}{}^2 = \frac{1}{2\pi}\left\{\int_{-\infty}^{\infty} \frac{1}{R^2(\omega) + I^2(\omega)}\left[\eta_1\left(X_1{}^2 + Y_1^2\right) + \eta_2\left(X_2{}^2 + Y_2{}^2\right) + \eta_3\left(X_3{}^2 + Y_3^2\right) + \eta_4\left(X_4{}^2 + Y_4{}^2\right)\right]d\omega\right\}$$

$$\sigma_{u_2}{}^2 = \frac{1}{2\pi}\left\{\int_{-\infty}^{\infty} \frac{1}{R^2(\omega) + I^2(\omega)}\left[\eta_1\left(X_5{}^2 + Y_5^2\right) + \eta_2\left(X_6{}^2 + Y_6^2\right) + \eta_3\left(X_7{}^2 + Y_7^2\right) + \eta_4\left(X_8{}^2 + Y_8^2\right)\right]d\omega\right\}$$

$$\sigma_{u_3}{}^2 = \frac{1}{2\pi}\left\{\int_{-\infty}^{\infty} \frac{1}{R^2(\omega) + I^2(\omega)}\left[\eta_1\left(X_9{}^2 + Y_9{}^2\right) + \eta_2\left(X_{10}{}^2 + Y_{10}{}^2\right) + \eta_3\left(X_{11}{}^2 + Y_{11}{}^2\right) + \eta_4\left(X_{12}{}^2 + Y_{12}{}^2\right)\right]d\omega\right\}$$

$$\sigma_{u_4}{}^2 = \frac{1}{2\pi}\left\{\int_{-\infty}^{\infty} \frac{1}{R^2(\omega) + I^2(\omega)}\left[\eta_1\left(X_{13}{}^2 + Y_{13}{}^2\right) + \eta_2\left(X_{14}{}^2 + Y_{14}{}^2\right) + \eta_3\left(X_{15}{}^2 + Y_{15}{}^2\right) + \eta_4\left(X_{16}{}^2 + Y_{16}{}^2\right)\right]d\omega\right\}$$

If the system's dynamics are now of interest (8) with either $\eta_1 = 0$ or $\eta_2 = 0,$ or $\eta_3 = 0$, or $\eta_4 = 0$ then the population variances are given by

For $\eta_1 = \eta_2 = \eta_3 = 0$ and then $\sigma_{u_1}{}^2 = \sigma_{u_2}{}^2 = \sigma_{u_3}{}^2 = 0$;

$$\sigma_{u_4}{}^2 = \frac{\eta_4}{2\pi}\int_{-\infty}^{\infty} \frac{(\omega^3 + \alpha\omega(\sigma - 1)S^* I^*)^2}{R^2(\omega) + I^2(\omega)}d\omega\ ;$$

For $\eta_1 = \eta_2 = \eta_4 = 0$ and then $\sigma_{u_1}{}^2 = \sigma_{u_2}{}^2 = \sigma_{u_4}{}^2 = 0$

$$\sigma_{u_3}{}^2 = \frac{\eta_3}{2\pi}\int_{-\infty}^{\infty} \frac{(\omega^3 + \alpha\omega(\sigma - 1)S^* I^*)^2}{R^2(\omega) + I^2(\omega)}d\omega;$$

For $\eta_2 = \eta_3 = \eta_4 = 0$ and then $\sigma_{u_3}{}^2 = \sigma_{u_4}{}^2 = 0$

$$\sigma_{u_1}{}^2 = \frac{\eta_1}{2\pi}\int_{-\infty}^{\infty} \frac{\omega^6}{R^2(\omega) + I^2(\omega)}d\omega;$$

$$\sigma_{u_2}{}^2 = \frac{\eta_1}{2\pi}\int_{-\infty}^{\infty}\frac{(\omega^2\alpha I^*(\sigma-1))^2}{R^2(\omega)+I^2(\omega)}d\omega$$

For $\eta_1 = \eta_3 = \eta_4 = 0$ and then $\sigma_{u_1}{}^2 = \sigma_{u_3}{}^2 = \sigma_{u_4}{}^2 = 0$

$$\sigma_{u_2}{}^2 = \frac{\eta_2}{2\pi}\int_{-\infty}^{\infty}\frac{\omega^6}{R^2(\omega)+I^2(\omega)}d\omega;$$

Although it is extremely challenging to determine the population variances analytically, they can be evaluated numerically for a variety of suggested parameter values.

