

# A Humble offering



# MODELLING AND OPTIMAL CONTROL OF TYPHOID FEVER DISEASE WITH COST-EFFECTIVE STRATEGIES

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# INTRODUCTION

- Typhoid is a bacterial infection.
- It is caused by *Salmonella paratyphi* A,B,C.
- This bacterium is gram negative,rod shaped, flagellated.It's only reservoir is human body.
- It can be transmitted through contaminated food and drinking water
- It can be spread through flies.
- Symptoms are fever,headache,weakness, abdominal pain and diarrhea.
- It can be treated by antibiotics(Ciprofloxacin and ofloxacin) and antipyretic drugs.
- It can be prevented by washing hands,drinking treated water,eating hot food etc.



- A mathematical model is a mathematical framework representing variables and their interrelationships to describe observed phenomena or predict future events.
- They are quick and easy to produce.
- They can simplify a complex situation.
- Mathematical techniques can explain how the world works and make it better.
- Mathematical models can be used to link the biological process.
- They have great benefits for describing the dynamics of the disease.
- They help to take decisions faster and more accurately.
- In this paper the investigation has been done in typhoid fever dynamics with the application of optimal control methods and cost-effectiveness analysis of the applied control strategies.

# MODEL DESCRIPTION AND FORMULATION

- This model considers human population( $N$ ) as well as bacteria population( $B_c$ ).
- The human population at time  $t$  is divided into four subclasses:
- Susceptible( $S$ ):This class includes all individuals who are more likely to catch infection.
- Infected( $I$ ):This class includes all individuals who show symptoms of the infection.
- Carrier( $C$ ):This class includes all who don't show any symptoms but they infect others.
- Recovered( $R$ ):This class includes all who have recovered from disease and got temporary immunity.
- $\Lambda$  is the rate at which susceptible class is increased by birth or emigration.
- The susceptible class is increased from recovered class by losing temporary immunity with  $\delta$  rate.
- The force of infection of the model is  $\lambda = B_c \nu / k + B_c$ .
- $\nu$  is the ingestion rate.

- $K$  is the concentration of salmonella bacteria in foods or waters.
- $B_c/k+B_c$  is the probability of individuals in consuming contaminated food which has bacteria.
- $\rho$  is the rate at which susceptible individuals join carriers.
- $1-\rho$  is the rate at which susceptible individuals join infected.
- The infected subclass is increased from carrier subclass by  $\theta$  rate.
- The infected subclass joins recovered subclass by  $\beta$  rate after getting treatment.
- The individuals in carrier subclass joins recovered subclass by  $\phi$  rate after getting natural immunity.
- $\mu$  is the natural death rate.
- In the infective class  $\alpha$  is the disease causing death rate.
- Carriers and infectives can contribute to increasing the bacteria population. with a discharge rate of  $\sigma_1$  and  $\sigma_2$  respectively.
- $\mu_b$  is the death rate of salmonella bacteria.

# Model Formulation

$$\frac{dS}{dt} = \Lambda + \delta R - (\mu + \lambda)S,$$

$$\frac{dC}{dt} = \rho\lambda S - (\sigma_1 + \theta + \mu + \phi)C,$$

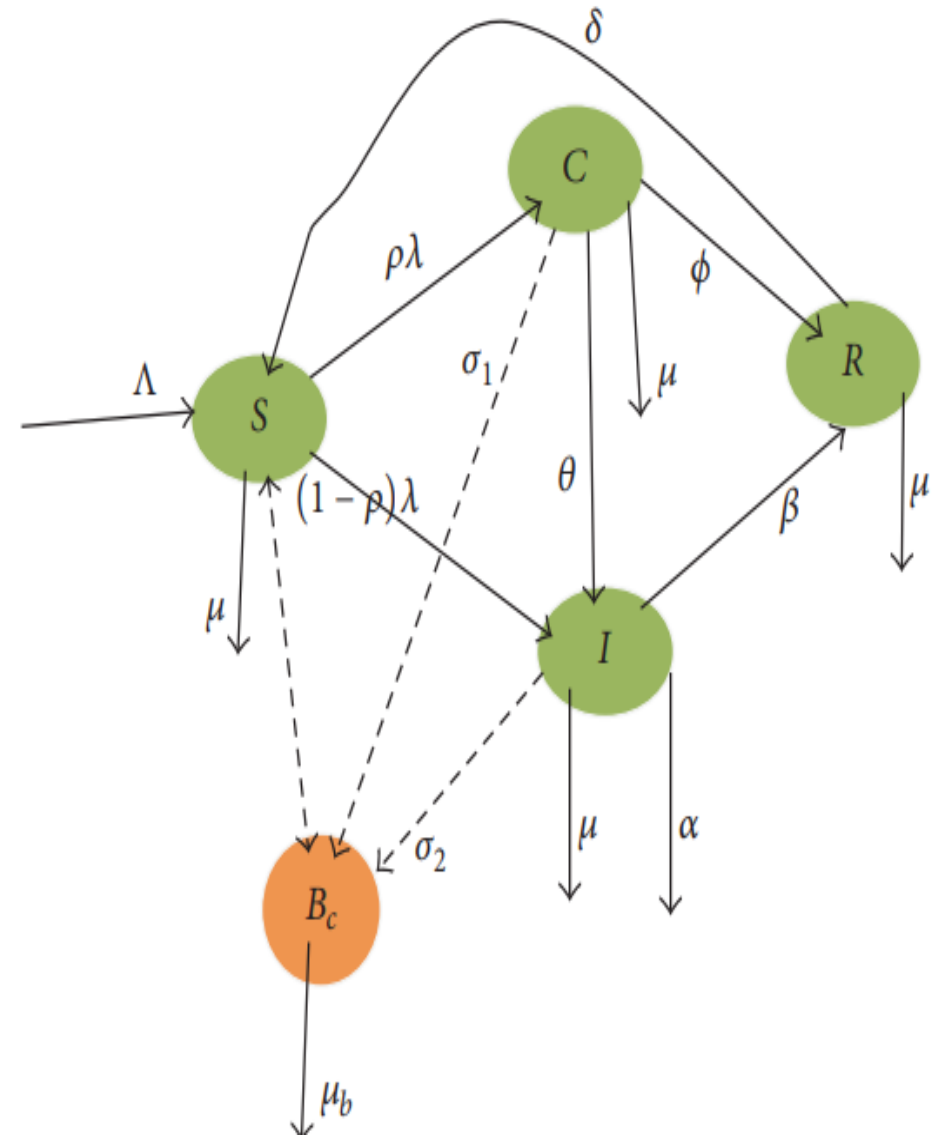
$$\frac{dI}{dt} = (1-\rho)\lambda S + \theta C - (\sigma_2 + \beta + \mu + \alpha)I,$$

