Modeling social response to disease spread using spatial game theory

by

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B.S., Isfahan University of Technology, 2008
M.S., Isfahan University of Technology, 2010

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Industrial and Manufacturing Systems Engineering
Carl R. Ice College of Engineering

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Manhattan, Kansas

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Abstract

Epidemic disease outbreaks are among the major threats to the sustenance and health of human societies. Many reports in public health show that even with the current state of prevention and treatment technologies, epidemic diseases still cause severe health issues and loss of life, and hence remain a source of large public health cost on societies. Consequently, controlling the spread of infectious diseases has become a main area of focus for public health policy makers. Modeling the dynamics of epidemic disease outbreaks and the corresponding social response is one of the techniques that can help public health policy makers to better design and evaluate relevant policies with more precise and detailed knowledge of such dynamics in social interactions and self-organization. Accordingly, we propose a modeling approach based on spatial game theory using public goods game, which is a prominent approach for capturing the behavior of individuals in response to local stimuli. The settings of public goods game enable this method to model the dilemma of not vaccinating and not paying the related costs of vaccination or vaccinating to provide a healthy living environment for the individual and other members of the community. This is the first time that a public goods game payoff function is used in modeling and capturing the behavior of populations in response to epidemics.

In this dissertation, two variants of the proposed model are introduced. The first captures the behavior of individuals in response to an epidemic, in which decision making is on whether to vaccinate or not. The second model aims to capture the behavior of interacting populations to an epidemic, and the decision is on how much to change the level of vaccination in each population. Also, the impact of considering the time-delay between infection and emergence of symptoms of the disease is studied. These models demonstrate that the adoption of public goods game based payoff function in the modeling of epidemics can capture the vaccination behavior of individuals,

and can lead to a better control of the epidemic spread in the population level. Moreover, this dissertation proposes two new strategy updating methods in spatial evolutionary games, which are shown to be capable of modeling the dynamics of decision making under different sensitivities to vaccination and fear of infection.

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Major Professor
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Dedication

To my parents, for their unconditional love and support.

Chapter 1 - Introduction

Prevention of infectious diseases has been an active area of research throughout the scientific endeavors of human civilizations. Infectious diseases can negatively affect large populations with severe morbidity or even mortality, thus imposing considerable costs on public health and state. In recent decades, the accelerating changes of the climate, which is known as global warming, has triggered a growing spike in infectious diseases among human societies (Wu, Lu, Zhou, Chen, & Xu, 2016). One consequence of this climate change is its impact on the development, reproduction, and survival of infectious diseases, which has led to the growing number of individuals at the risk of becoming infected. Furthermore, a report conducted by the World Health Organization (WHO) notes that globalization and its effect on economic, environmental, and demographic variation of societies, has increased the risk of infectious diseases in populations (Saker, Lee, Cannito, Gilmore, & Campbell-Lendrum, 2004). These, along with the paramount importance of devising effective regulations, have escalated the necessity of developing accurate models of disease transmissions and the corresponding behavioral prevention response. Hence, this project aims to contribute to this field of research by proposing novel methodologies that include not only the transmission dynamics of diseases, but also the decision-making processes of individuals in response to such outbreaks.

1.1 Research motivation and objectives

While prevention of infectious diseases is usually achieved by increasing the number of individuals who are using prevention techniques such as vaccinating or social distancing, in spite of vaccination being a proven and potent remedy to the spread of infectious diseases, in some regions of the US there is a growing trend of parents opting out of vaccinating their children (Haelle, 2017). Moreover, vaccines are not required in order for children to attend school in most states to respect religious and personal beliefs (Hinman, Orenstein, Williamson, & Darrington, 2002).

The main motivation of this research stems from the aforementioned behavior that many people avoid vaccination in the face of epidemics, mainly due to their localized predictions of probable risk of contraction and the expenses involved. This behavior is mostly prominent in communities with initially low infection rates, as well as the agents' assumption that most members of the community are opting in for vaccinations. These conditions may give rise to a sense of immunity to the infection and consequent free-rider behavior in individuals. However, the idea of being protected by the population of vaccinated individuals is not always effective if there are not enough vaccinated individuals or motivators to encourage individuals to get vaccinated. In certain configurations, this type of response to epidemics may result in rapid spread of disease due to insufficient vaccination. To illustrate, in 2015, California faced the worst measles epidemic in the last decades because many parents declined to vaccinate their children due to perceived vaccine side-effects and by relying on the other vaccinated ones to be safe (Salzberg, 2015). Also, in 2019 United States faced another measles outbreak due to similar behavioral reaction to vaccination (Nelson, R., 2019). Moreover, the idea of free protection has always been partnered with voluntary vaccination. Thus, accounting for such behaviors in the models of infectious disease outbreaks can greatly enhance the accuracy of predictions and decision-support, which can translate into more effective policies for the mitigation and control of epidemic outbreaks.

Thus, the objective of this research is to describe the behavior of individuals in response to an epidemic of diseases such as measles, with respect to vaccination, when people have the choice of free-riding, and to design a mechanism to find the most effective set of policies to control an epidemic outbreak in such situations. Moreover, it is also of interest to study the behavior of interacting populations and communities in response to an epidemic to see the effect of changing strategies for these societies. Since network of interactions is proven to affect the dynamic of epidemics, the objective of this research is to capture the behavioral response to the disease spread in a network setting. This research aims to create a novel understanding and approach in the modeling of disease outbreaks. Owing to the similarities of this problem with many others, such as influence propagation and decentralized management, the outcomes of this project may also be applicable to modeling of public behavior in other domains as well.

1.2 Proposed methods

In order to model the behavior of individuals in epidemics different methods are used. Some of them have shown the existence of free-riding behavior (Bhattacharyya & Bauch, 2011). When considering the "free protection" one of the things which comes to mind is modeling the spread of an infectious disease as a public goods games in which some free-riders get the advantage from the contribution of other individuals in the group (i.e., vaccination). However, although some studies have mentioned the public goods effect of vaccination and prevention behavior in epidemic, none of them have used it as an approach to calculate the payoff of individuals in game theory based models (Fu, Rosenbloom, Wang, & Nowak, 2010). This dissertation is proposed models to capture the dynamic of epidemics using a public goods game based payoff as a base for individual's decision when facing an epidemic. In order to implement this behavior in response to epidemic disease, evolutionary game theory can be used, which is a method that can show the choice of individuals in population of interacting players with different payoffs when individuals are going through evolution (Nowak, 2006). Evolutionary game theory is widely used to study epidemic dynamics (Wang, Z., Andrews, Wu, Wang, & Bauch, 2015). To take the spatial interactions of individuals into account, spatial evolutionary game theory can be used. The advantage of adopting a spatial evolutionary game is that it can take the location information into consideration when individuals balance their costs and benefits.

Thus, we proposed methods to model the behavior of individuals when facing an epidemic outbreak based on spatial game theory using public goods game, demonstrating that this approach has the potential to describe the behavior of individuals in response to an epidemic.

We studied epidemic spread in two levels, individual level and population level. In individual level we developed a model based on the public goods game in the setting of a spatial game on a lattice. In this model, individuals are considered as agents whose aim is to maximize their collective benefit by imitating other agent's behavior, and may choose to contribute to the public health by paying the cost of vaccination, or choose to be protected by those who are vaccinated, rather than incurring the costs and risks involved in vaccination themselves but get the shared benefit of living in a healthy society. This model accounts for various factors affecting the cost assessment of individuals, including the monetary cost of vaccination, the cost of contracting the disease, and an "awareness" factor due to the dissemination of information through public media. Furthermore, the transmission dynamics of the disease are captured within the well-known Susceptible-Infected-Resistant (SIR) model. Consequently, this approach allows for capturing the effect of enhanced immunity due to communal behaviors.

Considering the issue of time delay between exposure to infection until appearance of syndromes, we extended our individual level model to take into account this phenomenon and compared the results of this model with the previous one based on different factors.

In the population level we developed a method for modeling the spread of diseases in a network of populations to see how different strategies can change the dynamics of disease spread and the percentage of infected and vaccinated individuals in each population. This approach is of great importance for policy evaluation, since there are usually not just individuals, but also populations who deal with epidemics according to different health policies, standards and regulations. To approach this problem, we developed a model based on the public goods game in the setting of a spatial game on a network. In this model, populations are considered as agents whose aim is to maximize the collective benefit to their society and the populations which are in close contact with them, and may choose the level of their contribution to the public health by changing their level of vaccination. This model accounts for various factors affecting the cost assessment of these groups, including the cost of vaccination, the cost of contracting the disease, and willingness to contribute due to the dissemination of information through public media. Furthermore, the transmission dynamics of the disease are captured within the well-known Susceptible-Infected-Resistant (SIR) model on both a scale-free network and a lattice.

1.3 Organization

This dissertation is organized in 6 chapters. Chapter 2 reviews the fundamentals of epidemic modeling describing the role of behavioral dynamic modeling, types of transmission models, economic and rule based approaches in modeling, population based and network based approaches and specifically use of spatial games in epidemic modeling. Chapter 3 provides the formulation of individual based model and the effect of changing several factors such as cost of vaccination, transmission rate of the disease, number of initially vaccinated and sensitivity of individuals to taking vaccination in the epidemic dynamic. Chapter 4 shows the revisions on the individual model to take into account the time delay in emergence of syndromes and shows the variation of the dynamic according to several factors. Chapter 5 provides information on modeling the population level model and effectiveness of public goods game based approach as well as sensitivity of the model to several factors. Finally, chapter 6 presents a conclusion on the three models on hand with some remarks on future directions of research.

Chapter 2 - Literature Review

The first attempt to model infectious disease transmission was done by Daniel Bernoulli in the 17th century (Dietz & Heesterbeek, 2002). Since then, several researches have used different methods to model epidemics. Mathematical modeling is one of the broadly used methods to elucidate the transmission of infectious diseases. The classical mathematical approach has treated human behavior as a fixed phenomenon without any dynamic pattern. However, to model a coupled system of human and disease, it is required to take the dynamic behavior of individuals into account (Wang, Z. et al., 2015). Game theory is a key tool in modeling the interactions between individual behaviors, and thus is used in modeling the disease transmission considering humans as rational decision makers in this process (Manfredi & D'Onofrio, 2013). In recent years, by the advance of large-scale simulations, many researchers started to use agent based simulations to capture the detailed behavior of agents in epidemic spread and have also taken the network of interactions into account.

In the following, in section 2.1 game theory and specifically spatial evolutionary game theory will be discussed and public goods game will be introduced. Then, in section 2.2 a literature of studies in modeling infectious disease based on different approaches to capture the behavioral dynamics of epidemics will be introduced, and finally in section 2.3 some of the works on epidemic modeling which have used spatial game theory will be discussed.

2.1 Evolutionary game theory

Game theory is defined as the study of mathematical models that capture conflict and cooperation between rational decision-makers (Myerson, 2013). Classical game has three elementary components: players, strategies, and payoffs. In these games a player is playing a game with another player and has to decide between different strategies to maximize his own payoff which depends on other player's strategy, while the other player is also trying to maximize his own payoff. It is assumed that each player has the complete information about the game and rationally chooses the strategy which maximizes his own payoff.

Although in classical game theory players choose the best strategy to maximize their own payoff, their best decision does not necessarily remain the best if the game is repeated several times (Nowak, 2006). There is a famous game named "prisoner's dilemma" which can clearly show this phenomenon (Kreps, Milgrom, Roberts, & Wilson, 1982).

In the prisoners' dilemma game, two persons are arrested because of a joint crime. Each of them can either cooperate with the other person and remain silent (strategy C), or can defect and confess (strategy D). If both cooperate, then both get M_{22} points. If one cooperates while the other one defects, then the cooperator gets M_{21} points which is less than M_{22} and the defector gets M_{12} points which is more than M_{22}. If both defect, they both get M_{11} points which is more than M_{21} but less than M_{22}. So, the relation between the payoffs is $M_{12} > M_{22} > M_{11} > M_{21}$. The payoff matrix is shown below.

$$\begin{array}{cc} & \begin{array}{cc} \text{D} & \text{C} \end{array} \\ \begin{array}{c} \text{D} \\ \text{C} \end{array} & \begin{pmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{pmatrix} \end{array}$$

In this case, both prisoners choose to defect to maximize their own payoff regardless of what choice the other prisoner makes. Defecting is the Nash equilibrium for prisoner's dilemma game since none of the players can gain more payoff by changing just their own strategy. However, it is apparent that prisoners can gain more payoff if both cooperate and remain silent since $M_{22} > M_{11}$, and in reality sometimes individuals cooperate with each other. Thus, Nash equilibrium in the classical game cannot explain this phenomenon.

To study this phenomenon, an extension to the classical game theory is created to give the players the chance of changing their strategies based on a rule, such as imitating others' strategies based on the previous game's outcome, when playing the game repeatedly. Thus, players do not behave rationally but they test how well their strategies are. This style of game is known as evolutionary game theory (Nowak, 2006). Evolutionary game theory is mainly the study of a population of competing players in which players interact with each other and go through evolution.

Evolutionary game theory was fostered by evolutionary biologist and then found many applications in non-biological fields such as economics and learning theory. One can say that evolutionary game theory, in contrast with classical game theory, deals with population of players who have to decide between different strategies, and strategies with high payoff will spread in the population through learning or copying those strategies (Hofbauer & Sigmund, 2003). This behavior is studied using the replicator equation which describes the evolution of frequencies of population types or strategies. In deriving the replicator equation, it is assumed that there exists a well-mixed population in which every individual interacts with all other individuals with the same probability. However, in many populations, individuals have different probabilities of interaction and the structure of the interactions between individuals can affect the outcome of evolution. Spatial evolutionary game theory was created to model these types of interactions (Roca, Cuesta, & Sánchez, 2009).

Spatial game theory has been introduced by Nowak and May in the beginning of the 90s and involves evolutionary games with strategies distributed over some spatial region. Therefore, spatial games use evolutionary game dynamics on a spatial structure combining evolutionary game theory and cellular automata (CA) (Killingback & Doebeli, 1996). In these games, each player plays the game with its neighbors on a grid, and based on the players' strategy the various positions will be occupied by the winning strategy (or species in evolutionary games). To illustrate, assume a lattice in which each cell is occupied with a player, each player has a set of strategies to adopt, and there is a payoff associated with each strategy. At time zero a strategy is assigned to each player from the set of strategies and the total payoff of a player is defined as the sum of the payoffs resulting from playing with all the neighbors of that player. Using the total payoff, one can define a dynamic process to assign a strategy to a cell at the next generation which is usually the strategy of the player with the highest total payoff in the neighborhood of that player including itself. This dynamic process continues until the lattice reaches a steady state in which no one changes its strategy (Soltanolkottabi, Ben-Arieh, & Wu, 2019b).

In the following, a simple example of spatial evolutionary game in a lattice is shown assuming two types of strategies available to each player and each player has eight neighbors which are the eight cells surrounding it (Moore neighborhood). It is also assumed that the boundaries are not wrapped and the number of neighbors for the cells at the edges and in the corners is equal to the number of their immediate contacted cells. Thus the cells at the edges have 5 neighbors and the cells in the corners have three neighbors. The payoff matrix which is used is as follows:

$$\begin{array}{cc} & \begin{array}{cc} A & B \end{array} \\ \begin{array}{c} A \\ B \end{array} & \begin{pmatrix} a & b \\ c & d \end{pmatrix} \end{array}$$

Thus, players could choose either strategy A or strategy B and payoff value could be a, b, c, or d correspondingly according to players' strategies. Considering the distribution of players in a lattice as is shown in initial strategy of Figure 2.1. Each player would play the game with all its neighbors and the summation of payoff values in the game against each neighbor is the payoff of each player as is shown in Figure 2.1 payoff. Then, each player will update its strategy to the strategy of its neighbor with highest payoff. If $(b = 4) > (d = 3) > (a = 2) > (c = 1)$ as in prisoner's dilemma, the result of the game will be the updated strategy in Figure 2.1.

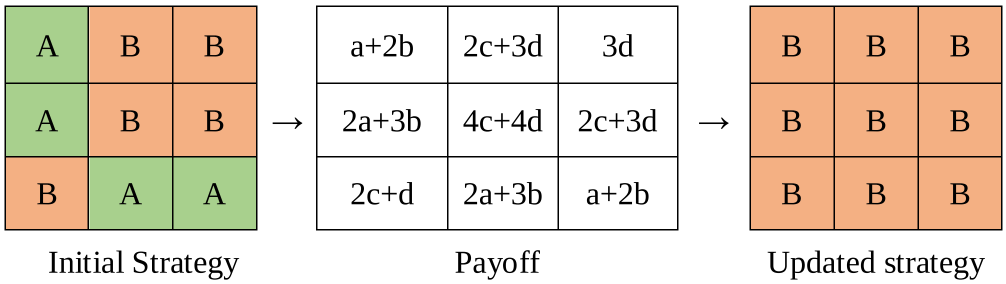


Figure 2.1 Illustration of the spatial game theory in a square lattice

2.1.1 Public goods game

The public goods game is a principle in experimental economics where players can invest into a common good, and then all the players get the shared benefit of the contributions irrespective of whether they paid in or not (Ledyard, 1994). The absence of infectious disease in a community or health care setting is considered a public good (Fisman & Laupland, 2009), and thus this approach can be used in modeling infectious disease dynamic and maintaining healthy communities in societies. In public goods game model, groups of players maximize their investment if everybody in the group contributes, but this behavior is vulnerable to "free-riders" where players get the shared benefit but do not invest themselves. In this game, it is advantageous for a player to defect while at the same time mutual cooperation would be beneficial for all; this is where the dilemma exists (Adami, Schossau, & Hintze, 2016).

Public goods game, in contrast with the prisoner's dilemma game which is discussed earlier, is a multi-player game. In such games, the payoff is a function of the state of more than two players in a group and the payoffs are not usually written in terms of a payoff matrix. The payoff function for a typical public goods game is as follows In which N_c is the number of cooperative individuals, C is the cost of cooperation (or contribution to the public welfare), N is the total number of members in a group and r is a multiplication factor.

$$payoff_i = \begin{cases} \frac{rN_cC}{N} & if\ i\ is\ not\ cooperative \\ \frac{rN_cC}{N} - C & if\ i\ is\ cooperative \end{cases} \qquad 2.1$$

Many studies have used public goods game in a spatial structure to model the evolution of cooperation regarding the allocation of public goods and have shown the importance of considering group cooperation in analyzing such dynamics (Perc, Gómez-Gardeñes, Szolnoki, Floría, & Moreno, 2013). The basic setup for a spatial public goods game with cooperators and defectors is on a lattice where each player and its K neighbors form a cooperation group, and each player can be either cooperative or defector. Then, each player enforces its strategy onto another player with some probability determined by their payoff difference. Li et al. (Li, Jin, Su, Kong, & Peng, 2010) also considered imitating the strategy of the player with the highest payoff in a neighborhood in their modeling. Some studies furthermore considered an extended cooperation group in which each person can be a member of several cooperation groups (Zhou, Ding, Fan, & Wang, 2016).

2.2 Epidemic dynamic models

Epidemics of infectious disease have influenced human civilization for many centuries. Epidemics have been documented as early as 430-427 BCE when the Athens epidemic killed as much as a half of the population of ancient Athens (Nelson, K. E. & Williams, 2001). From early times, people have tried to understand the causes and remedies to infectious diseases epidemics that took a huge toll on the human civilization. Only after the later part of the 19th century did vaccination become a successful tool in the fight against infectious disease.

In recent decades, the shift in climate and global temperature has raised the concern of increasing exposure to infectious diseases (Wu et al., 2016). The World Health Organization (WHO) has stated that the climate change and warming of the atmosphere are likely causes of increase in transmission of many infectious diseases (World Health Organization, 2003). Similarly, an article in the New England Journal of Medicine, has raised the concern that the climate change will cause a significant increase in infectious disease (Shuman, 2010). Moreover, there are also studies reporting that climate change has facilitated the spread of certain infectious into geographical areas that were previously unaffected (Lafferty, 2009).

Another concern raised in a report conducted by World Health Organization is that globalization and its effect on economic, environmental, demographic and topological change of societies has caused people in today's world to be in an increased risk of confronting infectious disease (Saker et al., 2004).

All these factors reemphasize the importance of controlling the spread of infectious diseases and motivated new approaches towards modeling infectious disease transmission and the behavioral response to it.

2.2.1 Behavioral model

Many studies have considered social and behavioral dynamics in impeding the spread of infectious disease since these behaviors can influence the dynamics of the spread of disease in populations (Wang, Z. et al., 2015). In such models, dynamic feedbacks between disease incident and individuals' behavior is modeled.

The behavioral or health belief model (HBM) is one of the models from the health psychology literature that represents individual behavior in response to an epidemic (Champion & Skinner, 2008). HBM has traditionally considered four main factors:

1) The perceived susceptibility of an individual or the probability that a person become infected

2) The perceived severity or the cost of being infected

3) The perceived barriers to behavior adoption or the cost of prevention

4) The perceived benefits or the benefits of adopting a behavior

Some studies have presented a mathematical framework to implement health belief model in modeling individual's decision making when facing an epidemic (Durham & Casman, 2011; Karimi, Schmitt, & Akgunduz, 2015).

A schematic illustration of the place of health belief model in the dynamic of disease behavior interactions is presented in Figure 2.2.

