

## Research Article

# Modelling of Rabies Transmission Dynamics Using Optimal Control Analysis

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We examine an optimal way of eradicating rabies transmission from dogs into the human population, using preexposure prophylaxis (vaccination) and postexposure prophylaxis (treatment) due to public education. We obtain the disease-free equilibrium, the endemic equilibrium, the stability, and the sensitivity analysis of the optimal control model. Using the Latin hypercube sampling (LHS), the forward-backward sweep scheme and the fourth-order Runge-Kutta numerical method predict that the global alliance for rabies control's aim of working to eliminate deaths from canine rabies by 2030 is attainable through mass vaccination of susceptible dogs and continuous use of pre- and postexposure prophylaxis in humans.

## 1. Introduction

Rabies is an infection that mostly affects the brain of an infected animal or individual, caused by viruses belonging to the genus *Lyssavirus* of the family Rhabdoviridae and order Mononegavirales [1, 2]. This disease has become a global threat and it is also estimated that rabies occurs in more than 150 countries and territories [2]. Raccoons, skunks, bats, and foxes are the main animals that transmit the virus in the United States [2]. In Asia, Africa, and Latin America, it is known that dogs are the main source of transmission of the rabies virus into the human population [2]. When the rabies virus enters the human body or that of an animal, the infection (virus) moves rapidly along the neural pathways to the central nervous system; from there the virus continues to spread to other organs and causes injury by interrupting various nerves [2]. The symptoms of rabies are quite similar to those of encephalitis (see [3]). Due to movement of dogs in homes or the surroundings, the risk of not being infected by a rabid dog can never be guaranteed. Rabies is a major health problem in many populations dense with dogs, especially in areas where there are less or no preventive measures

(vaccination and treatment) for dogs and humans. Treatment after exposure to the rabies virus is known as postexposure prophylaxis (PEP) and vaccination before exposure to the infection is known as preexposure prophylaxis.

The study of optimal control analysis in maximizing or minimizing a said target was introduced by Pontryagin and his collaborators around 1950. They developed the key idea of introducing the adjoint function to a differential equation, by forming an objective functional [4], and since then there has been a considerable study of infectious disease using optimal control analysis (see [4–12]).

Research published by Aubert [13], on the advancement of the expense of wildlife rabies in France, incorporated various variables. They follow immunization of domestic animals, the reinforcement of epidemiological reconnaissance system and the bolster given to indicative research laboratories, the costs connected with outbreaks of rabies, the clinical perception of those mammals which had bitten humans, the preventive immunization, and postexposure treatment of people. A significant percentage (72%) of the cost was the preventive immunization of local animals. In France, as in other European nations in which the red fox (*Vulpes*) is the

species most affected, two primary procedures for controlling rabies were assessed in [13] at the repository level to be specific: fox termination and the oral immunization of foxes. The consolidated costs and advantages of both systems were looked at and included either the expenses of fox separation or the cost of oral immunization. The total yearly costs of both techniques stayed practically identical until the fourth year, after which the oral immunization methodology turned out to be more cost effective. This estimate was made in 1988 and readjusted in 1993 and affirmed by ex-postinvestigation five years later. Accordingly, it was presumed that fox termination brought about a transient diminishment in the event of the infection while oral immunization turned out to be equipped for wiping out rabies even in circumstances in which fox population was growing. Anderson and May [14] formulated a mathematical model based on each time step dynamic which was calculated independently in every cell. Later, Bohrer et al. [15] published a paper on the viability of different rabies spatial immunization designs in a simulated host population.

The research presented by Bohrer [15] stated that, in desert environments, where host population size varies over time, nonuniform spreading of oral rabies vaccination may, under certain circumstances, be more effective than the commonly used uniform spread. The viability of a nonarbitrary spread of the immunization depends, to some extent, on the dispersal behavior of the carriers. The outcomes likewise exhibit that, in a warm domain in a few high-density regions encompassed by populations with densities below the critical threshold for the spread of the disease, the rabies infection can persist.

Levin et al. [16] also presented a model for the immune responses to rabies virus in bats. Coyne et al. [17] proposed an SEIR model, which was also used in a study predicting the local dynamics of rabies among raccoons in the United States. Childs et al. [18] also researched rabies epidemics in raccoons with a seasonal birth pulse, using optimal control of an SEIRS model which describes the population dynamics. Hampson et al. [19] also noted that rabies epidemic cycles have a period of 3–6 years in dog populations in Africa, so they built a susceptible, exposed, infectious, and vaccinate model with an intervention response variable, which showed significant synchrony.

Carroll et al. [20] also used compartmental models to describe rabies epidemiology in dog populations and explored three control methods: vaccination, vaccination pulse fertility control, and culling. An ordinary differential equation model was used to characterize the transmission dynamics of rabies between humans and dogs by [21, 22]. The work by Zinsstag et al. [23] further extended the existing models on rabies transmission between dogs to include dog-to-human transmission and concluded that human postexposure prophylaxis (PEP) with a dog vaccination campaign was the more cost effective in controlling the disease in the long run. Furthermore, Ding et al. [24] formulated an epidemic model for rabies in raccoons with discrete time and spatial features. Their goal was to analyze the strategies for optimal distribution of vaccine baits to minimize the spread of the disease and the cost of carrying out the control.

Smith and Cheeseman [25] show that culling could be more effective than vaccination, given the same efficacy of control, but Tchuente and Bauch suggest that culling could be counterproductive, for some parameter values (see [26]).

The work in [27, 28] also presented a mathematical model of rabies transmission in dogs and from the dog population to the human population in China. Their study did not consider the use optimal control analysis to the study of the rabies virus in dogs and from the dog population to the human population. Furthermore, the insightful work of Wiraningsih et al. [29] studied the stability analysis of a rabies model with vaccination effect and culling in dogs, where they introduced postexposure prophylaxis to a rabies transmission model, but the paper did not consider the noneffectiveness of the pre- and postprophylaxis on the susceptible humans and exposed humans and that of the dog population and the use of optimal control analysis. Therefore, motivated by the research predictions of the global alliance of rabies control [30] and the work mention above, we seek to adjust the model presented in [27–29], by formulating an optimal control model, so as to ascertain an optimal way of controlling rabies transmission in dogs and from the dog population to the human population taking into account the noneffectiveness (failure) of vaccination and treatment.

The paper is petition as follows. Section 2 contains the model formulation, mathematical assumptions, the mathematical flowchart, and the model equations. Section 3 contains the model analysis, invariant region, equilibrium points, basic reproduction number  $\mathcal{R}_0$ , and the stability analysis of the equilibria. In Section 4 we present the parameter values leading to numerical values of the basic reproduction number  $\mathcal{R}_0$ , the herd immunity threshold and sensitivity analysis using Latin hypercube sampling (LHS), and some numerical plots. Section 5 contains the objective functional and the optimality system of the model. Finally, Sections 6 and 7 contain discussion and conclusion, respectively.

## 2. Model Formulation

We present two subpopulation transmission models of rabies virus in dogs and that of the human population (see Figure 1), based on the work presented in [27–29]. The dog population has a total of four compartments. The compartments represent the susceptible dogs,  $S_D(t)$ , exposed dogs,  $E_D(t)$ , infected dogs,  $I_D(t)$ , and partially immune dogs,  $R_D(t)$ . Thus, the total dog population is  $N_D(t) = S_D(t) + E_D(t) + I_D(t) + R_D(t)$ . The human population also has four compartments representing susceptible humans,  $S_H(t)$ , exposed humans,  $E_H(t)$ , infected humans,  $I_H(t)$ , and partially immune humans,  $R_H(t)$ . Thus, the total human population is  $N_H(t) = S_H(t) + E_H(t) + I_H(t) + R_H(t)$ . It is assumed that there is no human to human transmission of the rabies virus in the human submodel (see [29]). In the dog submodel, it is assumed that there is a direct transmission of the rabies virus from one dog to the other and from the infected dog compartment to the susceptible human population. It is further assumed that the susceptible dog population,  $S_D(t)$ , is increased by recruitment at a rate  $A_D$  and  $B_H$  is the birth or immigration rate into the susceptible human population,  $S_H(t)$ . It is assumed that the transmission

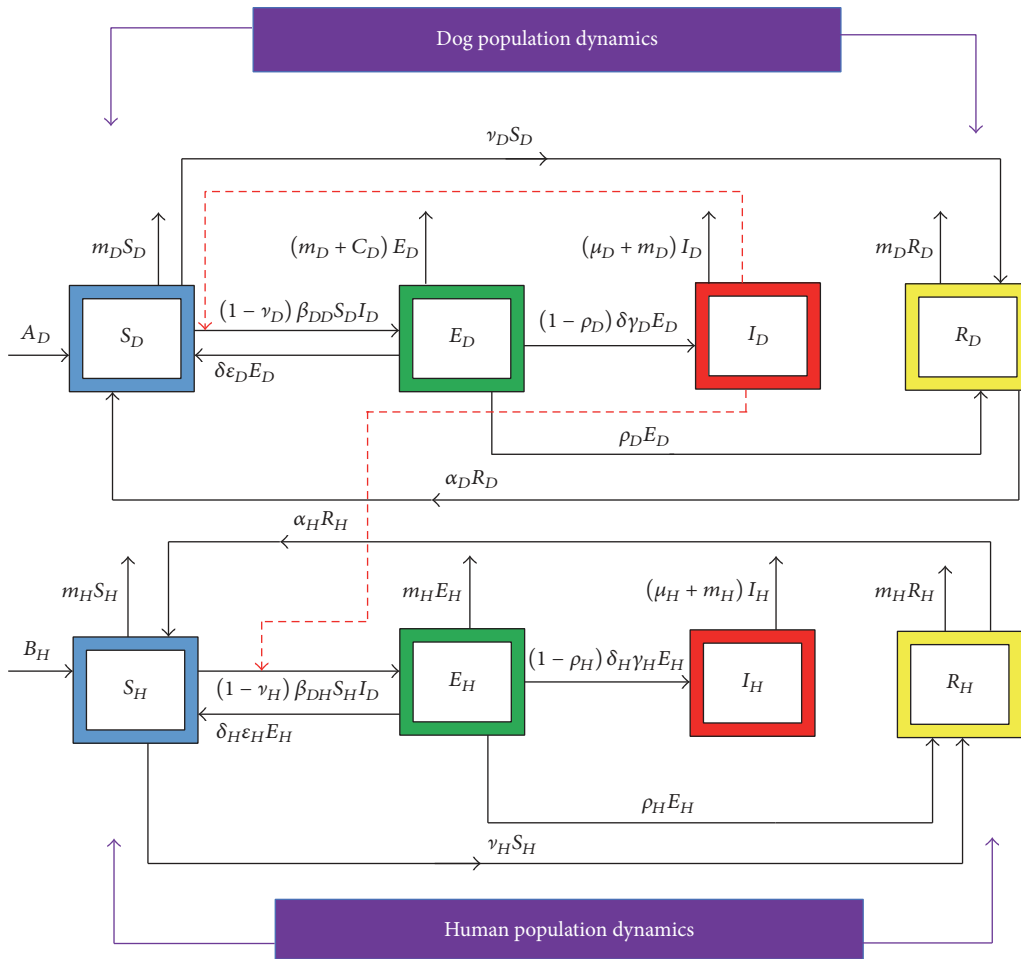


FIGURE 1: Optimal control model of rabies transmission dynamics.

and contact rate of the rabid dog into the dog compartment is  $\beta_{DD}$ . Suppose that  $v_D$  represents the control strategy due to public education and vaccination in the dogs compartment; then the transmission dynamics become  $(1 - v_D)\beta_{DD}S_D I_D$ , where  $(1 - v_D)$  is the noneffectiveness (failure) of the vaccine. It is also assumed that the contact rate of infectious dogs to the human population is  $\beta_{DH}$ . Similarly, administrating vaccination to the susceptible humans the progression rate of the susceptible humans to the exposed stage becomes  $(1 - v_H)\beta_{DH}S_H I_D$ , where  $v_H$  is the preexposure prophylaxis (vaccination),  $(1 - v_H)$  represents the failure of the preexposure prophylaxis in the human compartment. Furthermore, administrating postexposure prophylaxis (treatment) to affected humans, at the exposed class to the infectious class as  $(1 - \rho_H)\delta_H\gamma_H E_H$ , where  $(1 - \rho_H)$  is the failure rate of the postexposure prophylaxis and  $\delta_H\gamma_H$  represents the rate at which exposed humans progress to the infected compartment [27]. The rate of losing immunity in both compartments is represented by  $\alpha_D$  and  $\alpha_H$ , respectively.

The exposed humans without clinical rabies that move back to the susceptible population are denoted by the rate  $\delta_H\epsilon_H$ . The natural death rate of dogs is  $m_D$ , and  $m_H$  denotes the mortality rate of humans (natural death rate),  $\mu_D$  represents the death rate associated with rabies infection in dogs, and  $\mu_H$  represents the disease induce death in humans. The rate at which exposed dogs die due to culling is  $C_D$ , and  $\delta\epsilon_D$  represents the rate at which exposed dogs without clinical rabies move back to the susceptible dog compartment. Subsequently, using the idea presented in [29], we assumed that the exposed dogs are treated or quarantined by their owners at the rate  $\rho_D$ ; this implies that  $(1 - \rho_D)\delta\gamma_D E_D$  is the progression rate of the exposed dogs to the infectious compartment, where  $(1 - \rho_D)$  is the failure of the treatment or quarantined strategy, and  $\delta\gamma_D E_D$  denotes those exposed dogs that develop clinical rabies [27]. Figure 1 shows the mathematical dynamics of the rabies virus in both compartments.

From Figure 1 transmission flowchart and assumptions give the disease pathways as

$$\frac{dS_D}{dt} = A_D - (1 - v_D)\beta_{DD}S_D I_D - (m_D + v_D)S_D + \delta\epsilon_D E_D + \alpha_D R_D,$$

$$\frac{dE_D}{dt} = (1 - \nu_D) \beta_{DD} S_D I_D - ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \epsilon_D + C_D) E_D,$$

$$\frac{dI_D}{dt} = (1 - \rho_D) \delta \gamma_D E_D - (m_D + \mu_D) I_D,$$

$$\frac{dR_D}{dt} = \nu_D S_D + \rho_D E_D - (m_D + \alpha_D) R_D,$$

$$\frac{dS_H}{dt} = B_H - (1 - \nu_H) \beta_{DH} S_H I_D - (m_H + \nu_H) S_H + \delta_H \epsilon_H E_H + \alpha_H R_H,$$

$$\frac{dE_H}{dt} = (1 - \nu_H) \beta_{DH} S_H I_D - ((1 - \rho_H) \delta_H \gamma_H + m_H + \rho_H + \delta_H \epsilon_H) E_H,$$

$$\frac{dI_H}{dt} = (1 - \rho_H) \delta_H \gamma_H E_H - (m_H + \mu_H) I_H,$$

$$\frac{dR_H}{dt} = \nu_H S_H + \rho_H E_H - (m_H + \alpha_H) R_H,$$

with  $S_D(0) > 0, E_D(0) \geq 0, I_D(0) \geq 0, R_D(0) \geq 0, S_H(0) > 0, E_H(0) \geq 0, I_H(0) > 0, R_H(0) > 0.$  (1)

### 3. Model Analysis

Model system (1) will be studied in a biological feasible region as outlined below. Model system (1) is basically divided into two regions; thus  $\Omega = \Omega_D \times \Omega_H$ .