$$\frac{dR}{dt} = \beta I + \phi C - (\mu + \delta)R,$$

$$\frac{dB_c}{dt} = \sigma_1 C + \sigma_2 I - \mu_b B_c$$

Where  $\lambda = B_c \nu / k + B_c$ , with initial conditions  $S(0)=S_0, C(0)=C_0, I(0) = I_0, R(0) = R_0$ , and  $B_c(0)=B_{c0}$ .

→ ①





# The Model Analysis

- We obtain the region in which the model solution is bounded.
- Total human population  $(N)=S+C+I+R$ .

differentiating  $N$  on both sides with respect to  $t$

$$\frac{dN}{dt} = \frac{dS}{dt} + \frac{dC}{dt} + \frac{dI}{dt} + \frac{dR}{dt} \rightarrow \textcircled{2}$$

By combining  $\textcircled{1}$  and  $\textcircled{2}$  we get

$$\frac{dN}{dt} = \Lambda - \mu(S + C + I + R) - \alpha I = \Lambda - \mu N - \alpha I$$

$$\frac{dN}{dt} \leq \Lambda - \mu N$$

Integrating on both sides

$$\int \frac{dN}{dt} \leq \int \Lambda - \mu N$$

$$\int \frac{dN}{\Lambda - \mu N} \leq \int dt$$

$$\frac{-1}{\mu} \ln(\Lambda - \mu N) \leq t+c \quad \text{where } c \text{ is constant of integration}$$

$$\ln(\Lambda - \mu N) \geq -\mu t - \mu c$$

$$\Lambda - \mu N \geq e^{-\mu(t+c)} = e^{-\mu t} * e^{-\mu c}$$

$$\text{Where } A = e^{-\mu c}$$

$$\Lambda - \mu N \geq A e^{-\mu t}$$

Where A is a constant and by applying initial condition  $N(0)=N_0$

$$\text{We get } A = \Lambda - \mu N_0$$

$$\Lambda - \mu N \geq (\Lambda - \mu N_0) e^{-\mu t}$$

$$-\mu N \geq (\Lambda - \mu N_0) e^{-\mu t} - \Lambda$$

$$\mu N \leq -(\Lambda - \mu N_0) e^{-\mu t} + \Lambda$$

$$N \leq \frac{\Lambda}{\mu} - \left[ \frac{\Lambda - \mu N_0}{\mu} \right] e^{-\mu t} \quad \text{As } t \rightarrow \infty \text{ the population size } N \rightarrow \frac{\Lambda}{\mu} \text{ which implies that}$$

$0 \leq N \leq \frac{\Lambda}{\mu}$ . The feasible solution set of the set of equation of the model enters and remains in the region  $\Omega = \{ (S, I, C, R) \in \mathfrak{R}_+^4 : N \leq \frac{\Lambda}{\mu} \}$

## Positivity of the solutions

▪ Theorem: Let  $\Omega = \{(S, C, I, R, B_c) \in \mathfrak{R}_+^5 : S_0 > 0, I_0 > 0, C_0 > 0, R_0 > 0, B_{c0} > 0\}$ ; then the solutions of  $\{S, C, I, R, B_c\}$  are positive for  $t \geq 0$ .