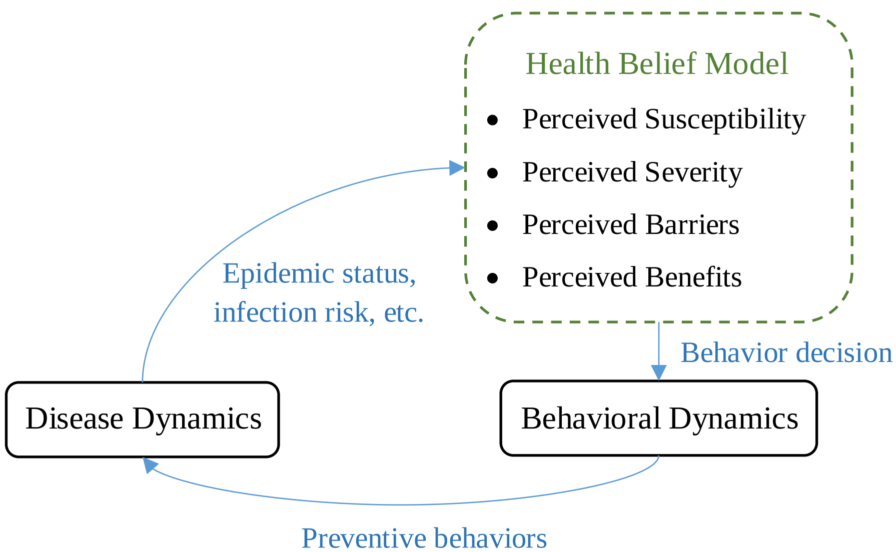


Figure 2.2 Schematic illustration of the place of health belief model in the dynamic of disease behavior interactions

The representation of the behavioral change in modeling the epidemics can be in form of changing one of these elements in the model, 1) the state of the individuals (see section SIS and

SIR model), 2) infection rate or 3) the contact network (Funk, Salathé, & Jansen, 2010). If the model is dealing with vaccination, usually changing the state for the vaccinated individuals is the approach for modeling. If social distancing and reducing the exposure to the infection is the behavioral change, either the change in infection rate or the contact network is a solution.

In this research we focus on vaccination as the behavioral response to the epidemic.

2.2.2 SIS and SIR model

Literature of epidemic spread modeling is very broad and extended. Researchers have used different methods to model this dynamic and behavior. In epidemic models it is usually assumed that a population can be divided into different categories based on the stage of the disease. Two of the well-known approaches in modeling epidemics are SIS and SIR models (Earn, Brauer, van den Driessche, & Wu, 2008).

SIS model is a 2-state epidemic model which is used to model the diseases with no immunity such as common cold or sexually transmitted diseases. The states for SIS model are susceptible individuals (S) and infected individuals (I). In these models, a susceptible person can become infected with probability β, which is the transmission rate of the disease, and an infected individual will become recovered with rate μ or after some time steps, and infected individuals will return to the susceptible class after recovering.

In classical understanding of dynamic of epidemics, the differential equations of the number of individuals in each stage of the disease is taken into account assuming a homogenous population with random interactions. The homogeneous random interaction leads to the conclusion that the larger the number of infectious individuals among one's interactions, the higher the probability of becoming infected (α). This probability is defined to be equal to $\beta\, N_I/N$, where

N_I/N is the portion of infected population. Thus, for the SIS model, the following set of equations shows the change in the number of susceptible and infected individuals.

$$\frac{dS}{dt} = -\alpha S + \mu I \qquad 2.2$$

$$\frac{dI}{dt} = \alpha S - \mu I \qquad 2.3$$

Equation 2.2 shows the changes in the number of susceptible in the population where S is the number of susceptible and I is the number of infected individuals, considering continuous time. Accordingly, the number of infected population changes based on Equation 2.3.

SIR model is a 3-state epidemic model in which a person can be susceptible (susceptible to become infected), infected or recovered, and is used to model the diseases in which an infected individual after becoming recovered is immune to the disease such chicken pox, mumps or measles. Thus the states for SIR model are susceptible individuals (S), infected individuals (I), and recovered individuals (R) which are immune. For the SIR model, the following set of equations shows the change in the number of susceptible, infected and recovered.

$$\frac{dS}{dt} = -\alpha S \qquad 2.4$$

$$\frac{dI}{dt} = \alpha S - \mu I \qquad 2.5$$

$$\frac{dR}{dt} = \mu I \qquad 2.6$$

Equation 2.4 shows the changes in the number of susceptible individuals. The number of infected population changes based on Equation 2.5, and Equation 2.6 shows the changes in the number of recovered individuals.

Figure 2.3 shows the schematic illustration of SIS and SIR modeling approach.

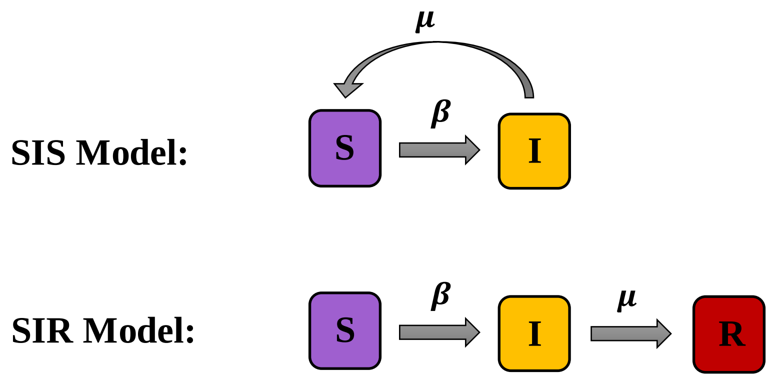


Figure 2.3 Schematic illustration of SIS and SIR models

Studies have used different methods to overcome the limitation of the classical mathematical model in considering the human behavior. Poletti et al. (Poletti, Caprile, Ajelli, Pugliese, & Merler, 2009) assumed two behaviors for a susceptible individual, one with the normal level of interactions and one with the reduced level of interactions (social distancing) resulting in a lower transmission rate. When considering vaccination as the behavioral response, these models can include an additional state for the individuals who are vaccinated. To illustrate, in the SIR model, one more state is added for the individuals who are vaccinated and the model is upgraded to the following form referred to as SIRV model (V for vaccinated) as shown in Figure 2.4. In this model, states R and V are absorbing states (Ruan, Tang, & Liu, 2012).

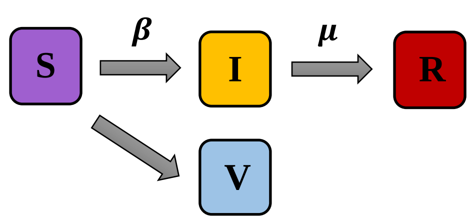


Figure 2.4 Schematic illustration of SIRV model

The following set of equations shows the change in the number of susceptible, infected, recovered and vaccinated individuals where γ shows the rate of vaccination.

$$\frac{dS}{dt} = -\alpha S - \gamma S \qquad 2.7$$

$$\frac{dI}{dt} = \alpha S - \mu I \qquad 2.8$$

$$\frac{dR}{dt} = \mu I \qquad 2.9$$

$$\frac{dV}{dt} = \gamma S \qquad 2.10$$

Equation 2.7 shows the changes in the number of susceptible individuals. The number of infected population changes based on Equation 2.8, Equation 2.9 shows the changes in the number of recovered individuals and Equation 2.10 shows the change in the number of vaccinated individuals.

In this research we focus on the transmission of the diseases which have characteristics of SIR systems considering vaccination as the preventive behavior.

2.2.3 Economic and rule based models

In modeling the epidemic disease spread, two types of behaviors exist. One type is emergent from individuals seeking to optimize their utility based on a cost function, and another is based on following pre-determined rule-sets. It is noteworthy that hybrids of both types also exist (Weston, Hauck, & Amlôt, 2018).

In the context of preventive strategies, cost-benefit calculation commonly involves agents comparing the utility of adopting protective behavior with their perceived payoff of not taking any action and remaining susceptible to infection. Thus, in the simplest form, considering λ as the probability of becoming infected, the agents decide to vaccinate if $C_V < \lambda C_I$ where C_V is the cost of prevention technique or vaccination and C_I is the cost of infection (Mbah et al., 2012). Game theory based models are the integral part of this category. In such studies, the payoff function for calculating the payoff of agent i is often of the following form:

$$P_i = \begin{cases} -C_V & if\ i\ is\ vaccinated \\ -C_I & if\ i\ is\ infected\ or\ recovered \\ 0 & if\ i\ is\ susceptible\ (free\ rider) \end{cases} \quad 2.11$$

The cost of vaccination can be in the form of the expense of vaccine administration and the potential risk of vaccine side-effects, and the cost of disease infection can include disease complications, expenses for treatment, or absence from work.

Bhattacharyya and Bauch (Bhattacharyya & Bauch, 2011) considered that individuals take vaccination behavior based on their perceived cost where the total number of vaccinated (herd immunity) in the society can inversely affect their perceived cost. They showed that this behavior will result in free-riding in society. Perisic et al. (Perisic & Bauch, 2009) considered the payoff of each agent to be the probability of being infected at each time and then individuals choose whether or not to vaccinate at any step according to perceived payoff of vaccination and infection.

On the other hand, in the rule-based models, the social or peer influence in decision making is incorporated. In these models, it is assumed that agents compare their behavior with behavior of other individuals in the society and through this comparison they can learn whether their behavior is optimal or not. Evolutionary game theory based models are the integral part of this category. Thus, agents typically sample other agents from the population and adopt either the most prevalent strategy, or rely on adopting the strategy implemented by a randomly selected agent (Verelst, Willem, & Beutels, 2016). Some studies have investigated behavior imitation using Fermi function, in which each individual i randomly chooses another individual j as role model, and imitates the behavior of j with the following probability (Wang, Z. et al., 2015) where P_i and P_j are respectively the payoff of individual i and j, and β shows the strength or sensitivity of selection.

$$\pi_{i \to j} = \frac{1}{1+\exp[-\beta(P_j - P_i)]} \quad 2.12$$

Thus, the larger the beneficial payoff difference and the larger the sensitivity of individuals to change their strategy, the larger the probability of changing the behavior. In these models, if the sensitivity of agents is very low, there is still a probability for the agents to adopt the behavior of an agent with a lower payoff.

Liu et al. (Liu, Wu, & Zhang, 2012) considered that the social influence affects the probability of changing the strategy to vaccination using Fermi function. Thus, instead of the difference in the payoffs they considered the difference in the social influence of vaccination and infection. They showed that individuals' high sensitivity to social influence will increase the vaccination coverage when the cost of vaccination is low, and will decrease it if the cost is high and the resulting vaccination coverage would converge to a certain level. Zhao et al. (Zhao, Wu, & Ben-Arieh, 2015) considered the payoff of each individual to be related to the estimated risk of infection in their neighborhood and the global risk of infection. They used the difference between the payoff of adopting prevention strategy and doing nothing in calculating the probability of changing strategy using Fermi function. Zhang (Zhang, Y., 2013) studied the impact of other-regarding behavior on voluntary vaccination considering the payoff of neighbors of each agent to also affect the payoff of the agent which is used in calculating the probability of switching to another agent's strategy. She showed that when the vaccination cost is small or moderate, the vaccination coverage is depending on the other regarding-behavior which will lead to an optimal total social cost.

2.2.4 Time delay

When modeling disease outbreaks, one of the factors that needs to be considered is time delay, which is intrinsic to various processes of epidemic outbreaks. Such delays can be due to the time it takes a population to become aware of an ongoing epidemic (awareness time), it can be due to the epidemiological time delay (incubation period), or due to an individual's delayed response to an outbreak (Agaba, Kyrychko, & Blyuss, 2017; Zuo & Liu, 2014; Zuo, Liu, & Wang, 2015).

The epidemiological delay can be classified as latency time and incubation time (Armenian & Lilienfeld, 1983). The incubation period is the time between exposure to a pathogenic organism and when symptoms and signs are first apparent, during which an infected person may or may not be contagious. On the other hand, latency is defined as the period in which a person is infected without being infectious. Some researchers have considered the incubation period and the time delay in transmitting a disease in mathematical models. Most of them consider the latent period a time delay for an infected individual to become infectious (Laarabi, Abta, & Hattaf, 2015; McCluskey, 2010; Xu, 2011). In the literature there are also mathematical models that have considered delay in individuals' response to a disease which can include a delay in reporting the disease or delay in responding with a preventive behavior (Greenhalgh et al., 2015). From the modeling point of view, the delay in reporting a disease is very similar to not being aware of an infection.

Other researchers have focused on the importance of the incubation period for epidemic control. Uys et al. (Uys, Warren, & Van Helden, 2007) analyzed the consequences of delay to the diagnosis of TB (Tuberculosis). They found that typical delays to diagnosis present a major problem to the control of the TB epidemics. Carpenter et al. (Carpenter, O'Brien, Hagerman, & McCarl, 2011) simulated delayed detection of a foot-and-mouth disease outbreak in California and showed that increasing the detection time to two weeks can cause dramatic increase in the number of infected cows and the loss of agricultural welfare. Since this type of time delay can affect the dynamics of an epidemic, it is an essential factor in modeling infectious disease transmission. However, models that have used game theoretic approach to represent the behavior of individuals when facing an epidemic overlooked this incubation period. Considering the incubation period in modeling is critical; during this period a disease can be infectious while the symptoms are still not apparent, and people are not aware of their risk of exposure, and thus oblivious to the need to change their behavior.

2.2.5 Population based and network based models

The spread of infectious disease can be studied at the population level or based on a social interacting network (Verelst et al., 2016). In the population-level studies, it is assumed that the population is homogeneously mixed and every individual is in contact with every other individual in the population. These studies usually consider the number or percentage of the individuals in each state in their analysis and model the changes in the average number of individuals in that state (d'Onofrio & Manfredi, 2010; Reluga & Galvani, 2011).

In contrast with population-based models, network-based models consider an individual as a node in a network and the relationships or contacts of that person as the edges. Epidemic modeling using network-based models has enormously progressed in the last years since many diseases are transmitted with a direct or close contact between individuals. Also, due to the fact that the increase of computational power has made the detailed simulation of network-based models easier (Pastor-Satorras, Castellano, Van Mieghem, & Vespignani, 2015) network-based modeling is increasingly used. In the class of network-based models, agent-based models are the ones in which nodes of the network are autonomous decision-makers.

Spatially structured models are of the most commonly used in the class of network-based modeling, since individuals usually interact with those who share close geographic proximity with them (Wang, Z. et al., 2015). The simplest spatial structure is a lattice in which each cell represents an individual, and the cells around it are the immediate contacts of that cell. Lattices are homogeneous at the individual level (Keeling & Eames, 2005).

Scale-free networks are a group of networks with a power-law degree distribution. Thus, as the degree k increases, the likelihood of finding a node with a very large degree decreases. This type of network indicates the presence of some few nodes (known as hubs) with a much higher degree than most other nodes. Consequently, in such networks there are some nodes that are highly connected to other nodes in the network, which is a common feature of real-world networks such as network of air travels. Scale-free networks are used in studying the transmission of diseases in populations (Barabási, 2016).

Network based models have been widely studied in recent research works. For example, Fu et al. (Fu et al., 2010) modeled the role of imitation behavior in a spatial structure and showed that the spatial structure is more sensitive to changes in cost of vaccination in comparison with the population based model. Fukuda et al. (Fukuda, Tanimoto, & Akimoto, 2015) applied the same model but instead of one network of interactions they defined two networks in which one is the disease transmission network and the other one is the information transmission network. This approach is useful when modeling the effect of interacting through social media on peoples' health belief.

2.2.6 Meta-population models

There are some studies which have modeled the disease spread for the interactive populations, known as meta-population, whose interactions are based on a network (Wang, L. & Li, 2014). In these models, it is assumed that the nodes of the network are not individuals but population of individuals who are interacting on a network. The necessity of these types of models stems from the fact that the large scale spatial transmission of infectious diseases is often related to the human mobility pattern which can hardly be captured in the network of a single population. To consider the effect of human mobility, it is intuitive to generalize the network model by defining each node as a population with a specific location such as cities, in which a population of individuals interact according to some rules and people are also permitted to make connections among populations through mobility networks.

Watts et al. (Watts, Muhamad, Medina, & Dodds, 2005) introduced a class of meta-population models for epidemic spread modeling and modeled the movement of individuals between population to analyze the dynamic of epidemic. Colizza et al. (Colizza, Pastor-Satorras, & Vespignani, 2007) also analyzed epidemic spread on a network using degree based mean field theory. Wang et al. (Wang, L., Wang, Zhang, & Li, 2013) modeled SIS like disease transmission considering the disease prevails inside each subpopulation assuming a homogeneously mixed population, and transmits between subpopulations through the travel of infected individuals. They assumed the total number of connections from other populations through traveling affects the transmission rate of the disease in each population.

2.3 Spatial game theory in epidemic dynamic modeling

Spatial game theory is one of the methods which is used in modeling epidemic dynamics. In such studies it is assumed that individuals are interacting with each other based on the network of interactions (usually a lattice) and they adopt different strategies based on their payoff and some rules of updating.

Representations of strategies are commonly based on the aforementioned transmission models (SIS and SIR model). The payoff calculation can be in several forms as mentioned in Economic and rule based models. Also, different updating methods are implemented such as imitating strategy of another player.

In Table 2.1 the studies with SIR transmission model having vaccination as the preventive strategy are classified based on the network of interactions, payoff function and updating methods.

Some studies have also considered different epidemic seasons in which people learn from their behavior in the previous season. This approach is useful in modeling disease such as influenza (Chang, Piraveenan, Pattison, & Prokopenko, 2019).

Table 2.1 Classification of papers used spatial game theory in modeling

Author	Type of network	Type of payoff function	Type of behavior
Zhang et al. (Zhang, H., Wu, Tang, & Lai, 2014)	Square lattice and scale-free network	Cost of vaccination if vaccinated and cost of infection if infected	Rule based (imitation)
Fukuda et al. (Fukuda et al., 2015)	Bi-level square lattice and scale-free network	Cost of vaccination if vaccinated and cost of infection if infected	Rule based (imitation)
Fu et al. (Fu et al., 2010)	Square lattice and random network	Cost of vaccination if vaccinated and cost of infection if infected	Rule based (imitation)
Perisic et al. (Perisic & Bauch, 2009)	Random network	Payoff is the probability of being infected at each time step	Economic based
Zhao et al. (Zhao et al., 2015)	Square lattice	Individual payoff plus the global payoff	Rule based (imitation)
Yan Zhang (Zhang, Y., 2013)	Square lattice	Considered the payoff of an individual's neighbors as a part of payoff function	Rule based (imitation)
Liu et al. (Liu et al., 2012)	Square lattice	Cost of vaccination if vaccinated and cost of infection if infected	Rule based (imitation)

In the literature of epidemic modeling, although it is mentioned that the problem of decision making for vaccination is a public goods, none of the studies has used a public goods game based payoff function to model the behavior of populations. This dissertation aims to address this gap in the current literature.

Chapter 3 - Modeling Individuals' Response to Epidemic

This chapter presents a public goods game based model for modeling the dynamic of epidemics in which the payoff of each individual is calculated based on its share of perceived cost of susceptibility, severity and barriers for the whole group where he is a member, rather than his personal cost of vaccination or infection. Spatial game theory is used to consider the spatial network-based structure of the population of players. In this model, in every time step, all susceptible players update their strategy for getting vaccine or not synchronously and then each of them might be infected based on its strategy and the probability of becoming infected. In order to update the strategy to get vaccine or not a new approach is used in which each susceptible player updates its strategy not just to the strategy of the neighbor with the highest payoff but also to the strategy of the number of neighbors with highest payoffs. Thus, if there is someone vaccinated among the neighbors with highest payoff, the player will change its strategy to get the vaccine. The sensitivity factor is a measure for the number of neighbors with highest payoff that a player refers to in order to update its strategy. This sensitivity factor can be considered as a surrogate form of fear factor or the effect of media on making people aware of the severity of a disease. The concept of effect of media and fear factor on individual's decision is studied in some research trying to show how it can affect the spread of infectious diseases (Johnston & Warkentin, 2010; Mummert & Weiss, 2013). The findings of this study are published in (Soltanolkottabi, Ben-Arieh, & Wu, 2019a).

In section 3.1 the proposed methodology in modeling spread of infectious disease is presented. Section 3.2 presents the result of using this methodology considering different parameters and discussing the behavior of individuals facing infectious disease outbreaks. Section 3.3 provides a summary and discussion.

3.1 Methodology

In this study, individuals' cost functions and payoffs are determined based on their contribution to the group and the group's shared payoff which can be seen as a public goods game. This means that any payoff in a group will be distributed among the members of the group.

In our model we have considered a person and all its immediate neighbors as a group; so, in a lattice, the center cell is the player in question and its cooperation group is the eight cells adjacent to it as shown in Figure 3.1 where the yellow cells show the cooperation group for player i.

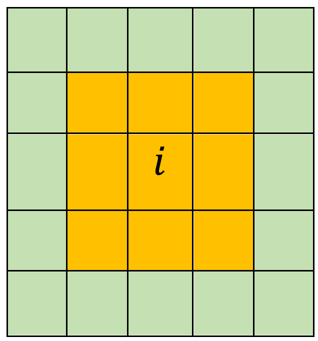


Figure 3.1 Cooperation group for individual *i*

The payoff for being a member of this group is defined as follows:

$$Payoff_g = -\left(\left(\frac{N_I}{N} \times C_I\right) + \left(\frac{N_V}{N} \times C_V\right) + \left(\frac{C_I \times \sum_{j \in Sm} P_{\inf j}}{N}\right) + \left(\frac{N_R}{N} \times C_R\right)\right) \qquad 3.1$$

Where N_I is the number of infected individuals in a group, C_I is the cost of infection, N_V is the number of vaccinated individuals in a group, C_V is the cost of vaccination, Sm is the group of susceptible members, $P_{\inf j}$ is the probability of getting infected for player j, N_R is the number of recovered individuals in a group, C_R is the cost of being recovered for the group and N is the total number of members of a group. In other words, we can say that the first and last portions of the equation show the perceived severity, the second portion is the perceived barriers and the third portion is the perceived susceptibility of a group. Note that the payoff is negative, treated as a cost rather than a benefit.

Also, in this function, $P_{\inf j}$ is calculated using the following formula (Section 2.2.2):

$$P_{\inf j} = \frac{N_{I\,j}}{N} \times \beta \qquad 3.2$$

Where $N_{I,j}$ is the number of infected neighbors of j, N is the total number of neighbors of j and β is the disease's transmission rate based on a one-on-one contact.