**Lemma 1.** *The solution set  $\{S_D, E_D, I_D, R_D, S_H, E_H, I_H, R_H\} \in \mathbb{R}_+^8$  of model system (1) is contained in the feasible region  $\Omega$ .*

*Proof.* Suppose  $\{S_D, E_D, I_D, R_D, S_H, E_H, I_H, R_H\} \in \mathbb{R}_+^8$  for all  $t > 0$ . We want to show that the region  $\Omega$  is positively invariant, so that it becomes sufficient to look at the dynamics of model system (1), given that

$$N_D(t) = S_D(t) + E_D(t) + I_D(t) + R_D(t), \tag{2}$$

$$N_H(t) = S_H(t) + E_H(t) + I_H(t) + R_H(t), \tag{3}$$

where  $N_D(t)$  is the total population of dogs at any time  $(t)$  and  $N_H(t)$  is total population of humans at any time  $(t)$ .

Equation (2) gives

$$\begin{aligned} \frac{dN_D}{dt} &= A_D - (S_D + E_D + I_D + R_D) m_D - \mu_D I_D \\ &\quad - C_D E_D, \end{aligned} \tag{4}$$

which yields

$$\frac{dN_D}{dt} = A_D - m_D N_D - \mu_D I_D - C_D E_D. \tag{5}$$

Similarly (3) gives

$$\frac{dN_H}{dt} = B_H - m_H N_H - \mu_H I_H. \tag{6}$$

Now, assuming that there are no disease induced death rate and culling effect in the dogs' compartment, it implies that (5) and (6) become

$$\frac{dN_D}{dt} = A_D - m_D N_D, \tag{7}$$

$$\frac{dN_H}{dt} = B_D - m_H N_H.$$

Suppose  $dN_D/dt \leq 0, dN_H/dt \leq 0, N_D \leq A_D/m_D$ , and  $N_H \leq B_H/m_H$ , and then imposing the theorem proposed in [32] on differential inequality results in  $0 \leq N_D \leq A_D/m_D$  and  $0 \leq N_H \leq B_H/m_H$ . Therefore (7) becomes

$$\frac{dN_D}{dt} \leq A_D - m_D N_D, \tag{8}$$

$$\frac{dN_H}{dt} \leq B_D - m_H N_H. \tag{9}$$

Solve (8) and (9) using the integrating factor (IF) method. Thus  $dy/dt + p(t)y = Q$ ,  $IF = e^{\int p(t)dt}$ . After some algebraic manipulation the feasible solution of the dogs' population in model system (1) is in the region

$$\Omega_D = \left\{ (S_D, E_D, I_D, R_D) \in \mathbb{R}_+^4, N_D \leq \frac{A_D}{m_D} \right\}. \tag{10}$$

Similarly the human population follows suit, and from (9) this implies that the feasible solution of the human population of model system (1) is in the region

$$\Omega_H = \left\{ (S_H, E_H, I_H, R_H) \in \mathbb{R}_+^4, N_H \leq \frac{B_H}{m_H} \right\}. \tag{11}$$

Therefore, the feasible solutions are contained in  $\Omega$ . Thus  $\Omega = \Omega_D \times \Omega_H$ . From the standard comparison theorem used on differential inequality in [33], it implies that

$$\begin{aligned} N_D(t) &\leq N_D(0)e^{-(m_D)t} + \frac{A_D}{m_D}(1 - e^{-(m_D)t}), \\ N_H(t) &\leq N_H(0)e^{-(m_H)t} + \frac{B_H}{m_H}(1 - e^{-(m_H)t}). \end{aligned} \tag{12}$$

Hence, the total dog population size  $N_D(t) \rightarrow A_D/m_D$  as  $t \rightarrow \infty$ . Similarly, the total human population size  $N_H(t) \rightarrow B_H/m_H$  as  $t \rightarrow \infty$ . This means that the infected state variables  $(E_D, I_D, E_H, I_H)$  of the two populations tend to zero as time goes to infinity. Therefore, the region  $\Omega$  is pulling (attracting) all the solutions in  $\mathbb{R}_+^8$ . This gives the feasible solution set of model system (1) as

$$\begin{pmatrix} S_D \\ E_D \\ I_D \\ R_D \\ S_H \\ E_H \\ I_H \\ R_H \end{pmatrix} \in \mathbb{R}_+^8 \mid \begin{pmatrix} S_D > 0 \\ E_D \geq 0 \\ I_D \geq 0 \\ R_D \geq 0 \\ S_H > 0 \\ E_H \geq 0 \\ I_H \geq 0 \\ R_H \geq 0 \\ N_D \leq \frac{A_D}{m_D} \\ N_H \leq \frac{B_H}{m_H} \end{pmatrix}. \tag{13}$$

□

Hence, (1) is mathematically well posed and epidemiologically meaningful.

**3.1. Disease-Free Equilibrium  $\mathcal{E}_0$ .** Suppose there is no infection of rabies in both compartments; then  $(E_D = 0, I_D = 0, E_H = 0, I_H = 0)$ . Incorporating this into (1) leads to

$$\begin{aligned} A_D - (m_D + \nu_D)S_D + \alpha_D R_D &= 0, \\ \nu_D S_D - (m_D + \alpha_D)R_D &= 0, \\ B_H - (m_H + \nu_H)S_H + \alpha_H R_H &= 0, \\ \nu_H S_H - (m_H + \alpha_H)R_H &= 0. \end{aligned} \tag{14}$$

After some algebraic manipulation of (14), the disease-free equilibrium point becomes  $\mathcal{E}_0 = (S_D^0, E_D^0, I_D^0, R_D^0, S_H^0, E_H^0, I_H^0, R_H^0)$  with

$$\mathcal{E}_0 = \left( \frac{A_D(m_D + \alpha_D)}{m_D(m_D + \alpha_D + \nu_D)}, 0, 0, \frac{A_D \nu_D}{m_D(m_D + \alpha_D + \nu_D)}, \frac{B_H(m_H + \alpha_H)}{m_H(m_H + \alpha_H + \nu_H)}, 0, 0, \frac{B_H \nu_H}{m_H(m_H + \alpha_H + \nu_H)} \right). \tag{15}$$

**3.2. Basic Reproduction Number  $\mathcal{R}_0$ .** Here, the basic reproduction number ( $\mathcal{R}_0$ ) measures the average number of new infections produced by one infected dog in a completely susceptible (dog and human) population (see also [34]). Now taking  $E_D, I_D, E_H,$  and  $I_H$  as our infected compartments gives

$$\begin{aligned} f_1 &= (1 - \nu_D)\beta_{DD}S_D I_D - ((1 - \rho_D)\delta\gamma_D + m_D + \rho_D + \delta\varepsilon_D + C_D)E_D, \\ f_2 &= (1 - \rho_D)\delta\gamma_D E_D - (m_D + \mu_D)I_D, \\ f_3 &= (1 - \nu_H)\beta_{DH}S_H I_D - ((1 - \rho_H)\delta_H\gamma_H + m_H + \rho_H + \delta_H\varepsilon_H)E_H, \\ f_4 &= (1 - \rho_H)\delta_H\gamma_H E_H - (m_H + \mu_H)I_H, \end{aligned} \tag{16}$$

where  $f_1 = dE_D/dt, f_2 = dI_D/dt, f_3 = dE_H/dt,$  and  $f_4 = dI_H/dt$ .

Now, using the next generation matrix operator  $G = FV^{-1}$  and the Jacobian matrix

$$J = \begin{pmatrix} \frac{\partial f_1}{\partial E_D} & \frac{\partial f_1}{\partial I_D} & \frac{\partial f_1}{\partial E_H} & \frac{\partial f_1}{\partial I_H} \\ \frac{\partial f_2}{\partial E_D} & \frac{\partial f_2}{\partial I_D} & \frac{\partial f_2}{\partial E_H} & \frac{\partial f_2}{\partial I_H} \\ \frac{\partial f_3}{\partial E_D} & \frac{\partial f_3}{\partial I_D} & \frac{\partial f_3}{\partial E_H} & \frac{\partial f_3}{\partial I_H} \\ \frac{\partial f_4}{\partial E_D} & \frac{\partial f_4}{\partial I_D} & \frac{\partial f_4}{\partial E_H} & \frac{\partial f_4}{\partial I_H} \end{pmatrix}, \tag{17}$$

as described in [34], results in

$$J = \begin{pmatrix} -((1 - \rho_D)\delta\gamma_D + m_D + \rho_D + \delta\varepsilon_D + C_D) & (1 - \nu_D)\beta_{DD}S_D & 0 & 0 \\ (1 - \rho_D)\delta\gamma_D & -(m_D + \mu_D) & 0 & 0 \\ 0 & (1 - \nu_H)\beta_{DH}S_H - ((1 - \rho_H)\delta_H\gamma_H + m_H + \rho_H + \delta_H\varepsilon_H) & 0 & 0 \\ 0 & 0 & (1 - \rho_H)\delta_H\gamma_H & -(m_H + \mu_H) \end{pmatrix}. \tag{18}$$

Using the fact that  $J = F - V$  gives  $F$  and  $V$  evaluated at  $\mathcal{E}_0$  as

$$F(\mathcal{E}_0) = \begin{pmatrix} 0 & \frac{(1-\nu_D)\beta_{DD}A_D(m_D+\alpha_D)}{m_D(m_D+\nu_D+\alpha_D)} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \frac{(1-\nu_H)\beta_{DH}(m_H+\alpha_H)B_H}{m_H(m_H+\nu_H+\alpha_H)} & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}, \quad (19)$$

$$V(\mathcal{E}_0) = \begin{pmatrix} ((1-\rho_D)\delta\gamma_D+m_D+\rho_D+\delta\varepsilon_D+C_D) & 0 & 0 & 0 \\ -(1-\rho_D)\delta\gamma_D & (m_D+\mu_D) & 0 & 0 \\ 0 & 0 & ((1-\rho_H)\delta_H\gamma_H+m_H+\rho_H+\delta_H\varepsilon_H) & 0 \\ 0 & 0 & -(1-\rho_H)\delta_H\gamma_H & (m_H+\mu_H) \end{pmatrix},$$

where the element in matrix  $F$  constitutes the new infection terms, while that of matrix  $V$  constitutes the new transfer of infection terms from one compartment to another.

Now, splitting matrix  $V$  into four  $2 \times 2$  submatrices and finding its corresponding inverses result in  $G = FV^{-1}$ , given by

$$G = \begin{pmatrix} \frac{(1-\rho_D)(1-\nu_D)\delta\gamma_D\beta_{DD}A_D(m_D+\alpha_D)}{((1-\rho_D)\delta\gamma_D+m_D+\rho_D+\delta\varepsilon_D+C_D)(m_D+\mu_D)m_D(m_D+\nu_D+\alpha_D)} & \frac{(1-\nu_D)\beta_{DD}A_D(m_D+\alpha_D)}{m_D(m_D+\nu_D+\alpha_D)} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ \frac{(1-\rho_D)\delta\gamma_D(1-\nu_H)\beta_{DH}B_H(m_H+\alpha_H)}{((1-\rho_D)\delta\gamma_D+m_D+\rho_D+\delta\varepsilon_D+C_D)(m_D+\mu_D)m_H(m_H+\nu_H+\alpha_H)} & \frac{(1-\nu_H)\beta_{DH}(m_H+\alpha_H)B_H}{(m_D+\nu_D)m_H(m_H+\nu_H+\alpha_H)} & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix} \quad (20)$$

Letting

$$a = \frac{(1-\rho_D)(1-\nu_D)\delta\gamma_D\beta_{DD}A_D(m_D+\alpha_D)}{((1-\rho_D)\delta\gamma_D+m_D+\rho_D+\delta\varepsilon_D+C_D)(m_D+\mu_D)m_D(m_D+\nu_D+\alpha_D)},$$

$$b = \frac{(1-\nu_D)\beta_{DD}A_D(m_D+\alpha_D)}{m_D(m_D+\nu_D+\alpha_D)},$$

$$c = \frac{(1-\rho_D)(1-\nu_H)\delta\gamma_D\beta_{DH}(m_H+\alpha_H)}{((1-\rho_D)\delta\gamma_D+m_D+\rho_D+\delta\varepsilon_D+C_D)(m_D+\mu_D)m_H(m_H+\nu_H+\alpha_H)},$$

$$d = \frac{(1-\nu_H)\beta_{DH}(m_H+\alpha_H)B_H}{(m_D+\nu_D)m_H(m_H+\nu_H+\alpha_H)}$$
(21)

implies

$$G = \begin{pmatrix} a & b & 0 & 0 \\ 0 & 0 & 0 & 0 \\ c & d & 0 & 0 \\ 0 & 0 & 0 & 0 \end{pmatrix}. \tag{22}$$

Finding the matrix determinant of (22) and denoting it by  $D$  give the expression  $D = |G - \mathbb{I}\lambda|$ , where  $\mathbb{I}$  is the identity matrix of a  $4 \times 4$  matrix; thus

$$D = \begin{vmatrix} a - \lambda & b & 0 & 0 \\ 0 & -\lambda & 0 & 0 \\ c & d & -\lambda & 0 \\ 0 & 0 & 0 & -\lambda \end{vmatrix} = 0. \tag{23}$$

This gives a characteristic equation of the form  $\lambda^3(a - \lambda) = 0$ ; solving the characteristic polynomial results in the following eigenvalues:  $\lambda_i = [0, 0, 0, a]$ . The basic reproduction number  $\mathcal{R}_0$  is the spectral radius (largest eigenvalue)  $\rho(FV^{-1})$ , also defined as the dominant eigenvalue of  $FV^{-1}$ .

Therefore,

$$\mathcal{R}_0 = \frac{(1 - \rho_D)(1 - \nu_D)\delta\gamma_D\beta_{DD}A_D(m_D + \alpha_D)}{((1 - \rho_D)\delta\gamma_D + m_D + \rho_D + \delta\varepsilon_D + C_D)(m_D + \mu_D)m_D(m_D + \nu_D + \alpha_D)}. \tag{24}$$

*Remark 2.*  $\mathcal{R}_0$  contains the secondary infection produced by the infectious compartment of dogs (in the presence of preexposure prophylaxis (vaccination), postexposure prophylaxis (treatment/quarantine), and culling of exposed dogs). When  $\mathcal{R}_0 < 1$ , the infection gradually leaves the dog compartment, but when  $\mathcal{R}_0 > 1$ , the rabies virus remains in the dog

compartments for a longer time, thereby increasing the rate at which the susceptible dogs and humans get infected by a rabid dog.

