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MODELLING THE EFFECT OF SOCIAL MEDIA ON RUMOR SPREADING

A DISSERTATION

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF

MASTER OF SCIENCE IN

MATHEMATICS

Submitted by:

CHARU

(2K21/MSCMAT/11)

SACHIN KUMAR SINGHAL

(2K21/MSCMAT/42)

Under the supervision of

PROF. NILAM

DEPARTMENT OF APPLIED MATHEMATICS

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Bawana Road, Delhi-110042

MAY, 2023

DEPARTMENT OF APPLIED MATHEMATICS

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi college of Engineering)

Bawana Road. Delhi-110042

DECLARATION

We, Charu, 2K21/MSCMAT/11 & Sachin Kumar Singhal, 2K21/MSCMAT/42 students of M.Sc. Mathematics, hereby declare that the project Dissertation titled "MODELLING THE EFFECT OF SOCIAL MEDIA ON RUMOR SPREADING" which is submitted by me to the Department of Applied Mathematics Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Science, is original and not copied from any source without proper citation. This work has not previously formed the basis for the award of any Degree, Diploma Associateship, Fellowship or other similar title or recognition.

Place: New Delhi | Charu

Date | Sachin Kumar Singhal

DEPARTMENT OF APPLIED MATHEMATICS

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi college of engineering)

Bawana Road, Delhi-110042

CERTIFICATE

We hereby certify that the Project Dissertation titled "MODELLING THE EFFECT OF SOCIAL MEDIA ON RUMOR SPREADING " which is Submitted by Charu, Roll No. 2K21/MSCMAT/11 & Sachin Kumar Singhal, Roll No. 2K21/MSCMAT/42 [Department of Applied Mathematics], Delhi Technological University, Delhi in partial fulfillment of the requirement for the award of the degree of Master of Science, is a record of the project work carried out by the students under my supervision. To the best of my knowledge this work has not been submitted in part or full for any Degree or Diploma to this University or elsewhere.

Place: New Delhi **Prof. Nilam**

Date: **SUPERVISOR**

DEPARTMENT OF APPLIED MATHEMATICS
DELHI TECHNOLOGICAL UNIVERSITY
(Formerly Delhi college of engineering)
Bawana Road, Delhi-110042

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I would like to acknowledge that this project was completed entirely by us and not by someone else.

Charu

Sachin kumar

singhal

ABSTRACT

Social media plays a significant role in the lives of individuals, and it can be broadly categorized into two groups: those who use social media and those who do not. People who use social media are more susceptible to being exposed to false information compared to those who do not use it. Furthermore, individuals who use social media can be further divided into two subgroups: those with a large fan following and those with a small fan following. If a rumor is initiated by someone with a substantial fan base, there is a higher likelihood that it will spread rapidly.

To enhance the understanding of this phenomenon, an extension of the classical SIR (Susceptible-Infectious-Recovered) rumor spreading model has been proposed. This extended model incorporates the influence of social media and the presence of individuals with a large following, resulting in the SEIR (Susceptible-Exposed-Infectious-Recovered) rumor spreading model. The dynamics of the SEIR rumor spreading model are described by a system of nonlinear ordinary differential equations, which captures the behavioral patterns and progression of the rumor withinthe population

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ABBREVATIONS USED

ODEs: Ordinary Differential Equations

SIR: Susceptible (S), Infected (I), and Recovered (R)

SEIR: Susceptible (S), Exposed(E), Infected(I), Recovered(R)

Ode45: Command in MATLAB

CHAPTER 1

INTRODUCTION

1.1 Rumors and its history

A rumor is a statement that has no basis in reality and is created arbitrarily or According to a person's wish, then it is spread by some method. In other words, a rumor is a piece of unfounded information that gets widely circulated. As society and the internet have developed, rumor spread has become more widespread, more powerful, and faster at disseminating information than conventional human communication. Rumors significantly affect how we live our daily lives. Rumors seriously threaten national and public security since they not only spread false information to the public, but also encourage undesirable social behaviors criminal activity, and financial losses.

Most local and foreign scholars who have studied rumor spreading have favored an epidemic model because of the similarities between the transmission of rumor sand epidemic diseases. Kermack and McKendrick first proposed the classic SIR epidemic model in 1927. Based on this research, numerous academics developed mathematical models such as SI, SIS , SIRS , SEIRS , and others, all of which are becoming more and more crucial in the prediction and management of infectious diseases.
These models give researchers more theories and insights into how rumors spread. Daley and Kendall discovered in 1964 that while infectious disease spreads and rumors have many superficial similarities, their transmission mechanisms are fundamentally different. This conclusion was based on theoretical analysis and empirical examination of infectious disease models.
As a result, Daley and Kendall created the traditional rumor-spreading model and gave it the name DK model. According to the DK model, the general public can be broken down into three groups: those who don't know about rumors (Ignorants), those who do know about rumors and spread them, and those who know about rumors but don't spread them (Stiflers). In 1973, Maki modified the DK model and created the MK model.
Because it suggested that rumors were spread through direct contact between the disseminator and others, this model more accurately captured the rumor propagation process. however DK and MK models are built using rigorous logic, they often ignore the factors that influence how rumors spread.

The DK, MK, and infectious disease models have served as the foundation for more thorough research on rumor spread from various angles, including small-world networks, complex networks, forgetting mechanisms, memory mechanisms, retweeting mechanisms, individual behavior, education, and internal and external influences.

In 2016, Zhang et al. emphasized the significance of studying the dynamics of information diffusion by applying existing epidemic models to complex networks. In 2018, Zhan et al. investigated the dynamics of the coupling between epidemic transmission and information diffusion using a nonlinear model of SIS in a complex network environment.

1.1 Effect of Social Media

Social media plays a crucial part in people's lives. The rapid proliferation of social media platforms has revolutionized the way information is disseminated and consumed in our interconnected world. Social media enables individuals to communicate, share opinions, and exchange news and rumors on an unprecedented scale. As social media's influence continues to grow, it becomes increasingly important to understand its role in shaping the spread of rumors and misinformation within populations.