Proof: From the system of differential equation ①, let us take the first equation

$$\frac{dS}{dt} = \Lambda + \delta R - (\mu + \lambda)S$$

$$\frac{dS(t)}{dt} \geq -(\mu + \lambda)S(t)$$

$$\frac{dS(t)}{S(t)} \geq -(\mu + \lambda)dt$$

$$\int \frac{dS(t)}{S(t)} \geq - \int (\mu + \lambda)dt$$

$$\ln S(t) \geq -(\mu + \lambda)t + c, S(0) = S_0$$

$$\text{and } \ln S_0 = c$$

$$\ln S(t) \geq -(\mu + \lambda)t + \ln S_0$$

$$\ln S(t) - \ln S_0 \geq -(\mu + \lambda)t$$

$$\ln\left(\frac{S(t)}{S_0}\right) \geq -(\mu + \lambda)t$$

$$S(t) \geq S_0 e^{-(\mu + \lambda)t} \geq 0.$$

$$\frac{dC}{dt} = \rho\lambda S - (\sigma_1 + \theta + \mu + \phi)C$$

$$\frac{dC}{dt} \geq -(\sigma_1 + \theta + \mu + \phi)C$$

$$\int \frac{dC}{C} \geq - \int (\sigma_1 + \theta + \mu + \phi) dt$$

$$\ln C(t) \geq -(\sigma_1 + \theta + \mu + \phi)t + c$$

By applying initial condition  $C(0)=C_0$

$$\text{So } c = \ln C_0$$

$$C(t) \geq C_0 e^{-(\sigma_1 + \theta + \mu + \phi)t} \geq 0$$

We take third equation of (1)

$$\frac{dI}{dt} = (1-\rho)\lambda S + \theta C - (\sigma_2 + \beta + \mu + \alpha)I$$

$$\frac{dI}{dt} \geq -(\sigma_2 + \beta + \mu + \alpha)I$$

$$\int \frac{dI}{I} \geq \int -(\sigma_2 + \beta + \mu + \alpha) dt$$

By applying initial condition  $I(0) = I_0$

$$\text{We get } I(t) \geq I_0 e^{-(\sigma_2 + \beta + \mu + \alpha)t} \geq 0$$

We take the fourth equation from (1)

$$\frac{dR}{dt} = \beta I + \phi C - (\mu + \delta)R$$

$$\frac{dR}{dt} \geq -(\mu + \delta)R$$

$$\int \frac{dR}{R(t)} \geq - \int (\mu + \delta) dt$$

By applying initial condition  $R(0) = R_0$

$$R(t) \geq R_0 e^{-(\mu + \delta)t} \geq 0$$

We take fifth equation of (1)

$$\frac{dB_c}{dt} = \sigma_1 C + \sigma_2 I - \mu_b B_c$$

$$\frac{dB_c}{dt} \geq -\mu_b B_c$$

$$\int \frac{dB_c}{B_c} \geq - \int \mu_b dt$$

By Separation of variables method and by applying initial condition  $B_c(0)=B_{c0}$

We get  $B_c \geq B_{c0}e^{-\mu_b t} \geq 0$

Therefore the solution of the model is positive.

The Disease free equilibrium point(DFE) : The point at which no disease is present in the population.

DFE of this model should be evaluated at  $C=0, I=0$ .

We solve for noninfected and noncarrier state variables

$$\frac{dS}{dt} = \Lambda + \delta R - (\mu + \lambda)S$$

$$\Lambda + \delta R - (\mu + \lambda)S = 0$$

$$\frac{dR}{dt} = \beta I + \phi C - (\mu + \delta)R$$

$$\beta I + \phi C - (\mu + \delta)R = 0$$

implies  $R=0$  since  $C=0, I=0$

$$\text{therefore } S = \frac{\Lambda}{\mu}$$

$$\text{So, DFE } E_0 = \left(\frac{\Lambda}{\mu}, 0, 0, 0, 0\right).$$

# Basic reproduction number

- Basic reproduction number of an infection is the expected number of cases directly generated by one case in a population where all the individuals are susceptible to infection.
- It is denoted by  $\mathfrak{R}_0$
- We obtain basic reproduction number by using the next generation matrix method

We consider the stages where disease is present

$$\frac{dC}{dt} = \rho\lambda S - (\sigma_1 + \theta + \mu + \phi)C,$$

$$\frac{dI}{dt} = (1-\rho)\lambda S + \theta C - (\sigma_2 + \beta + \mu + \alpha)I,$$

$$\frac{dB_c}{dt} = \sigma_1 C + \sigma_2 I - \mu_b B_c$$

We construct matrices  $f$  and  $v$

$$\mathbf{f} = \begin{bmatrix} \rho(B_c v/k + B_c)S \\ (1 - \rho)(B_c v/k + B_c)S \end{bmatrix}$$

$$\mathbf{V} = \begin{bmatrix} (\sigma_1 + \theta + \mu + \phi)C \\ (\sigma_2 + \beta + \mu + \alpha)I - \theta C \\ -(\sigma_1 C + \sigma_2 I - \mu_b B_c) \end{bmatrix}$$