3.3. *Endemic Equilibrium*  $\mathcal{E}_1$ . The endemic equilibrium is given as

$$\begin{aligned} S_D^* &= \frac{A_D(m_D + \alpha_D)}{m_D(m_D + \nu_D + \alpha_D)\mathcal{R}_0}, \\ E_D^* &= \frac{(m_D + \mu_D)}{(1 - \rho_D)\delta\gamma_D} I_D^*, \\ I_D^* &= \frac{[(1 - \rho_D)\delta\gamma_D + m_D + \rho_D + \delta\varepsilon_D](m_D + \mu_D)m_D(m_D + \nu_D + \alpha_D)(\mathcal{R}_0 - 1)}{(m_D + \alpha_D)(1 - \nu_D)\beta_{DD}[(1 - \rho_D)\delta\gamma_D + m_D + C_D] + m_D(1 - \nu_D)\beta_{DD}\rho_D}, \\ R_D^* &= \frac{A_D\nu_D(1 - \nu_D)\beta_{DD}(1 - \rho_D)\delta\gamma_D(m_D + \alpha_D) + (1 - \nu_D)\beta_{DD}\rho_D(m_D + \mu_D)I_D^*}{m_D(m_D + \nu_D + \alpha_D)\mathcal{R}_0(1 - \nu_D)\beta_{DD}(1 - \rho_D)\delta\gamma_D(m_D + \alpha_D)}, \\ S_H^* &= \frac{B_H(m_H + \alpha_H) + [\delta_H\varepsilon_H + \alpha_H\rho_H]E_H^*}{[(1 - \nu_H)(m_H + \alpha_H)\beta_{DH}I_D^* + m_H(m_H + \alpha_H + \nu_H)]}, \\ E_H^* &= \\ &= \frac{(1 - \nu_H)B_H(m_H + \alpha_H)\beta_{DH}I_D^*}{(m_H + \alpha_H)[(1 - \nu_H)\beta_{DH}I_D^*((1 - \rho_H)\delta_H\gamma_H + m_H + \rho_H) + (m_H + \nu_H)((1 - \rho_H)\delta_H\gamma_H + m_H + \rho_H + \delta_H\varepsilon_H)] - (1 - \nu_H)\beta_{DH}I_D^*\alpha_H\rho_H}, \\ I_H^* &= \frac{(1 - \rho_H)\delta_H\gamma_H E_H^*}{m_H + \mu_H}, \\ R_H^* &= \frac{B_H\nu_H(m_H + \nu_H) + [(1 - \nu_H)\delta_H\varepsilon_H + \nu_H\alpha_H\rho_H] + \rho_H(1 - \nu_H)(m_H + \alpha_H)\beta_{DH}I_D^* + \rho_H m_H(m_H + \alpha_H + \nu_H)] E_H^*}{[(1 - \nu_H)(m_H + \alpha_H)^2\beta_{DH}I_D^* + (m_H + \alpha_H)m_H(m_H + \alpha_H + \nu_H)]}. \end{aligned} \tag{25}$$

Note that if  $\mathcal{R}_0 = 1$ , it results in the disease-free equilibrium; if  $\mathcal{R}_0 > 1$ , then there exists a unique endemic

equilibrium; if  $\mathcal{R}_0 < 1$ , then there exist two endemic equilibriums.

3.4. Stability Analysis of  $\mathcal{E}_0$ . Linearizing (1) at  $\mathcal{E}_0$  and subtracting eigenvalue  $\lambda$  along the main diagonal yield

$$\mathbb{J}(\mathcal{E}_0) = \begin{pmatrix} b_1 - \lambda & b_7 & a_1 & \alpha_D & 0 & 0 & 0 & 0 \\ 0 & a_2 - \lambda & a_3 & 0 & 0 & 0 & 0 & 0 \\ 0 & b_{10} & b_2 - \lambda & 0 & 0 & 0 & 0 & 0 \\ \nu_D & \rho_D & 0 & b_3 - \lambda & 0 & 0 & 0 & 0 \\ 0 & 0 & a_4 & 0 & b_4 - \lambda & b_5 & 0 & \alpha_H \\ 0 & 0 & a_5 & 0 & 0 & a_6 - \lambda & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & b_9 & b_6 - \lambda & 0 \\ 0 & 0 & 0 & 0 & \nu_H & \rho_H & 0 & b_8 - \lambda \end{pmatrix}, \tag{26}$$

where

$$\begin{aligned} a_1 &= \frac{-(1 - \nu_D) \beta_{DD} (m_D + \alpha_D) A_D}{m_D (m_D + \nu_D + \alpha_D)}, \\ a_2 &= -((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D), \\ a_3 &= \frac{(1 - \nu_D) \beta_{DD} (m_D + \alpha_D) A_D}{m_D (m_D + \nu_D + \alpha_D)}, \\ a_4 &= \frac{-(1 - \nu_H) \beta_{DH} (m_H + \alpha_H)}{m_H (m_H + \nu_H + \alpha_H)}, \\ a_5 &= \frac{(1 - \nu_H) \beta_{DH} (m_H + \alpha_H)}{m_H (m_H + \nu_H + \alpha_H)}, \\ a_6 &= -((1 - \rho_H) \delta_H \gamma_H + m_H + \rho_H + \delta_H \varepsilon_H), \\ b_1 &= -(m_D + \nu_D), \\ b_2 &= -(m_D + \mu_D), \\ b_3 &= -(m_D + \alpha_D), \\ b_4 &= -(\nu_H + m_H), \\ b_5 &= \delta_H \varepsilon_H, \\ b_6 &= -(m_H + \mu_H), \\ b_7 &= \delta \varepsilon_D, \\ b_8 &= -(m_H + \alpha_H), \\ b_9 &= (1 - \rho_H) \delta_H \gamma_H, \\ b_{10} &= (1 - \rho_D) \delta \gamma_D. \end{aligned} \tag{27}$$

Simplifying matrix  $\mathbb{J}(\mathcal{E}_0)$  gives

$$(b_6 - \lambda) (a_6 - \lambda) (b_4 - \lambda) (b_8 - \lambda) \cdot [\lambda^4 + a_{11} \lambda^3 + a_{12} \lambda^2 + a_{13} \lambda + a_{14}] = 0, \tag{28}$$

where

$$\begin{aligned} a_{11} &= (-b_2 - a_2 - b_1 - b_3), \\ a_{12} &= \nu_D \alpha_D + a_2 b_3 + a_2 b_1 + b_2 b_3 + b_2 b_1 + b_3 b_1 + b_2 a_2 \\ &\quad - (1 - \rho_D) \delta \gamma_D a_3, \\ a_{13} &= -a_2 \nu_D \alpha_D - b_2 \nu_D \alpha_D + a_3 (1 - \rho_D) \delta \gamma_D b_2 + a_3 (1 - \rho_D) \delta \gamma_D b_1 \\ &\quad - a_2 b_2 b_3 - b_2 a_2 b_1 - a_2 b_3 b_1 - b_2 b_3 b_1, \\ a_{14} &= (b_1 b_2 b_3 a_2 + (1 - \rho_D) \delta \gamma_D a_3 b_3 b_1 \\ &\quad + (1 - \rho_D) \delta \gamma_D a_3 \nu_D + \nu_D \alpha_D b_2 a_2). \end{aligned} \tag{29}$$

From (28) the four characteristic factors that are negative are

$$\begin{aligned} \lambda_1 &= b_6, \\ \lambda_2 &= a_6, \\ \lambda_3 &= b_4, \\ \lambda_4 &= b_8, \end{aligned} \tag{30}$$

where  $a_6 = -((1 - \rho_H) \delta_H \gamma_H + m_H + \rho_H + \delta_H + \delta_H \varepsilon_H)$ ,  $b_6 = -(m_H + \mu_H)$ ,  $b_4 = -(\nu_H + m_H)$ , and  $b_8 = -(m_H + \alpha_H)$ . The other four characteristic factors can be obtained using the Routh-Hurwitz criterion. Routh-Hurwitz stability criterion is a test to ascertain the nature of the eigenvalues. If the roots of the polynomial are all positive, then the polynomial has a negative real part [35, 36]. The remaining four characteristic eigenvalues are obtained as follows:

$$\lambda^4 + a_{11} \lambda^3 + a_{12} \lambda^2 + a_{13} \lambda + a_{14} = 0. \tag{31}$$

Hence, simplifying the coefficient of the above characteristic polynomial in (31) yields

$$\begin{aligned} a_{11} &= ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) \\ &\quad + (m_D + \mu_D) + (m_D + \alpha_D) + (m_D + \nu_D), \end{aligned}$$



$$\begin{aligned}
 a_{12} = & \nu_D \alpha_D + ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) \\
 & \cdot [(m_D + \alpha_D) + (m_D + \nu_D)] + (m_D + \mu_D) \\
 & \cdot [(m_D + \alpha_D) + (m_D + \nu_D)] + (m_D + \alpha_D) \\
 & \cdot (m_D + \nu_D) + ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + C_D) \\
 & \cdot (m_D + \mu_D) (1 - \mathcal{R}_0), \\
 a_{13} = & ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) \nu_D \alpha_D \\
 & + (m_D + \mu_D) \nu_D \alpha_D + (m_D + \mu_D) (m_D + \alpha_D) \\
 & \cdot (m_D + \nu_D) \\
 & + ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) \\
 & \cdot (m_D + \alpha_D) (m_D + \mu_D) \left[ 1 - \frac{\mathcal{R}_0 (m_D + \mu_D)}{m_D + \alpha_D} \right] \\
 & + ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) \\
 & \cdot (m_D + \alpha_D) (m_D + \nu_D) \left[ 1 - \frac{\mathcal{R}_0}{m + \alpha} \right], \\
 a_{14} = & \nu_D \alpha_D (m_D + \nu_D) \\
 & \cdot ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) \\
 & + \frac{(1 - \rho_D) \delta \gamma_D (1 - \nu_D) \beta_{DD} (m_D + \alpha_D) A_D \nu_D}{m_D (m_D + m_D + \nu_D + \alpha_D)} \\
 & + (m_D + \nu_D) (m_D + \mu_D) (m_D + \alpha_D) \\
 & \cdot ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) \\
 & \cdot (1 - \mathcal{R}_0).
 \end{aligned} \tag{32}$$

Therefore, from the Routh-Hurwitz criterion of order four, it implies that the conditions,  $a_{11} > 0$ ,  $a_{12} > 0$ ,  $a_{13} > 0$ ,  $a_{14} > 0$ , and  $a_{11} a_{12} a_{13} > a_{13}^2 + a_{11}^2 a_{14}$ , are satisfied if  $\mathcal{R}_0 < 1$ . Hence, the disease-free equilibrium  $\mathcal{E}_0$  is locally asymptotically stable when  $\mathcal{R}_0 < 1$  (see [37]).

### 3.4.1. Global Stability of $\mathcal{E}_0$

**Theorem 3.** *The disease-free equilibrium  $\mathcal{E}_0$  of model (1) is globally asymptotically stable if  $\mathcal{R}_0 \leq 1$  and unstable if  $\mathcal{R}_0 > 1$ .*

*Proof.* Let  $\mathcal{V}$  be a Lyapunov function with positive constants  $\mathcal{K}_1, \mathcal{K}_2, \mathcal{K}_3$ , and  $\mathcal{K}_4$  such that

$$\begin{aligned}
 \mathcal{V} = & \left( S_D - S_D^0 - S_D^0 \ln \frac{S_D}{S_D^0} \right) + \mathcal{K}_1 E_D + \mathcal{K}_2 I_D \\
 & + \left( R_D - R_D^0 - R_D^0 \ln \frac{R_D}{R_D^0} \right)
 \end{aligned}$$

$$\begin{aligned}
 & + \left( S_H - S_H^0 - S_H^0 \ln \frac{S_H}{S_H^0} \right) + \mathcal{K}_3 E_H + \mathcal{K}_4 I_H \\
 & + \left( R_H - R_H^0 - R_H^0 \ln \frac{R_H}{R_H^0} \right).
 \end{aligned} \tag{33}$$

Taken the derivative of the Lyapunov function with respect to time gives

$$\begin{aligned}
 \frac{d\mathcal{V}}{dt} = & \left( 1 - \frac{S_D^0}{S_D} \right) \frac{dS_D}{dt} + \mathcal{K}_1 \frac{dE_D}{dt} + \mathcal{K}_2 \frac{dI_D}{dt} \\
 & + \left( 1 - \frac{R_D^0}{R_D} \right) \frac{dR_D}{dt} + \left( 1 - \frac{S_H^0}{S_H} \right) \frac{dS_H}{dt} \\
 & + \mathcal{K}_3 \frac{dE_H}{dt} + \mathcal{K}_4 \frac{dI_H}{dt} + \left( 1 - \frac{R_H^0}{R_H} \right) \frac{dR_H}{dt}.
 \end{aligned} \tag{34}$$

Plugging (1) into (34) results in

$$\begin{aligned}
 \frac{d\mathcal{V}}{dt} = & \left( 1 - \frac{S_D^0}{S_D} \right) [A_D - (1 - \nu_D) \beta_{DD} S_D I_D \\
 & - (m_D + \nu_D) S_D + \delta \varepsilon_D E_D + \alpha R_D] \\
 & + \mathcal{K}_1 [(1 - \nu_D) \beta_{DD} S_D I_D \\
 & - ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) E_D] \\
 & + \mathcal{K}_2 [(1 - \rho_D) \delta \gamma_D E_D - (m_D + \mu_D) I_D] + \left( 1 - \frac{R_D^0}{R_D} \right) [\nu_D S_D + \rho_D E_D - (m_D + \alpha_D) R_D] + \left( 1 - \frac{S_H^0}{S_H} \right) [B_H - (1 - \nu_H) \beta_{DH} S_H I_D - (m_H + \nu_H) S_H \\
 & + \delta_H \varepsilon_H E_H + \alpha_H R_H] + \mathcal{K}_3 [(1 - \nu_H) \beta_{DH} S_H I_D \\
 & - ((1 - \rho_H) \delta_H \gamma_H + m_H + \rho_H + \delta_H \varepsilon_H) E_H] \\
 & + \mathcal{K}_4 [(1 - \rho_H) \delta_H \gamma_H E_H - (m_H + \mu_H) I_H] + \left( 1 - \frac{R_H^0}{R_H} \right) [\nu_H S_H + \rho_H E_H - (m_H + \alpha_H) R_H].
 \end{aligned} \tag{35}$$

Now, after forming the Lyapunov function  $\mathcal{V}$  on the space of the eight state variables, thus  $(S_D, E_D, I_D, R_D, S_H, E_H, I_H, R_H)$ , and introducing the idea from [37], it is clear that if  $E_D(t), I_D(t), E_H(t)$ , and  $I_H(t)$  at the disease-free equilibrium are globally stable (thus,  $E_D = 0, I_D = 0, E_H = 0$ , and  $I_H = 0$ ), then  $S_D(t) \rightarrow A_D (m_D + \alpha_D) / m_D (m_D + \alpha_D + \nu_D)$ ,  $R_D(t) \rightarrow A_D \nu_D / m_D (m_D + \alpha_D + \nu_D)$ ,  $S_H(t) \rightarrow B_H (m_H + \alpha_H) / m_H (m_H + \alpha_H + \nu_H)$ , and  $R_H(t) \rightarrow B_H \nu_H / m_H (m_H + \alpha_H + \nu_H)$  as  $t \rightarrow \infty$ .