The total payoff of a player is equal to the payoff that a player can earn from participating in a group minus the cost of being infected or getting the vaccine. The following formula shows the total payoff of a player:

$$Payoff_i = \begin{cases} Payoff_g - C_V & if\ i\ is\ vaccinated \\ Payoff_g - C_I & if\ i\ is\ infected\ or\ recovered \\ Payoff_g & if\ i\ is\ susceptible\ (free\ rider) \end{cases} \qquad 3.3$$

3.1.1 Updating rule

The updating rule is such that in every time step the top s neighbors with highest payoff in the neighborhood of a player will be chosen and if there is someone vaccinated among them and its payoff is higher than the payoff of that player itself, the player will decide to get vaccinated, otherwise it remains susceptible. We call s the sensitivity factor.

To illustrate, in the following lattice, consider the sensitivity factor equal to 3 for the center player. The set of first 3 neighbors with highest payoff will be $\{(-2.111, S), (-3.055, S), (-12.38, V)\}$ (Figure 3.2). The updating strategy of the center player will be to vaccinate if one of the top three neighbors is vaccinated, which is the case in Figure 3.2-a. If we change the sensitivity factor to 2, then the player will not vaccinate as shown in the Figure 3.2-b, since the top two players are not vaccinated. The numbers in the cells show the payoff for the center player and its neighbors, and the payoff of neighbors are calculated based on their 8 neighbors some of which are not shown here. We have considered (C_I, C_V, C_R, β) equal to $(100, 10, 0, 0.2)$.

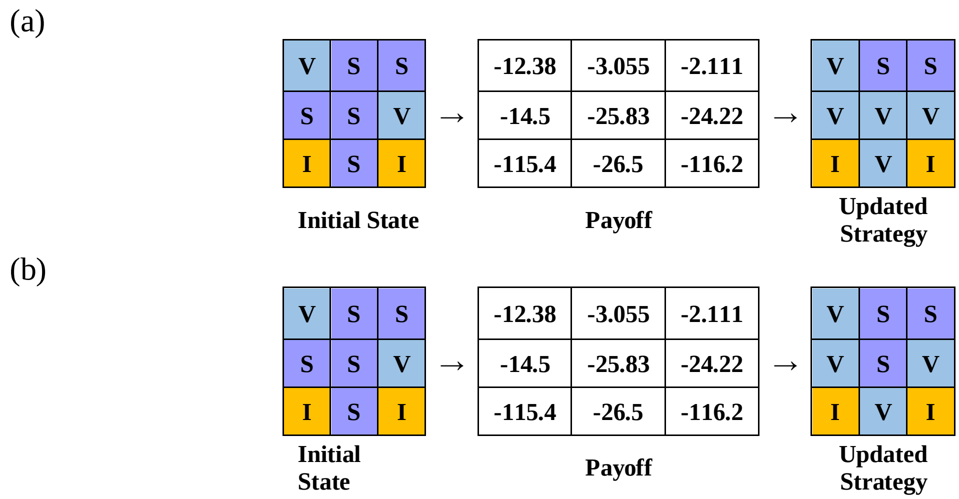


Figure 3.2 Illustrating updating strategy

3.2 Experimental results

In the following, the result of changing different factors that can affect the dynamics of an epidemic are studied. In the lattices, the purple cells show susceptible, yellow cells show infected, red cells show recovered and light blue cells show vaccinated individuals. The parameters which are used in the models are presented in Table 3.1.

Table 3.1 Parameters of the model

Parameter	Meaning	Value
N	Population size	2500
I_0	Percentage of initially infected individuals	5%
R_0	Percentage of initially recovered individuals	0%
L	Duration of infectious period	19 time steps
C_R	Cost of being recovered	0
C_I	Cost of infection	1000
C_V	Cost of vaccination	10 or variable
β	Transmission rate	0.2 or variable
V_0	Percentage of initially vaccinated individuals	5% or variable
s	Sensitivity factor	4 or variable

Figure 3.3 shows the change in the percentage of vaccinated individuals, infected individuals and susceptible for the values given in Table 3.1. In the figure, the purple line shows susceptible, yellow line shows infected, red line shows recovered and light blue line shows percentage of vaccinated individuals. It can be seen that during the epidemic, the percentage of infected individuals increases at first and then it decreases. Also, the number of vaccinated and recovered individuals increases and consequently, the number of susceptible will decrease until the epidemic dies out.

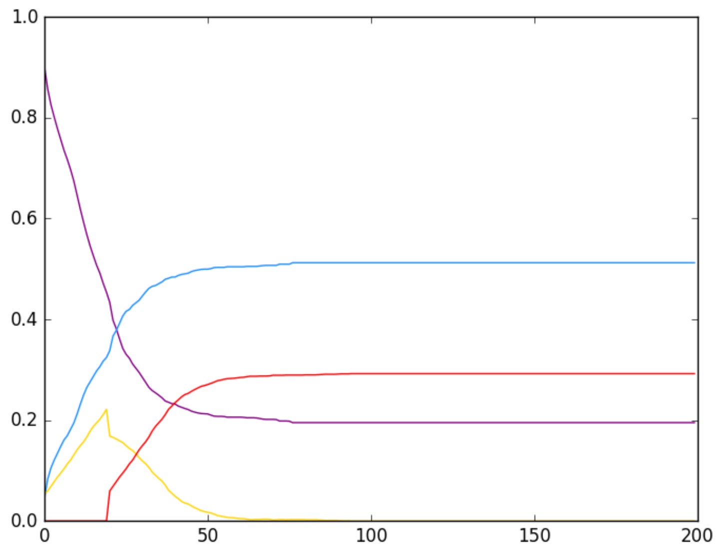


Figure 3.3 Changes in the percentage of vaccinated, infected, recovered and susceptible individuals during an epidemic

3.2.1 Effect of changing the cost of vaccination

One of the variables that can affect the spread of infectious disease and is under control of the health policy makers is the cost of vaccination. It is reasonable for the cost of vaccination to be less than the cost of infection and practically it should be much less than the cost of infection otherwise people will prefer not to pay the cost of vaccination. Thus, to examine the effect of C_V

on the epidemic and the number of vaccinated individuals, a simulation model was generated. The model was run on a 50 by 50 lattice in which the initial number of infected and vaccinated individuals are distributed randomly and $\beta = 0.2$. It is updated for 200 time steps to make sure that epidemic has reached the steady state situation, then the result of steady state lattice is used for evaluations.

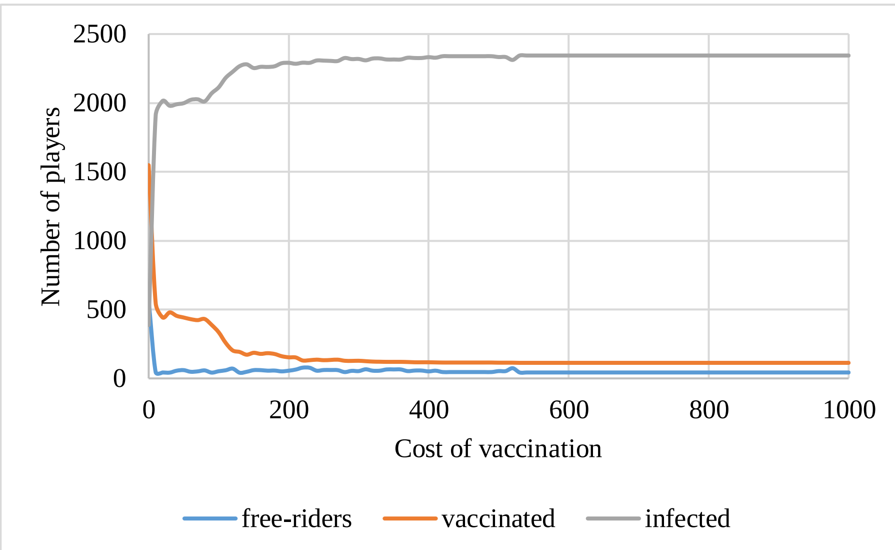
In Figure 3.4, the results of updating a lattice using different vaccination cost from 0 to a cost equal to the cost of infection is presented.

Figure 3.4-a shows the number of free-riders, infected and vaccinated individuals under different vaccination cost when $s = 1$. The figure shows that as predicted increasing the vaccination cost will decrease the number of vaccinated individuals to the point that no one decides to get vaccinated other than the initially vaccinated ones. However, comparing this result with the one with a higher sensitivity factor ($s = 4$, Figure 3.4-b) shows that increasing the sensitivity can result in more vaccinated individuals and also more free riders which is beneficial to the society. Moreover, in the experiments it can be seen that higher sensitivity factor can result in better control of the epidemic for any vaccination cost C_V as long as the value of C_V is not too high resulting in no additional vaccinated individual. This phenomena can be seen in Figure 3.5. Figure 3.5-a is the result of updating the lattice when $C_V = 10$ (left) and $C_V = 100$ (right) for $s = 1$ and Figure 3.5-b is the result of updating the lattice when $C_V = 10$ (left) and $C_V = 100$ (right) for $s = 4$. It can be seen that when s is higher there are some clusters of vaccinated individuals who surround infected individuals and cause the epidemic to be controlled more effectively. As a result, the number of free riders (purple cells) increases because there is enough protection provided by vaccinated individuals. Thus, the society benefits from a lower cost of vaccination and disease in comparison with the same level of protection when all individuals are vaccinated. It is worth to

mention that the epidemic season length did not show a meaningful relation with the cost of vaccination.

This also shows the benefit of increasing *s*, indicating a higher public awareness of the risk and harm of the disease. Increasing *s* can be done practically by using public media, social networks and similar mass communication channels.

(a)



(b)

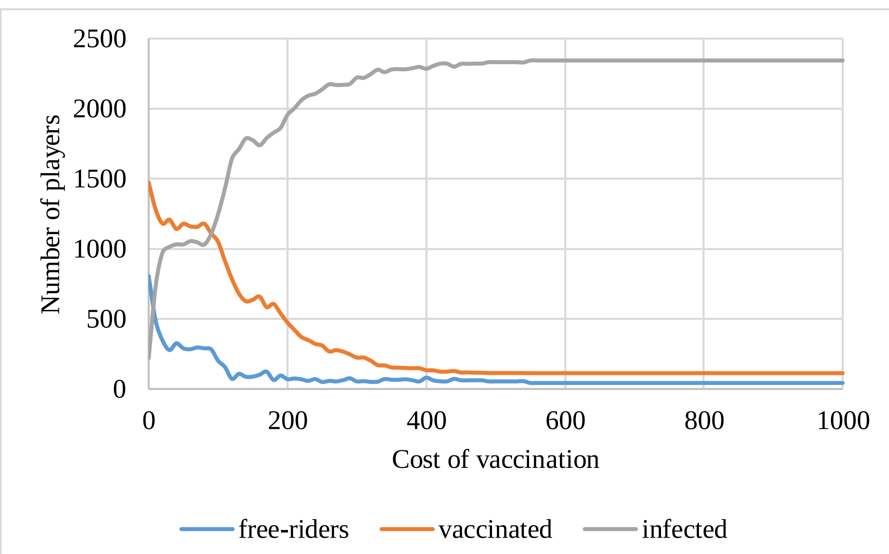
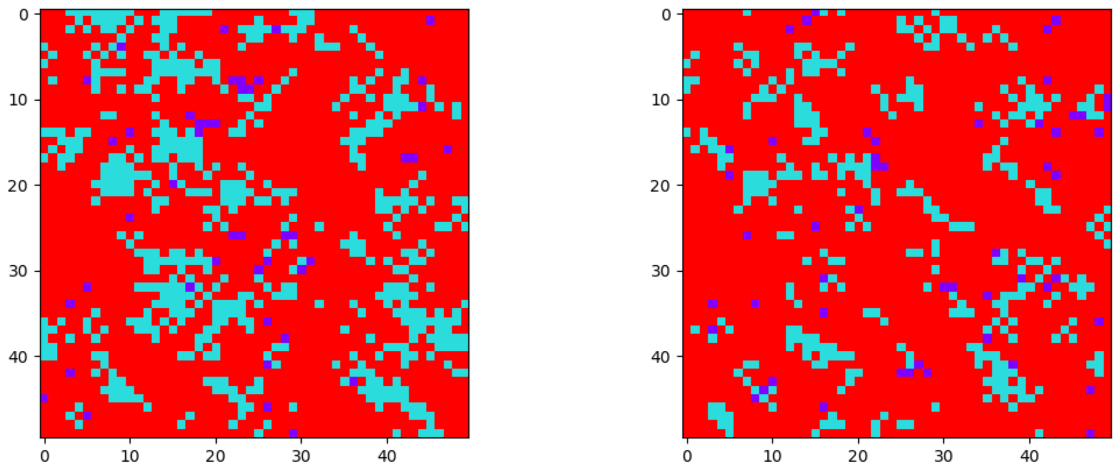


Figure 3.4 Number of free riders, infected and vaccinated individuals for different vaccination costs when $s = 1$ (a) and $s = 4$ (b)

(a)



(b)

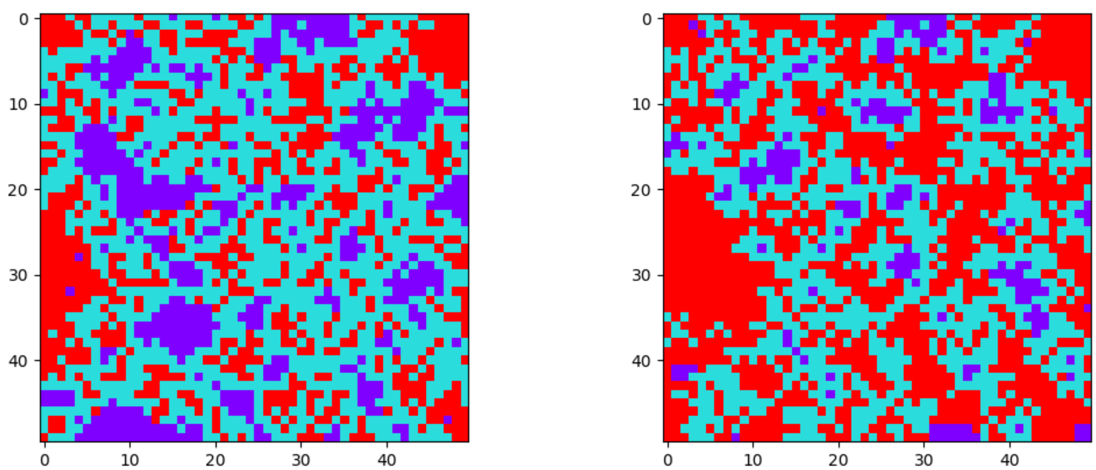


Figure 3.5 Distribution of players in the last lattice for $C_V = 10$ and $C_V = 100$ when $s = 1$ (a) and $s = 4$ (b)

3.2.2 Effect of changing the transmission rate

The disease transmission rate is another variable in the model which depends on the characteristic of the disease. In order to examine the behavior of this model facing different disease with different transmission rates, the number of finally vaccinated and infected individuals for different transmission rates are studied. In Figure 3.6, the lattice on the left side shows the result of updating a 50 by 50 lattice when $C_V = 10$ and $s = 4$ for $\beta = 0.2$ and the lattice on the right side shows the result of updating a 50 by 50 lattice when $C_V = 10$ and $s = 4$ for $\beta = 0.9$. It can be seen that more people get vaccinated when the transmission rate is high (especially in the lower rates of transmission) to save themselves and their community. This phenomenon can better be seen in Figure 3.7 in which the number of vaccinated, infected and free riders is plotted for different transmission rates from 0.1 to 1. The figure shows that the public behavior is sensitive to the transmission rate at the lower end, and is more stable at high rates of transmission. This sensitivity was experienced during the 2003 SARS episode in Hong Kong (Durham & Casman, 2011) .

Moreover, the epidemic tends to end sooner with a higher transmission rate, due to the faster response of individuals to the epidemic because of its high threat to the players (i.e. higher cost) as seen in Figure 3.8.

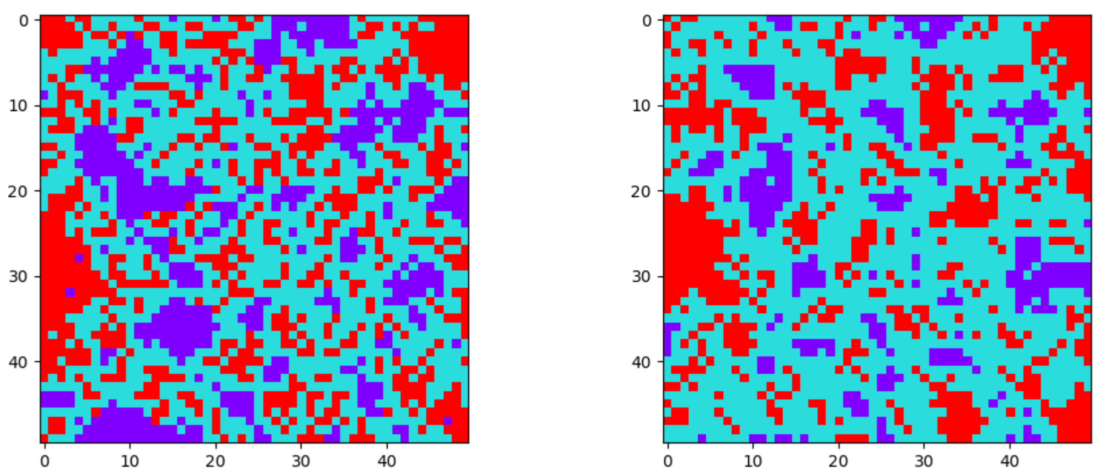


Figure 3.6 Distribution of players in the last lattice when $\boldsymbol{\beta = 0.2}$ (left) and $\boldsymbol{\beta = 0.9}$ (right)

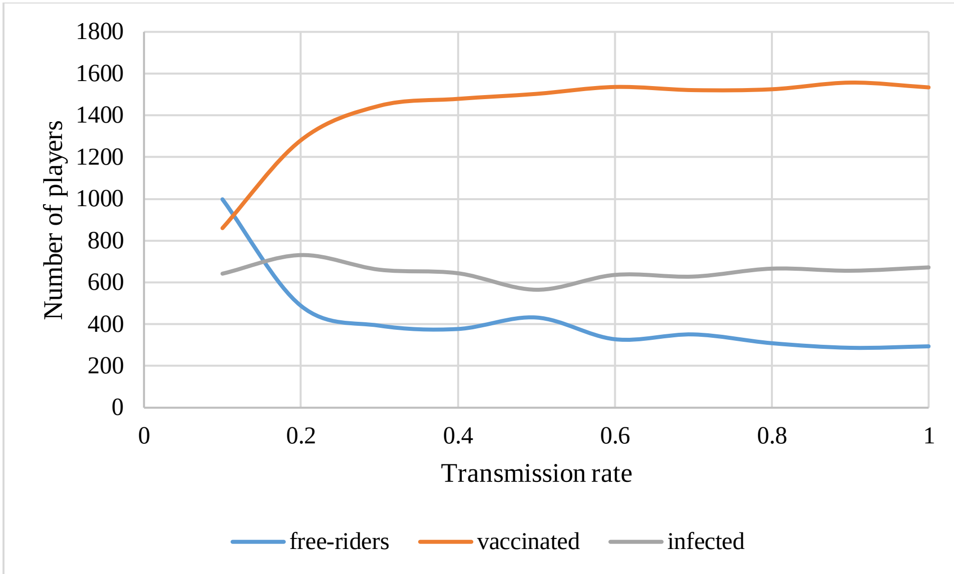


Figure 3.7 The number of vaccinated, infected and free riders for different transmission rates

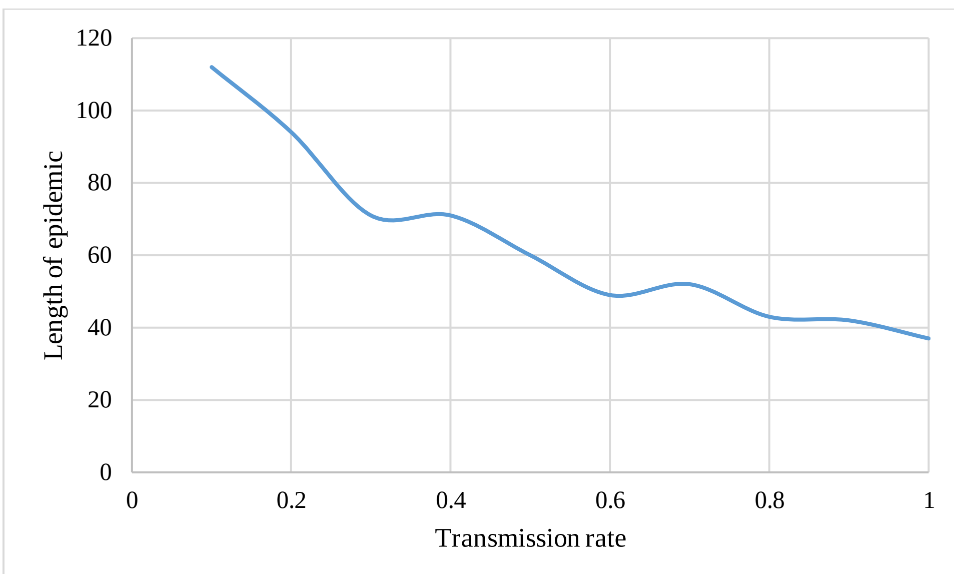


Figure 3.8 The length of epidemic for different transmission rates

3.2.3 Effect of changing the initially vaccinated population

The number of initially vaccinated individuals in the population is another parameter that can be controlled by the health policy makers by encouraging some individuals in the population to get vaccinated either using free-subsidy policy or partial-subsidy policy. The result of changing the percentage of initially vaccinated individuals shows that increasing the percentage of vaccinated individuals is beneficial to the society as long as the number of vaccinated is not beyond a certain percentage causing some individuals to get the benefits of living among vaccinated individuals in an immune society. As it is apparent in Figure 3.9, the number of free-riders will increase as the number of initially vaccinated increase, but it will start to decrease as the number of vaccinated increase more than 20%. These experiments are done in a 50 by 50 lattice when $C_V = 10$, $\beta = 0.2$ and $s = 4$ while changing percentage of initially vaccinated ones (V_0) from 1% to 50%. Moreover, the number of finally vaccinated individuals does not exhibit a large change for different experiments while as the number of initially vaccinated ones increase the number of individuals who decide to get vaccine decrease. This can be better seen when we plot the number of individuals who decide to get vaccine during the epidemic (Figure 3.9- yellow line). This decrease in the number of voluntary vaccination can be explained by the "group protection" that more vaccinated individuals provide. Additionally, the graph of infected individuals shows that as we increase the number of initially vaccinated people linearly, the number of infected people will decrease much faster. In all the experiments for Figure 3.9, the number of initially infected individuals was 5% of the population.