This research paper aims to explore the effect of social media and the effect of people with large following on rumor propagation, employing the SEIR (Susceptible, Exposed, Infected, Recovered) model as a framework for analysis. The SEIR model divides the population into six compartments: susceptible who uses social media (Sus), susceptible who do not use social media (Sns), people who are exposed to rumor and having a large fan following(Elf), people who are exposed to rumor and having a small fan following (Esf), infected, I represents people who are spreading the rumor and R represents people who are not spreading the rumor. Here Susceptible has been divided into two distinct groups - individuals who actively use social media and those who do not Further exposedpopulation has been divided into two groups based on the number of followers – people having a large fan following and people having a small fan following

CHAPTER 2

Model Formulation

2.1 Model Formulation

The SEIR rumor-spreading model results from expanding the traditional SIR rumor-spreading model to take into account the impact of social media and large fan following. Users can be thought of as nodes and direct connections between users as edges. The foundation of our model is the division of the population into the four states of S, E, I, and R. At each time step, each individual adopts one of four states S, E, I, or R, whichrespectively stand for

- the people who have never been contacted with rumor (susceptible),
- the people who have been infected, the people who have been in hesitant stateand do not spread rumor (exposed),
- The people who are actively spreading it (infected) and the people who haveknown the rumor but never believed and spread it (recovered)

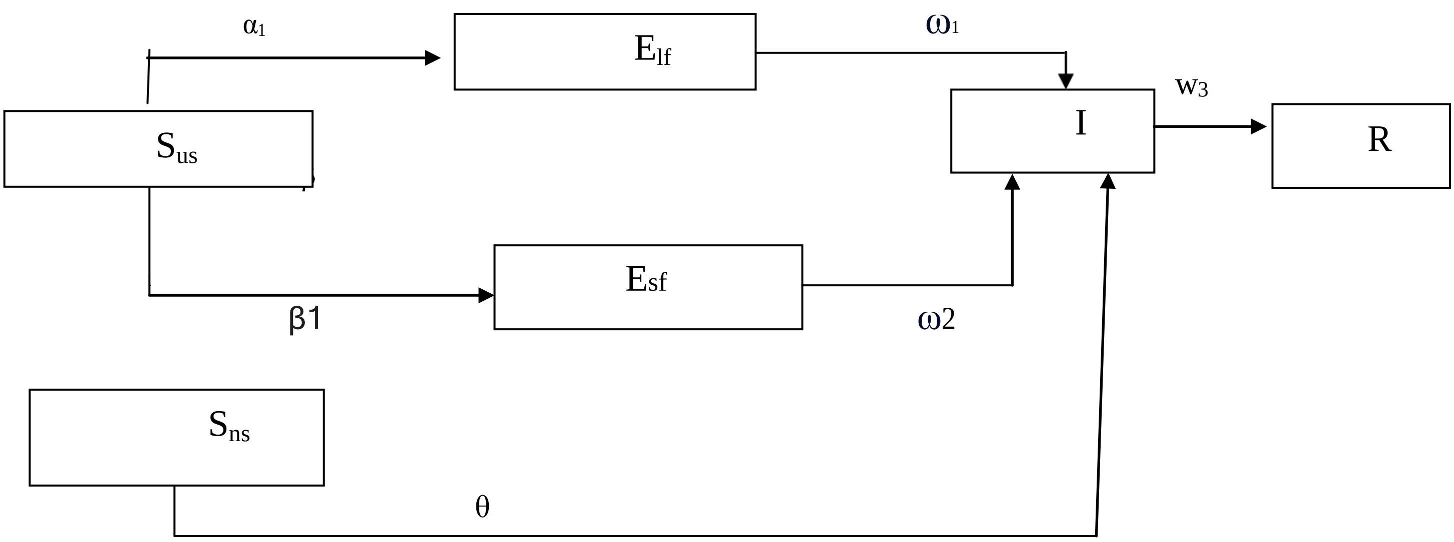
The population sizes of Sus, Sns, Elf, Esf ,I, R individuals at time t are denoted by Sus(t),Sns(t), Elf(t), Esf(t), I(t) and R(t) respectively.

1. S_{us} (t): This represents the number of people who uses social media and are susceptible to hearing the rumor at time t.
2. S_{ns} (t): This represents the number of people who do not use social media andare susceptible to hearing the rumor at time t.
3. E_{lf} (t): This represents the number of people who are exposed to rumors and have large fan following at time t. These people are aware of the rumor through social media.
4. E_{sf} (t): This represents the number of people who are exposed to rumors through social media and have small fan following at time t. These people are aware of the rumor through social media.
5. I(t): This represents the number of people who are infected at time t. these people are previously exposed to rumor either through social media or by physical contact and now they are actively spreading the rumor.
6. R(t): This represents the number of recovered people at time t who are not spreadingthe rumor. These people were previously spreading the rumor but have recovered.

The parameters in the above model are expressed as follows:

- α_1, the spreading rate that a susceptible using social media turns into an exposed having a large following after he comes into contact with the spreader;
- β, the spreading rate that a susceptible using social media turns into an exposed having a small following after he comes into contact with the spreader;
- θ, the spreading rate that a susceptible not using social media turns into infected after he comes into contact with the spreader;
- w_1, the rate that the exposed having large following converts into infected.
- w_2, the rate that an exposed having small following converts into infected.
- $w_3 = \alpha_2 I/(1+ \beta_2 I)$, the rate of infected people getting recovered;

COMPARTMENT MODEL



2.3 DIFFERENTIAL EQUATION FORM OF THE MODEL

$$\frac{dSus}{dt} = -\alpha_1 * Sus * Elf - \beta 1 * Sus * Esf$$

$$\frac{dSns}{dt} = -\theta * Sns * I$$

$$\frac{dElf}{dt} = \alpha_1 * Sus * Elf - \omega 1 * Elf * I$$

$$\frac{dEsf}{dt} = \beta 1 * Sus * Esf - \omega 2 * Esf * I$$

$$\frac{dI}{dt} = \beta 1 * Sus * Esf + \omega 2 * Esf * I + \theta * Sns * I - \frac{\alpha_2 * I}{1 + \beta 2 * I} * IR$$

$$\frac{dR}{dt} = \frac{\alpha_2 * I}{1 + \beta 2 * I} * IR$$

CHAPTER 3

STABILITY ANALYSIS

3.1 DEFINITION

In mathematics, stability is the state in which a little change in a system does not have a very disruptive impact on that system. The capacity of a moving item, like a ship or an airplane, to keep balance or return to its original, upright posture after being moved by sea or high winds.

Example:

- if the flow of water into and out of a lake is equal, the volume of the lake will be constant.

- Another type of stable state is a cyclic pattern a consistent The pattern of day and night exists while the Earth revolves.

3.2 IMPORTANCE OF STABILITY

In mathematical modeling, stability is a key term, especially in the study of dynamic systems and numerical simulations. Stability in mathematical modeling describes how a system behaves over time and its capacity to preserve a desired state or equilibrium. Here are some main arguments in favor of stability in mathematical modeling:

3.21 Long-Term Behavior:

A system's long-term behavior may be understood through a stability analysis. It aids in predicting whether a system will move toward a stable equilibrium, show oscillations, or behave in an unstable way. Researchers can forecast a system's behavior over long time periods and evaluate the system's overall performance by looking at a mathematical model's stability.

3.22 Control and Optimization

Stability analysis is crucial to solving efficiency and monitoring system issues. Designing control techniques that maintain unstable systems or keep them within acceptable boundaries is aided by stability criteria. Stability evaluation in enhancement helps make sure that the method converges to a stable solution and does not fluctuate or diverge.