Therefore, it can be assumed that

$$\begin{aligned}
 S_D &\leq S_D^0 = \frac{A_D(m_D + \alpha_D)}{m_D(m_D + \alpha_D + \nu_D)}, \\
 R_D &\leq R_D^0 = \frac{A_D\nu_D}{m_D(m_D + \alpha_D + \nu_D)}, \\
 S_H &\leq S_H^0 = \frac{B_H(m_H + \alpha_H)}{m_H(m_H + \alpha_H + \nu_H)}, \\
 R_H &\leq R_H^0 = \frac{B_H\nu_H}{m_H(m_H + \alpha_H + \nu_H)},
 \end{aligned}
 \tag{36}$$

(see [38]) and replacing it into (35) yields

$$\begin{aligned}
 \frac{d\mathcal{V}}{dt} &\leq \mathcal{K}_1 \left[ \frac{(1 - \nu_D)\beta_{DD}A_D(m_D + \alpha_D)}{m_D(m_D + \alpha_D + \nu_D)} I_D \right. \\
 &\quad \left. - ((1 - \rho_D)\delta\gamma_D + m_D + \rho_D + \delta\varepsilon_D + C_D) E_D \right] \\
 &\quad + \mathcal{K}_2 [(1 - \rho_D)\delta\gamma_D E_D - (m_D + \mu_D) I_D] \\
 &\quad + \mathcal{K}_3 \left[ \frac{(1 - \nu_H)\beta_{DH}B_H(m_H + \alpha_H)}{m_H(m_H + \alpha_H + \nu_H)} I_H \right. \\
 &\quad \left. - ((1 - \rho_H)\delta_H\gamma_H + m_H + \rho_H + \delta_H\varepsilon_H) E_H \right] \\
 &\quad + \mathcal{K}_4 [(1 - \rho_H)\delta_H\gamma_H E_H - (m_H + \mu_H) I_H],
 \end{aligned}
 \tag{37}$$

This implies that

$$\begin{aligned}
 \frac{d\mathcal{V}}{dt} &\leq \left[ \frac{\mathcal{K}_1(1 - \nu_D)\beta_{DD}A_D(m_D + \alpha_D)}{m_D(m_D + \alpha_D + \nu_D)} \right. \\
 &\quad \left. - \mathcal{K}_2(m_D + \mu_D) \right. \\
 &\quad \left. + \frac{\mathcal{K}_3(1 - \nu_H)\beta_{DH}B_H(m_H + \alpha_H)}{m_H(m_H + \alpha_H + \nu_H)} \right] I_D \\
 &\quad + [\mathcal{K}_2(1 - \rho_D)\delta\gamma_D \\
 &\quad - \mathcal{K}_1((1 - \rho_D)\delta\gamma_D + m_D + \rho_D + \delta\varepsilon_D + C_D)] E_D \\
 &\quad + [\mathcal{K}_4(1 - \rho_H)\delta_H\gamma_H \\
 &\quad - \mathcal{K}_3((1 - \rho_H)\delta_H\gamma_H + m_H + \delta_H\varepsilon_H)] E_H \\
 &\quad - \mathcal{K}_4(m_H + \mu_H).
 \end{aligned}
 \tag{38}$$

Equating the coefficient of  $I_D$ ,  $E_D$ ,  $I_H$ , and  $E_H$  in (38) to zero gives

$$\begin{aligned}
 \mathcal{K}_4 &= \mathcal{K}_3 = 0, \\
 \mathcal{K}_2 &= ((1 - \rho_D)\delta\gamma_D + m_D + \rho_D + \delta\varepsilon_D + C_D), \\
 \mathcal{K}_1 &= (1 - \rho_D)\delta\gamma_D,
 \end{aligned}
 \tag{39}$$

and we obtain

$$\begin{aligned}
 \frac{d\mathcal{V}}{dt} &\leq ((1 - \rho_D)\delta\gamma_D + m_D + \rho_D + \delta\varepsilon_D + C_D) \\
 &\quad \cdot (m_D + \mu_D)(\mathcal{R}_0 - 1) I_D, \\
 &\leq 0, \quad \text{if } \mathcal{R}_0 \leq 1.
 \end{aligned}
 \tag{40}$$

Additionally  $d\mathcal{V}/dt = 0$  if and only if  $I_D = 0$ . Therefore, for  $E_D = I_D = E_H = I_H = 0$  it shows that  $S_D(t) \rightarrow A_D(m_D + \alpha_D)/m_D(m_D + \alpha_D + \nu_D)$ ,  $R_D(t) \rightarrow A_D\nu_D/m_D(m_D + \alpha_D + \nu_D)$ ,  $S_H(t) \rightarrow B_H(m_H + \alpha_H)/m_H(m_H + \alpha_H + \nu_H)$ , and  $R_H(t) \rightarrow B_H\nu_H/m_H(m_H + \alpha_H + \nu_H)$  as  $t \rightarrow \infty$ . Hence, the largest compact invariant set in  $\{(S_D, E_D, I_D, R_D, S_H, E_H, I_H, R_H) \in \Omega : d\mathcal{V}/dt \leq 0\}$  is the singleton set  $\{\mathcal{E}_0\}$ . Therefore, from La Salle's invariance principle, we conclude that  $\mathcal{E}_0$  is globally asymptotically stable in  $\Omega$  if  $\mathcal{R}_0 \leq 1$  (see also [38, 39]).  $\square$

### 3.5. Global Stability of Endemic Equilibrium $\mathcal{E}_1$

**Theorem 4.** *The endemic equilibrium  $\mathcal{E}_1$  of model (1) is globally asymptotically stable whenever  $\mathcal{R}_0 > 1$ .*

*Proof.* Suppose  $\mathcal{R}_0 > 1$ ; then the existence of the endemic equilibrium point is assured. Using the common quadratic Lyapunov function

$$V(x_1, x_2, \dots, x_n) = \sum_{i=1}^n \frac{c_i}{2} (x_i - x_i^*)^2, \tag{41}$$

as illustrated in [40], we consider a Lyapunov function with the following candidate:

$$\begin{aligned}
 \mathcal{V}(S_D, E_D, I_D, R_D, S_H, E_H, I_H, R_H) &= \frac{1}{2} [(S_D - S_D^*) \\
 &\quad + (E_D - E_D^*) + (I_D - I_D^*) + (R_D - R_D^*)]^2 \\
 &\quad + \frac{1}{2} [(S_H - S_H^*) + (E_H - E_H^*) + (I_H - I_H^*) \\
 &\quad + (R_H - R_H^*)]^2.
 \end{aligned}
 \tag{42}$$

Now, differentiating (42) along the solution curve of (1) gives

$$\begin{aligned}
 \frac{d\mathcal{V}}{dt} &= [(S_D - S_D^*) + (E_D - E_D^*) + (I_D - I_D^*) \\
 &\quad + (R_D - R_D^*)] \frac{d(S_D + E_D + I_D + R_D)}{dt} \\
 &\quad + [(S_H - S_H^*) + (E_H - E_H^*) + (I_H - I_H^*) \\
 &\quad + (R_H - R_H^*)] \frac{d(S_H + E_H + I_H + R_H)}{dt}.
 \end{aligned}
 \tag{43}$$

From (1) it implies that  $d(S_D + E_D + I_D + R_D)/dt = A_D - m_D(S_D + E_D + I_D + R_D) - C_D E_D - \mu_D I_D$  and  $d(S_H + E_H + I_H + R_H)/dt = B - m(S_H + E_H + I_H + R_H) - \mu_H I_H$ , which when plugged into (43) gives

$$\begin{aligned} \frac{d\mathcal{V}}{dt} = & [(S_D - S_D^*) + (E_D - E_D^*) + (I_D - I_D^*) \\ & + (R_D - R_D^*)] (A_D - m_D(S_D + E_D + I_D + R_D) \\ & - C_D E_D - \mu_D I_D) + [(S_H - S_H^*) + (E_H - E_H^*) \\ & + (I_H - I_H^*) + (R_H - R_H^*)] (B_H \\ & - m(S_H + E_H + I_H + R_H) - \mu_H I_H). \end{aligned} \tag{44}$$

Now assuming

$$\begin{aligned} A_D = & m_D(S_D^* + E_D^* + I_D^* + R_D^*) + C_D E_D^* + \mu_D I_D^*, \\ B_H = & m_H(S_H^* + E_H^* + I_H^* + R_H^*) + \mu_H I_H^* \end{aligned} \tag{45}$$

and substituting it into (44), we have

$$\begin{aligned} \frac{d\mathcal{V}}{dt} = & [(S_D - S_D^*) + (E_D - E_D^*) + (I_D - I_D^*) + (R_D \\ & - R_D^*)] [m_D(S_D^* + E_D^* + I_D^* + R_D^*) + C_D E_D^* + \mu_D I_D^* \\ & - m_D(S_D + E_D + I_D + R_D) - C_D E_D - \mu_D I_D] \\ & + [(S_H - S_H^*) + (E_H - E_H^*) + (I_H - I_H^*) + (R_H \\ & - R_H^*)] [m_H(S_H^* + E_H^* + I_H^* + R_H^*) + \mu_H I_H^* \\ & - m(S_H + E_H + I_H + R_H) - \mu_H I_H], \\ \frac{d\mathcal{V}}{dt} = & [(S_D - S_D^*) + (E_D - E_D^*) + (I_D - I_D^*) + (R_D \\ & - R_D^*)] [(-m_D(S_D - S_D^*) - m_D(E_D - E_D^*) \\ & - m_D(I_D - I_D^*) - m_D(R_D - R_D^*) - C_D(E_D - E_D^*) \\ & - \mu_D(I_D - I_D^*)) + [(S_H - S_H^*) + (E_H - E_H^*) \\ & + (I_H - I_H^*) + (R_H - R_H^*)] [(-m_H(S_H - S_H^*) \\ & - m_H(E_H - E_H^*) - m_H(I_H - I_H^*) \\ & - m_H(R_H - R_H^*) - \mu_H(I_H - I_H^*))]. \end{aligned} \tag{46}$$

This also implies that

$$\begin{aligned} \frac{d\mathcal{V}}{dt} = & -m_D(S_D - S_D^*)^2 - (C_D + m_D)(E_D - E_D^*)^2 \\ & - (m_D + \mu_D)(I_D - I_D^*)^2 - m_D(R_D - R_D^*)^2 - (2m_D \\ & + C_D)(S_D - S_D^*)(E_D - E_D^*) - (2m_D + \mu_D)(S_D \\ & - S_D^*)(I_D - I_D^*) - (2m_D + \mu_D + C_D)(E_D - E_D^*)(I_D \\ & - I_D^*) - 2m_D(R_D - R_D^*)(I_D - I_D^*) - (2m_D + \mu_D \end{aligned}$$

$$\begin{aligned} & + C_D)(R_D - R_D^*)(I_D - I_D^*) - m_H(S_H - S_H^*)^2 \\ & - m_H(E_H - E_H^*)^2 - (m_H - \mu_H)(I_H - I_H^*)^2 \\ & - m_H(R_H - R_H^*)^2 - 2m_H(S_H - S_H^*)(E_H - E_H^*) \\ & - (2m_H - \mu_H)(S_H - S_H^*)(I_H - I_H^*) - (2m_H + \mu_H) \\ & \cdot (E_H - E_H^*)(I_H - I_H^*) \\ & - m_H[(I_H - I_H^*)(R_H - R_H^*) \\ & + (S_H - S_H^*)(R_H - R_H^*)]. \end{aligned} \tag{47}$$

This shows that  $d\mathcal{V}/dt$  is negative and  $d\mathcal{V}/dt = 0$ , if and only if  $S_D = S_D^*, E_D = E_D^*, I_D = I_D^*, R_D = R_D^*, S_H = S_H^*, E_H = E_H^*, I_H = I_H^*, R_H = R_H^*$ . Additionally every solution of (1) with the initial conditions approaches  $\mathcal{E}_1$  as  $t \rightarrow \infty$  (see [38, 39]); therefore, the largest compact invariant set in  $\{(S_D, E_D, I_D, R_D, S_H, E_H, I_H, R_H) \in \Omega : d\mathcal{V}/dt \leq 0\}$  is the singleton set  $\{\mathcal{E}_1\}$ . Therefore, from Lasalle's invariant principle [41], it implies that the endemic equilibrium  $\mathcal{E}_1$  is globally asymptotically stable in  $\Omega$  whenever  $\mathcal{R}_0 > 1$ .  $\square$

### 4. Numerical Analysis

Considering the parameter values in Table 1, we will ascertain the numerical importance of our analysis.

4.1. Different Scenarios of the Basic Reproduction Number  $\mathcal{R}_0$ . We shall denote  $\mathcal{R}_0$  without pre- and postexposure prophylaxis (treatment) as  $\mathcal{R}_0^*$  and  $\mathcal{R}_0$  without preexposure prophylaxis and culling as  $\mathcal{R}_0^{**}$  and the  $\mathcal{R}_0$  without postexposure prophylaxis (treatment) and culling as  $\mathcal{R}_0^{***}$ . Therefore, using the parameter values in Table 1,  $\mathcal{R}_0^*, \mathcal{R}_0^{**}$ , and  $\mathcal{R}_0^{***}$  are given as follows:

$$\begin{aligned} \mathcal{R}_0^* = & \frac{\beta_{DD} A_D \delta \gamma_D}{(\delta \gamma_D + m_D + \delta \varepsilon_D + C_D) \times (m_D + \mu_D) m_D}, \\ \mathcal{R}_0^* = & 3.027, \\ \mathcal{R}_0^{**} = & \frac{(1 - \rho_D) \delta \gamma_D \beta_{DD} A_D}{((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D) (m_D + \mu_D) m_D}, \\ \mathcal{R}_0^{**} = & 2.181, \\ \mathcal{R}_0^{***} = & \frac{(1 - \nu_D) \delta \gamma_D \beta_{DD} A_D (m_D + \alpha_D)}{(\delta \gamma_D + m_D + \delta \varepsilon_D) (m_D + \mu_D) m_D (m_D + \nu_D + \alpha_D)}, \\ \mathcal{R}_0^{***} = & 1.914. \end{aligned} \tag{48}$$

Therefore, from the above calculations it indicates that the best way in reducing or minimizing the rabies virus in the dogs compartment is to use more of preexposure prophylaxis (vaccination).

TABLE 1: Parameter values.