Studying the behavior of population using different sensitivity factors and initial vaccination rate shows that the higher sensitivity will cause the number of free riders to grow faster. In Figure 3.10, each line shows the number of free-riders for each value of s from 1 to 6 and it is apparent that as the value of s increases the number of free-riders increase. This can be explained by the fact that increasing the number of vaccinated individuals in the comparison group provides more protection and reduces the number of infected individuals, reducing the need of individuals to get vaccinated. This result is true when the number of initially vaccinated is less than 20% because the number of free-riders will start to decrease as we increase the number of initially vaccinated individuals as it can be seen in Figure 3.9.

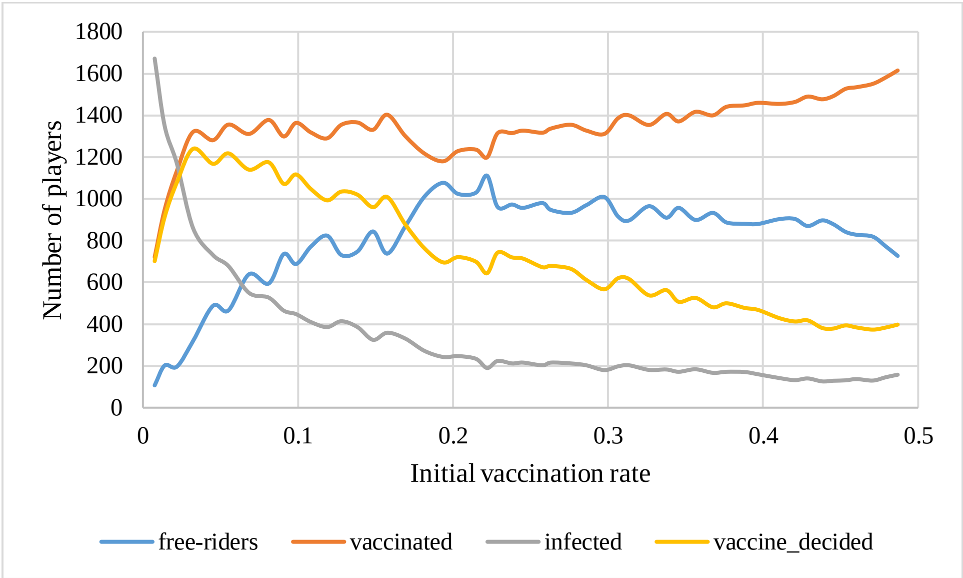


Figure 3.9 The number of vaccinated, infected and free riders for different initial vaccination rate

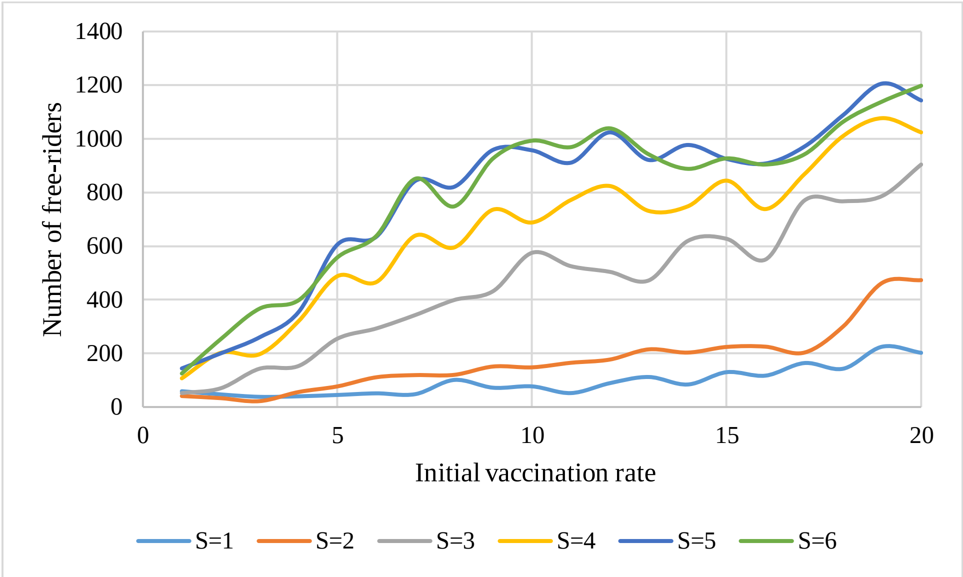


Figure 3.10 The number free-riders for different initial vaccination rate and sensitivity factor

3.2.4 Effect of changing the initial distribution of players in the lattice

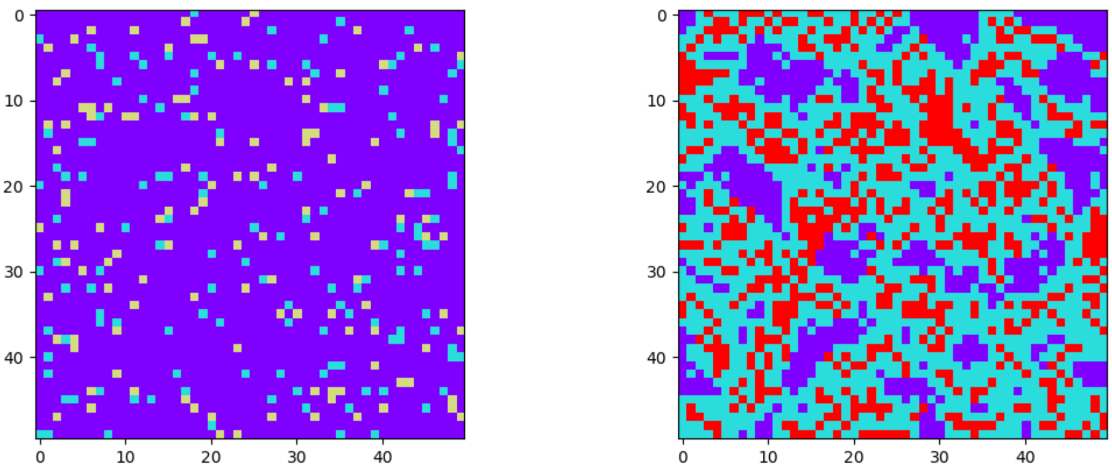
The distribution of players in the lattice is also a factor that can be controlled to achieve better vaccine coverage. Although the health policy makers can influence the initially vaccinated individuals in society, they have no control over the number of initially infected ones. Thus, to model the effect of changing distribution of players, the initially infected individuals are randomly distributed in the lattice, but three scenarios are considered. In the first scenario the vaccinated individuals are distributed randomly in the population (Figure 3.11 – a), in the second one the vaccinated individuals are evenly distributed in the lattice (Figure 3.11 – b) and in the third scenario the vaccinated individuals grouped into larger clusters (of 9 individuals) that are evenly distributed in the lattice (Figure 3.11 – c). In all scenarios the number of vaccinated and infected individuals are the same. These experiments are done in a 50 by 50 lattice considering $C_V = 10$, $\beta = 0.2$ and $s = 4$.

Table 3.2 shows the result of each scenario. In all three scenarios the number of initially vaccinated is 144 which is approximately 5% of the population. We can see in Table 3.2 that if the individuals are evenly distributed, we will have fewer infected and vaccinated individuals and more free-riders. This result is the effect of accessibility of vaccinated individuals in all cooperation groups, so, individuals can decide sooner to get vaccine confronting a disease epidemic and can also save others from being infected. Moreover, the result shows that group vaccination is less effective while there might be some vaccination not necessary for people who are not at risk of being infected, and also more initial vaccinations are needed to support this society. However, if we distribute groups such that they are more reachable for other individuals for imitating their behavior the result will be improved.

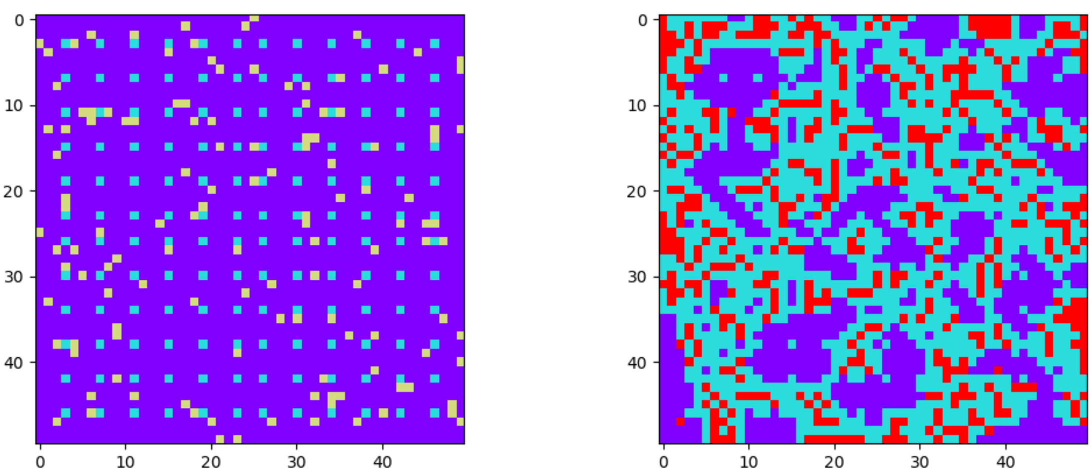
Table 3.2 Result of each scenario

Scenario	Free-riders	Vaccinated	Infected	Length of epidemic
Random	517	1347	636	98
Even	759	1240	501	90
Cluster	232	1205	1063	100

(a)



(b)



(c)

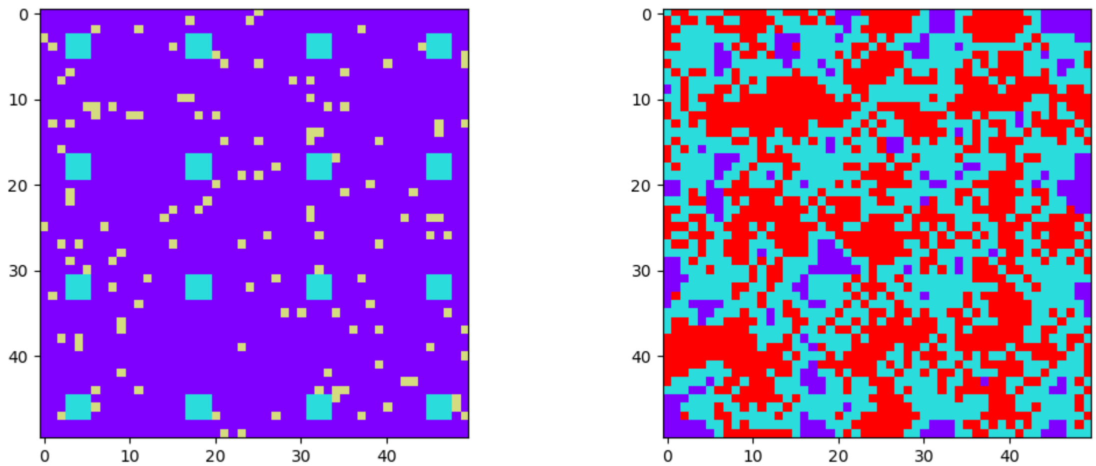
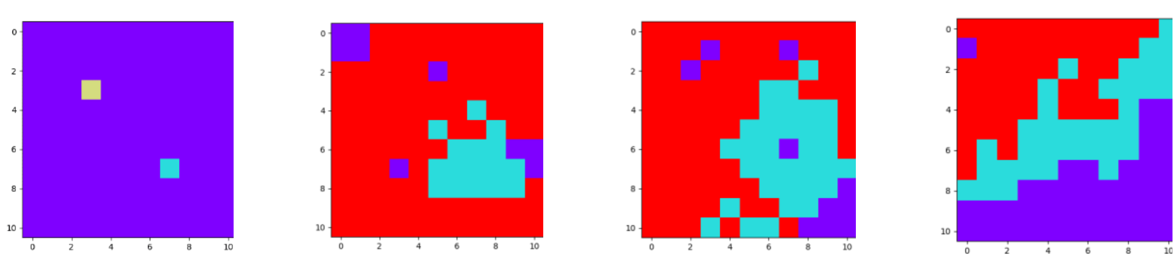


Figure 3.11 The first and last lattice for different distribution of vaccinated individuals

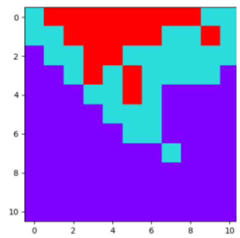
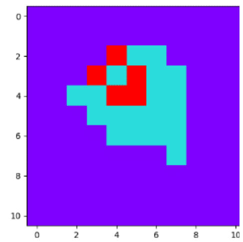
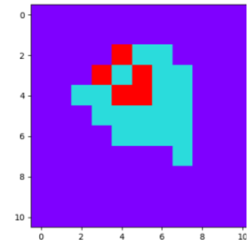
3.2.5 Effect of changing the sensitivity factor

In order to examine the behavior of the model to changing sensitivity factor, the steady state results of updating three different starting lattices under different sensitivity factors are presented in Figure 3.12. The figure shows that as the sensitivity factor increases the infection has a lower chance to affect other people while individuals respond sooner to epidemic. In these experiments we have considered $C_V = 1$ and $\beta = 0.2$. It can be seen in all figures that as sensitivity factor increases in all three cases, vaccination has a better coverage and vaccinated individuals can better control the spread of infectious disease.

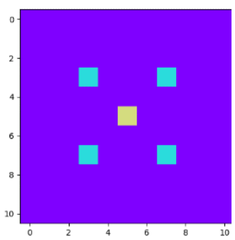
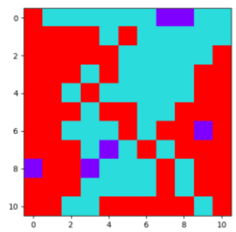
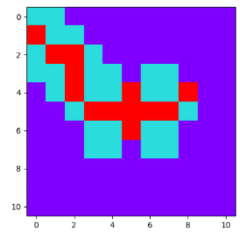
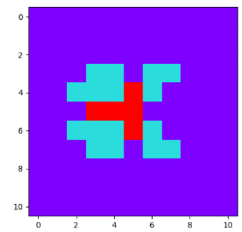
Initial lattice $s = 1$ $s = 2$ $s = 3$



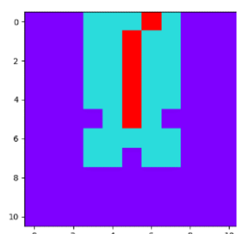
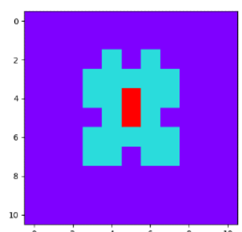
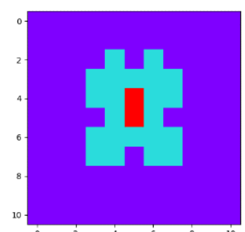
$s = 4$ $s = 5$ $s = 6$

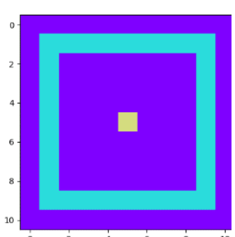
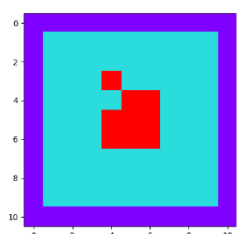
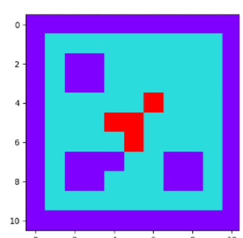
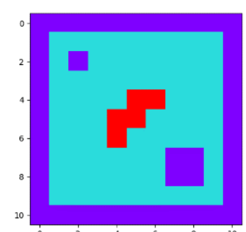
Initial lattice $s = 1$ $s = 2$ $s = 3$

$s = 4$ $s = 5$ $s = 6$

Initial lattice $s = 1$ $s = 2$ $s = 3$

$s = 4$ $s = 5$ $s = 6$

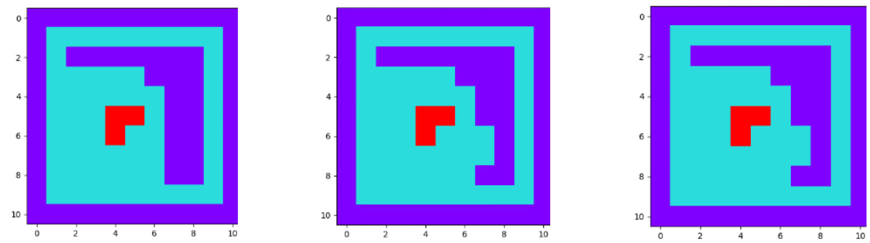


Figure 3.12 Results of updating three custom starting lattices

We have also examined the result of changing sensitivity factor when updating a lattice with distribution of players for three different vaccination costs (Figure 3.13-Figure 3.17). In the diagrams, the blue lines show the experiments for $C_V = 1$, orange lines show the experiments for $C_V = 10$ and gray lines show the experiments for $C_V = 100$.

Figure 3.13 illustrates the total cost of each lattice of players. This cost is calculated using the following formula which shows the total cost of being infected or vaccinated for the society.

$$Total\ cost = C_I(N_I + N_R) + C_V N_V \quad 3.4$$

In this case N_I, N_R and N_V are the number of infected, recovered and vaccinated individuals in the entire lattice.

We can see that as the number of free-riders increases, and the ratio of infected to vaccinated individuals decreases, the total cost decreases. This means that the society could control the spread of disease with minimum number of vaccinated individuals. In Figure 3.13, the total cost decreases for all three different vaccination costs as the sensitivity factor increases but it does not change much for $s \geq 5$.

Figure 3.14 shows the number of vaccinated players in the last lattice for each scenario. We can see that for sensitivity factors greater than 4, the number of vaccinated individuals does not change notably. However, the final number of vaccinated individuals is greater when the cost of vaccination is low.

Figure 3.15 shows the number of recovered individuals in the last lattice. In the last lattice, the epidemic season is over and all the infected individuals have changed their state to "recovered". Thus the number of recovered individuals is used to represent the number of individuals infected during each run. The figure shows that the number of recovered individuals has the same behavior as the total cost; this is due to the high cost of infection relative to the cost of vaccination and the effect of the high number of infected individuals on the total cost. Also, the figure demonstrates again that more people will be infected as the cost of vaccine increases.

Figure 3.16 shows the number of free riders in each experiment. As can be seen this number increases as sensitivity increases but levels off after $s = 5$. Based on this output, we conclude that the sensitivity factor that maximizes the number of free riders is $s = 5$ independently from the cost of vaccination. It is interesting to observe as discussed earlier that a higher s factor that relates to the fear of individuals from being infected is proportional to the number of free-riders (who choose not to vaccinate). This counter intuitive result can be explained as a society that is more active in protecting itself also provides protection to free-riders who benefit from this anxiety. Also, s of 5 implies that a simple majority of the neighbors decides on the strategy of the individual. This shows that the best policy in society is to follow the majority of the comparison group.

Figure 3.17 shows the duration of the epidemic season in each experiment. Based on this result we can conclude that the length of an episode is mainly affected by the cost of vaccination; since cheaper vaccination results in an increase in the number of vaccinated individuals and cause the epidemic to end sooner. Similarly, if the sensitivity factor is increased, the duration of an epidemic is reduced. This is explained by the society that exhibits a higher sensitivity to the risk of being infected and is more proactive in vaccinating.