We Jacobian matrices of  $\mathbf{f}$  and  $\mathbf{v}$

$$f(C, I, B_c) = \rho(B_c v/k + B_c)S$$

$$g(C, I, B_c) = (1 - \rho)(B_c v/k + B_c)S$$

$$\mathbf{F} = \begin{bmatrix} \frac{\partial f}{\partial C} & \frac{\partial f}{\partial I} & \frac{\partial f}{\partial B_c} \\ \frac{\partial g}{\partial C} & \frac{\partial g}{\partial I} & \frac{\partial g}{\partial B_c} \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 & \frac{\rho v \Lambda}{\mu K} \\ 0 & 0 & \frac{(1-\rho)\Lambda v}{\mu K} \\ 0 & 0 & 0 \end{bmatrix}$$



$$a(C, I, B_c) = (\sigma_1 + \theta + \mu + \phi)C$$

$$b(C, I, B_c) = (\sigma_2 + \beta + \mu + \alpha)I - \theta C$$

$$h(C, I, B_c) = -(\sigma_1 C + \sigma_2 I - \mu_b B_c)$$

$$V = \begin{bmatrix} \frac{\partial a}{\partial C} & \frac{\partial a}{\partial I} & \frac{\partial h}{\partial B_c} \\ \frac{\partial b}{\partial C} & \frac{\partial b}{\partial I} & \frac{\partial h}{\partial B_c} \\ \frac{\partial h}{\partial C} & \frac{\partial h}{\partial I} & \frac{\partial h}{\partial B_c} \end{bmatrix} = \begin{bmatrix} (\sigma_1 + \theta + \mu + \phi) & 0 & 0 \\ -\theta & (\sigma_2 + \beta + \mu + \alpha) & 0 \\ -\sigma_1 & -\sigma_2 & \mu_b \end{bmatrix}$$

By using Augmented matrix method we get  $V^{-1} = \begin{bmatrix} \frac{1}{k_1} & 0 & 0 \\ \frac{\theta}{k_1 k_2} & \frac{1}{k_2} & 0 \\ \frac{\theta \sigma_2 + \sigma_1 k_2}{k_1 k_2 \mu_b} & \frac{\sigma_2}{k_2 \mu_b} & \frac{1}{\mu_b} \end{bmatrix}$

Where  $k_1 = (\sigma_1 + \theta + \mu + \phi)$  and  $k_2 = (\sigma_2 + \beta + \mu + \alpha)$

We calculate  $F V^{-1}$

$$F V^{-1} = \begin{bmatrix} \frac{\rho \Lambda v (\theta \sigma_2 + \sigma_1 k_2)}{\mu K k_1 k_2 \mu_b} & \frac{\rho \Lambda v \sigma_2}{\mu K k_2 \mu_b} & \frac{\rho \Lambda v}{v K \mu_b} \\ \frac{(1-\rho) \Lambda v (\theta \sigma_2 + \sigma_1 k_2)}{\mu K k_1 k_2 \mu_b} & \frac{(1-\rho) \Lambda v \sigma_2}{\mu K k_2 \mu_b} & \frac{(1-\rho) \Lambda v}{v K \mu_b} \\ 0 & 0 & 0 \end{bmatrix}$$

The characteristic polynomial of  $F V^{-1}$  is obtained as

$$(\lambda^2 - 0) \left( \lambda - \left( \frac{\rho \Lambda v (\theta \sigma_2 + \sigma_1 k_2)}{\mu K k_1 k_2 \mu_b} + \frac{(1-\rho) \Lambda v \sigma_2}{\mu K k_2 \mu_b} \right) \right) = 0$$

We get three Eigen values  $\lambda_1 = 0, \lambda_2 = 0, \lambda_3 = \left( \frac{\rho \Lambda v (\theta \sigma_2 + \sigma_1 k_2)}{\mu K k_1 k_2 \mu_b} + \frac{(1-\rho) \Lambda v \sigma_2}{\mu K k_2 \mu_b} \right)$

The dominant Eigen value gives the basic reproduction number

$$\mathfrak{R}_0 = \left( \frac{\rho \Lambda v (\theta \sigma_2 + \sigma_1 k_2)}{\mu K k_1 k_2 \mu_b} + \frac{(1-\rho) \Lambda v \sigma_2}{\mu K k_2 \mu_b} \right) = \left( \frac{\rho \Lambda v (\theta \sigma_2 + \sigma_1 (\sigma_2 + \beta + \mu + \alpha))}{(\sigma_1 + \theta + \mu + \phi)} + (1-\rho) \sigma_2 \right) \frac{\Lambda v}{\mu K (\sigma_2 + \beta + \mu + \alpha) \mu_b}$$

Proposition: The disease free equilibrium point is locally asymptotically stable if  $\mathfrak{R}_0 < 1$  and unstable if  $\mathfrak{R}_0 > 1$ .

Proof: We obtain Jacobian matrix of system (1) at  $E_0$

$$\text{Let us take } f(S, C, I, R, B_c) = \Lambda + \delta R - (\mu + \lambda)S$$

$$g(S, C, I, R, B_c) = \rho\lambda S - (\sigma_1 + \theta + \mu + \phi)C$$

$$h(S, C, I, R, B_c) = (1 - \rho)\lambda S + \theta C - (\sigma_2 + \beta + \mu + \alpha)I$$