Parameter	Description	Standard value	Source
$A_D$	Recruitment rate of dogs	$3 \times 10^6 y^{-1}$	[27]
$\alpha_D$	Loss of immunity in dogs	$1 y^{-1}$	[27]
$C_D$	Death rate of dogs due to culling	$0.3 y^{-1}$	Assumed
$m_D$	Natural death rate of dogs	$0.056 y^{-1}$	[27]
$\mu_D$	Disease induced mortality in dogs	$1 y^{-1}$	[27]
$\nu_D$	Preexposure prophylaxis for dogs	$0.25 y^{-1}$	Assumed
$\rho_D$	Postexposure prophylaxis for dogs	$0.2 y^{-1}$	[27]
$\beta_{DD}$	Transmission rate in dogs	$1.58 \times 10^{-7} y^{-1}$	[27]
$\gamma_D$	Latency period in dogs	$(2.37/6) y^{-1}$	[27]
$\delta\epsilon_D$	Rate of no clinical rabies	$0.4 y^{-1}$	[27]
$B_H$	Birth rate (humans)	$0.0314 y^{-1}$	[31]
$\beta_{DH}$	Transmission rate (dog-humans)	$2.29 \times 10^{-12} y^{-1}$	[27]
$\alpha_H$	Loss of immunity (humans)	$1 y^{-1}$	[27]
$m_H$	Natural death rate (humans)	$0.0074 y^{-1}$	[31]
$\mu_H$	Disease induced mortality (humans)	$1 y^{-1}$	[27]
$\nu_H$	Preexposure prophylaxis for humans	$0.54 y^{-1}$	Assumed
$\rho_H$	Postexposure prophylaxis for humans	$0.1 y^{-1}$	[27]
$\gamma_H$	Latency rate (humans)	$(1/6) y^{-1}$	[27]
$\gamma_H\epsilon_H$	Rate of no clinical rabies (humans)	$2.4 y^{-1}$	[27]

4.1.1. *Herd Immunity Threshold  $H_1$ .* Therefore, from the above numerical values, we are motivated to know the number of humans or dogs that should be vaccinated when  $\mathcal{R}_0^* = 3.027$ .

$$H_1 := 1 - \frac{1}{\mathcal{R}_0^*} = 0.66. \quad (49)$$

This shows that if  $\mathcal{R}_0^* = 3.027$ , then 66% of individuals and dogs should receive vaccination.

4.2. *Sensitivity Analysis.* To determine parameters that contribute most to the rabies transmission, we used two sensitivity analysis approach: the normalised forward sensitivity index as presented in [37] and the Latin hypercube sampling as described in [42]. To determine the dependence of parameters in  $\mathcal{R}_0$ , using a sampling size,  $n = 1000$ , the partial rank correction coefficients (PRCC) value of the ten parameters in  $\mathcal{R}_0$  are shown in Figure 2(a). The longer the bar in Figure 2(a) suggests that the statistical influence of those parameters to changes in  $\mathcal{R}_0$  is high. Also, using the normalised forward sensitivity index gives the following values and the nature of their signs in Table 2, based on the parameter value given in Table 1. The plus sign or minus sign signifies that the influence is positive or negative, respectively [42],

$$\Gamma_{\mathcal{R}_0}^{\beta_{DD}} = \frac{\partial \mathcal{R}_0}{\partial \beta_{DD}} \frac{\beta_{DD}}{\mathcal{R}_0} = 1,$$

$$\Gamma_{\mathcal{R}_0}^{A_D} = \frac{\partial \mathcal{R}_0}{\partial A_D} \frac{A_D}{\mathcal{R}_0} = 1,$$

$$\Gamma_{\mathcal{R}_0}^{\mu_D} = \frac{\partial \mathcal{R}_0}{\partial \mu_D} \frac{\mu_D}{\mathcal{R}_0} = \frac{-\mu_D}{(m_D + \mu_D)} = -0.95,$$

$$\begin{aligned} \Gamma_{\mathcal{R}_0}^{\delta\epsilon_D} &= \frac{\partial \mathcal{R}_0}{\partial \delta\epsilon_D} \frac{\delta\epsilon_D}{\mathcal{R}_0} \\ &= \frac{\delta\epsilon_D}{((1 - \rho_D) \delta\gamma_D - \delta\epsilon_D - C_D - m_D - \rho_D)} \\ &= -1.61, \end{aligned}$$

$$\begin{aligned} \Gamma_{\mathcal{R}_0}^{C_D} &= \frac{\partial \mathcal{R}_0}{\partial C_D} \frac{C_D}{\mathcal{R}_0} \\ &= \frac{C_D}{((1 - \rho_D) \delta\gamma_D - \delta\epsilon_D - C_D - m_D - \rho_D)} \\ &= -0.45, \end{aligned}$$

$$\Gamma_{\mathcal{R}_0}^{\alpha_D} = \frac{\partial \mathcal{R}_0}{\partial \alpha_D} \frac{\alpha_D}{\mathcal{R}_0} = 0.28,$$

$$\Gamma_{\mathcal{R}_0}^{m_D} = \frac{\partial \mathcal{R}_0}{\partial m_D} \frac{m_D}{\mathcal{R}_0} = -1.64,$$

$$\Gamma_{\mathcal{R}_0}^{\delta\gamma_D} = \frac{\partial \mathcal{R}_0}{\partial \delta\gamma_D} \frac{\delta\gamma_D}{\mathcal{R}_0} = 1.33,$$

$$\Gamma_{\mathcal{R}_0}^{\rho_D} = \frac{\partial \mathcal{R}_0}{\partial \rho_D} \frac{\rho_D}{\mathcal{R}_0} = -0.5,$$

$$\Gamma_{\mathcal{R}_0}^{\nu_D} = \frac{\partial \mathcal{R}_0}{\partial \nu_D} \frac{\nu_D}{\mathcal{R}_0} = -0.52.$$

(50)

Therefore, from Table 2 it shows that an addition or a reduction in the values of  $\beta_{DD}$ ,  $\alpha_D$ ,  $\delta\gamma_D$ , and  $A_D$  will have an increase or a decrease in the spread of the rabies virus. For

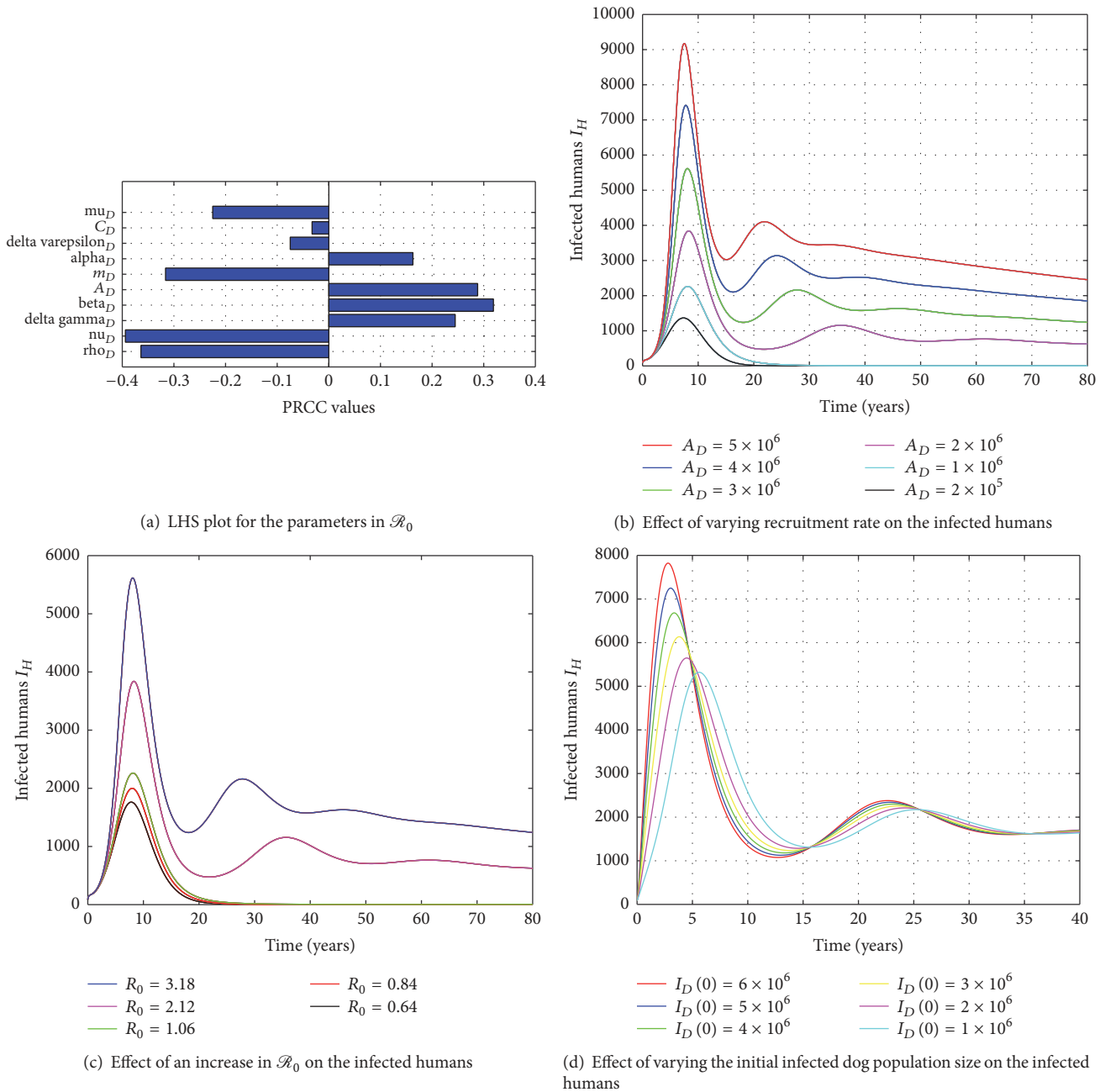


FIGURE 2: The graphical representation of some parameters in  $\mathcal{R}_0$  and the effect of varying some initial state values on the model.

example,  $\Gamma_{\mathcal{R}_0}^{\beta_D} = 1$  indicates that increasing or reducing the transmission rate by 5% may increase or reduce the number of secondary infection by 5%. The negative sign in Table 2 will have a reduction in the basic reproduction number,  $\mathcal{R}_0$ , when the values of those parameters are increased, and a reduction in the values of  $\rho_D$ ,  $\nu_D$ ,  $\mu_D$ ,  $m_D$ , and  $\delta\varepsilon_D$  will lead to an increase in the number of secondary infections.

The Latin hypercube sampling (LHS) in Figure 2(a) shows that  $\mu_D$ ,  $C_D$ ,  $\alpha_D$ , and  $\delta\gamma_D$  have a minimal influence on the rate at which the rabies virus is spread. The Latin hypercube sampling (LHS) plots for the ten parameters in  $\mathcal{R}_0$  show that culling of exposed dogs does not actually minimize the spread

of rabies as compared to vaccination of susceptible dogs. Figure 2(a) also shows that the most influential parameter in spreading the infection is  $\beta_{DD}$  followed by  $A_D$ . Figure 2(c) shows that an increase in the basic reproduction number will contribute to a high level of secondary infection in the human population. Similarly, Figure 2(a) shows that vaccination of dogs  $\nu_D$  is the most effective way of controlling the rabies virus in the dog population as compared to the treatment/quarantine of exposed dogs,  $\rho_D$ . Figure 3(a) gives the contour nature of  $\nu_D$  and  $\rho_D$ , which shows a more saturated effect on the basic reproduction number. Figure 3(b) shows that  $\beta_{DD}$  and  $\alpha_D$  have a positive relation with the basic

TABLE 2: Sensitivity signs of  $\mathcal{R}_0$  to the parameters in (24).

Parameter	Description	Sensitivity sign
$\beta_{DD}$	Transmission rate of dogs	+ve
$A_D$	Recruitment rate of dogs	+ve
$\mu_D$	Disease induce death rate of dogs	-ve
$\delta\varepsilon_D$	Rate of no clinical rabies	-ve
$C_D$	Culling of exposed dogs	-ve
$\alpha_D$	Loss of immunity in dogs	+ve
$m_D$	Natural death rate of dogs	-ve
$\delta\gamma_D$	Rate at which exposed dogs become infective (infective rate)	+ve
$\rho_D$	Postexposure prophylaxis (treatment/quarantined)	-ve
$\nu_D$	Preexposure prophylaxis (vaccination)	-ve

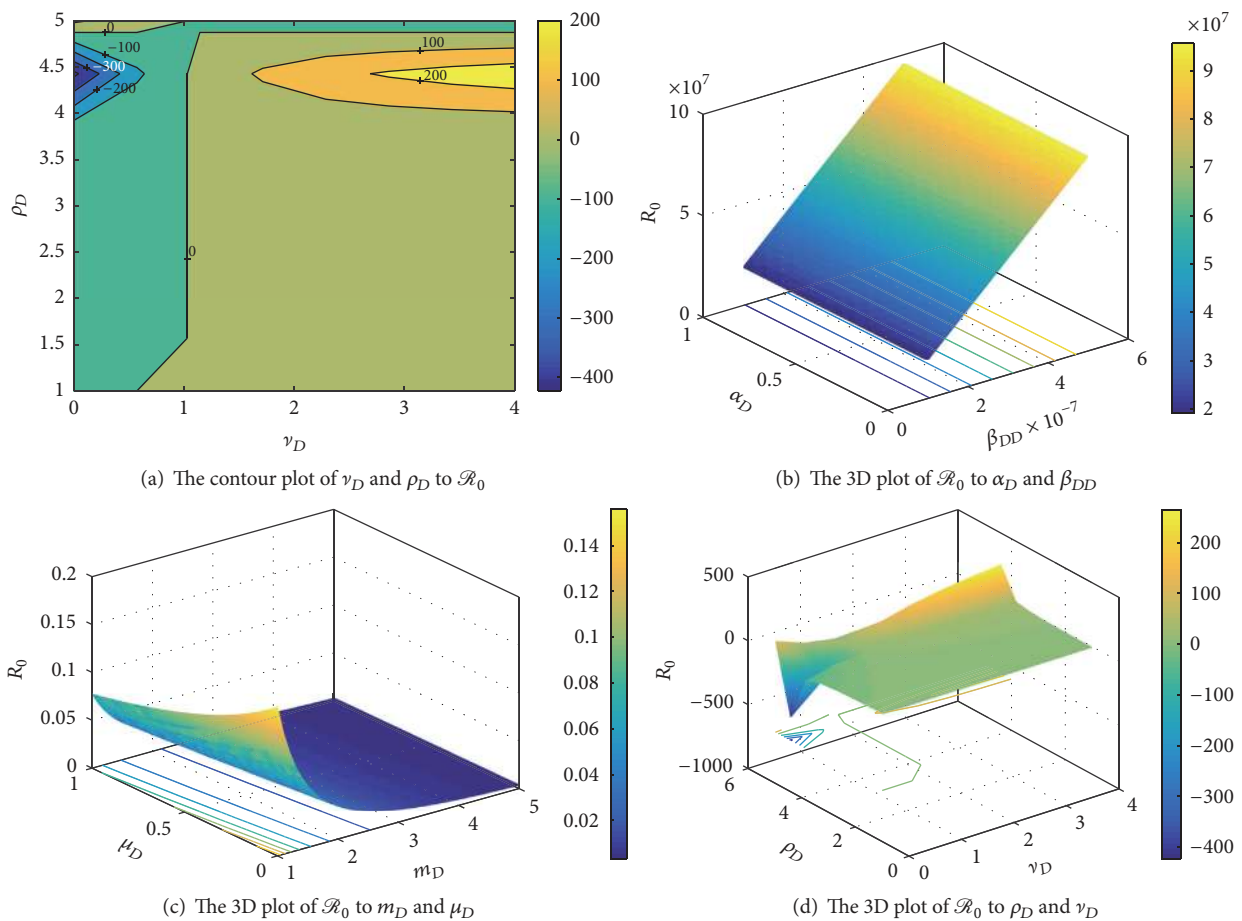


FIGURE 3: The graphical representation of some parameters in  $\mathcal{R}_0$ .

reproduction number  $\mathcal{R}_0$ . Therefore, an increase in  $\beta_{DD}$  and  $\alpha_D$  will have a direct increase in the spread of the rabies virus. Figure 2(b) indicates that with a high number of recruitment of dogs into the susceptible dog's compartment will have a corresponding high increase in the number of infected humans. Figure 2(d) demonstrates that a high number of infected dogs in the compartment will lead to an increase

in the number of infected humans. Figure 3(c) shows that a high increase in the number of disease induce death rate and natural death rate will have a negative reflection on  $\mathcal{R}_0$ ; biologically, we would not recommend this approach in minimizing the spread of the disease, since an increase in both  $\mu_D$  and  $m_D$  may result in a high rate of the disease in the human population, even though  $\mu_D$  and  $m_D$  naturally

reduce the number of susceptible and infected dogs in the population. Finally, Figure 3(d) shows the 3D plot of Figure 3(a).