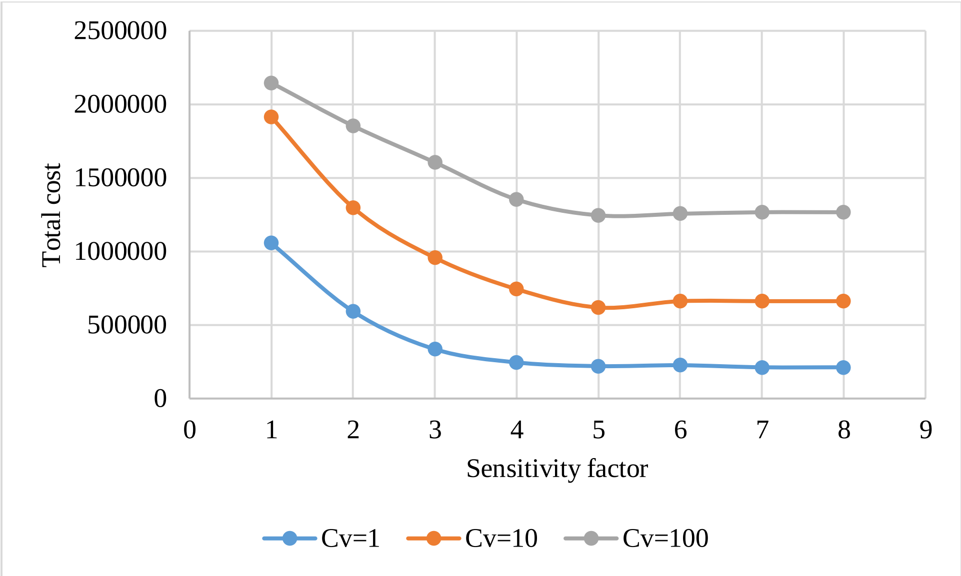


Figure 3.13 Total cost of each experiment

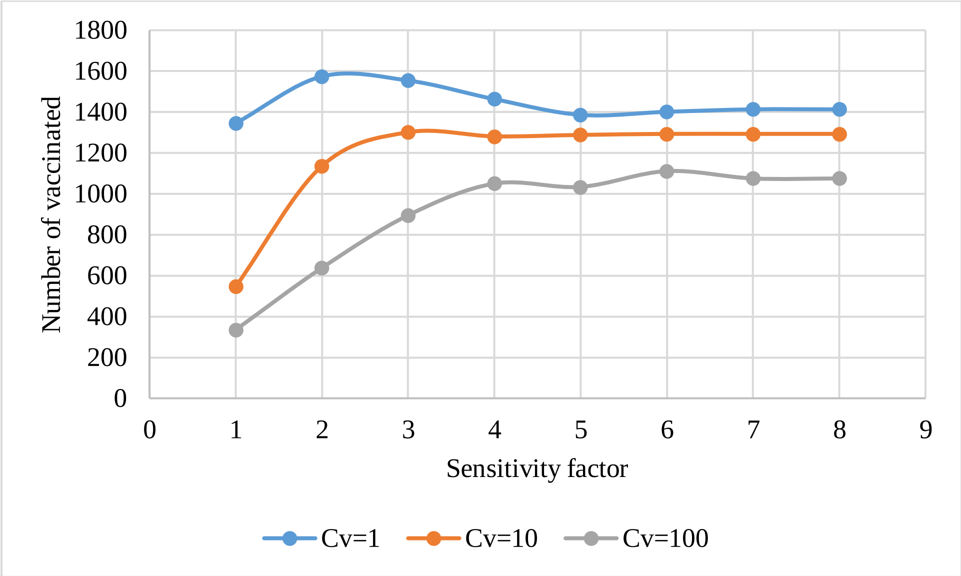


Figure 3.14 Number of vaccinated individuals in each experiment

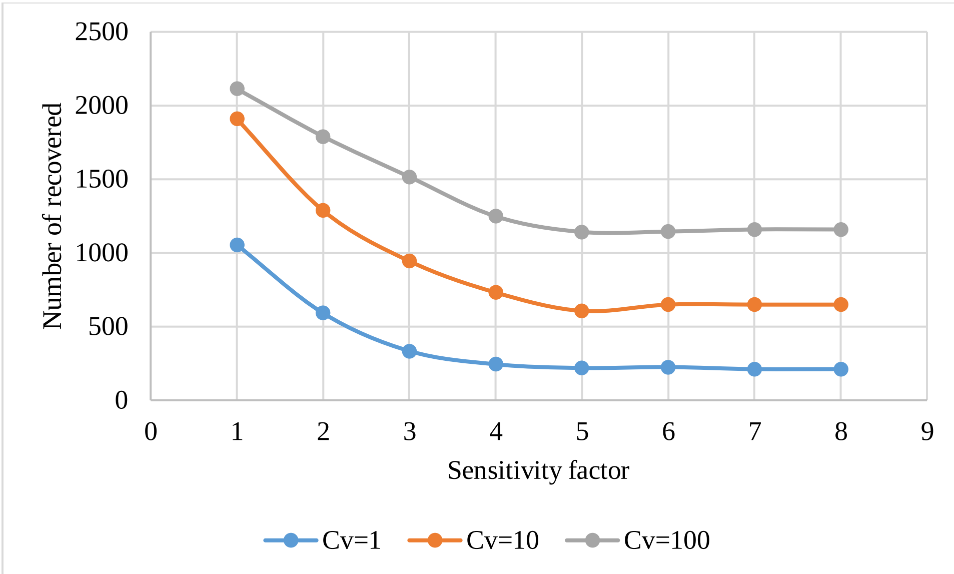


Figure 3.15 Number of recovered individuals in each experiment

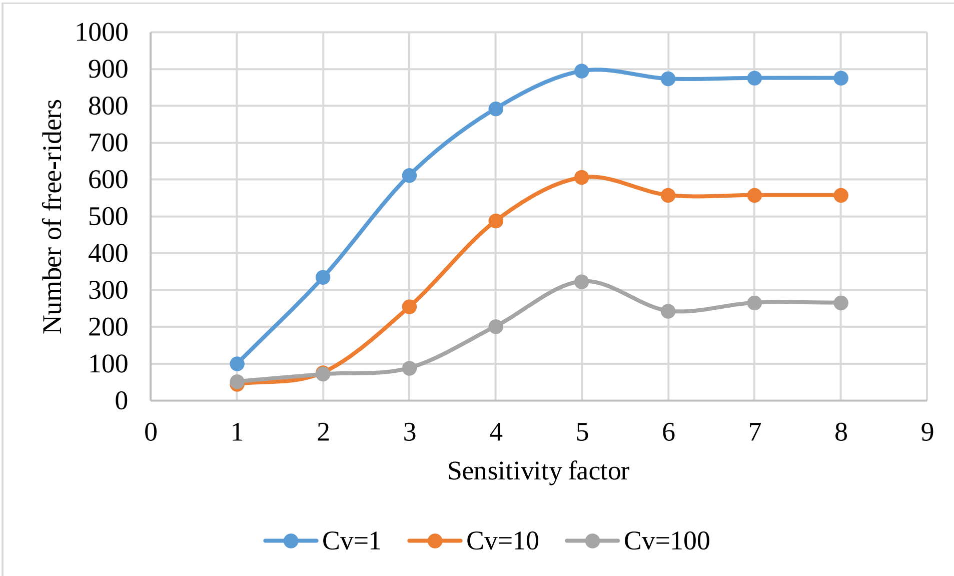


Figure 3.16 Number of free riders in each experiment

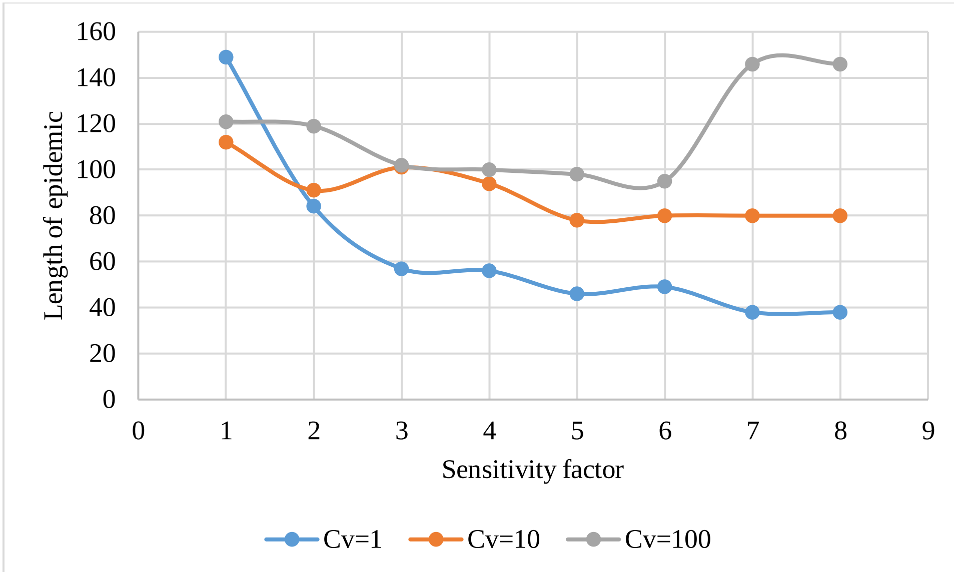


Figure 3.17 Length of epidemic season in each experiment

3.2.6 Effect of different factors on the total cost

When setting policies for controlling the epidemics, there are some factors that are under our control. Those factors are the level of sensitivity of individuals to getting vaccination, fraction of initially vaccinated individuals and their distribution and to some extent the cost of vaccination. In order to see the behavior of the model when changing more than one of these factors at the same time, the model is run for different cost of vaccination changing initially vaccinated percentage from 1 to 20 percent and sensitivity factor from 1 to 7. We define the total cost as the total cost of vaccination plus cost of infection for all the society as defined in Equation 3.4. The model is run on a 50 by 50 lattice when $\beta = 0.2$ in which the initial number of infected and vaccinated individuals are distributed randomly. The following figures shows the value of total cost when changing sensitivity and initial vaccination rate for different cost of vaccinations.

Figure 3.18 shows that when the total cost of vaccination is not high, a little increase in the sensitivity and initial vaccination will greatly decrease the total cost. However, increasing the cost of vaccination will result in more effort to be needed to decrease the total cost (Figure 3.19).

Consequently, although more initial vaccination and sensitivity will result in lower total cost, it is not beneficial to invest too much on them mainly when the cost of vaccination is low, because the rate of changes in the total cost will decrease as we increase these factors.

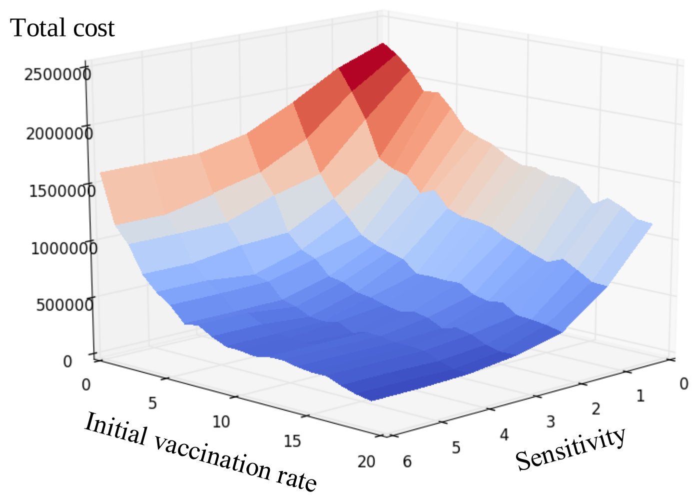


Figure 3.18 Total cost for different initial vaccination rate and sensitivity when $C_V = 10$

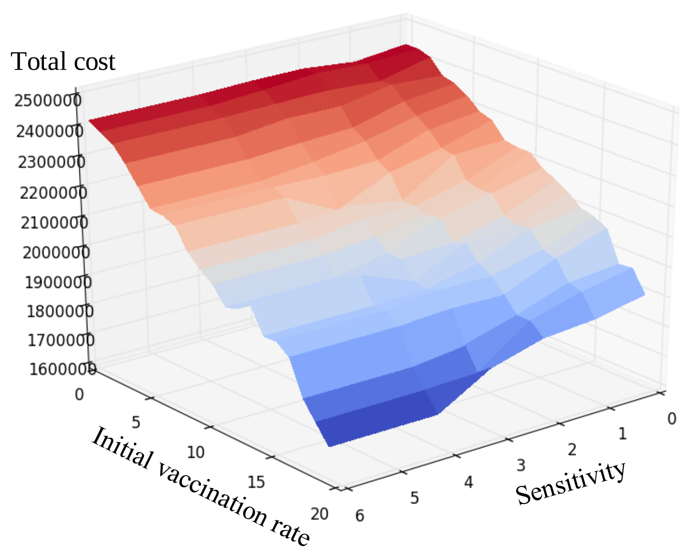


Figure 3.19 Total cost for different initial vaccination rate and sensitivity when $C_V = 300$

3.2.7 Comparing individual and community based payoff function

As discussed in chapter 2.2.3, the payoff function for calculating the payoff of player i is usually calculated based on the individual's cost of taking prevention techniques such as vaccination and individual's cost of being infected. Thus, vaccinated individuals pay the cost of vaccination C_v, infected individuals pay the cost of infection C_I and free-riders who are neither vaccinated nor infected pay nothing (Equation 2.11). We call this payoff function "Individual based" payoff function.

Also, in our model we considered that the payoff of a player is the payoff of its community and the payoff of the player itself (Equation 3.3) which we refer to as "community based" payoff function.

Considering the proposed updating method in which a player changes its strategy to vaccinated if there is someone vaccinated with higher payoff than the individual's payoff in the sorted list of its neighbors based on sensitivity factor, in the individual based payoff function, none of the players will change their strategy and all the susceptible individuals will become infected. This is due to the higher payoff of free-riders in comparison with other players which cause them to not find anyone with higher payoff than themselves to change to their strategy.

However, if for the updating rule, we just consider the sensitivity factor on the sorted list of neighbors based on payoff without considering the attribute to choose a player with a higher payoff and update a 50 by 50 lattice based on this new updating rule using both "individual based" and "community based" payoff function, the result will be as follows having $C_V = 10$, $\beta = 0.2$ and $s = 4$. Table 3.3 shows the number of vaccinated, infected and free-riders in each case. We can see that, community based payoff function has more free-riders, less infected and more vaccinated individuals with a lower epidemic length. Figure 3.20 illustrates this result in which the purple cells show susceptible individuals, red cells show recovered individuals and light blue cells show vaccinated individuals.

Table 3.3 Number of vaccinated, infected, free-riders and length of epidemic

	Free-riders	Vaccinated	Infected	Epidemic length
Individual based payoff	27	1143	1330	116
Community based payoff	310	1865	325	55

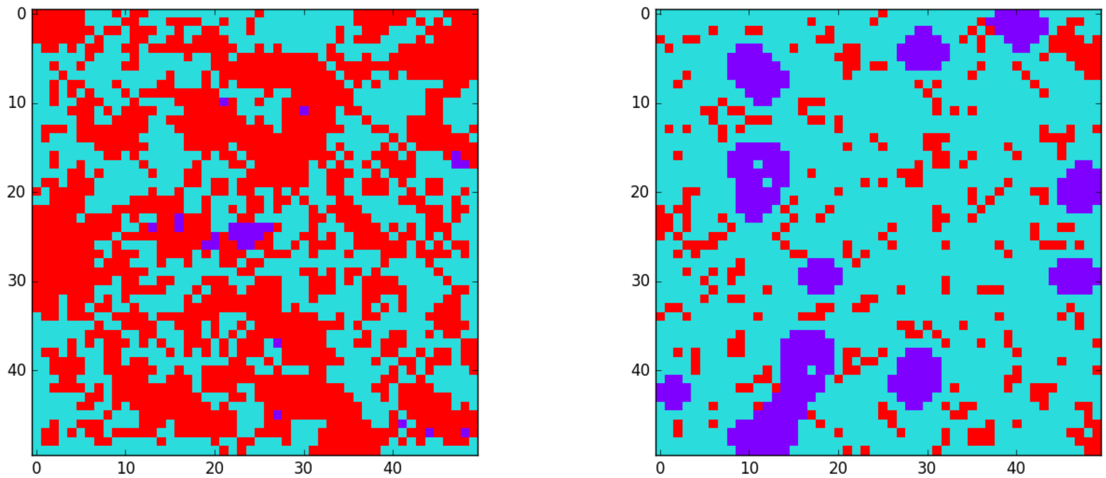


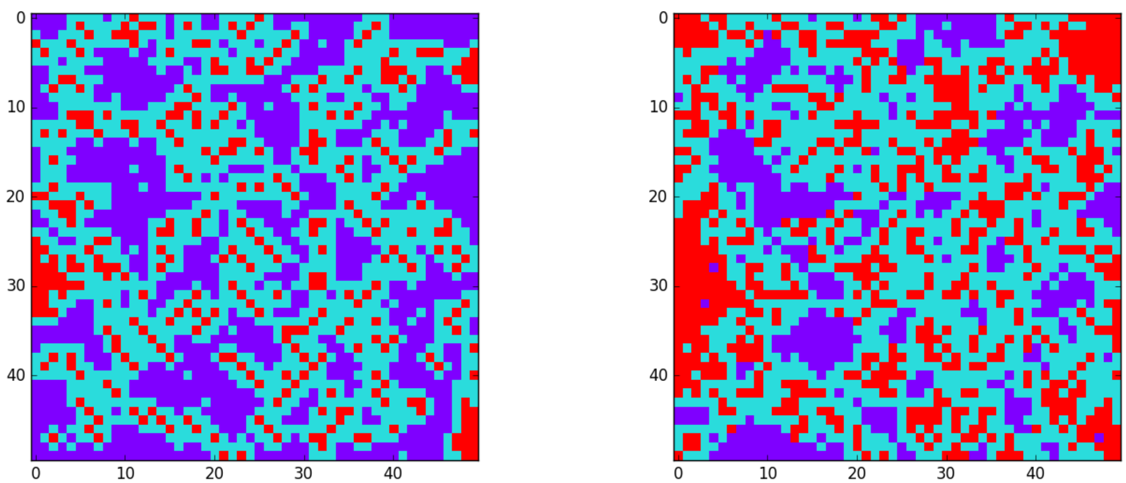
Figure 3.20 Distribution of players in the final lattice (Right – community based payoff, left – individual based payoff)

Moreover, considering the payoff function similar to the individual based payoff function, but assuming the payoff of free-riders to be their probable cost of infection as defined in the following equation, where $P_{\inf i}$ is the probability of infection for node i as defined in Equation 3.2, we will get a different result.

$$P_i = \begin{cases} -C_V & if\ i\ is\ vaccinated \\ -C_I & if\ i\ is\ infected\ or\ recovered \\ -C_I P_{\inf i} & if\ i\ is\ susceptible\ (free\ rider) \end{cases} \quad 3.5$$

Figure 3.21 shows the result of updating a lattice using the public goods game method and the revised individual based method. It can be seen that when the cost of vaccination is low, the revised model shows a similar behavior to the community based payoff function and with a better control of the epidemic. However, when increasing the cost of vaccination, it fails to show the free-riders behavior.

(a)



(b)

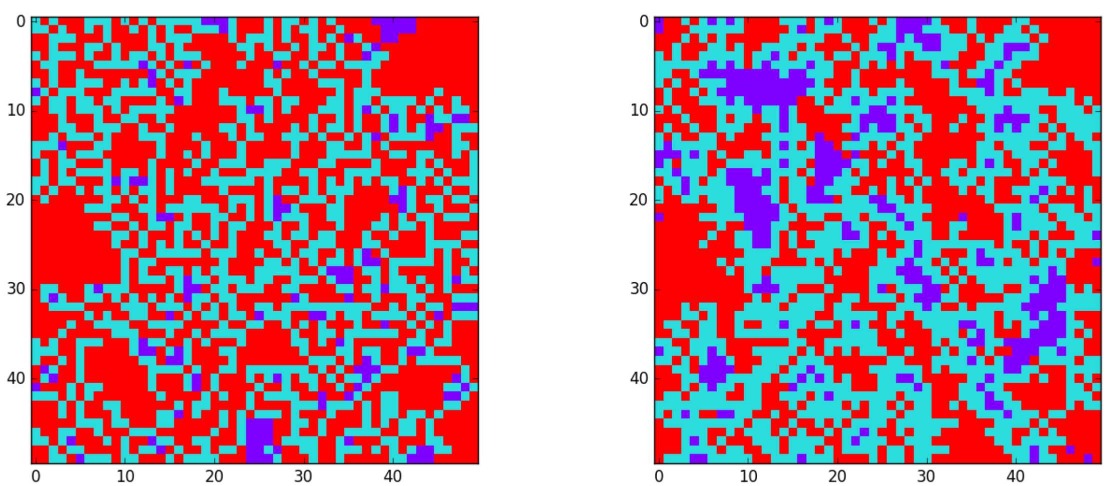


Figure 3.21 Distribution of players in the final lattice (Right – community based payoff, left – individual based payoff) when $C_V = 10$ (a) and $C_V = 50$ (b)

3.2.8 Basic reproduction number

The basic reproduction number (R_0), is defined as the expected number of secondary cases produced by a single infection in a completely susceptible population (Jones, 2007). This value can be defined as follow:

$$R_0 = \beta \cdot C \cdot L \qquad 3.6$$

where β is the transmissibility which is the probability of infection given contact between a susceptible and infected individual, C is the average rate of contact between susceptible and infected individuals, and L is the duration of infectiousness.

In our model, the contact rate is different for different locations in the lattice and it also varies during the epidemic because of the changeing behavior of individuals, causing the contact rate to decrease. To illustrate this we have plotted the number of infections in each period over the number of infection in its previous period to see the changes in R_0 (Figure 3.21).

Figure 3.22 shows the ratio of infection in each period over the infection in its previous period during an epidemic for a 50 by 50 square lattice when $(C_I, C_V, C_R, \beta, s)$ equal to $(1000, 10, 0, 0.2, 4)$, blue line, when $(C_I, C_V, C_R, \beta, s)$ equal to $(1000, 101, 0, 0.2, 4)$, red line, and $(C_I, C_V, C_R, \beta, s)$ equal to $(1000, 10, 0, 0.2, 1)$, green line. It can be seen that at first the value of R_0 is more than 1, meaning that the epidemic is expanding. Then, after some steps this value falls below 1 because of the protective behavior of individuals and the infectiousness of recovered individuals, meaning that not everybody will become infected and the epidemic will end. Also, we can see that when the cost of vaccination is low and the sensitivity is high (blue line), R_0 is less than the time that cost of vaccination is high (red line) and sensitivity is low (green line). Moreover, it can be observed that the value of R_0 in the expanding period is much higher when the transmission rate of the disease is higher (Figure 3.23).