$$a(S, C, I, R, B_c) = \beta I + \phi C - (\mu + \delta)R$$

$$b(S, C, I, R, B_c) = \sigma_1 C + \sigma_2 I - \mu_b B_c$$

$$J = \begin{bmatrix} \frac{\partial f}{\partial S} & \frac{\partial f}{\partial C} & \frac{\partial f}{\partial I} & \frac{\partial f}{\partial R} & \frac{\partial f}{\partial B_c} \\ \frac{\partial g}{\partial S} & \frac{\partial g}{\partial C} & \frac{\partial g}{\partial I} & \frac{\partial g}{\partial R} & \frac{\partial g}{\partial B_c} \\ \frac{\partial h}{\partial S} & \frac{\partial h}{\partial C} & \frac{\partial h}{\partial I} & \frac{\partial h}{\partial R} & \frac{\partial h}{\partial B_c} \\ \frac{\partial a}{\partial S} & \frac{\partial a}{\partial C} & \frac{\partial a}{\partial I} & \frac{\partial a}{\partial R} & \frac{\partial a}{\partial B_c} \\ \frac{\partial b}{\partial S} & \frac{\partial b}{\partial C} & \frac{\partial b}{\partial I} & \frac{\partial b}{\partial R} & \frac{\partial b}{\partial B_c} \end{bmatrix}$$

After doing partial derivation we get

$$J = \begin{bmatrix} -(\mu + \lambda) & 0 & 0 & \delta & \frac{vSK}{(K+B_c)^2} \\ \frac{\rho B_c v}{K+B_c} & -(\sigma_1 + \theta + \mu + \phi) & 0 & 0 & \frac{\rho vSK}{(K+B_c)^2} \\ (1 - \rho)\lambda & \theta & -(\sigma_2 + \beta + \mu + \alpha) & 0 & \frac{(1-\rho)vSK}{(K+B_c)^2} \\ 0 & \phi & \beta & -(\mu + \delta) & 0 \\ 0 & \sigma_1 & \sigma_2 & 0 & -\mu_b \end{bmatrix}$$

After substituting  $E_0 = (\frac{\Lambda}{\mu}, 0, 0, 0, 0)$  in the Jacobian matrix

$$J_{E_0} = \begin{bmatrix} -\mu & 0 & 0 & \delta & \frac{v\Lambda}{K\mu} \\ 0 & -(\sigma_1 + \theta + \mu + \phi) & 0 & 0 & \frac{\rho v\Lambda}{\mu K} \\ 0 & \theta & -(\sigma_2 + \beta + \mu + \alpha) & 0 & \frac{(1-\rho)v\Lambda}{\mu K} \\ 0 & \phi & \beta & -(\mu + \delta) & 0 \\ 0 & \sigma_1 & \sigma_2 & 0 & -\mu_b \end{bmatrix}$$

The characteristic polynomial is  $(-\lambda - \mu)(-\lambda - (\mu + \delta))(\lambda^3 + L_1\lambda^2 + L_2\lambda + L_3) = 0$

Where  $L_1 = \sigma_2 + \beta + 2\mu + \alpha + \sigma_1 + \phi + \theta + \mu_b$

$$L_2 = \mu_b(\sigma_2 + \beta + 2\mu + \alpha + \sigma_1 + \phi + \theta) + (\sigma_2 + \beta + \mu + \alpha)(\sigma_1 + \mu + \phi + \theta) - (\rho\sigma_1 + (1-\rho)\sigma_2)\frac{v\lambda}{\mu K}$$

$$L_3 = \mu_b(\sigma_2 + \beta + \mu + \alpha)(\sigma_1 + \mu + \phi + \theta)(1 - \mathfrak{R}_0)$$

$$-\lambda - \mu = 0 \text{ or } -\lambda - (\mu + \delta) = 0 \text{ or } \lambda^3 + L_1\lambda^2 + L_2\lambda + L_3 = 0$$

$$\text{Implies } \lambda_1 = -\mu < 0, \lambda_2 = -(\mu + \delta) < 0$$

Let us take the last expression  $\lambda^3 + L_1\lambda^2 + L_2\lambda + L_3=0 \rightarrow \textcircled{3}$

By applying Routh-Hurwitz criteria to  $\textcircled{3}$

$$a_0 = 1, a_1 = L_1, a_2 = L_2, a_3 = L_3$$

$$\Delta_1 = a_1 = L_1 > 0$$

$$\Delta_2 = \begin{vmatrix} a_1 & a_0 \\ a_3 & a_2 \end{vmatrix} = \begin{vmatrix} L_1 & 1 \\ L_3 & L_2 \end{vmatrix} = L_1L_2 - L_3 > 0$$

$$\Delta_3 = a_3 \Delta_2 = L_3(L_1L_2 - L_3) > 0$$

So,  $L_3 > 0$  and  $L_1L_2 > L_3$

For  $L_3$  to be positive  $(1 - \mathfrak{R}_0)$  must be positive which leads to  $\mathfrak{R}_0 < 1$ .

Therefore, DFE will be locally asymptotically stable if and only if  $\mathfrak{R}_0 < 1$

If  $\mathfrak{R}_0 > 1$  the disease free equilibrium is unstable.