6. Numerical simulations

In the section (6), we use Runge Kutta fourth order method in Mat lab to solve the system (18) and simulate the stochastic differential equations of our social networking game addiction disease model

$$\left.\begin{aligned}
S^1(t) &= 0.05 - 0.2SI - 0.05S + \eta_1\psi_1(t)\\
I^1(t) &= 0.2SI - 0.2\alpha SI - (0.05+0.2+0.05)I + \eta_2\psi_2(t)\\
P^1(t) &= 0.2\alpha SI + 0.05I - (0.5+0.05)P + \eta_3\psi_3(t)\\
Q^1(t) &= 0.2I + 0.5P - 0.05Q + \eta_4\psi_4(t)
\end{aligned}\right\}$$

(18)

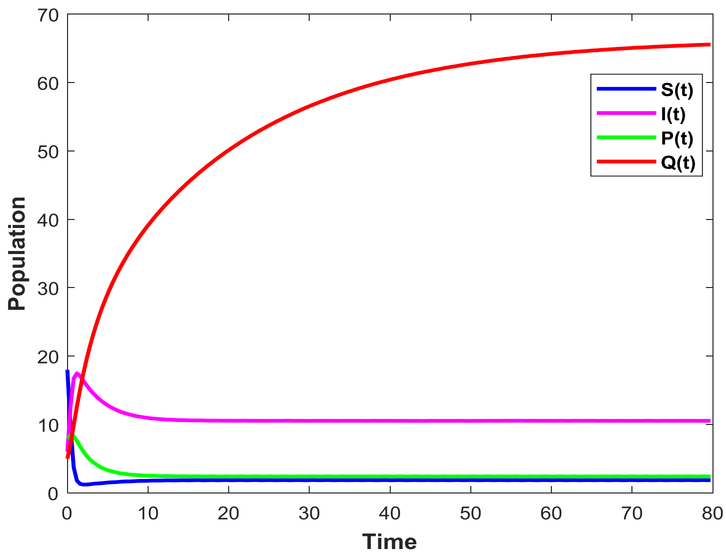

Fig 1

Time series evaluation of S-I-P-Q with noise intensities 0.05, 0.04, 0.05, 0.04

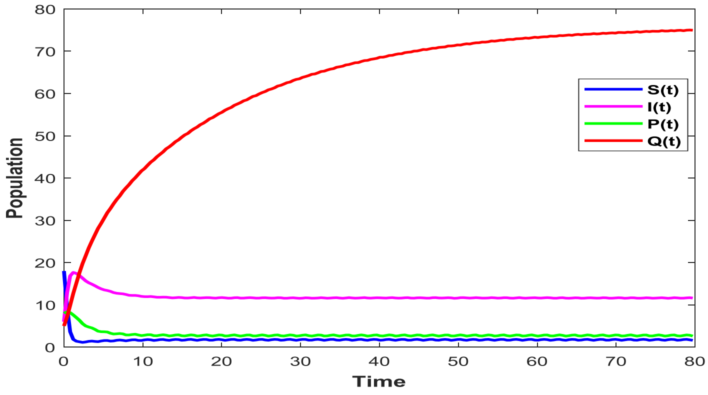

Fig 2

Time series evaluation of S-I-P-Q with noise intensities 0.5, 0.4, 0.5, 0.4

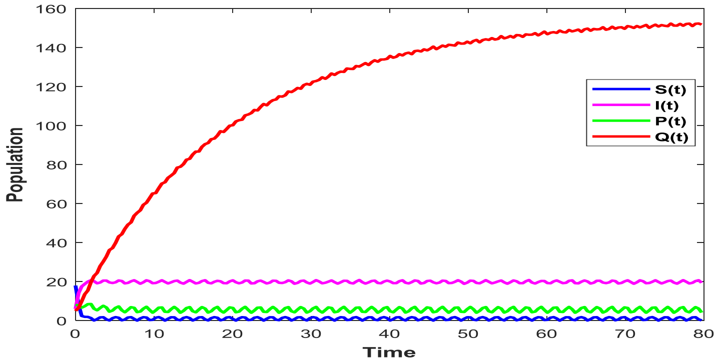

Fig 3

Time series evaluation of S-I-P-Q with noise intensities 5, 4, 5, 4

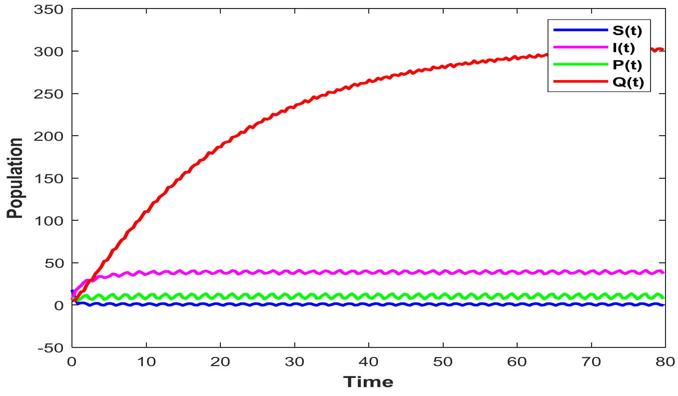

Fig 4

Time series evaluation of S-I-P-Q with noise intensities 10, 10, 10, 10

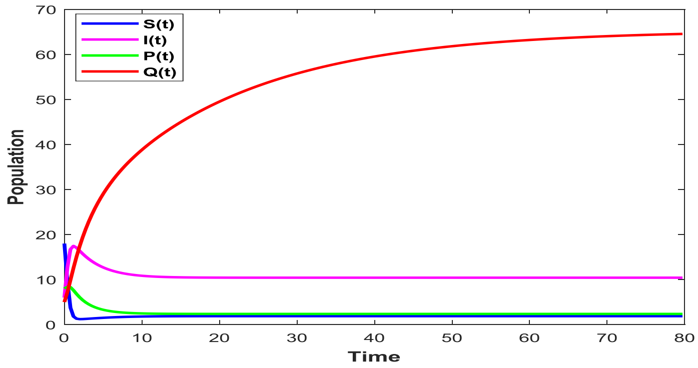

Fig 5

Comparison between S-I-P-Q populations with Table 1 parameter values

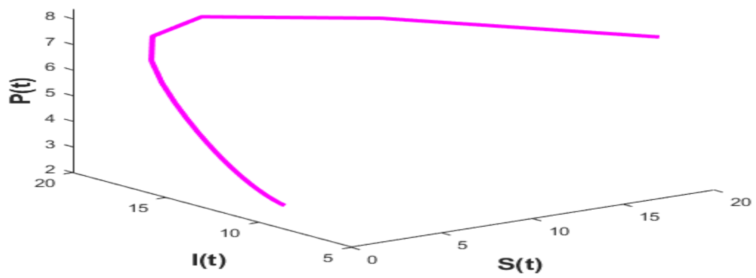

Fig 6

Phase portrait of S-I-P population with Table 1 parameter values

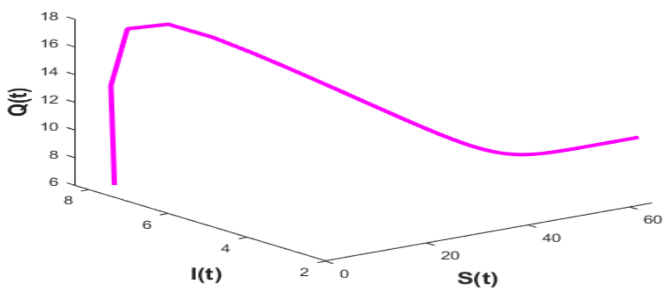

Fig 7

Phase portrait of S-I-Q population with Table 1 parameter values

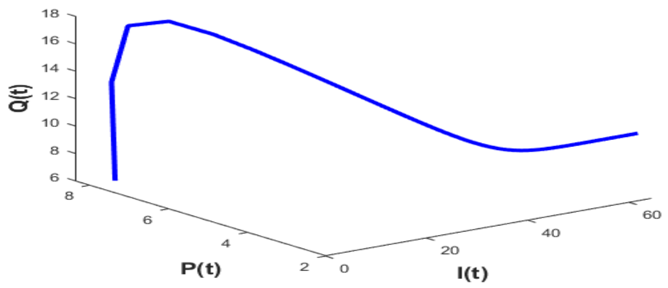

Fig 8

Phase portrait of I-P-Q population with Table 1 parameter values