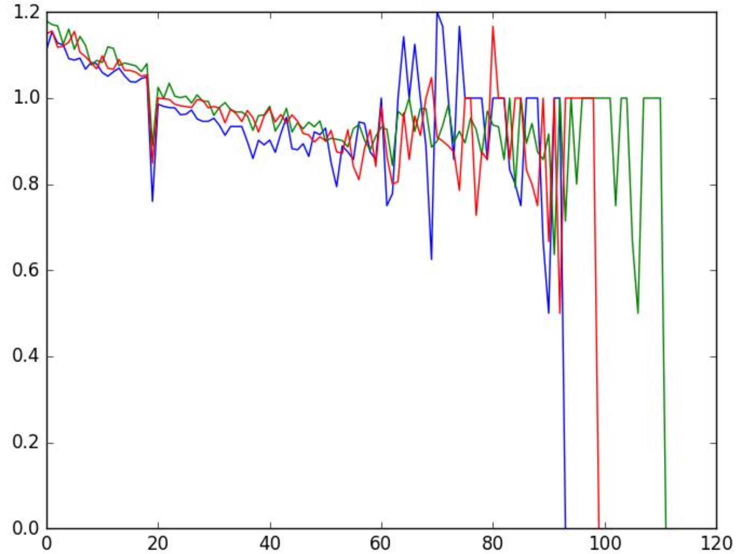


Figure 3.22 The ratio of infection in each period over the infection in its previous period for different scenarios

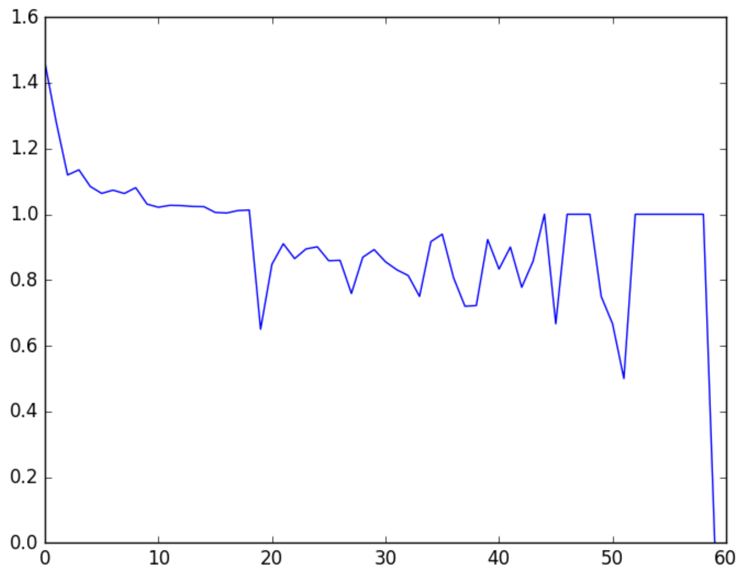


Figure 3.23 The ratio of infection in each period over the infection in its previous period when $\boldsymbol{\beta = 0.5}$

3.3 Conclusion

In this study, a public goods game based model for modeling the behavior of population of players in response to an epidemic is illustrated. In this model, the payoff of each player is calculated using a function in which every cost of individuals in a 3 by 3 group is divided between the members of that group. These costs are the cost of infection for infected people in the group, cost of vaccination for vaccinated individuals, probable cost of being infected for susceptible people and cost of being recovered for recovered individuals. Using the payoff of each player, individuals try to imitate the behavior of the people who are in the groups with the lowest cost or highest payoff. Sensitivity factor is one of the parameters which is introduced to show the risk tolerance (fear) of players encouraging switching to the strategy of their neighbors. The sensitivity factor can show the number of neighbors with highest payoffs in the candidate list of a players, so, if any vaccinated individual is in this candidate list the player will be encouraged to get vaccinated. Although in our model the sensitivity factor is not varying among players and is considered to be influenced by the social media, it can cause different behaviors in populations. Using this model, we can show that if the cost of vaccination is increased, players have less tendency to get vaccinated, which is a representative behavior to a real-world situation.

However, increasing the sensitivity of individuals can result in more vaccination in the same situation. This behavior is very similar to the effect of fear of being infected in real-world epidemics. Moreover, increasing the sensitivity can be beneficial for the society as individuals react to the epidemic sooner and decide faster to get vaccine in order to save themselves and their community, but increasing the sensitivity factor too much does not lead to an optimal cost for the society. The results show that increasing the sensitivity factor to more than 5 does reduce cost while the number of free-riders dose not increase and the number of vaccinated and infected individuals does not change. This behavior is the result of dissuasive effect of selecting the strategy of the neighbors who have a higher payoff than the payoff of the player itself on the candidate list.

Additionally, the model tests the effect of the infection transmission rate, and, the epidemic length is lower when facing a disease with high transmission rate. This is explained by the fact that individuals respond sooner to the disease spread when there is a higher probability of being infected (represented as a strategy with a higher potential cost).

In this model we also examined the effect of the number of initially vaccinated individuals on the epidemic which shows that mandatory vaccination can be beneficial when it does not force too many individuals to get the vaccine. Also, the distribution of vaccinated players in the lattice can affect the final result. When the players are distributed evenly in the lattice, more people are in contact with vaccinated individuals and this can cause them to get vaccine sooner when facing an epidemic and can result a better control of epidemic compared to the same number of vaccinated individuals who are randomly distributed.

Last but not least, it is shown in this study that considering community based payoff function in modeling the spread of infectious diseases can better capture the dynamic of epidemic sand therefore it is recommended to be used when modeling the epidemic outbreaks to study the behavior of populations and when such models are used for decision making for public health.

Chapter 4 - Modeling Individuals' Response to Epidemic with Delayed Emergence of Syndromes

One of the factors to be considered in the accurate modeling of epidemic outbreaks is the incubation period - the period in which an individual has contracted the disease and is infectious, but is not yet aware of it. This chapter studies the effects of the delay between the infection for an individual and its diagnosis. Thus, it is assumed that from the time that a person is infected until he becomes aware of his infection, he can transmit the disease but his contacts consider him a susceptible individual in their social group and not an infectious one. This study investigates the social dynamics of vaccination and transmission with delays in such epidemic outbreaks using a model of the public goods game.

In section 4.1 the proposed methodology and updating rule to consider the time delay in emergence of syndromes is presented. Section 4.2 presents the result of using this methodology considering different parameters and discussing the behavior of individuals facing infectious disease outbreaks. Section 4.3 provides a summary and discussion.

4.1 Methodology

In this study, individuals' cost functions and payoffs are determined based on their contribution to the group and the group's shared payoff as it is described in chapter 3.1. However, when updating the strategy of players, a time delay in showing the syndromes is considered. In the following the updating rule for this model is illustrated.

4.1.1 Updating rule

In each iteration of the game after calculating the payoff of each player, the strategy of susceptible individuals is updated. Thus, a susceptible individual can decide whether to get vaccinated or remain susceptible. In order to update the strategy of susceptible players, at every time step the top s neighbors with the highest payoff in the neighborhood of a player will be chosen. If one of them has a higher payoff than that of the player itself, and it is vaccinated then the player will decide to get vaccinated, borrowing the strategy of that "successful" player, otherwise it remains susceptible. This s is referred to as a sensitivity factor which can be controlled by investing in awareness programs regarding the disease raising individuals' sensitivity to the risk of being infected.

Following an update of the strategy of all players, the epidemic season advances one step further. At this time the individuals who are still susceptible can be infected based on the probability of infection, which is calculated using Equation 4.1.

$$AP_{\inf j} = \frac{G_{Ij}}{N_j} \times \beta \qquad 4.1$$

Where G_{Ij} is the actual number of infected neighbors of j, N is the total number of neighbors of j and β is the disease's transmission rate based on a one-on-one contact.

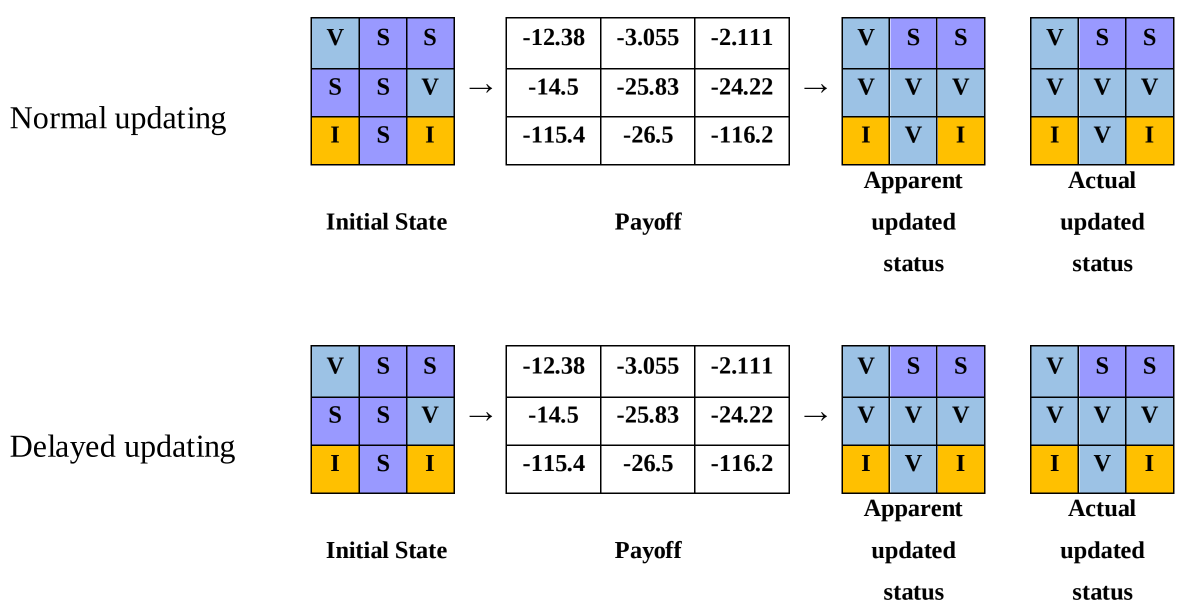
This paper looks at two types of updating: Normal updating and Delayed updating and compares the result of updating under each scenario. In Normal updating, if an individual becomes infected, his apparent strategy is available right after being infected. However, in Delayed updating, if an individual becomes infected in one period, his apparent strategy will not be released for some time steps, which is equal to the incubation period of the disease (D). An infected individual will become recovered and will be immune to the disease after L time steps which is the duration of the infection period.

An example of the updating rule is demonstrated below. The payoff for the center player and its neighbors are the numbers in the cells, where the payoff of each neighbor is calculated based on their 8 neighbors, some of which are not shown here. The vector of initial values in this example is $(C_I, C_V, C_R, \beta) = (100, 10, 0, 0.2)$.

When the sensitivity factor is equal to 3, the set of first 3 neighbors with highest payoff will be $\{(-2.111, S), (-3.055, S), (-12.38, V)\}$ (Figure 4.1-a). This means that the updating strategy of the center player will be to get vaccinated since one of the top three neighbors is vaccinated and has a higher payoff than the center player. Sensitivity factor of 3 has similar results for Delayed and Normal updating.

When the sensitivity factor is equal to 2, the player will not vaccinate since there is no vaccinated player among the top two players in the neighborhood of the center player and with a higher payoff than the player itself (Figure 4.1-b). If this player becomes infected during this period (because of an infected neighbor), in Delayed updating, its apparent status will not change, so its neighbors cannot learn about this infection, but its actual status will change to infected. Consequently, at this time the disease can be transmitted to other players. This behavior is shown in Figure 4.1 as apparent status and as actual status.

(a) $s = 3$



(b) $s = 2$

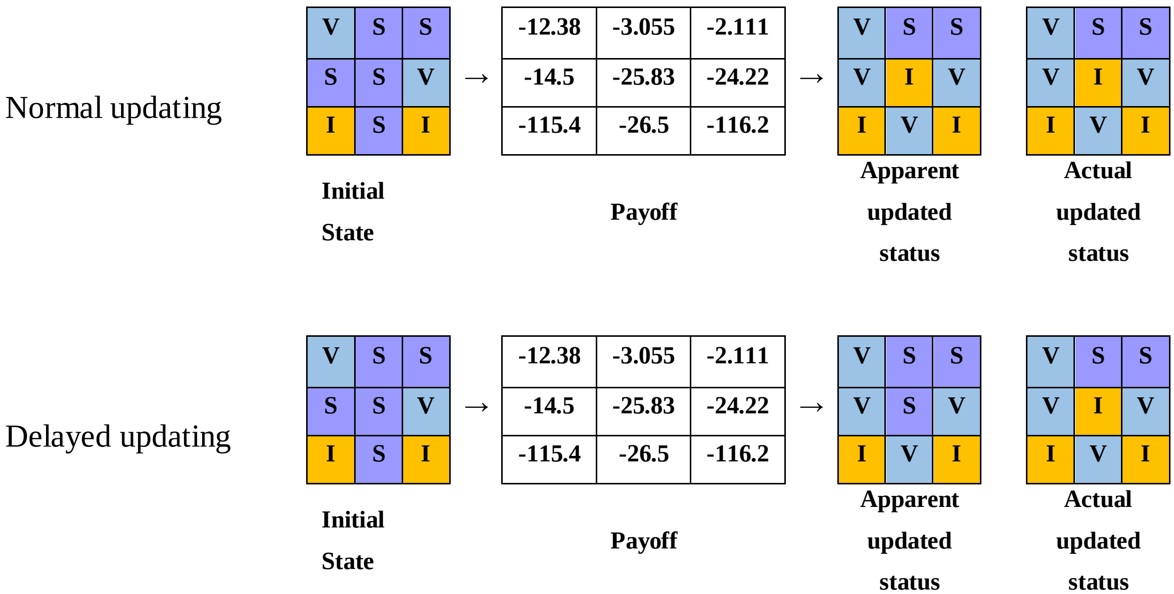


Figure 4.1 Illustrating Normal and Delayed updating for different sensitivities

4.2 Experimental results

The example below illustrates the effect of an incubation period on the dynamics of an epidemic. This example starts with one infected and one vaccinated individuals distributed on a 5 by 5 lattice in which the infected individual is at the top-left corner of the inner 3 by 3 square and the vaccinated individual is at the bottom-right corner of the inner square; all other players are susceptible to the disease as it is shown in Figure 4.2-a. Updating this initial lattice using Normal and Delayed updating will result in completely different outbreaks and outcomes (Figure 4.2-b and Figure 4.2-c). In Figure 2, the purple cells represent susceptible individuals, yellow cells are infected individuals, red cells are recovered ones and those vaccinated are shown as blue cells. The vector of the initial values is $(C_I, C_V, C_R, \beta, L, D, s) = (100, 10, 0, 0.2,19,6,4)$. A comparison of Figure 4.2-b and Figure 4.2-c shows that when an incubation period is taken into account (Delayed updating), the number of infected individuals will increase (more red cells) and fewer people will be protected by vaccinated individuals in their neighborhood which we refer to as free-riders (purple cells).

a) Initial lattice   b) Normal Updating   c) Updating with delay

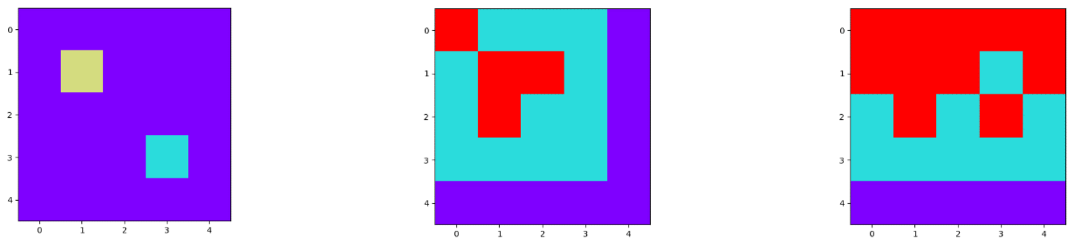


Figure 4.2 Result of updating a custom lattice for Normal updating and Delayed updating

To generalize this example, the result of Normal and Delayed updating of a 50 by 50 lattice with random distribution of 5% initially vaccinated and 5% initially infected individuals is illustrated. Table 4.1 shows the number of vaccinated, infected and free-riders for each scenario. It can be seen that for the parameters in Table 4.1, the final number of free-riders and vaccinated individuals is smaller considering a Delayed updating and the number of infected individuals is higher. This can also be seen in Figure 4.3. Similar to Figure 4.1, the purple cells represent susceptible individuals, red cells are recovered individuals and blue cells are vaccinated ones. It should be noted that not only the number of infected individuals is increased and the number of vaccinated individuals is decreased with delayed updating, but also the number of free-riders decreases due to not having enough vaccinated individuals in the population to ensure immunity in their communities.

Table 4.1 Number of vaccinated, infected, free-riders and length of epidemic

	Free-riders	**Vaccinated**	**Infected**	**Epidemic length**
Normal updating	488	1281	731	94
Delayed updating	237	1123	1140	98

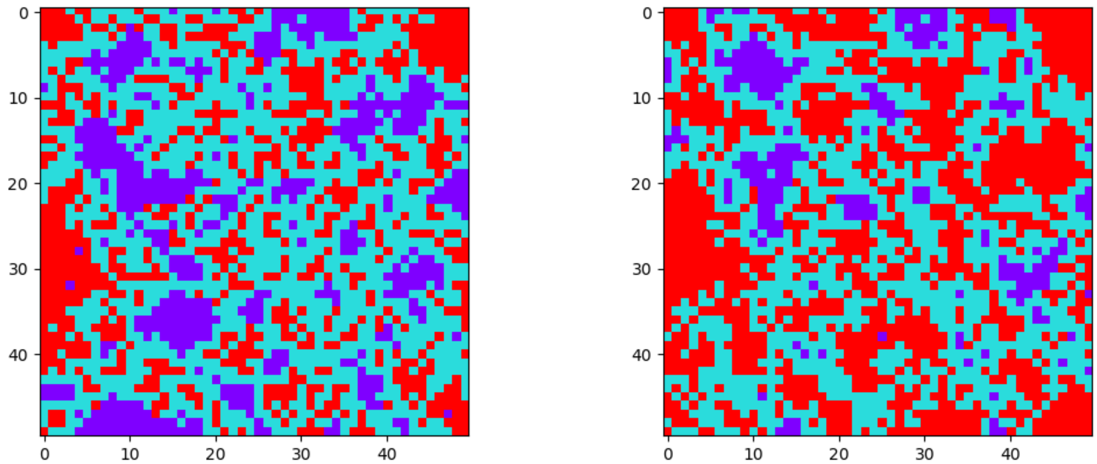


Figure 4.3 Distribution of players in the final lattice (Left - Normal updating, Right – Delayed updating)

The following section discusses the sensitivity of the dynamics of an epidemic to changing various factors for Normal and for Delayed updating. In the graphs below the blue line shows the result of Normal updating and the orange line shows the result of Delayed updating. The parameters used in the models are presented in Table 4.2.

Table 4.2 Parameters of the model

Parameter	Meaning	Value
N	Population size	2500
I_0	Percentage of initially infected individuals	5%
V_0	Percentage of initially vaccinated individuals	5% or variable
R_0	Percentage of initially recovered individuals	0%
L	Duration of infectious period	19 time steps
D	Delay time in emergence of symptoms	6 time steps or variable
C_R	Cost of being recovered	0
C_I	Cost of infection	1000
C_V	Cost of vaccination	10 or variable
β	Transmission rate	0.2 or variable
s	Sensitivity factor	4 or variable

4.2.1 Effect of changing the cost of vaccination

Cost of vaccination is one of the factors that can change the dynamics of an epidemic affecting the decision of individuals to get vaccinated. Figure 4.4 to Figure 4.6 show the result of changing the cost of vaccination considering Delayed or Normal updating. It can be seen that for a lower vaccine cost, the number of free-riders is lower without considering the incubation period (Figure 4.4). Moreover, the number of vaccinated individuals is also lower when the time delay in becoming aware of an infection is considered (Figure 4.5). This decrease in the number of vaccinated and free-riders is caused by a higher number of infected people not being aware of their status due to the delayed response (Figure 4.6).