3.23 Numerical simulation

In numerical simulations, where mathematical models are addressed using computing techniques, stability is of the highest significance. Numerical instabilities are of the highest significance. Numerical instabilities such as quantitative variation or divergentsolutions, can be a result of unstable methods of computation. Stability analysis is a crucial step in verifying the of numerical simulations since these instabilities have the potential to impair the reliabilityand accuracy of the simulation findings.

3.3 METHODS FOR STABILITY ANALYSIS

Depending on the type of system and the mathematical equations used, there are several ways to calculate stability in mathematical modeling. The following are some typical techniques for stability analysis:

3.31 EIGENVALUE ANALYSIS

This approach is frequently used for linear differential equation systems. In order to assess stability, one must examine the eigenvalues of the system's Jacobian matrix or distinctive polynomial.

- The system is stable if all of the eigenvalues havenegative real components.
- The system is unstable if any eigenvalue has a positivereal portion.
- The Routh-Hurwitz criteria and the Lyapunov stability criterion are twoinstances of eigenvalue-based stability analysis.

3.32 LYAPUNOV STABILITY ANALYSIS

Lyapunov stability analysis is a versatile technique applicable to both linear and nonlinear systems. It involves the identification of a Lyapunov function, which is a scalar function that quantifies the system's energy or potential. For the system to be stable, the Lyapunov function must satisfy specific properties. It should be positive definite, meaning it is alwaysgreater than zero except at the origin, and its derivative should be negative definite, meaning it is always less than zero. If a Lyapunov function meeting these criteria can be found, the system is deemed stable.

Two common approaches used in Lyapunov stability analysis are Lyapunov's direct method and LaSalle's invariance principle. Lyapunov's direct method involves constructing a Lyapunov function and evaluating its derivative along the system's trajectories. By examining the signs of the derivative, stability conclusions can be drawn. LaSalle's invariance principle, on the other hand, focuses on finding a region within the system's state space called a "LaSalle's invariant set" where the trajectories of the system converge. This principle allows for stability analysis even when the system does not possess an equilibrium point
In conclusion, Lyapunov stability analysis uses Lyapunov functions to evaluate the stability of both linear and nonlinear systems. The Lyapunov function denotes stability by meeting particular conditions, such as the positive and negative definiteness of the derivative. In Lyapunov stability analysis, the direct approach by Lyapunov and the LaSalle invariance principle are both frequently employed methods

3.33 PHASE PLANE ANALYSIS

Phase plane analysis is a valuable method employed to study two-dimensional systems. It revolves around the graphical representation of the system's state variables against each other, facilitating the visualization of the system's behavior and stability. By plotting the state variables on a phase plane, various stability properties can be inferred, including the identification of fixed points, limit cycles, and trajectories.

The phase plane analysis provides a visual framework for understanding the system's dynamics. Fixed points, also known as equilibrium points or critical points, are represented by intersections of the state variable curves on the phase plane. These points correspond to states where the system remains unchanged over time.

Limit cycles, which are closed curves on the phase plane, indicate periodic behavior in the system. They represent recurrent patterns or oscillations that the system undergoes. By observing the trajectories traced by the state variables on the phase plane, valuable insights into stability can be gained. Stable trajectories tend to converge towards fixed points or limit cycles, while unstable trajectories diverge or exhibit chaotic behavior.

In summary, phase plane analysis provides a graphical approach to explore the dynamics and stability of two-dimensional systems. It involves plotting state variables on a phase plane to identify fixed points, limit cycles, and trajectories, shedding light on the system's behavior and stability properties.

CHAPTER 4

NUMERICAL SIMULATION

4.1 TOTAL POPULATION VS TIME

```
syms Sus(t) Sns(t) Elf(t) Esf(t) I(t) R(t) T Y
Eqns= [diff(Sus(t),t)==-0.0052*Sus(t)*Elf(t)-0.0065*Sus(t)*Esf(t);
diff(Sns(t),t)==-.0099*I(t)*Sns(t);
diff(Elf(t),t)==-0.0110*I(t)*Elf(t) + 0.0052*Sus(t)*Elf(t);
diff(Esf(t),t)==0.0065*Sus(t)*Esf(t)-(0.0132)*Esf(t)*I(t);
diff(I(t),t)==0.0110*Elf(t)*I(t)+.0099*I(t)*Sns(t)+
0.0132*Esf(t)*I(t)(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t);

diff(R(t),t)==(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t)];
[DEsys,Subs] = odeToVectorField(Eqns);
Funchf = matlabFunction(DEsys, 'Vars',{T,Y});
tspan = [0,20000];
y0 = [0.48 0.32 0.02 .096 0.068 0.012];
[T,Y] = ode45(funchf, tspan, y0);
figure(1)
plot(T,Y)
legend(Sus(t)', Sns(t)',' Elf(t)', Esf(t)',' I(t)',' R(t)')
grid,
```

OUTPUT:

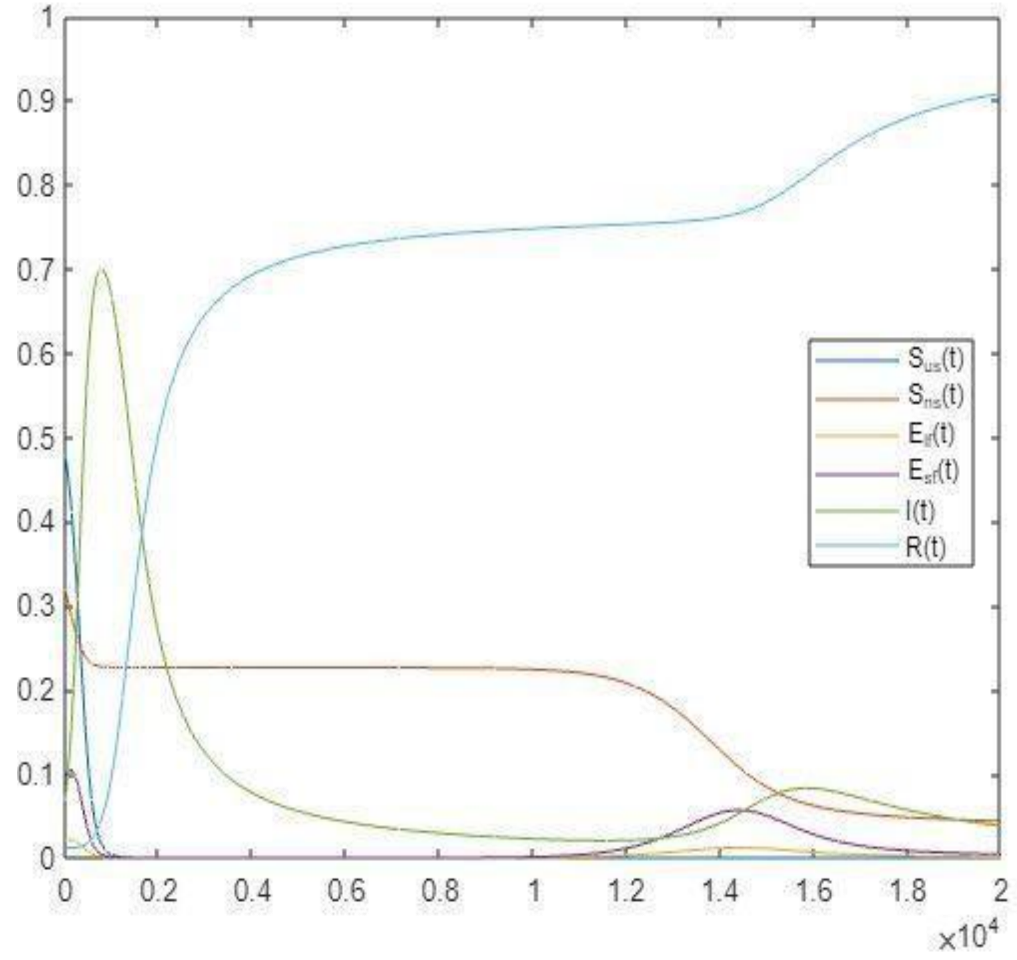


figure1: TOTAL POPULATION VS TIME

CHAPTER 5

BEHAVIOR OF POPULATION AS CHANGES IN PARAMETER

5.1 Infected vs time as w1

changes

CODE

```
syms Sus(t) Sns(t) Elf(t) Esf(t) I(t) R(t) T Y
Eqns= [diff(Sus(t),t)==-0.0052*Sus(t)*Elf(t)-0.0065*Sus(t)*Esf(t);
diff(Sns(t),t)==-.0099*I(t)*Sns(t);
diff(Elf(t),t)==-0.0110*I(t)*Elf(t) + 0.0052*Sus(t)*Elf(t);
diff(Esf(t),t)==0.0065*Sus(t)*Esf(t)-(0.0132)*Esf(t)*I(t);
diff(I(t),t)==0.0110*Elf(t)*I(t)+.0099*I(t)*Sns(t)+ 0.0132*Esf(t)*I(t)
(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t);
diff(R(t),t)==(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t)];
[DEsys,Subs] = odeToVectorField(Eqns);
funchf = matlabFunction(DEsys, 'Vars',{T,Y});
tspan = [0,80];
y0 = [0.48 0.32 0.02 .096 0.068 0.012];
[T,Y] = ode45(funchf, tspan, y0);
figure(2)
plot(T,Y(:,5))
xlabel('Time (t)')
ylabel('Infected Individuals (I(t))')
legend('\omega1=0.0015','\omega1=0.0033','\omega1=0.0052','\omega1=0.0072',
'\omega1=0.0094’)
```

OUTPUT:

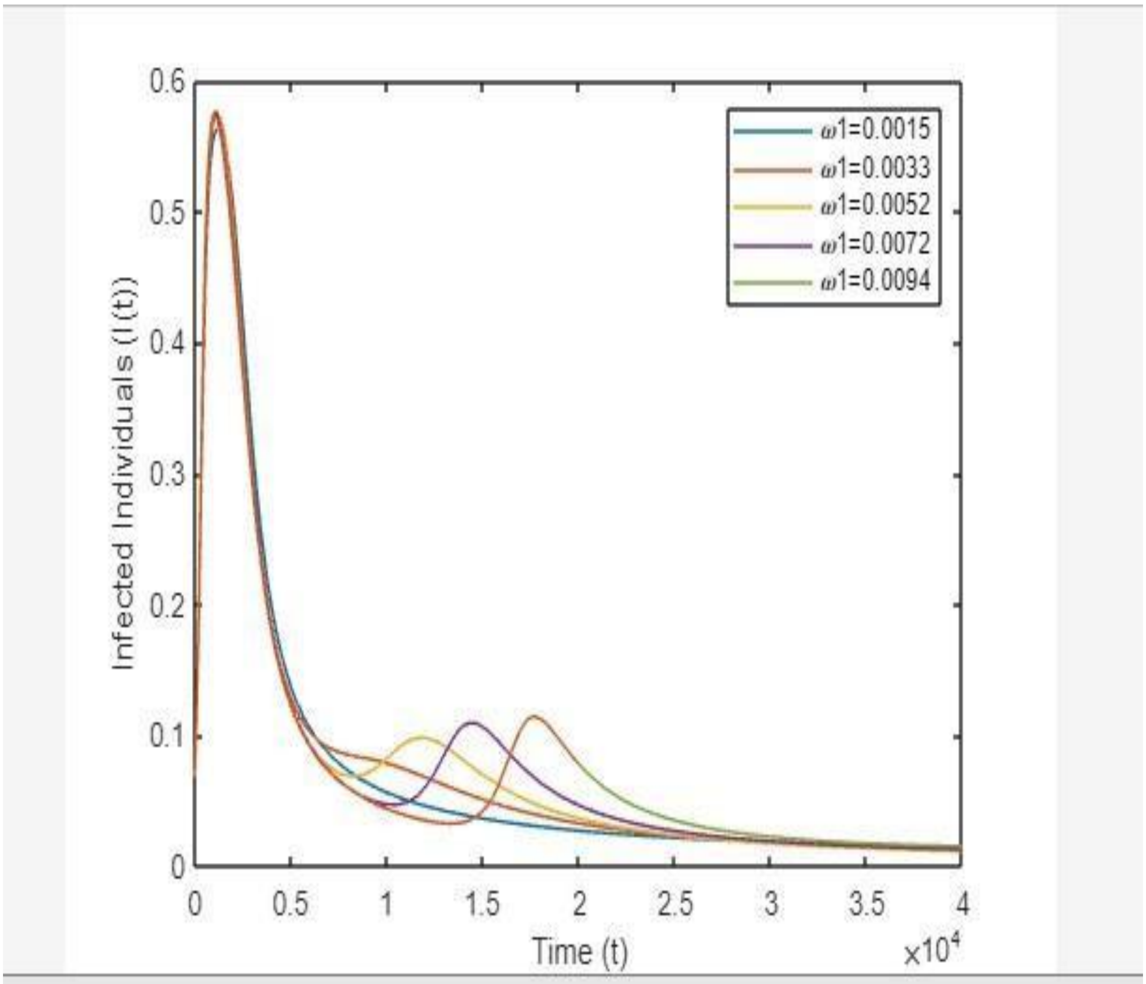


Figure2: Infected vs time as ω_1 changes

ω_1 is the rate of exposed individuals having a large following getting infected The number of people spreading rumors also rises as ω_1 rises because more people who are exposed to rumors with large following start doing so.