### 5. Objective Functional

Given that  $y(t) \in Y \in \mathbb{R}^n$  is a state variable of model system (1) and  $u(t) \in U \in \mathbb{R}^n$  are the control variables at any time ( $t$ ) with  $t_{(0)} \leq t \leq t_{(f)}$ , then an optimal control problem consists of finding a piecewise continuous control  $u(t)$  and its corresponding state  $y(t)$ . This optimizes the cost functional  $J[y(t), u(t)]$  using Pontryagin's maximum principle [43]. Therefore we set the following likelihood control strategies:

- (1)  $u_1 = \nu_D$  is the control effort aimed at increasing the immunity of susceptible dogs (preexposed prophylaxis).
- (2)  $u_2 = \rho_D$  is the control effort aimed at treating the exposed dogs (postexposed prophylaxis).
- (3)  $u_3 = \nu_H$  is the control effort aimed at increasing the immunity of susceptible humans (preexposure prophylaxis).
- (4)  $u_4 = \rho_H$  is the control effort aimed at treating the exposed humans (postexposed prophylaxis).

Our goal is to seek optimal controls such as  $\nu_D^*$ ,  $\rho_D^*$ ,  $\nu_H^*$ , and  $\rho_H^*$  that minimize the objective functional:

$$J = \min \int_{t_0}^{t_f} \left[ A_1 E_D + A_2 E_H + A_3 I_D + A_4 I_H + \frac{B1}{2} \nu_D^2 + \frac{B2}{2} \rho_D^2 + \frac{B3}{2} \nu_H^2 + \frac{B4}{2} \rho_H^2 \right] dt. \tag{51}$$

Therefore, (51) is subject to

$$\begin{aligned} \frac{dS_d}{dt} &= A_D - (1 - \nu_D) \beta_{DD} S_D I_D - (m_D + \nu_D) S_D + \delta \epsilon_D E_D + \alpha_D R_D, \\ \frac{dE_d}{dt} &= (1 - \nu_D) \beta_{DD} S_D I_D - ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \epsilon_D + C_D) E_D, \\ \frac{dI_D}{dt} &= (1 - \rho_D) \delta \gamma_D E_D - (m_D + \mu_D) I_D, \\ \frac{dR_D}{dt} &= \nu_D S_D + \rho_D E_D - (m_D + \alpha_D) R_D, \\ \frac{dS_H}{dt} &= B_H - (1 - \nu_H) \beta_{DH} S_H I_d - (m_H + \nu_H) S_H + \delta_H \epsilon_H E_H + \alpha_H R_H, \\ \frac{dE_H}{dt} &= (1 - \nu_H) \beta_{DH} S_H I_d - ((1 - \rho_H) \delta_H \gamma_H + m_H + \rho_H + \delta_H \epsilon_H) E_H, \\ \frac{dI_H}{dt} &= (1 - \rho_H) \delta_H \gamma_H E_H - (m_H + \mu_H) I_H, \\ \frac{dR_H}{dt} &= \nu_H S_H + \rho_H E_H - (m_H + \alpha_H) R_H, \end{aligned} \tag{52}$$

$$S_D > 0, E_D \geq 0, I_D \geq 0, R_D \geq 0, S_H > 0, E_H \geq 0, I_H \geq 0, R_H \geq 0.$$

From (51) the quantities  $A_1$  and  $A_2$  denote the weight constants of the exposed classes and  $A_3$  and  $A_4$  are the weight of the infectious classes, respectively.  $B1, B2, B3, B4$  are the weight constants for the dog and human controls.  $B1\nu_D^2, B2\rho_D^2, B3\nu_H^2, B4\rho_H^2$  describe the cost associated with rabies vaccination and treatment. The square of the control variables shows the severity of the side effects of the vaccination and treatment. Employing Pontryagin's maximum principle, we form the Hamiltonian equation with state variables  $S_D = S_D^*$ ,

$E_D = E_D^*, I_D = I_D^*, R_D^*$  and  $S_H = S_H^*, E_H = E_H^*, I_H = I_H^*, R_H^*$  as

$$\begin{aligned} H &= A_1 E_D^* + A_2 E_H^* + A_3 I_D^* + A_4 I_H^* + \frac{B1}{2} \nu_D^2 + \frac{B2}{2} \\ &\cdot \rho_D^2 + \frac{B3}{2} \nu_H^2 + \frac{B4}{2} \rho_H^2 + \lambda_1 [A_D \\ &- (1 - \nu_D) \beta_{DD} S_D^* I_D^* - (m_D + \nu_D) S_D^* + \delta \epsilon E_D^* \end{aligned}$$

$$\begin{aligned}
 & + \alpha_D R_D^*] + \lambda_2 [(1 - \nu_D) \beta_{DD} S_D^* I_D^* \\
 & - ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) E_D^*] \\
 & + \lambda_3 [(1 - \rho_D) \delta \gamma_D E_D^* - (m_D + \mu_D) I_D^*] \\
 & + \lambda_4 [\nu_D S_D^* + \rho_D E_D^* - (m_D + \alpha_D) R_D^*] + \lambda_5 [B_H \\
 & - (1 - \nu_H) \beta_{DH} S_H^* I_D^* - (m_H + \nu_H) S_H^* + \delta_H \varepsilon_H E_H^* \\
 & + \alpha_H R_H^*] + \lambda_6 [(1 - \nu_H) \beta_{DH} S_H^* I_D^* \\
 & - ((1 - \rho_H) \delta_H \gamma_H + m_H + \rho_H + \delta_H \varepsilon_H) E_H^*] \\
 & + \lambda_7 [(1 - \rho_H) \delta_H \gamma_H E_H^* - (m_H + \mu_H) I_H^*] \\
 & + \lambda_8 [\nu_H S_H^* + \rho_H E_H^* - (m_H + \alpha_H) R_H^*].
 \end{aligned} \tag{53}$$

Considering the existence of adjoint functions  $\lambda_i, i = 1, 2, \dots, 8$ , satisfying

$$\begin{aligned}
 \frac{d\lambda_1}{dt} &= -\frac{\partial H}{\partial S_D^*} \\
 &= \lambda_1 ((1 - \nu_D) \beta_{DD} I_D^* + m_D + \nu_D) \\
 &\quad - \lambda_2 (1 - \nu_D) \beta_{DD} I_D^* - \lambda_4 \nu_D, \\
 \frac{d\lambda_2}{dt} &= -\frac{\partial H}{\partial E_D^*} \\
 &= \lambda_2 ((1 - \rho_D) \delta \gamma_D + m_D + \rho_D + \delta \varepsilon_D + C_D) \\
 &\quad - \lambda_1 \delta \varepsilon_D - \lambda_3 (1 - \rho_D) \delta \gamma_D - \lambda_4 \rho_D - A_1, \\
 \frac{d\lambda_3}{dt} &= -\frac{\partial H}{\partial I_D^*} \\
 &= \lambda_3 (m_D + \mu_D) + \lambda_1 (1 - \nu_D) \beta_{DD} S_D^* \\
 &\quad + \lambda_5 (1 - \nu_H) \beta_{DH} S_H^* - \lambda_2 (1 - \nu_D) \beta_{DD} S_D^* \\
 &\quad - \lambda_6 (1 - \nu_H) \beta_{DH} S_H^* - A_3, \\
 \frac{d\lambda_4}{dt} &= -\frac{\partial H}{\partial R_D^*} = \lambda_4 (m_D + \alpha_D) - \lambda_1 \alpha_D, \\
 \frac{d\lambda_5}{dt} &= -\frac{\partial H}{\partial S_H^*} \\
 &= \lambda_5 ((1 - \nu_H) \beta_{dH} I_D^* + m_H + \nu_H) \\
 &\quad - \lambda_6 (1 - \nu_H) \beta_{DH} I_D^* - \lambda_8 \nu_H, \\
 \frac{d\lambda_6}{dt} &= -\frac{\partial H}{\partial E_H^*} \\
 &= \lambda_6 ((1 - \rho_H) \delta_H \gamma_H + m_H + \rho_H + \delta_H \varepsilon_H) \\
 &\quad - \lambda_5 \delta_H \varepsilon_H - \lambda_7 (1 - \rho_H) \delta_H \gamma_H - \lambda_8 \rho_H - A_2,
 \end{aligned}$$

$$\begin{aligned}
 \frac{d\lambda_7}{dt} &= -\frac{\partial H}{\partial I_H^*} = \lambda_7 (m_H + \mu_H) - A_4, \\
 \frac{d\lambda_8}{dt} &= -\frac{\partial H}{\partial R_H^*} = \lambda_8 (m_H + \alpha_H) - \lambda_5 \alpha_H,
 \end{aligned} \tag{54}$$

with transversality condition  $\lambda_i(t_f) = 0$  for  $i = 1, \dots, 8$  for the control set  $u_i$ , hence we have

$$\begin{aligned}
 \frac{\partial H}{\partial u_i} &= 0, \quad \text{where } i = 1, 2, 3, 4, \\
 \frac{\partial H}{\partial \nu_D} \Big|_{\nu_D = \nu_D^*} &:= B1 \nu_D^* - \lambda_1 S_D^* + \lambda_4 S_D^* + \lambda_1 \beta_{DD} S_D^* I_D^* \\
 &\quad - \lambda_2 \beta_{DD} S_D^* I_D^* = 0, \\
 \nu_D^* &= \frac{(\lambda_1 S_D^* - \lambda_4 S_D^*) + (\lambda_2 - \lambda_1) \beta_{DD} I_D^* S_D^*}{B1}, \\
 \frac{\partial H}{\partial \rho_D} \Big|_{\rho_D = \rho_D^*} &:= B2 \rho_D^* - \lambda_1 E_D^* + \lambda_4 E_D^* + \lambda_2 E_D \delta \gamma_D E_D^* \\
 &\quad - \lambda_3 \delta \gamma_D E_D^* = 0, \\
 \rho_D^* &= \frac{(\lambda_2 E_D^* - \lambda_4 E_D^*) + (\lambda_3 - \lambda_2) \delta \gamma_D E_D^*}{B2}, \tag{55} \\
 \frac{\partial H}{\partial \nu_H} \Big|_{\nu_H = \nu_H^*} &:= B3 \nu_H^* - \lambda_5 S_H + \lambda_8 S_H + \lambda_5 \beta_{DH} S_H I_D \\
 &\quad - \lambda_6 \beta_{DH} S_H^* I_D^* = 0, \\
 \nu_H^* &= \frac{(\lambda_5 S_H^* - \lambda_8 S_H^*) + (\lambda_6 - \lambda_5) \beta_{DH} S_H^* I_D^*}{B3}, \\
 \frac{\partial H}{\partial \rho_H} \Big|_{\rho_H = \rho_H^*} &:= B4 \rho^* - \lambda_6 E_H^* + \lambda_8 E_H^* + \lambda_6 \delta_H \gamma_H E_H^* \\
 &\quad - \lambda_7 \delta_H \gamma_H E_H^* = 0, \\
 \rho_H^* &= \frac{(\lambda_6 E_H^* - \lambda_8 E_H^*) + (\lambda_7 - \lambda_6) \delta_H \gamma_H E_H^*}{B4}.
 \end{aligned}$$

Now, using an appropriate variation argument and taking the bounds into account, the optimal control strategies are given as

$$\nu_D^* = \min \left\{ \max \left( 0, \frac{(\lambda_1 - \lambda_4) S_D^* + (\lambda_2 - \lambda_1) \beta_{DD} I_D^* S_D^*}{B1} \right), \nu_{D\max} \right\}, \tag{56}$$

$$\rho_D^* = \min \left\{ \max \left( 0, \frac{(\lambda_2 - \lambda_4) E_D^* + (\lambda_3 - \lambda_2) \delta \gamma_D E_D^*}{B2} \right), \rho_{D\max} \right\}, \tag{57}$$



$$v_H^* = \min \left\{ \max \left( 0, \frac{(\lambda_5 - \lambda_8) S_H^* + (\lambda_6 - \lambda_5) \beta_{DH} S_H^* I_D^*}{B3} \right), \right. \\ \left. v_{Hmax} \right\}, \tag{58}$$

$$\rho_H^* = \min \left\{ \max \left( 0, \frac{(\lambda_6 - \lambda_8) E_H^* + (\lambda_7 - \lambda_6) \delta_H \gamma_H E_H^*}{B4} \right), \right. \\ \left. \rho_{Hmax} \right\}. \tag{59}$$