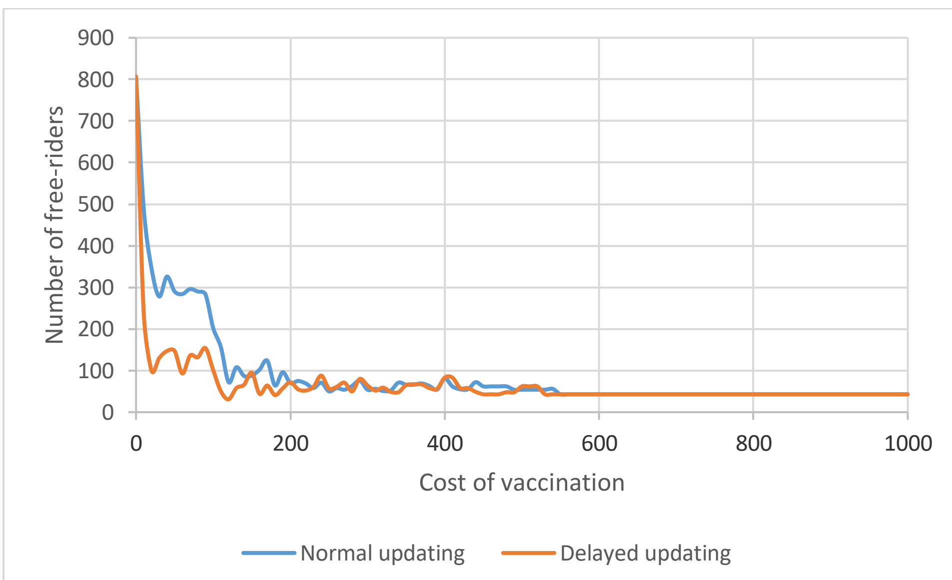


Figure 4.4 Number of free riders for Normal and Delayed updating when changing C_V from 0 to 1000

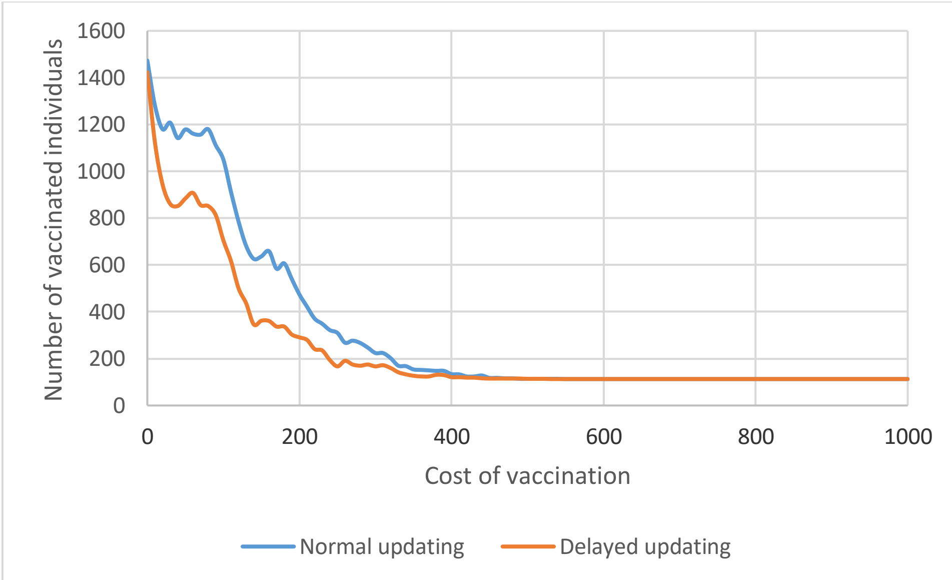


Figure 4.5 Number of vaccinated individuals for Normal and Delayed updating when changing C_V from 0 to 1000

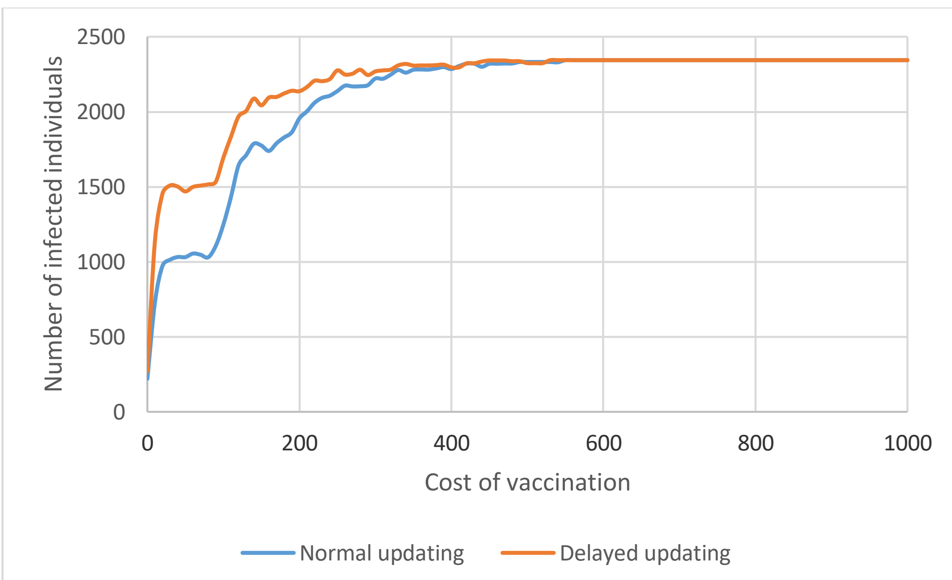


Figure 4.6 Number of infected individuals for Normal and Delayed updating when changing C_V from 0 to 1000

4.2.2 Effect of changing the transmission rate

Transmission rate is another factor that can change the dynamics of an epidemic. If the transmission rate is high, there is a higher possibility for individuals to become infected. But this is only true if people are not aware of the infection near them; otherwise, they will respond to it sooner and get vaccinated showing a relatively flat curve (Figure 4.7). Usually, in real world situations diseases with a higher transmission rate have more victims. As a result of this higher number of infected people, fewer people have the chance to remain healthy without being vaccinated themselves. The number of individuals who remain healthy without vaccine (free-riders here) is even lower if the incubation time of the disease is also considered, as illustrated in Figure 4.9. The number of vaccinated individuals will increase with the growing transmission rate without considering the incubation period. Yet, taking into account the hidden period of the disease when people might become infeceted before they are aware of the disease, the number of the vaccinated individuals will be even lower (Figure 4.8). This decline in the number of vaccinated indviduals when using delayed updating is caused by two factors. First, players are not aware of an infection and consider an incorrect payoff in deciding whether to vaccinate. Secondly, there is a risk of being infected by an undiagnosed infected neighbor. Figure 4.7 shows that the number of infected individulas when using normal updating scheme does not change much with the change of trasmission rate. This phenomenon occurs due to faster response of individuals to the epidemic when they know that they are in a higher risk of being infected, which is not percieved in delayed updating.

Generally, the delayed updating model has always more infected individuals compard to the normal updating one, regardless of the parameters used in the model.

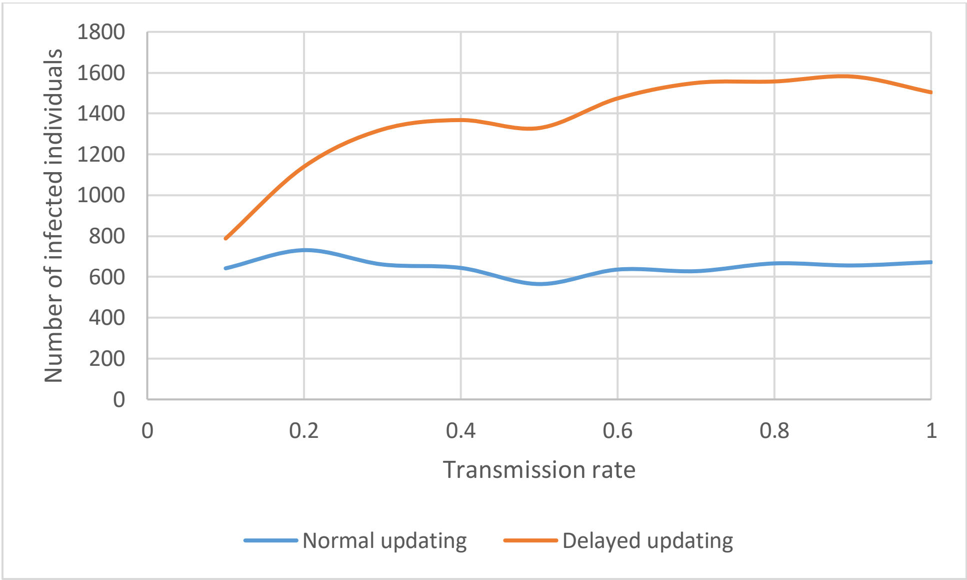


Figure 4.7 Number of infected individuals for Normal and Delayed updating changing β

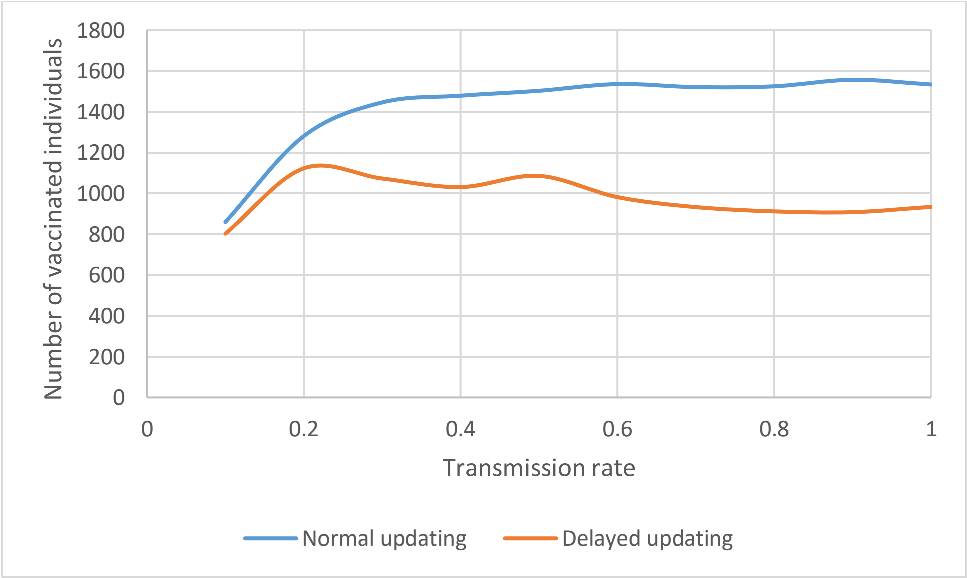


Figure 4.8 Number of vaccinated individuals for Normal and Delayed updating when changing β

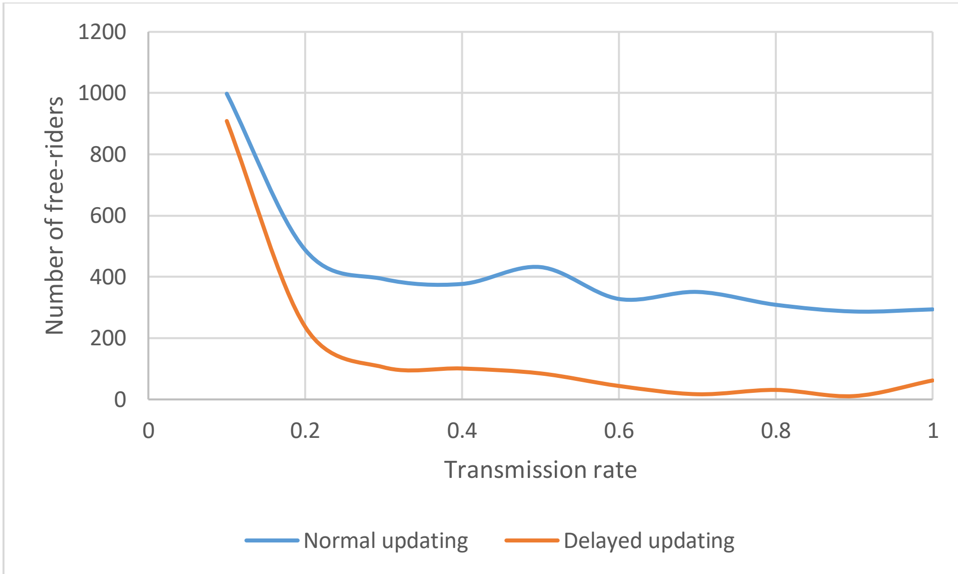


Figure 4.9 Number of free-riders for Normal and Delayed updating when changing β

4.2.3 Effect of changing the initially vaccinated population V_0

The number of initially vaccinated individuals is one of the parameters that public health policy makers can influence, thus influencing the spread of an epidemic. The result of the time-delay in becoming aware of an infection is more apparent when a small percentage of the population is forced to get vaccinated, while the alternative of over-vaccinating the population results in people having immunity over the possible threat and reducing the risk of being infected due to unawareness (Figure 4.10 to Figure 4.13). Figure 4.10 shows that the number of free-riders when considering the incubation period is lower than the number of free-riders without considering the time-delay. This can be explained by not having enough vaccinated individuals who can provide immunity for others when there is an incubation period.

However, a higher number of initially vaccinated individuals can provide better immunity and results in a lower difference in the number of free-riders for both models. The total number of vaccinated individuals and the number of people who decide to get vaccinated is also lower for a lower V_0 when the incubation period is taken into account.

In studying the effect of an initial vaccination program, it is important to consider the change in the number of people who decide to get vaccinated themselves rather than the total number of vaccinated individuals (many of which were initially vaccinated).

This comparison is illustrated in Figure 4.11 and Figure 4.12. Here, the total number of vaccinated individuals and the number of individuals who decided to get vaccinated does not vary much for delayed and normal updating for a higher number of initially vaccinated individuals due to the provided immunity as a result of the mandatory vaccination. Also, the number of infected individuals is higher for models with time-delay and a lower number of initially vaccinated individuals (Figure 4.13). This higher number of infections is again the result of the hidden risk of infection and not responding to it in the form of preventive behavior (vaccination in this case). The lower number of infection for higher V_0 is again the result of the provided immunity through the mandatory vaccination.

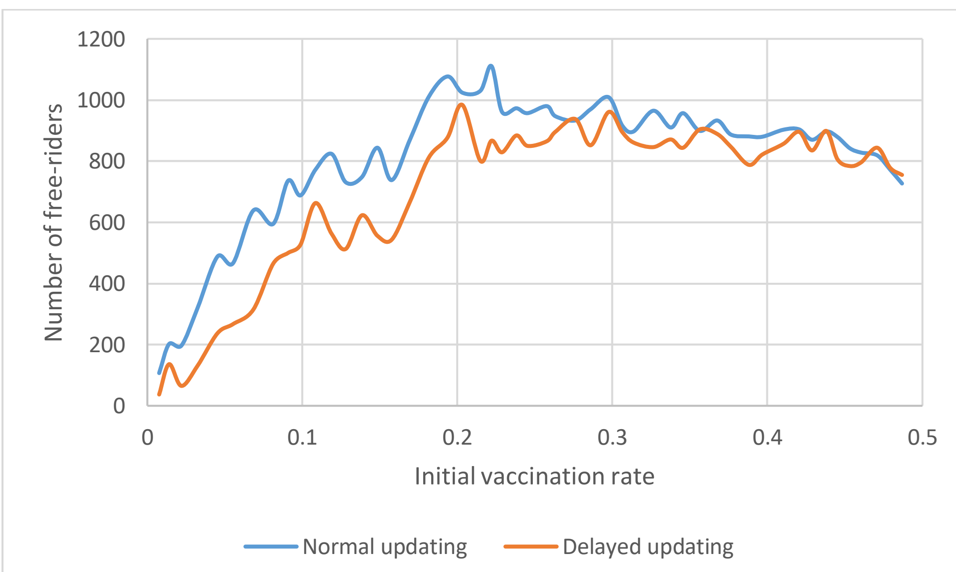


Figure 4.10 Number of free-rider for Normal and Delayed updating when changing V_0 from 0.01 to 0.5

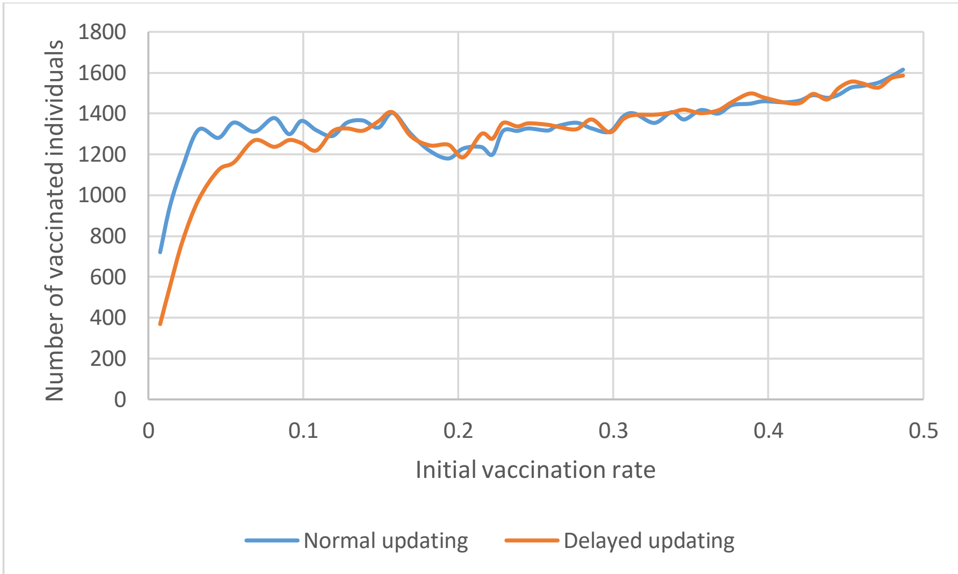


Figure 4.11 Number of vaccinated individuals for Normal and Delayed updating when changing V_0 from 0.01 to 0.5

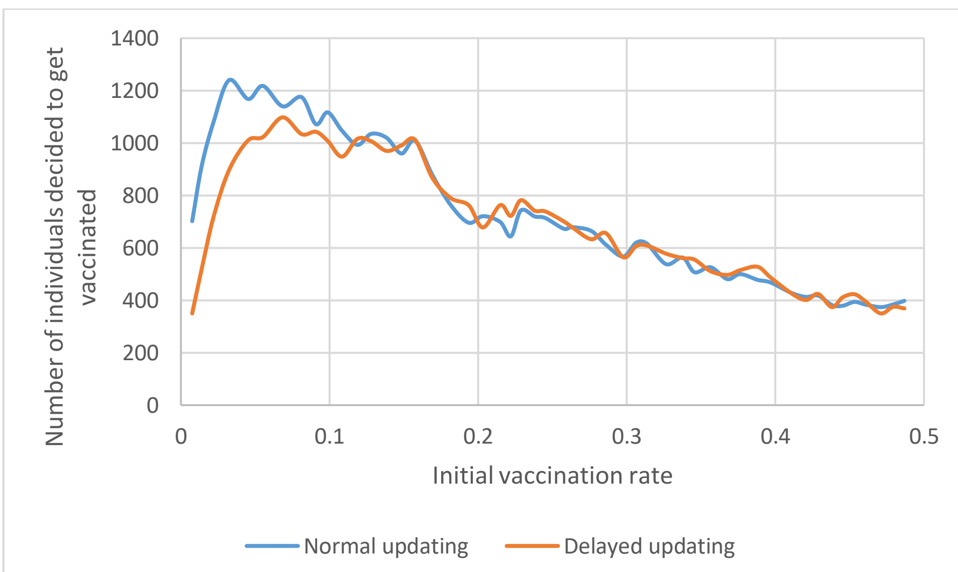


Figure 4.12 Number of vaccinated individuals who decided to get vaccine for Normal and Delayed updating when changing V_0 from 0.01 to 0.5

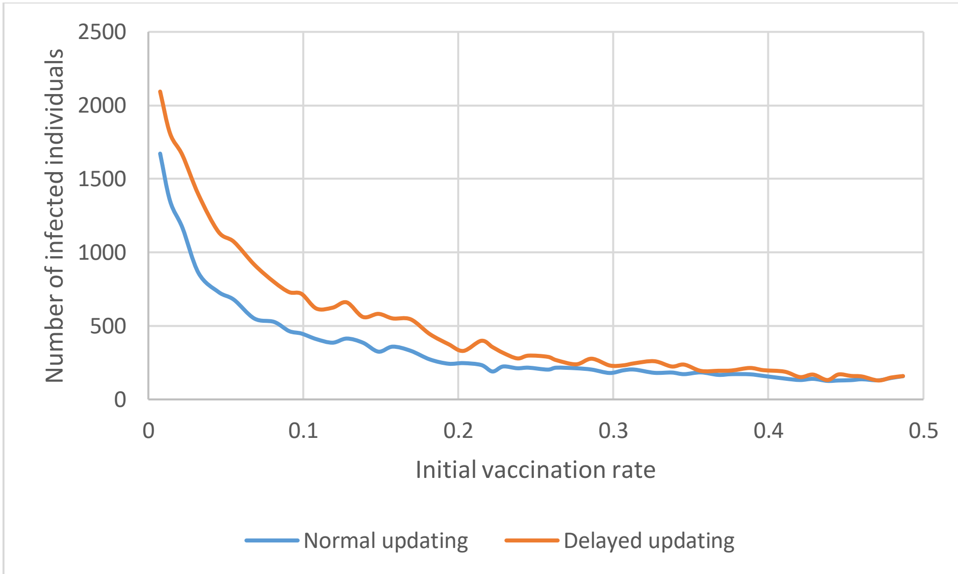


Figure 4.13 Number of infected individuals for Normal and Delayed updating when changing V_0 from 0.01 to 0.5

4.2.4 Effect of changing the sensitivity factor

The sensitivity parameter s represents the degree of social awareness as well as the fear of individuals of the disease. It represents the degree of sensitivity of individuals to reported infected and vaccinated cases around them. This sensitivity and willingness to change a strategy from doing nothing in response to an epidemic to getting vaccinated, can be the result of investment in media campaigns and awareness programs. Taking the disease incubation period into account decreases the number of free-riders and vaccinated individuals, and also increases the number of infected individuals in the same way for all sensitivity factors above 4. However, for values of s less than or equal to 4, the existence of infection awareness time-delay results in fewer vaccinated and free-riders individuals. Increasing the sensitivity causes players to decide sooner to get vaccinated. When not aware of a possible threat of a disease, more players choose to defer vaccination. This causes an increase in infection rate among the payers in comparison to a similar situation with a higher sensitivity factor (Figure 4.14 to Figure 4.16).

Figure 4.14 shows the effect of different sensitivity factors on the number of free-riders. This figure shows that increasing the sensitivity factor results in more free-riders. However, when considering the incubation period, this increase is lower when there is a time-delay in becoming aware of an infection.

The results of this analysis show that both *s* and the time delay act as types of "responsiveness". Thus, the model with lower "responsiveness" (Delayed updating with a lower *s*) will have fewer free-riders, fewer vaccinated and more infected individuals in comparison with the model with higher "responsiveness" (Normal updating with higher *s*) as shown in Figure 4.15 and Figure 4.16. This is due to the delay in becoming aware of the infection threat whether because of the nature of the disease or lack of appropriate awareness programs.

This discussion also applies to the number of vaccinated individuals as illustrated in Figure 4.15. Increased awareness and sensitivity results in a higher level of vaccination, and lower sensitivity and awareness results in fewer vaccinations.