Theorem: The disease-free equilibrium is globally asymptotically stable in the feasible region  $\Omega$  if  $\mathfrak{R}_0 < 1$

Proof: We develop the Lyapunov function, technically

$$L = \left[ \frac{\theta\sigma_2 + \sigma_1 k_2}{k_1} \right] C + \sigma_2 I + k_2 B_c$$

Where  $k_1 = (\sigma_1 + \theta + \mu + \phi)$  and  $k_2 = (\sigma_2 + \beta + \mu + \alpha)$

Then differentiating L on both sides

$$\frac{dL}{dt} = \left[ \frac{\theta\sigma_2 + \sigma_1 k_2}{k_1} \right] \frac{dC}{dt} + \sigma_2 \frac{dI}{dt} + k_2 \frac{dB_c}{dt}$$

We substitute  $\frac{dC}{dt}$ ,  $\frac{dI}{dt}$ , and  $\frac{dB_c}{dt}$  from (1)

$$\frac{dL}{dt} = \left[ \frac{\theta\sigma_2 + \sigma_1 k_2}{k_1} \right] (\rho\lambda S - (\sigma_1 + \theta + \mu + \phi)C) + \sigma_2 ((1-\rho)\lambda S + \theta C - (\sigma_2 + \beta + \mu + \alpha)I) + k_2 (\sigma_1 C + \sigma_2 I - \mu_b B_c)$$

$$\frac{dL}{dt} = \left[ \rho \frac{\theta \sigma_2 + \sigma_1 k_2}{k_1} + (1 - \rho) \sigma_2 \right] \lambda S + (\theta \sigma_2 - \theta \sigma_2 - \sigma_1 k_2) C - \sigma_2 k_2 I + k_2 (\sigma_1 C + \sigma_2 I - \mu_b B_c)$$

$$\frac{dL}{dt} = \left[ \rho \frac{\theta \sigma_2 + \sigma_1 k_2}{k_1} + (1 - \rho) \sigma_2 \right] \lambda S - k_2 \mu_b B_c$$

$$\text{Since } \mathfrak{R}_0 = \left( \frac{\rho \Lambda \nu (\theta \sigma_2 + \sigma_1 k_2)}{\mu K k_1 k_2 \mu_b} + \frac{(1 - \rho) \Lambda \nu \sigma_2}{\mu K k_2 \mu_b} \right)$$

$$\frac{dL}{dt} = \left( \mathfrak{R}_0 \mu_b k_2 \frac{\mu K}{\Lambda \nu} \right) \lambda S - k_2 \mu_b B_c$$

$$\frac{dL}{dt} = \left( \mathfrak{R}_0 \mu_b k_2 \frac{\mu K}{\Lambda \nu} \right) \lambda \frac{\Lambda}{\mu} - k_2 \mu_b B_c$$

$$\frac{dL}{dt} = (\mathfrak{R}_0 - 1) k_2 \mu_b B_c$$

$$\frac{dL}{dt} < 0 \text{ if } \mathfrak{R}_0 < 1$$

If there is a Lyapunov function  $L$  in the neighbourhood of DFE with a negative definite derivative then DFE is globally asymptotically stable.



## Sensitivity analysis of model parameters

- On the basic parameters we carry out sensitivity analysis.
- This helps us to check and identify parameters that can impact basic reproductive Number.
- The sensitivity index of all basic parameters is defined as  $\Delta_x^{\mathfrak{R}_0} = \left( \frac{\partial \mathfrak{R}_0}{\partial x} \right) \left( \frac{x}{\mathfrak{R}_0} \right)$ .

here  $x$  represents all the basic parameters.

For example the values of the parameters are taken as  $\Lambda = 100, \phi = 0.0003, \sigma_1 = 0.9, \sigma_2 = 0.8, \beta = 0.0002, \rho = 0.3, \mu = 0.0247, \mu_b = 0.0001, \alpha = 0.052, \theta = 0.2, \nu = 0.9$ , and  $K = 50,000$ .

- The sensitivity indices of  $\mathfrak{R}_0$  with respect to all basic parameters are  $\Delta_\nu^{\mathfrak{R}_0}, \Delta_K^{\mathfrak{R}_0}, \Delta_{\sigma_1}^{\mathfrak{R}_0}, \Delta_{\sigma_2}^{\mathfrak{R}_0}, \Delta_\beta^{\mathfrak{R}_0}, \Delta_\rho^{\mathfrak{R}_0}, \Delta_\mu^{\mathfrak{R}_0}, \Delta_{\mu_b}^{\mathfrak{R}_0}, \Delta_\alpha^{\mathfrak{R}_0}, \Delta_\theta^{\mathfrak{R}_0}, \Delta_\phi^{\mathfrak{R}_0}$ .

- The parameters( $\nu, k, \sigma_1, \sigma_2$ , and  $\rho$ ) that have positive indices increases  $\mathfrak{R}_0$  value if their values increase.
- The parameters( $\mu, \mu_b, \alpha, \theta, \beta$ , and  $\phi$ ) that have negative indices decreases  $\mathfrak{R}_0$  value if their values increase.