*Optimality System.* Substituting the representation of the optimal vaccination and treatment control with corresponding adjoint function, we have the optimality system as

$$\frac{dS_D}{dt} = A_D - \left( 1 - \min \left\{ \max \left( 0, \right. \right. \right. \\ \left. \left. \frac{(\lambda_1 - \lambda_4) S_D^* + (\lambda_2 - \lambda_1) \beta_{DD} I_D^* S_D^*}{B1} \right), v_{Dmax} \right\} \right) \\ \cdot \beta_{DD} S_D I_D - m_D S_D - \min \left\{ \max \left( 0, \right. \right. \\ \left. \left. \frac{(\lambda_1 - \lambda_4) S_D^* + (\lambda_2 - \lambda_1) \beta_{DD} I_D^* S_D^*}{B1} \right), v_{Dmax} \right\} S_D \\ + \delta \varepsilon_D E_D + \alpha_D R_D,$$

$$\frac{dE_D}{dt} = \left( 1 - \min \left\{ \max \left( 0, \right. \right. \right. \\ \left. \left. \frac{(\lambda_1 - \lambda_4) S_D^* + (\lambda_2 - \lambda_1) \beta_{DD} I_D^* S_D^*}{B1} \right), v_{Dmax} \right\} \right) \\ \cdot \beta_{DD} S_D I_D - \left( \left( 1 \right. \right. \\ \left. \left. - \min \left\{ \max \left( 0, \frac{(\lambda_2 - \lambda_4) E_D^* + (\lambda_3 - \lambda_2) \delta \gamma_D E_D^*}{B2} \right), \right. \right. \right. \\ \left. \left. \rho_{max} \right\} \right) \delta \gamma_D + m_D + \delta \varepsilon_D + C_D \right) E_D - \min \left\{ \max \left( 0, \right. \right. \\ \left. \left. \frac{(\lambda_2 - \lambda_4) E_D^* + (\lambda_3 - \lambda_2) \delta \gamma_D E_D^*}{B2} \right), \rho_{Dmax} \right\} E_D,$$

$$\frac{dI_D}{dt} = \delta \gamma_D E_D - (m_D + \mu_D) I_D,$$

$$\frac{dR_D}{dt} = \min \left\{ \max \left( 0, \right. \right. \\ \left. \left. \frac{(\lambda_1 - \lambda_4) S_D^* + (\lambda_2 - \lambda_1) \beta_{DD} I_D^* S_D^*}{B1} \right), v_{Dmax} \right\} S_D \\ - (m_D + \alpha_D) R_D + \min \left\{ \max \left( 0, \right. \right. \\ \left. \left. \frac{(\lambda_2 - \lambda_4) E_D^* + (\lambda_3 - \lambda_2) \delta \gamma_D E_D^*}{B2} \right), \rho_{Dmax} \right\} E_D,$$

$$\frac{dS_H}{dt} = B_H - \left( 1 - \min \left\{ \max \left( 0, \right. \right. \right. \\ \left. \left. \frac{(\lambda_5 - \lambda_8) S_H^* + (\lambda_6 - \lambda_5) \beta_{DH} S_H^* I_D^*}{B3} \right), v_{Hmax} \right\} \right)$$

$$\cdot \beta_{DH} S_H I_D - m_H S_H - \min \left\{ \max \left( 0, \right. \right. \\ \left. \left. \frac{(\lambda_5 - \lambda_8) S_H^* + (\lambda_6 - \lambda_5) \beta_{DH} S_H^* I_D^*}{B3} \right), v_{Hmax} \right\} S_H \\ + \delta_H \varepsilon_H E_H + \alpha_H R_H,$$

$$\frac{dE_H}{dt} = \left( 1 - \min \left\{ \max \left( 0, \right. \right. \right. \\ \left. \left. \frac{(\lambda_6 - \lambda_8) E_H^* + (\lambda_7 - \lambda_6) \delta_H \gamma_H E_H^*}{B4} \right), \rho_{Hmax} \right\} \right) \\ \cdot \beta_{DH} S_H I_D - (\delta_H \gamma_H + m_H + \delta_H \varepsilon_H) E_H \\ - \min \left\{ \max \left( 0, \right. \right. \\ \left. \left. \frac{(\lambda_6 - \lambda_8) E_H^* + (\lambda_7 - \lambda_6) \delta_H \gamma_H E_H^*}{B4} \right), \rho_{Hmax} \right\} E_H,$$

$$\frac{dI_H}{dt} = \delta_H \gamma_H E_H - (m_H + \mu_H) I_H,$$

$$\frac{dR_H}{dt} = \min \left\{ \max \left( 0, \right. \right. \\ \left. \left. \frac{(\lambda_5 - \lambda_8) S_H^* + (\lambda_6 - \lambda_5) \beta_{DH} S_H^* I_D^*}{B3} \right), v_{Hmax} \right\} S_H \\ - (m_H + \alpha_H) R_H + \min \left\{ \max \left( 0, \right. \right. \\ \left. \left. \frac{(\lambda_6 - \lambda_8) E_H^* + (\lambda_7 - \lambda_6) \delta_H \gamma_H E_H^*}{B4} \right), \rho_{Hmax} \right\} E_H,$$

$$\frac{d\lambda_1}{dt}, \frac{d\lambda_2}{dt}, \frac{d\lambda_3}{dt}, \frac{d\lambda_4}{dt}, \frac{d\lambda_5}{dt}, \frac{d\lambda_6}{dt}, \frac{d\lambda_7}{dt}, \frac{d\lambda_8}{dt},$$

with,  $\lambda_i(t_f) = 0, i = 1, 2, 3, 4, 5, 6, 7, 8.$

(60)

*5.1. Numerical Simulations of the Optimality System.* To determine the control strategies  $v_D, \rho_D, v_H,$  and  $\rho_H,$  as given in the objective functional, we began an iteration of the model until convergence is achieved. The results of the simulation of the control strategies are displayed below. We consider equal weights of ( $A_1 = 1, A_2 = 1, A_3 = 1, A_4 = 1$ ) for both exposed and infected classes. We varied the cost associated with the objective functional, which indicate that, with low cost of vaccination, the rate at which individuals will seek for vaccination of their susceptible dogs will increase, and this could result in low transmission of rabies in a heterogeneous population. We consider the various cost of preexposure prophylaxis and postexposure prophylaxis to be ( $B1 = 1,$

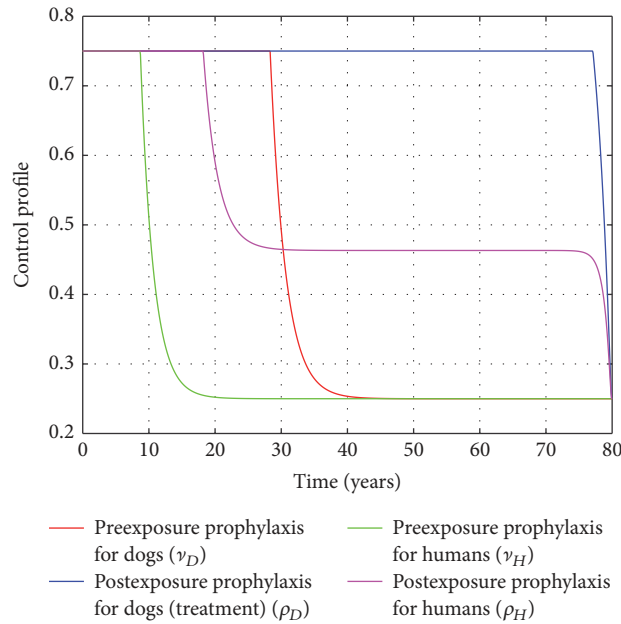


FIGURE 4: The simulation effect of the controls.

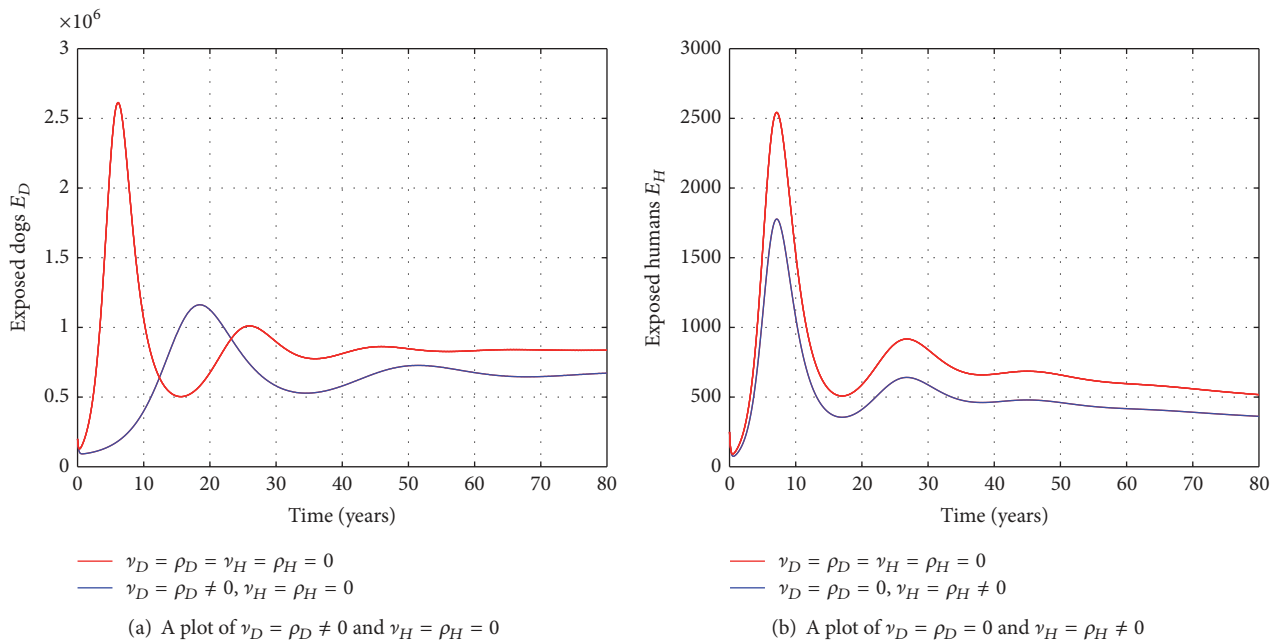


FIGURE 5: The trajectories of the model with and without pre- and postexposure prophylaxis on exposed humans and that of the exposed dogs.

$B_2 = 4, B_3 = 1, B_4 = 4$ ). We found that the optimal time in controlling the infection using preexposure prophylaxis in dogs is much better than using postexposure prophylaxis in dogs, as shown by the trajectories of the red line and blue line in Figure 4, respectively. The blue line in Figure 4 indicates that applying postexposure prophylaxis will considerably take a longer time in controlling of rabies in dogs. The green line in Figure 4 signifies that preexposure prophylaxis in humans

increases the immunity levels of humans and hence reduces the rate at which individuals move to the infected stage. Figures 5 and 6 show the effect of using only one control strategy on the model. Therefore, Figure 5(a) shows that applying only postexposure prophylaxis (treatment or quarantine) of dogs has a low positive impact on the model. Figure 5(b) shows that sticking to the use of pre- and postexposure prophylaxis in human without administering pre- and postexposure

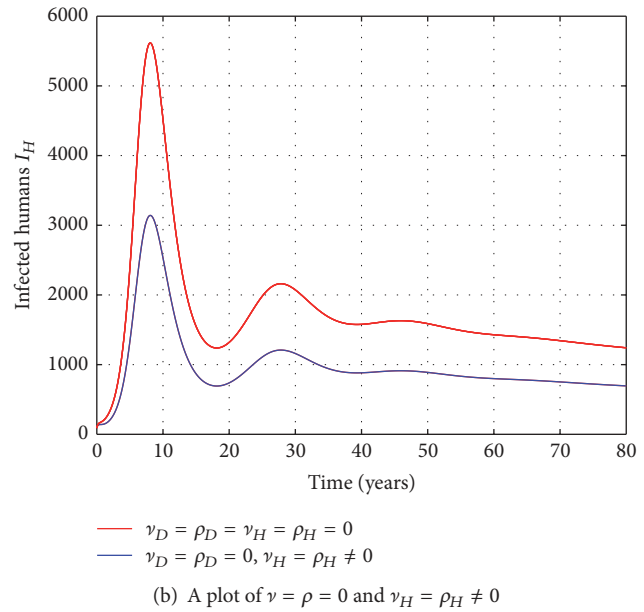
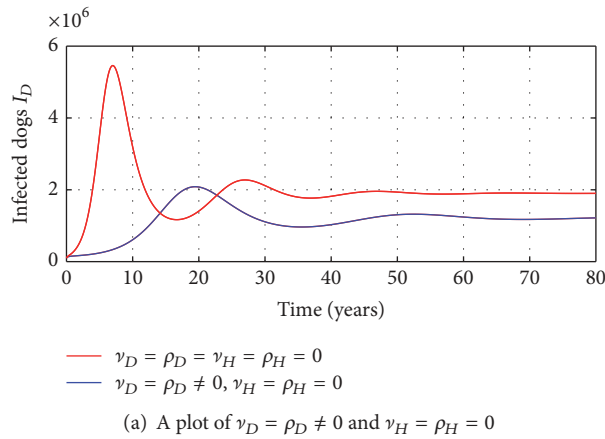


FIGURE 6: The trajectories of the model with and without pre- and postexposure prophylaxis on infected humans and that of the infected dogs.

prophylaxis in the dog population will result in a high of the rabies infection in the human population. Figure 6(a) also shows that combining pre- and postexposure prophylaxis (vaccination and treatment/quarantine) in the dog compartment will reduce the spread of the rabies virus, thereby reducing the using of pre- and postexposure prophylaxis (vaccination and treatment) in humans. Figure 6(b) indicates that a rapid use of pre- and postexposure prophylaxis in the human population will reduce the number of rabies deaths in the human population. Figure 7 shows the simulation effects of applying both controls on the model. Figure 7(a) shows that, with the use of the optimal control strategies, the rate of the infection in the susceptible dogs will reduce significantly. Figures 7(b) and 7(c) show that there is a proportional decrease in the number of exposed and infected dogs when the control measures are applied. Similarly, Figures 7(e) and 7(f) show a significant decrease in the number of infected and exposed humans when the control measures are applied. Figure 7(d) shows that there is a proportional increase in the number of recovered dogs when the control measures are applied. Finally, Figures 8(a)–8(h) show the simulation effect of corresponding adjoint functions.

### 6. Discussion

The numerical simulations of the resulting optimality system show that, during the case where it is more expensive to vaccinate than treatment, more resources should be invested in treating affected individuals until the disease prevalence begins to fall. This option, however, does not reduce the number of individuals expose to the disease quickly enough, thus resulting in an overall increase in the infected human population. On the other hand, if it is more expensive to

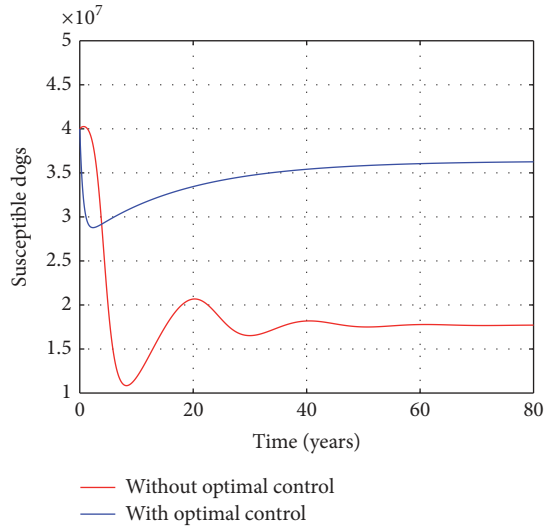
treat than to vaccinate, then more susceptible dogs should be vaccinated, so as to lower the rate at which newborn dogs get infected. Nevertheless, in the case where both measures are equally expensive, the simulation shows that the optimal way to drive the epidemic towards eradication within any specified period is to use more preexposure prophylaxis in both compartments.

### 7. Conclusion

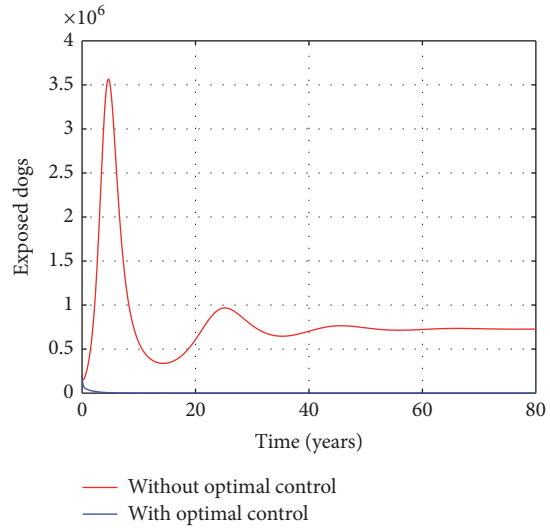
We studied an optimal control model of rabies transmission dynamics in dogs and the best way of reducing death rate of rabies in humans. The stability analysis shows that the disease-free equilibrium is locally and globally asymptotically stable. We also obtained an optimal control solution for the model which predicts that the optimal way of eliminating deaths from canine rabies as projected by the global alliance for rabies control [30] is using more of preexposure prophylaxis in both dogs and humans and public education; however, the results show that the effective and optimal consideration of preexposure prophylaxis and postexposure prophylaxis in humans without an optimal use of vaccination in the dog population is not beneficial if total elimination of the disease is desirable in Africa and Asia. Any combination strategy which involves vaccination in the dogs' population gives a better result and hence it may be beneficial in eliminating the disease in Asia, Africa, and Latin America.