5.2 Infected vs time as ω2 changes

CODE:

```
syms Sus(t) Sns(t) Elf(t) Esf(t) I(t) R(t) T Y
Eqns= [diff(Sus(t),t)==-0.0052*Sus(t)*Elf(t)-0.0065*Sus(t)*Esf(t);

diff(Sns(t),t)==-.0099*I(t)*Sns(t);
diff(Elf(t),t)==-0.0110*I(t)*Elf(t) + 0.0052*Sus(t)*Elf(t);
diff(Esf(t),t)==0.0065*Sus(t)*Esf(t)-(0.0132)*Esf(t)*I(t);
diff(I(t),t)==0.0110*Elf(t)*I(t)+.0099*I(t)*Sns(t)+ 0.0132*Esf(t)*I(t)-
(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t);
diff(R(t),t)==(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t)];
[DEsys,Subs] = odeToVectorField(Eqns);
funchf = matlabFunction(DEsys, 'Vars',{T,Y});
tspan = [0,80];
y0 = [0.48 0.32 0.02 .096 0.068 0.012];
[T,Y] = ode45(funchf, tspan, y0);
figure(3)
plot(T,Y(:,5))
xlabel('Time (t)')
ylabel('Infected Individuals (I(t))')
legend('\omega1=0.0042','\omega1=0.0061','\omega1=0.0089','\omega1=0.0
098','\omega1=0.01132’)
```

OUTPUT:

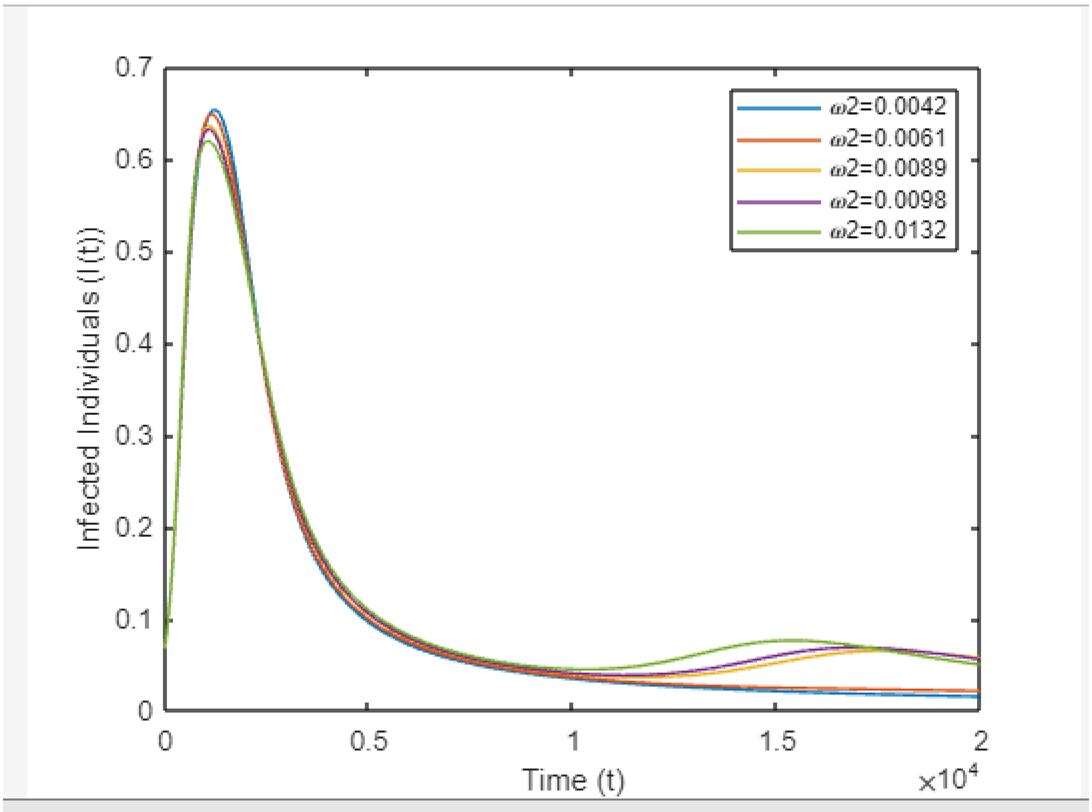


Figure3: Infected vs time as ω2 changes

ω2 is the rate of exposed individuals having a small following getting infected The number of people spreading rumors also rises as ω2 rises because more people who are exposed to rumors with small following start doing so.

5.3 Infected vs time as θ changes

Code:

```
syms Sus(t) Sns(t) Elf(t) Esf(t) I(t) R(t) T Y
Eqns= [diff(Sus(t),t)==-0.0052*Sus(t)*Elf(t)-0.0065*Sus(t)*Esf(t);
diff(Sns(t),t)==-.0099*I(t)*Sns(t);
diff(Elf(t),t)==-0.0110*I(t)*Elf(t) + 0.0052*Sus(t)*Elf(t);
diff(Esf(t),t)==0.0065*Sus(t)*Esf(t)-(0.0132)*Esf(t)*I(t);
diff(I(t),t)==0.0110*Elf(t)*I(t)+.0099*I(t)*Sns(t)+ 0.0132*Esf(t)*I(t)-
(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t);
diff(R(t),t)==(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t)];

[DEsys,Subs] = odeToVectorField(Eqns);
funchf = matlabFunction(DEsys, 'Vars',{T,Y});
tspan = [0,80];
y0 = [0.48 0.32 0.02 .096 0.068 0.012];
[T,Y] = ode45(funchf, tspan, y0);

figure(4)
plot(T,Y(:,5))
xlabel('Time (t)')
ylabel('Infected Individuals (I(t))')
legend('\theta1=0.12','\theta1=0.33','\ theta1=0.58','\ theta1=0.79','\ theta1=0.98’)
```

OUTPUT:

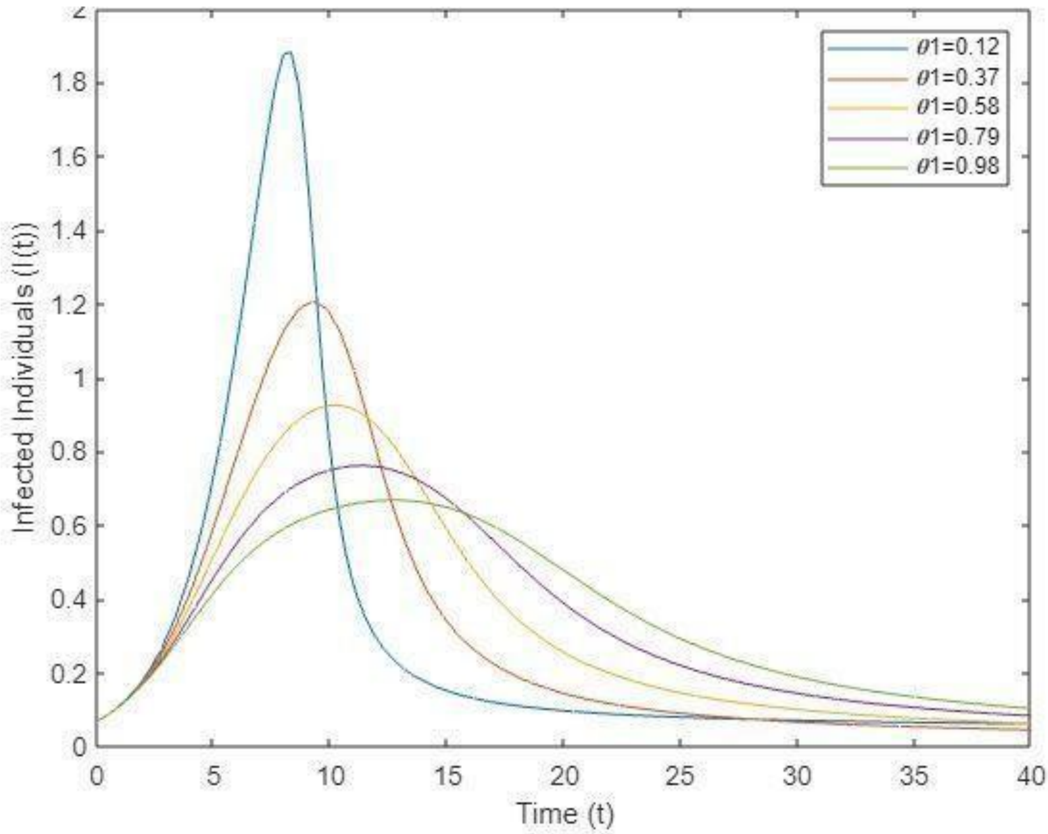


Figure4: Infected vs time as θ1 changes

θ is the rate of exposed individuals having small following getting infected Here more people who do not use social media start spreading rumors, thus number of people spreading rumors also increases as theta increases.

5.4 Recovered vs time as beta2 changes

Code:

```
syms Sus(t) Sns(t) Elf(t) Esf(t) I(t) R(t) T Y
 Eqns=[diff(Sus(t),t)==-0.0052*Sus(t)*Elf(t)-0.0065*Sus(t)*Esf(t);
diff(Sns(t),t)==-.0099*I(t)*Sns(t);
diff(Elf(t),t)==-0.0110*I(t)*Elf(t) + 0.0052*Sus(t)*Elf(t);
diff(Esf(t),t)=0.0065*Sus(t)*Esf(t)-(0.0132)*Esf(t)*I(t);
diff(I(t),t)==0.0110*Elf(t)*I(t)+.0099*I(t)*Sns(t)+ 0.0132*Esf(t)*I(t)-
(0.0073*I(t)/(1+0.0030*I(t)))*I(t)*R(t);
diff(R(t),t)==(0.0073*I(t)/(1+0.0030*I(t)))*I(t)*R(t)];

[DEsys,Subs]   =   odeToVectorField(Eqns);
funchf = matlabFunction(DEsys, 'Vars',{T,Y});
tspan = [0,20000];
y0 = [0.48 0.32 0.02 .096   0.068 0.012];
[T,Y] = ode45(funchf, tspan, y0);
figure(43)
plot(T,Y(:,6));
xlabel('Time (t)')
ylabel('RECOVERED Individuals (R(t))')
legend('\beta2=0.007','\beta2=0.0216','\beta2=0.432','\beta2=0.615','\
beta2=0.849')
```

OUTPUT:

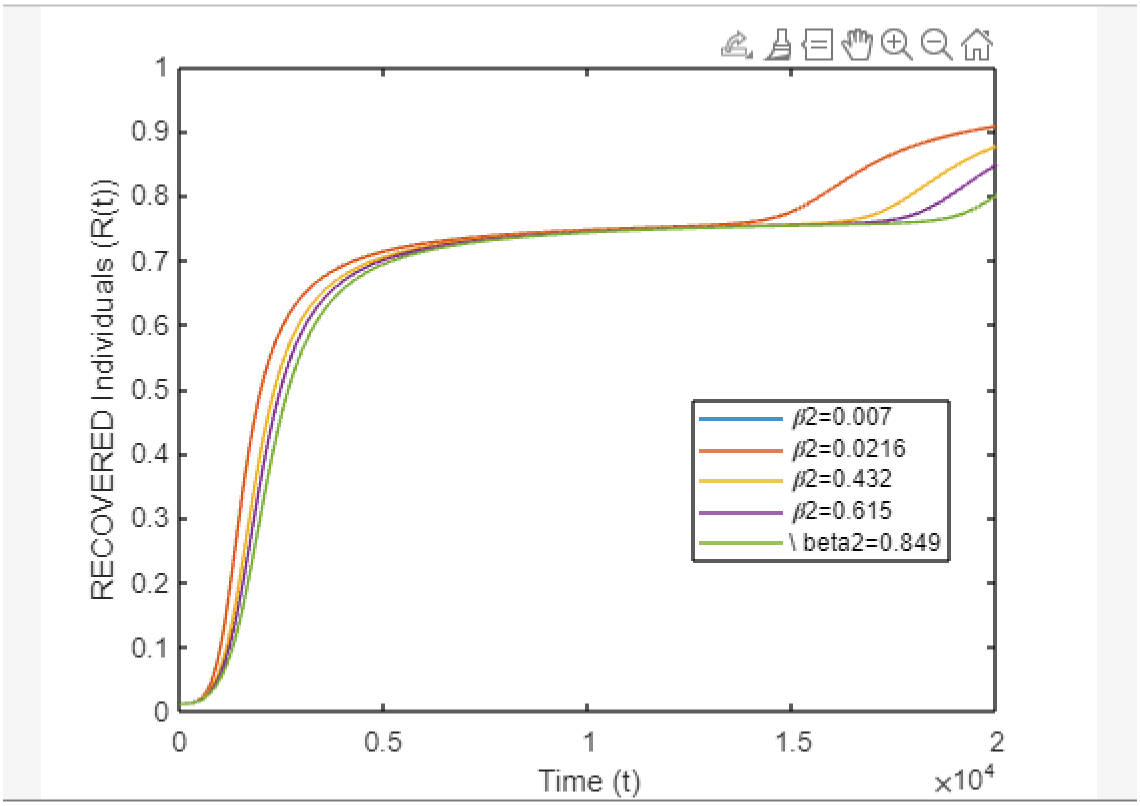


Figure5: Recovered vs time as beta2 changes

5.4Recovered vs time as α_2 changes

Code:

```
syms Sus(t) Sns(t) Elf(t) Esf(t) I(t) R(t) T Y
 Eqns=[diff(Sus(t),t)==-0.0052*Sus(t)*Elf(t)-0.0065*Sus(t)*Esf(t);
diff(Sns(t),t)==-.0099*I(t)*Sns(t);
diff(Elf(t),t)==-0.0110*I(t)*Elf(t) + 0.0052*Sus(t)*Elf(t);
diff(Esf(t),t)==0.0065*Sus(t)*Esf(t)-(0.0132)*Esf(t)*I(t);
diff(I(t),t)==0.0110*Elf(t)*I(t)+.0099*I(t)*Sns(t)+ 0.0132*Esf(t)*I(t)-
(0.0212*I(t)/(1+0.0037*I(t)))*I(t)*R(t);
diff(R(t),t)==(0.0212*I(t)/(1+0.0037*I(t)))*I(t)*R(t)];
[DEsys,Subs] = odeToVectorField(Eqns);
funchf = matlabFunction(DEsys, 'Vars',{T,Y});
tspan = [0,20000];
y0 = [0.48 0.32 0.02 .096 0.068 0.012];
[T,Y] = ode45(funchf, tspan, y0);
figure(6)
plot(T,Y(:,6))
xlabel('Time (t)')
ylabel('Recovered Individuals (R(t))')
legend('\alpha2=0.0010','\alpha2=0.0059','\alpha2=0.0115','\alpha2=0.0162','\
alpha2=0.0212')
```