Sensitivity  
indices table

Parameter symbol	Sensitivity indices
$\nu$	1
K	0.999
$\sigma_1$	0.26
$\sigma_2$	0.03
$\rho$	0.00506
$\mu$	-1.028
$\mu_b$	-1
$\alpha$	-0.0592
$\theta$	0.009
$\beta$	-0.00017
$\phi$	-0.000089

## Extension of Model into Optimal control

- The basic model of typhoid fever is generalized by incorporating three control interventions.
- The controls are prevention( $u_1$ )(Sanitation and proper hygiene controls),treatment( $u_2$ ),and screening of carriers( $u_3$ )
- After incorporating the controls into basic model

$$\frac{dS}{dt} = \Lambda + \delta R - (1 - u_1) \lambda S - \mu S,$$

$$\frac{dC}{dt} = (1 - u_1) \rho \lambda S - (\theta + u_3) C - (\sigma_1 + \mu + \phi) C,$$

$$\frac{dI}{dt} = (1 - u_1) (1 - \rho) \lambda S + (1 - u_3) \theta C - (u_2 + \beta) I - (\sigma_2 + \mu + \alpha) I,$$

$$\frac{dR}{dt} = (u_2 + \beta) I + \phi C - (\mu + \delta) R,$$

$$\frac{dB_c}{dt} = \sigma_1 C + \sigma_2 I - \mu_b B_c$$

Where  $\lambda = B_c \nu / k + B_c$ ,  $\{0 \leq u_1 < 1, 0 \leq u_2 < 1, 0 \leq u_3 < 1, 0 \leq t < T\}$

- Our main objective is to obtain the optimal levels of the controls that optimize the objective function.

- The objective function is taken as  $J = \min_{u_1, u_2, u_3} \int_0^{t_f} (b_1 C + b_2 I + \frac{1}{2} \sum_{i=1}^3 w_i u_i^2) dt$ .

where  $b_1$  and  $b_2$  are coefficients of state variables and  $\frac{1}{2} w_i u_i^2$  is the cost expression.

- We get an optimal triple  $(u_1^*, u_2^*, u_3^*)$  in order to minimize the optimal function.

$$J(u_1^*, u_2^*, u_3^*) = \min \{J(u_1, u_2, u_3) \mid u_i \in U\}, \text{ where } U = \{(u_1, u_2, u_3) \mid 0 \leq u_i < 1\}$$

- We construct the function H

$$\text{Hamiltonian}(H) = \frac{dJ}{dt} + \lambda_1 \frac{dS}{dt} + \lambda_2 \frac{dC}{dt} + \lambda_3 \frac{dI}{dt} + \lambda_4 \frac{dR}{dt} + \lambda_5 \frac{dB_c}{dt}.$$

$$H(S, C, I, R, B_c) = L(C, I, u_1, u_2, u_3, t) + \lambda_1 \frac{dS}{dt} + \lambda_2 \frac{dC}{dt} + \lambda_3 \frac{dI}{dt} + \lambda_4 \frac{dR}{dt} + \lambda_5 \frac{dB_c}{dt}$$

Where  $L(C, I, u_1, u_2, u_3, t) = (b_1 C + b_2 I + \frac{1}{2} \sum_{i=1}^3 w_i u_i^2)$ ,  $\lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5$  are the adjoint variable functions.

We use Pontryagin's principle.

To get system of adjoint variables, We write state equations

$$\frac{dS}{dt} = \frac{dH}{d\lambda_1}, \frac{dC}{dt} = \frac{dH}{d\lambda_2}, \frac{dI}{dt} = \frac{dH}{d\lambda_3}, \frac{dR}{dt} = \frac{dH}{d\lambda_4}, \frac{dB_c}{dt} = \frac{dH}{d\lambda_5}$$

We write Co-state adjoint equations

$$\frac{d\lambda_1}{dt} = \frac{-dH}{ds}, \frac{d\lambda_2}{dt} = \frac{-dH}{dC}, \frac{d\lambda_3}{dt} = \frac{-dH}{dI}, \frac{d\lambda_4}{dt} = \frac{-dH}{dR}, \frac{d\lambda_5}{dt} = \frac{-dH}{dB_c}$$

$$\frac{d\lambda_1}{dt} = \frac{-dH}{ds} = -\lambda_1 \left( -\mu - \frac{B_c \nu (1-u_1)}{K+B_c} \right) - \frac{\lambda_2 (1-\rho)(1-u_1) B_c \nu}{K+B_c} - \frac{\lambda_3 (1-u_1) \rho \nu B_c}{K+B_c}$$

$$\frac{d\lambda_2}{dt} = \frac{-dH}{dC} = -b_1 - \lambda_2(-\theta - u_3) - \lambda_3(1 - u_3)\theta - \lambda_4\phi - \lambda_5(\sigma_1 + \phi + \mu),$$

$$\frac{d\lambda_3}{dt} = \frac{-dH}{dI} = -b_2 - \lambda_3(-u_2 - \beta - \sigma_2) - \lambda_4(u_2 + \beta) - \lambda_5(\sigma_2 + \mu + \alpha),$$

$$\frac{d\lambda_4}{dt} = \frac{-dH}{dR} = -\lambda_1\delta - \lambda_4(-\mu - \delta),$$

$$\frac{d\lambda_5}{dt} = \frac{-dH}{dB_c} = -\frac{\lambda_1 B_c (1 - u_1) S}{(K + B_c)^2} - \lambda_2 \left( \frac{(1 - u_1) \rho \nu S}{K + B_c} - \frac{(1 - u_1) \rho \nu B_c S}{(K + B_c)^2} \right) -$$

$$\lambda_3 \left( \frac{(1 - \rho)(1 - u_1) \nu S}{K + B_c} - \frac{(1 - \rho)(1 - u_1) B_c \nu S}{(K + B_c)^2} \right) + \lambda_5 \mu_b$$