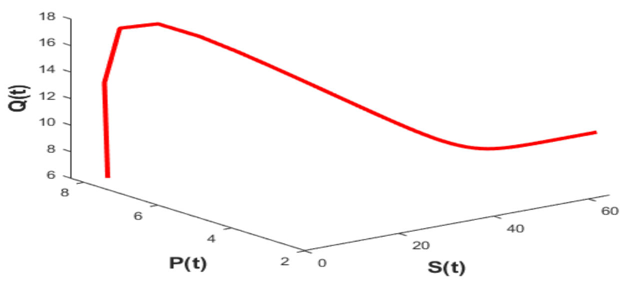

Fig 9

Phase portrait of S-P-Q population with Table 1 parameter values

Numerical observations on graphical simulations

Figures 1-4 represents the stochastic modelled simulations at various noise intensities.

Figure 1 shows the impact of noise on population classes S(t), I(t), P(t) and Q(t) with intensities 0.05, 0.04, 0.05, and 0.04. Figure says that population classes doesn't much oscillate or fluctuate under the influence of noise. At these intensity values, noise impact on proposed system is almost ignorable.

Figure 2 shows the impact of noise on population classes S(t), I(t), P(t) and Q(t) with intensities 0.5, 0.4, 0.5, and 0.4. Figure says that population classes are less oscillate and undergo less impact of noise. At these intensity values, noise impact on population classes is little remarkable.

Figure 3 shows the impact of noise on population classes S(t), I(t), P(t) and Q(t) with intensities 5, 4, 5, and 4. Figure says that population classes are little oscillate and undergo notable/remarkable impact of noise. At these intensity values, noise impact on population classes is very remarkable and notable.

Figure 4 shows the impact of noise on population classes S(t), I(t), P(t) and Q(t) with intensities 10, 10, 10, and 10. Figure says that population classes are little oscillate and undergo remarkable impact of noise. At these intensity values, noise impact on population classes is highly remarkable and notable.

Figure 5 shows the time series evaluation of population classes S(t), I(t), P(t) and Q(t) for the values of all attributes from example-1

Figure 6 shows the phase portrait projection among the population classes S(t), I(t) and P(t) with highly remarkable projection.

Figure 7 shows the phase portrait projection among the population classes S(t), I(t) and Q(t) with notable projection.

Figure 8 shows the phase portrait projection among the population classes I(t), P(t) and Q(t) with notable projection.

Figure 9 shows the phase portrait projection among the population classes S(t), P(t) and Q(t) with notable projection.

8. Conclusions

In this article, we analyzed a stochastic model to explain the behaviour of the people addicted to social networking games. This model included behaviour changes in gaming addicts as a result of environmental randomization as one of its main objectives. To comprehend how the random noise affects our model, we conducted analytical and numerical analyses of it. Since it is highly challenging to get biological experimental data in practise, we infer from the study of the stochastic social networking game addiction model that the solution to (1) can be a source of investigational data for social networking game adductor dynamics. The interpretation analysis of sample routes of the suggested stochastic social networking game addiction model will be the logical next step.

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