### Disclosure

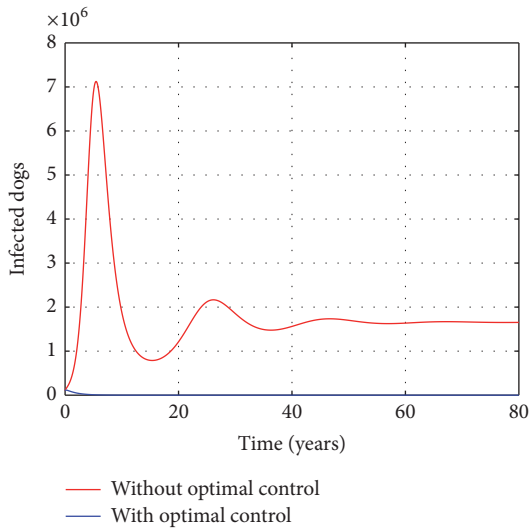
The authors fully acknowledge that this paper was developed as a result of the first author's thesis work submitted to the Department of Mathematics, Kwame Nkrumah University of



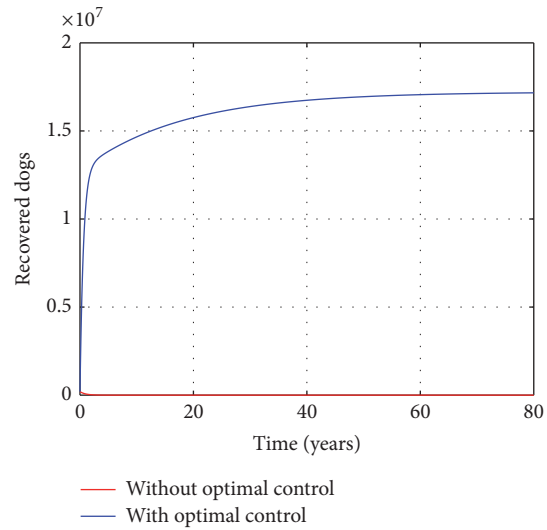
(a) Susceptible dogs with and without control



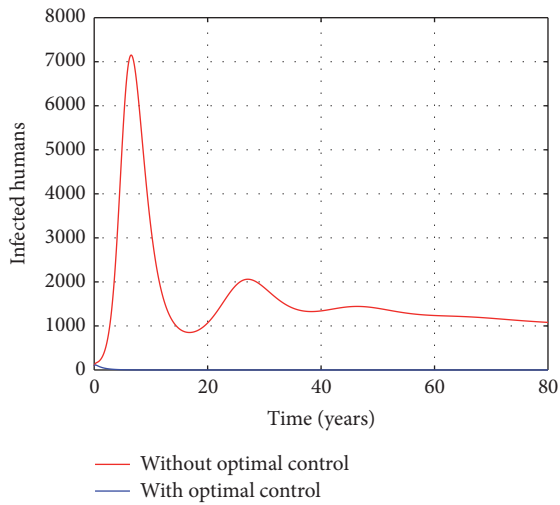
(b) Exposed dogs with and without control



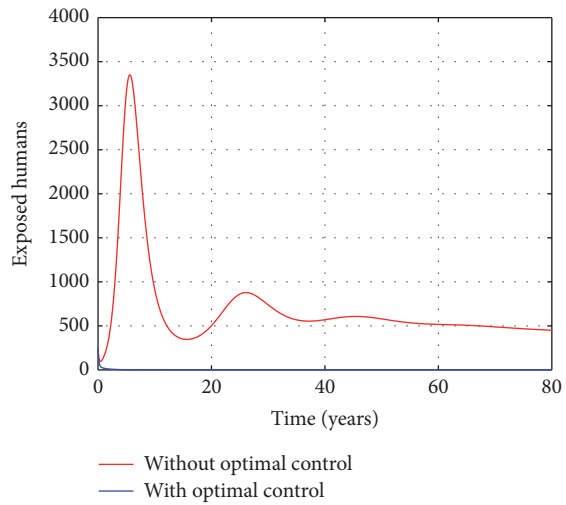
(c) Infected dogs with and without control



(d) Recovered dogs with and without control

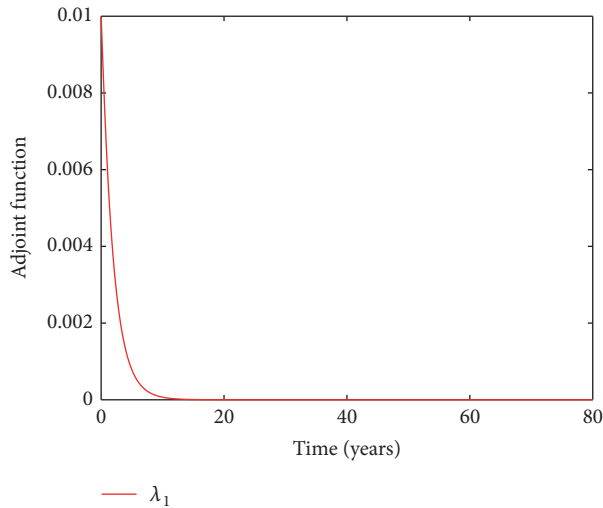


(e) Infected humans with and without control

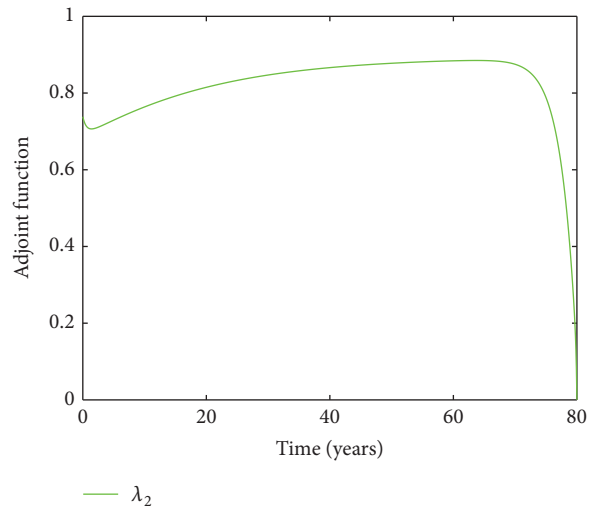


(f) Exposed humans with and without control

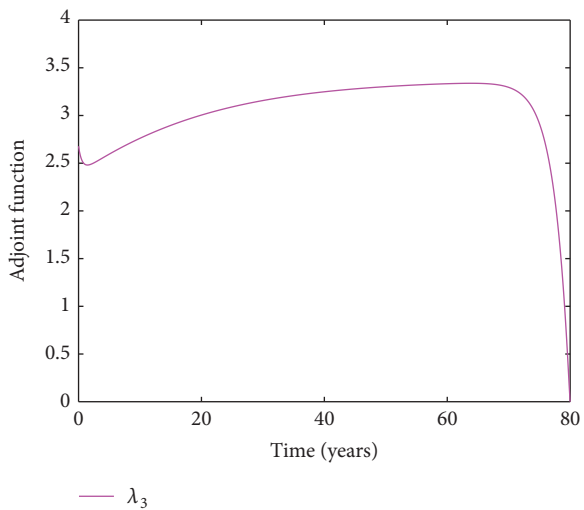
FIGURE 7: The trajectories of the model with and without optimal control on individual compartments.



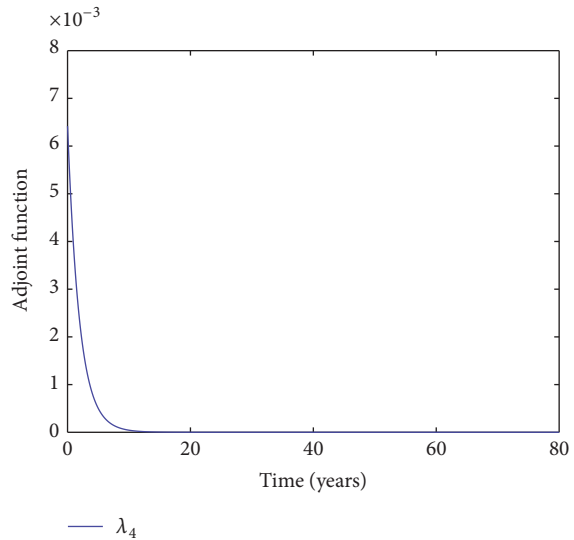
(a) The cost function  $\lambda_1$  for  $A_1 = A_2 = A_3 = A_4 = 1$  and  $B1 = 1, B2 = 4, B3 = 1, B4 = 4$



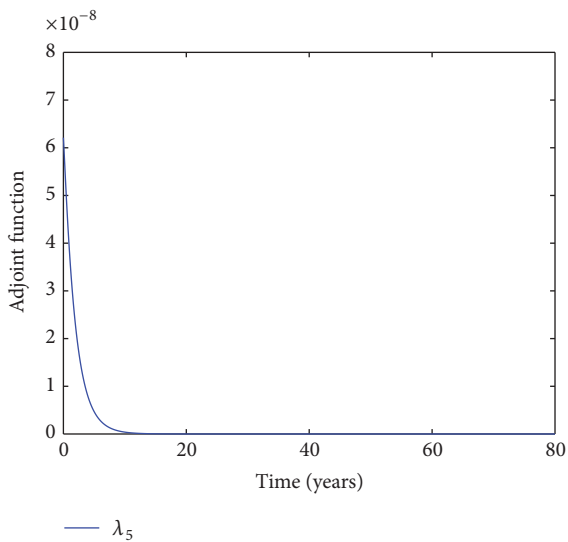
(b) The cost function  $\lambda_2$  for  $A_1 = A_2 = A_3 = A_4 = 1$  and  $B1 = 1, B2 = 4, B3 = 1, B4 = 4$



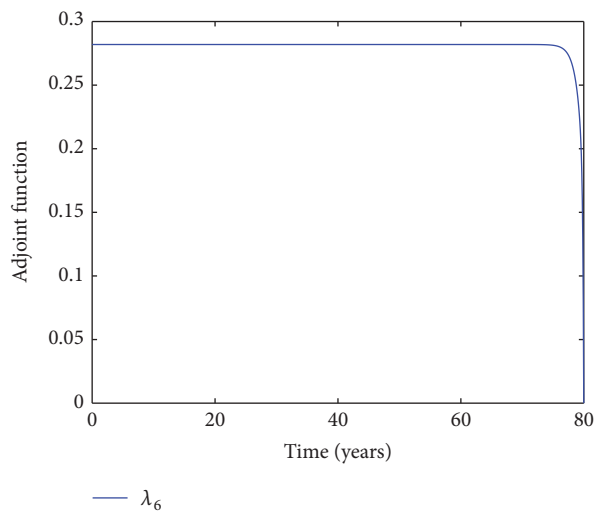
(c) The cost function  $\lambda_3$  for  $A_1 = A_2 = A_3 = A_4 = 1$  and  $B1 = 1, B2 = 4, B3 = 1, B4 = 4$



(d) The cost function  $\lambda_4$  for  $A_1 = A_2 = A_3 = A_4 = 1$  and  $B1 = 1, B2 = 4, B3 = 1, B4 = 4$



(e) The cost function  $\lambda_5$  for  $A_1 = A_2 = A_3 = A_4 = 1$  and  $B1 = 1, B2 = 4, B3 = 1, B4 = 4$



(f) The cost function  $\lambda_6$  for  $A_1 = A_2 = A_3 = A_4 = 1$  and  $B1 = 1, B2 = 4, B3 = 1, B4 = 4$

FIGURE 8: Continued.

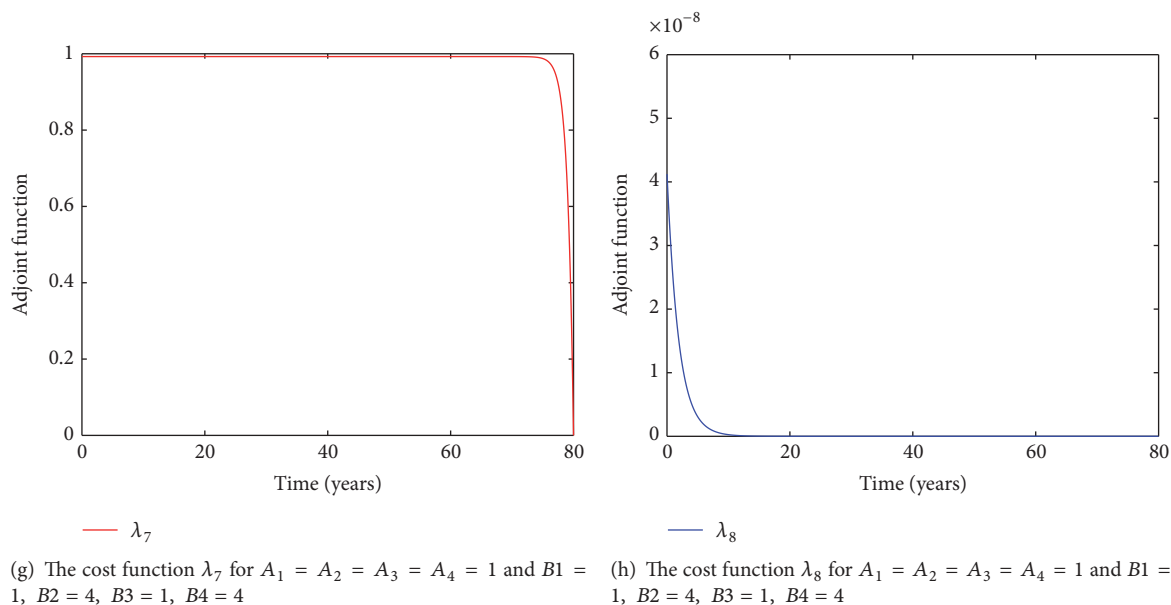


FIGURE 8: The trajectories of the model with and without optimal control on individual compartments and corresponding adjoint function.

Science and Technology (see <http://ir.knust.edu.gh/xmlui/handle/123456789/10053>).

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

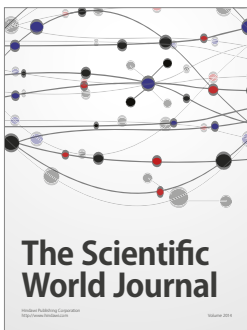
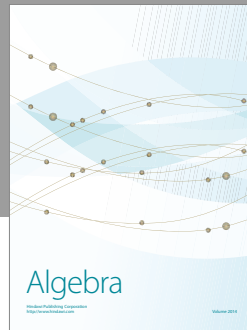
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