We find the optimal control set  $u_1, u_2, u_3$  that minimizes  $J(u_1, u_2, u_3)$  over  $U$

$$\frac{\partial H}{\partial u_i} = 0 \text{ at } u_i = u_i^*, \text{ where } i=1,2,3$$

For  $i=1$

$$\frac{\partial H}{\partial u_1} = 0 \text{ at } u_1^* \rightarrow u_1^* = \frac{S(\lambda_2 \rho \nu B_c - B_c \rho \nu \lambda_3 + B_c \nu \lambda_3 - \lambda_1 B_c \nu)}{(K + B_c) w_1}$$

For  $i=2$

$$\frac{\partial H}{\partial u_2} = 0 \text{ at } u_2^* \rightarrow u_2^* = \frac{I(\lambda_3 - \lambda_4)}{w_2}$$

For  $i=3$

$$\frac{\partial H}{\partial u_3} = 0 \text{ at } u_3^* \rightarrow u_3^* = \frac{C(\lambda_3 \theta + \lambda_2)}{w_3}.$$

We can write in a compact notation

$$u_1^* = \max \left\{ 0, \min \left( 1, \frac{S(\lambda_2 \rho \nu B_c - B_c \rho \nu \lambda_3 + B_c \nu \lambda_3 - \lambda_1 B_c \nu)}{(K + B_c) w_1} \right) \right\},$$

$$u_2^* = \max \left\{ 0, \min \left( 1, \frac{I(\lambda_3 - \lambda_4)}{w_2} \right) \right\},$$

$$u_3^* = \max \left\{ 0, \min \left( 1, \frac{C(\lambda_3 \theta + \lambda_2)}{w_3} \right) \right\}.$$



# Cost-Effectiveness Analysis

- We identify a strategy which is cost-effective compared to other strategies.
- We use incremental cost-effectiveness ratio(ICER)

$$\text{ICER} = \frac{\text{difference of costs between two strategies}}{\text{difference of the total number of their infections averted}}$$

- The cost of each strategy is obtained by their respective cost function  $\frac{1}{2}w_1u_1^2$ ,  $\frac{1}{2}w_2u_2^2$ ,  $\frac{1}{2}w_3u_3^2$ .
- We do not consider strategies that implement one intervention only.
- We incorporate more than one intervention  
i.e., strategy A (prevention and screening)  
Strategy B (treatment and screening)  
Strategy C (prevention and treatment)  
Strategy D (prevention, treatment, and screening)

We compare the cost-effectiveness of strategies

Cost-effectiveness of strategies A and B:

$$ICER(A) = \frac{733.07}{11,977} = 0.06$$

$$ICER(B) = \frac{(733.07 - 800)}{(11,977 - 13,805)} = 0.037$$

We exclude strategy A

Cost-effectiveness of strategies B and C

$$ICER(B) = \frac{800}{13,805} = 0.058$$

$$ICER(C) = \frac{(800 - 573.19)}{(13,805 - 19,699)} = -0.039$$

We exclude strategy B

Cost-effectiveness of strategies C and D

Strategies	Description	Total infections averted	Total cost (USD)
A	Prevention and screening	11,977	733.07
B	Treatment and screening	13,805	800
C	Prevention and treatment	19,699	573.19
D	Prevention, treatment, and screening	19,987	1104.5

$$\text{ICER}(C) = \frac{573.19}{19,699} = 0.029$$

$$\text{ICER}(D) = \frac{573.19 - 1104.5}{19,699 - 19,987} = 1.845$$

We exclude Strategy D.

So Strategy C(prevention and treatment)is the best strategy from all compared strategies due to it's cost-effectiveness and healthy benefit.

## Conclusion

- In this study, a deterministic model for the dynamics of typhoid fever disease is proposed.
- Free equilibrium point of the Model is obtained and it's local as well as global stability conditions are obtained.
- The basic reproduction number of the disease reveals the intensity of the spread of the disease.
- Sensitivity analysis of the basic reproductive number is done.
- The optimal control problem is formulated and the conditions for optimal control of the disease are analyzed.
- The results indicate that prevention and the cost put into treatment have a strong impact on the disease control.

## References

- Mathematical modelling and control of Infectious diseases by Gul Zaman, Il H. Jung, Delfim F.M. Torres and Anwar Zeb.
- <https://www.sciencedirect.com/topics/immunology-and-microbiology/basic-reproduction-number>
- [https://en.m.wikipedia.org/wiki/Pontryagin%27s\\_maximum\\_principle](https://en.m.wikipedia.org/wiki/Pontryagin%27s_maximum_principle)
- S.M. Lenhart and J.T. Workman, optimal Control applied to Biological Models, CRC press 2007.
- <https://www.routledge.com/Optimal-Control-Applied-to-Biological-Models/Lenhart-Workman/p/book/9781584886402>

*THANK YOU*