OUTPUT:

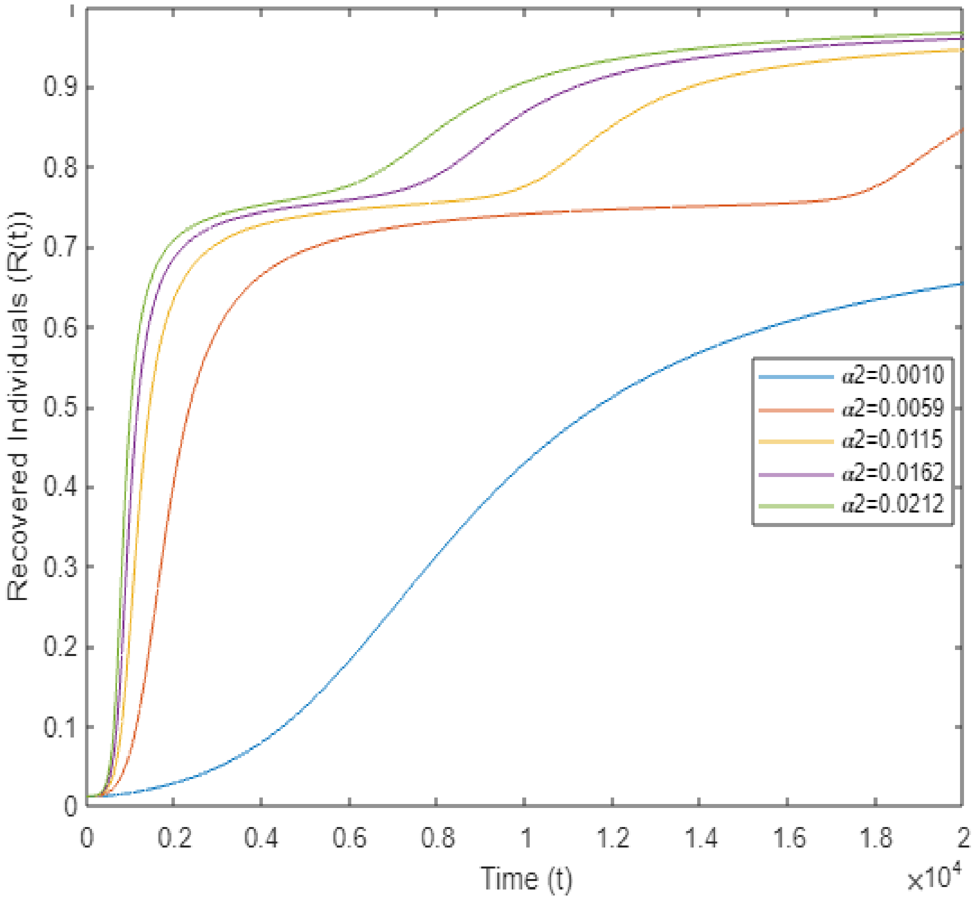


figure 6: Recovered vs time as alpha2 changes

CHAPTER 6

3-d PLOTS

6.1Infected vs exposed with large following vs time

<u>Code:</u>

```
syms Sus(t) Sns(t) Elf(t) Esf(t) I(t) R(t) T Y
Eqns=[diff(Sus(t),t)==-0.0052*Sus(t)*Elf(t)-0.0065*Sus(t)*Esf(t);
diff(Sns(t),t)==-.0099*I(t)*Sns(t);
diff(Elf(t),t)==-0.0030*I(t)*Elf(t)+0.0052*Sus(t)*Elf(t);
diff(Esf(t),t)==0.0065*Sus(t)*Esf(t)-(0.0132)*Esf(t)*I(t);
diff(I(t),t)==0.0030*Elf(t)*I(t)+.0099*I(t)*Sns(t)+ 0.0132*Esf(t)*I(t)-
(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t);
diff(R(t),t)==(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t)];

[DEsys,Subs] = odeToVectorField(Eqns);
funchf = matlabFunction(DEsys, 'Vars',{T,Y});
tspan = [0,20000];
y0 = [0.48 0.32 0.02 .096 0.068 0.012];
[T,Y] = ode45(funchf, tspan, y0);
figure(7)
plot3(T,Y(:,3),Y(:,5));
xlabel('Time (t)')
ylabel('Infected Individuals (I(t))')
zlabel('Exposed with large following')
```

OUTPUT:

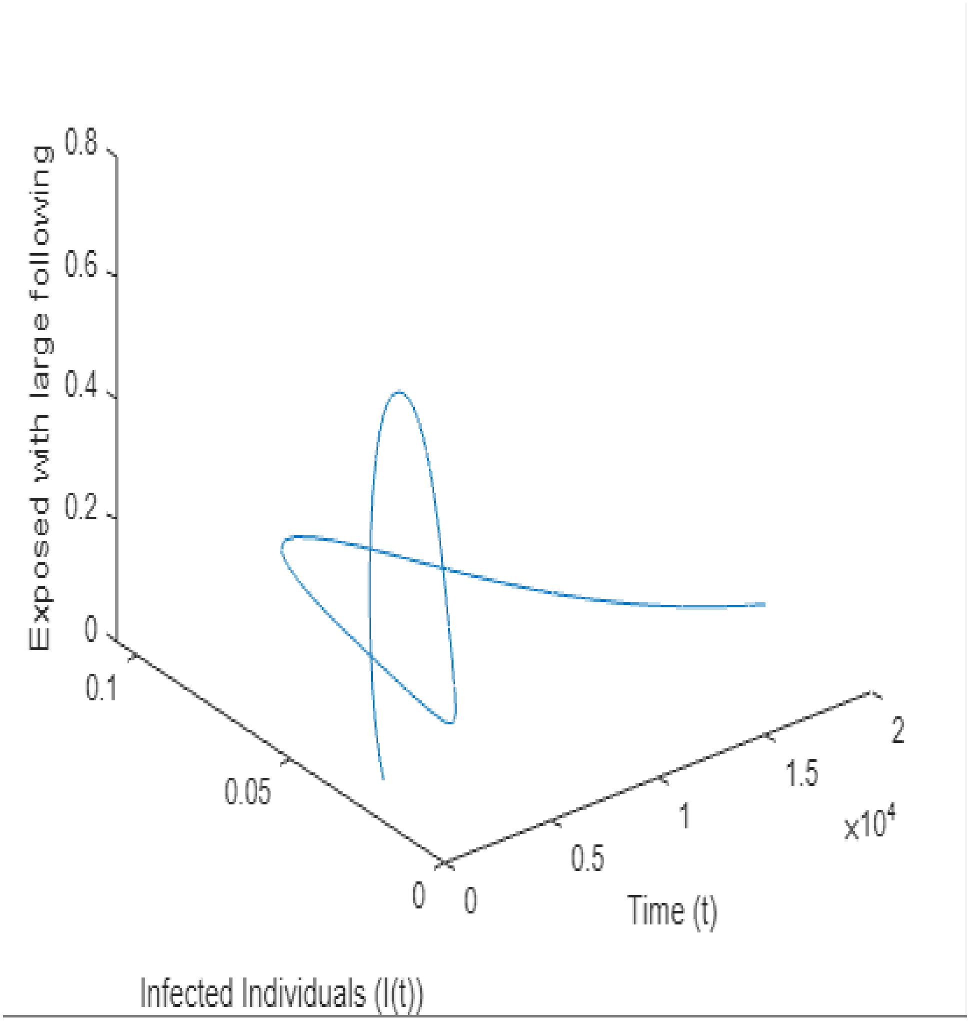


Figure7: Infected vs exposed with large following vs time

6.2Infected vs exposed with small following vs time

Code:

```
syms Sus(t) Sns(t) Elf(t) Esf(t) I(t) R(t)
Eqns=[diff(Sus(t),t)==-0.0052*Sus(t)*Elf(t)-0.0065*Sus(t)*Esf(t);
diff(Sns(t),t)==-.0099*I(t)*Sns(t);
diff(Elf(t),t)==-0.0110*I(t)*Elf(t) + 0.0052*Sus(t)*Elf(t);
diff(Esf(t),t)==0.0065*Sus(t)*Esf(t)-(0.0132)*Esf(t)*I(t);
diff(I(t),t)==0.0110*Elf(t)*I(t)+.0099*I(t)*Sns(t)+0.0132*Esf(t)*I(t)-
(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t);
diff(R(t),t)==(0.0073*I(t)/(1+0.0037*I(t)))*I(t)*R(t)];

[DEsys,Subs] = odeToVectorField(Eqns);
funchf = matlabFunction(DEsys, 'Vars',{T,Y});
tspan = [0,20000];
y0 = [0.48 0.32 0.02 .096 0.068 0.012];
[T,Y] = ode45(funchf, tspan, y0);
figure(8)
plot3(T,Y(:,4),Y(:,5));
xlabel('Time (t)')
ylabel('Infected Individuals (I(t))')
zlabel('Exposed with small following')
```

OUTPUT

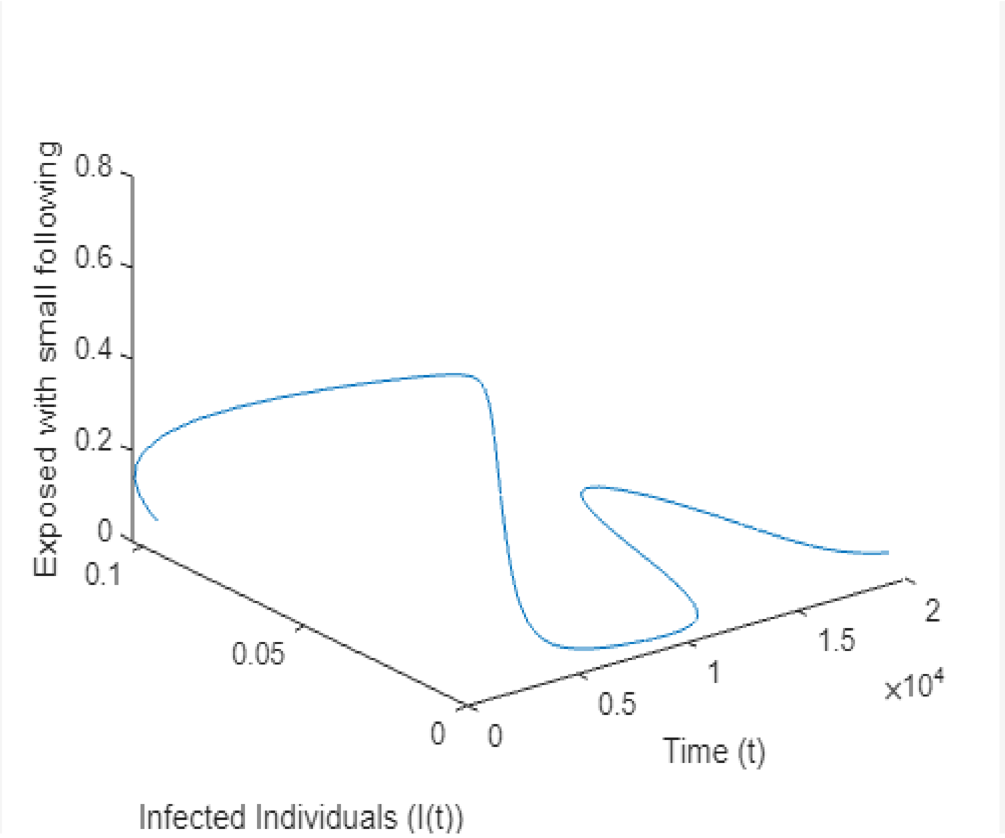


Figure8: Infected vs exposed with small following vs time

CHAPTER 7

RESULTS

The prevalence of social media has considerably heightened the dissemination of rumors, as it has emerged as a primary platform for the propagation of such information. This widespread connectivity allows rumors to spread rapidly and reach a larger audience than ever before.

Additionally, individuals who possess a substantial number of followers on social media platforms hold a greater power to influence others. Their extensive reach and influence amplify the impact of rumors within their networks. When someone with a large fan base spreads a rumor, it has the potential to gain atraction quickly and reach a significant number of people within a short span of time.

This combination of social media as a rumor propagation channel and the influential effect of individuals with a large following contributes to the accelerated and amplified spread ofrumors in today's interconnected society.

REFRENCES

1. file:///D:/Dissertation/research%20paper/effect%20of%20education%20on%20rumor.pdf

2. file:///D:/Dissertation/research%20paper/rumor/SIR%20influence.pdf

3. file:///D:/Dissertation/research%20paper/Dynamics%20of%20a%20glucose%20insulin%20model.pdf

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5. file:///D:/Dissertation/research%20paper/SEIR%20Model%20in%20complex%20social%20networks.pdf

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