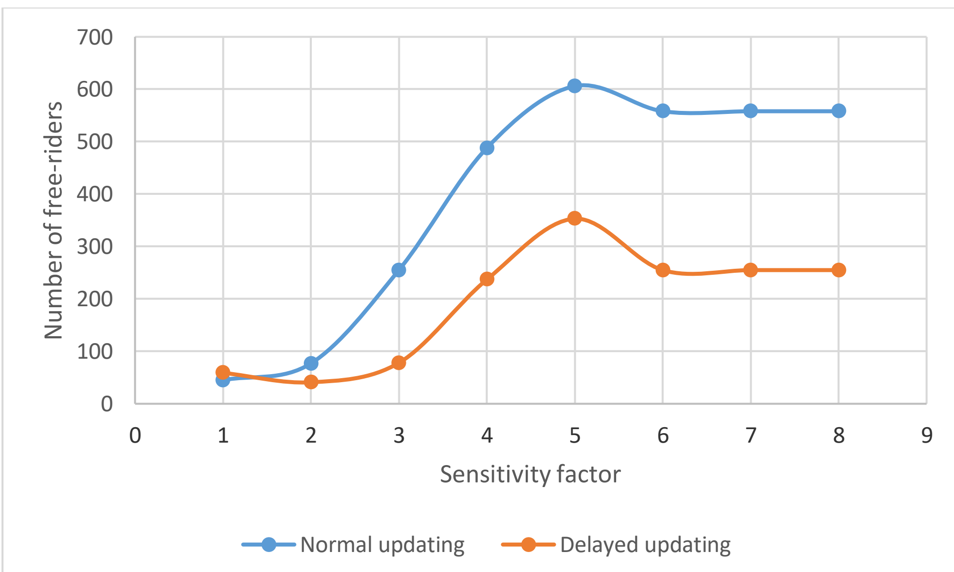


Figure 4.14 Number of free-riders for Normal and Delayed updating when changing *s* from 1 to 8

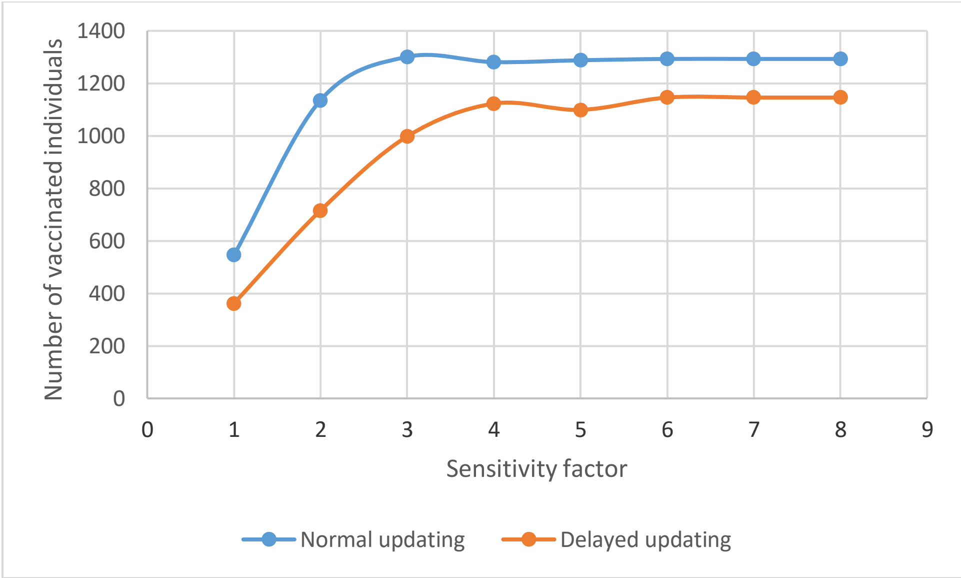


Figure 4.15 Number of vaccinated individuals for Normal and Delayed updating when changing *s* from 1 to 8

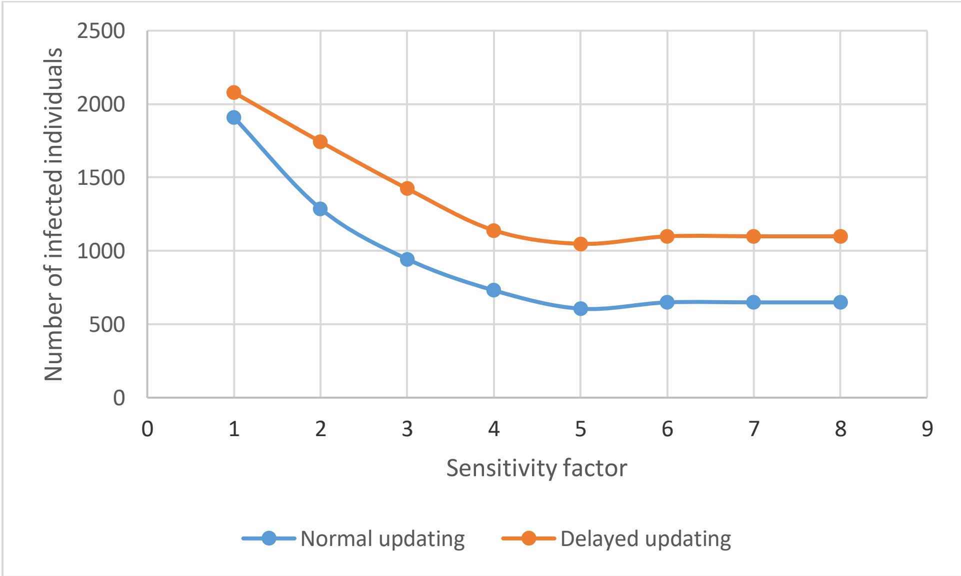


Figure 4.16 Number of infected individuals for Normal and Delayed updating when changing *s* from 1 to 8

4.2.5 Effect of changing the incubation period in Delayed updating

One of the factors of interest is the effect of the length of the incubation period on the dynamics of an epidemic and its impact on the number of free-riders, vaccinated and infected individuals in a population. As shown in Figure 4.17, the main parameters have an approximately linear relation to the length of the time delay of an epidemic. Therefore, a longer time delay (incubation period) results in more infected individuals (red line), fewer vaccinated individuals (blue line) and fewer free-riders (purple line).

However, the length of the epidemic does not show a meaningful relation to the length of an incubation period (Figure 4.18). In summary, although an increase in the incubation period results in more infected individuals, fewer vaccinated and free-rider ones, it will not affect the epidemic length. So, on average, an epidemic with a higher incubation period will not last a longer period of time.

As discussed above, the result of increasing the incubation period is very similar to the result of lowering the sensitivity factor, generally indicating lower awareness of the epidemic. Lower awareness will ultimately result in more infected and fewer free-riders and vaccinated individuals.

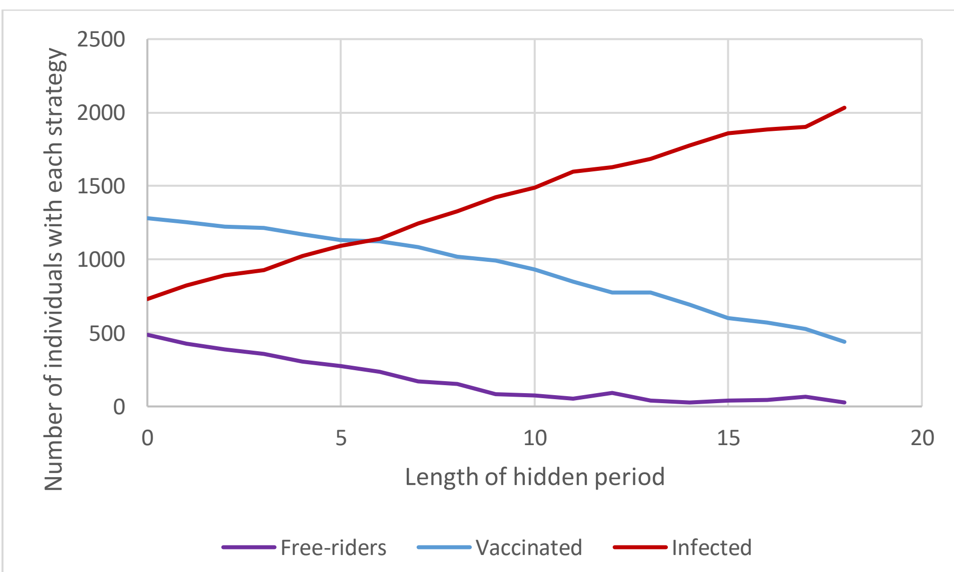


Figure 4.17 Number of free-riders, vaccinated and infected individuals when changing the incubation period from 0 to 18

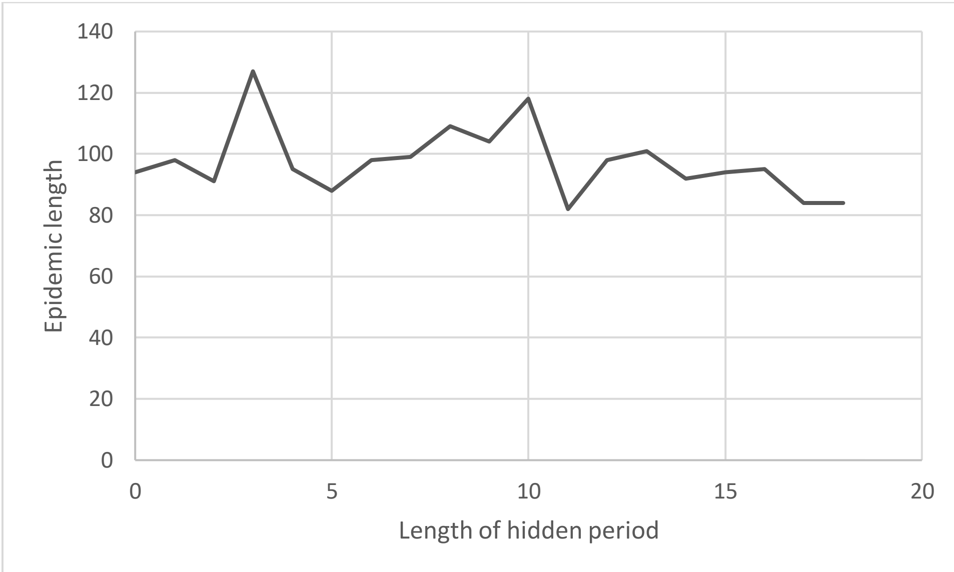


Figure 4.18 The length of epidemic when changing the incubation period from 0 to 18

4.3 Conclusion

This paper studies the effect of an incubation period on the spread of infectious diseases. It is assumed that during an incubation period, individuals are infectious but they and their contacts are not aware of their threat of transmitting the disease. This changes the response of people to an epidemic and consequently can result in different epidemic dynamics. Considering the time delay in responding to an epidemic requires different public health management strategies.

This study analyzes the factors that can affect the epidemic spread. These factors are the cost of vaccination, initial vaccination rate, transmission rate and sensitivity of individuals to the threat of a disease. The results show that in comparison with the same model without considering the incubation period, time delay results in fewer vaccinated individuals, fewer free-riders and more infected individuals. However, this effect is more pronounced when the cost of vaccination is relatively low, transmission rate is high and mandatory initial vaccination is low. When considering the effect of the sensitivity factor s to the threat of a disease the analysis shows that an increase of the sensitivity s results in fewer infected individuals and more free-riders but may not affect the number of vaccinated individuals. Moreover, the results show that increasing the length of the incubation period in comparison to the total time of an infection results in more infected individuals and fewer vaccinated and free-riders.

Chapter 5 - Modeling Meta-populations' Response to Epidemic

This chapter models the spread of diseases for a network of populations to analyze how different strategies can change the dynamic of disease spread and the percentage of infected and vaccinated individuals in each population. To approach this problem, an agent-based model is used in which agents are different populations and spatial evolutionary game theory with a public goods payoff is used to model the behavior of agents.

In section 5.1 the proposed methodology is presented. Section 5.2 presents the result of using this methodology considering different parameters and discussing the behavior of populations facing infectious disease outbreaks. Section 5.3 provides a summary and discussion.

5.1 Methodology

In this study, populations' cost functions and payoffs are determined based on their contribution to the group and the group's shared payoff which can be seen as a public goods game.

When considering populations instead of individuals at each node, each population can have a level of contribution to the public health. Thus, instead of having vaccinated individuals just paying the cost of vaccination and infected and recovered ones paying the cost of infection as their contribution in the public health, we have different levels of vaccination and infection as the contribution of each society in the public health of its communication group.

In our model we considered each node of a graph as a society and the edges in the graph demonstrate the temporary transfer of individuals from one society to another one. Also, each node and its first order connected nodes form a communication group. To illustrate, in Figure 5.1 the orange nodes show cooperation group for society i.

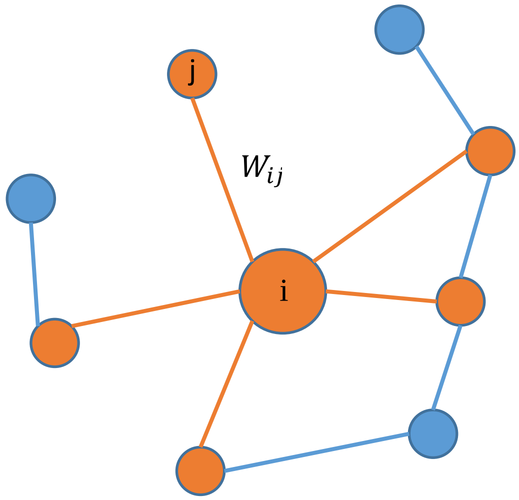


Figure 5.1 Cooperation group for society i (W_{ij} is the communication weight from node i to node j)

5.1.1 Calculating λ

As described before, the infection rate in a population can be calculated using the following formula:

$$\lambda = \beta \times \frac{N_I}{N} \qquad 5.1$$

In which β is the transmission rate of the disease, N is the population size of the node and N_I is the number of infected individuals at the node, and λ is the effective infection rate.

However, when a population has contacts with other populations the infection can spread in a society by the contacts from outside. To model this phenomena, it is considered that at each time step a number of links will form between chosen individuals in one society and some other individuals from the other societies. If an infected individual meets a susceptible one there is β chance for the susceptible individual to become infected. The weight of communication W_{ji} is equal to the number of links that can form from node j to node i which can resemble the travels from node j to i. Thus, the expected value of the number of new infections in node i caused as result of communication with node j can be calculated using the following formula:

$$E(N_{I\,ji}) = W_{ji} \times \beta \times \frac{N_{Ij}}{N_j} \times \frac{N_{Si}}{N_i} \qquad 5.2$$

Where W_{ji} is the weight of communication between node j and node i, β is the transmission rate of the disease, N_{Ij} is the number of infected individuals in node j, N_j is the population size of node j, N_{Si} is the number of susceptible individuals in node i and N_i is the population size of node i. Thus, $\beta \times \frac{N_{Ij}}{N_j} \times \frac{N_{Si}}{N_i}$ shows the probability that a link between an individual in node i and an individual in node j result in a new infection in node i.

Consequently, the number of new infections in node i caused as a result of communication with its neighbors can be calculated using the below formula where g_i is the group of neighbors of node i:

$$N_{I\,i\,out} = \sum_{j \in g_i} N_{I\,ji} \qquad 5.3$$

Therefore, the number of infected individuals in node i will increase by $N_{I\,i\,out}$ and consequently a new population of infected individuals will enforce infection spread in node i. Thus at period t, $\lambda = \beta \times \frac{N_I}{N}$ in which N_I is the number of infected individuals at the end of period $t-1$ ($N_{I\,t-1}$) in node i plus $N_{I\,i\,out}$ in period t.

In this study, whenever λ is used to estimate the number of infections in a period, the expected value of infection from outside $E(N_{I\,i\,out})$ is used for calculating the $E(N_I)$ and thus,

$$E(\lambda) = \beta \times \frac{E(N_I)}{N} = \beta \times \frac{E(N_{I\,t-1}) + E(N_{I\,i\,out})}{N} \qquad 5.4$$

In simulating this model, it is assumed that W_{ji} is the number of contacts of travelers from node j to node i. It is calculated based on the percentage of contacts times the population size. Thus, if the population of node j is 100 and 2% is the percentage of communication, the value of W_{ji} is $100 \times 0.02 = 2$, representing the actual number of contacts.

To calculate the value of $N_{I\,ji}$ we start with $N_{I\,ji} = 0$. At each time step, for each link from node j to node i (1 to W_{ji}) a random number between 0 and 1 is generated. If the number is less than $\beta \times \frac{N_{Ij}}{N_j} \times \frac{N_{Si}}{N_i}$ the value of $N_{I\,ji}$ will increase by one. The last value of $N_{I\,ji}$ will be used in calculating $N_{I\,i\,out}$.

5.1.2 Payoff calculation

Based on the public good game we can consider that each society has two payoffs. Local payoff (cost) which is the cost of its contribution to the communication group and global payoff which is the shared payoff in the communication group.

The local payoff for each node is related to the cost that is paid by that society to contribute towards the health status of the community which is the cost of vaccination, cost of infection and cost of recovery.

$$P_{local\ i} = -(C_V N_{Vi} + C_I N_{Ii} + C_R N_{Ri}) \qquad 5.5$$

Where C_V, C_I and C_R are cost of vaccination, cost of infection and cost of being recovered respectively. N_{Vi} is the total number of vaccinated individuals in the node, N_{Ii} is the number of infected individuals in the node and N_{Ri} is the number of recovered individuals in the node.

When comes to the global payoff, it is assumed that all the nodes in a community have a shared payoff resulting from their contribution to the community that they belong to. This shared payoff can be defined as the vaccination and infection status of the whole society and also the infection risk in the society resulting from the vaccination and infection status of each node and its neighbors. The vaccination and infection status can be described as the perceived barriers to behavior adoption or the cost of prevention and the perceived severity or the cost of being infected for the society, and the infection risk is the perceived susceptibility in a communication group. Note that the group payoff is distributed based on the population size of the nodes. Thus, a higher payoff occurs in the more populated nodes.

Based on the above definition, the shared payoff of the node i in the community G is defined as follows:

$$P_{global\ i} = -\frac{N_i \sum_{\forall j \in G} \left(C_V N_{Vj} + C_I N_{Ij} + C_R N_{Rj} + C_I E(\lambda_j) N_{Sj} \right)}{\sum_{\forall j \in G} N_j} \qquad 5.6$$

Where C_V, C_I and C_R are cost of vaccination, cost of infection and cost of being recovered respectively. N_{Vj} is the total number of vaccinated individuals in node j, N_{Ij} is the number of infected individuals in node j, N_{Rj} is the number of recovered individuals in node j, N_{Sj} is the number of susceptible individuals in node j, N_i and N_j are the population sizes of the node i and j respectively, G is the cooperation group for node i and $E(\lambda_j)$ is the expected infection rate for the node j.

The total payoff of each node is then calculated using the following formula:

$$P_i = P_{local\ i} + P_{global\ i} \qquad 5.7$$

5.1.3 Updating strategy

In every time step, each node which is in risk of being infected $(\lambda_j N_{Sj} > 0)$ can decide to change its vaccination rate (γ) to contribute towards controlling the epidemic. The updating rule is such that at every time step a node will update this vaccination rate strategy using the following formula.

$$\gamma_{it} = \alpha \gamma_{i\ t-1} + (1-\alpha) \frac{\max\left(P_j \middle| j \in G\right) - P_i}{\max\left(P_j \middle| j \in G\right) - \min\left(P_j \middle| j \in G\right)} \qquad 5.8$$

In which P_i is the payoff of node i and G is the cooperation group for node i. α shows the willingness of a node to keep its previous strategy.

5.1.4 Updating epidemic spread

After updating the strategy of each node, the new number of vaccinated, infected and recovered individuals given the new strategy is calculated.

To find these values, we use a population based model for the given strategy. Since the status of each node is also related to the number of interactions with other nodes, to consider the interactions with other nodes and the effect of their statuses on each node status we consider that the number of vaccinated and infected individuals from other nodes can affect the vaccination rate and infection rate in the node and also the possibility that a node becomes infected.

The following equations can be used for calculating the new status of a node:

$$\frac{dN_S}{dt} = -\lambda N_S - \gamma N_S \quad 5.9$$
$$\frac{dN_I}{dt} = \lambda N_S - gN_I$$
$$\frac{dN_R}{dt} = gN_I$$
$$\frac{dN_V}{dt} = \gamma N_S$$

Where N_V, N_I, N_R and N_s are the number of vaccinated, infected, recovered and susceptible individuals respectively. λ is the infection rate, g is the rate of recovery and γ is the vaccination rate.

5.1.5 Initialization

In the first step of building the model, the network of interacting populations is built. To do that, we consider a lattice and a scale-free network.

We assume that each population has the following attributes:

1. Size of population
2. List of neighbors and their weights (weight shows the number of individuals traveling to each node from the neighboring nodes)
3. strategy (vaccination rate (γ))
4. Infection status (#susceptible (N_S), # vaccinated (N_V), #infected (N_I) and #recovered (N_R))

After defining the network of populations, it is required to determine which nodes are infected and what is the initial infection status of each node. In modeling, we assume that p% of nodes are infected which are generated randomly. The initial status of those nodes is equal to 5% infected, 0 vaccinated and 0 recovered individuals.

5.2 Experimental results

In the following, the result of changing different factors that can affect the dynamics of an epidemic are studied. The experiments are done in 20 by 20 lattice and also a scale-free network with 400 nodes and an average degree of 8 generated using the Barabási–Albert model (Figure 5.2).

The Barabási–Albert model is a known model which is used to generate scale-free networks (Barabási, 2016). In this model, first we start with m_0 nodes in which the links between the nodes are chosen arbitrarily, and each node has at least one link. Then, the network growth using the following two steps:

At each time step we add a new node with m ($\leq\ m_0$) links that connect the new node to m nodes which already exist in the network. We know this step as "Growth".

The probability that a link of the new node connects to node i depends on the degree of i (k_i) (Equation). We know this step as "Preferential attachment".

$$\pi(k_i) = \frac{k_i}{\sum_j k_j} \qquad 5.10$$

Following these two steps, we can see that while most nodes in the network have only a few links, a few gradually turn into hubs. This behavior is because of the preferential attachment which leads new nodes to become more likely connected to the more connected nodes than to the smaller nodes.

The parameter values for running the model are given in Table 5.1. In the figures which represent the number of susceptible, infected and recovered, the purple line shows the total number of susceptible, blue line shows the total number of vaccinated and the red line shows the total number of recovered (infected) individuals.

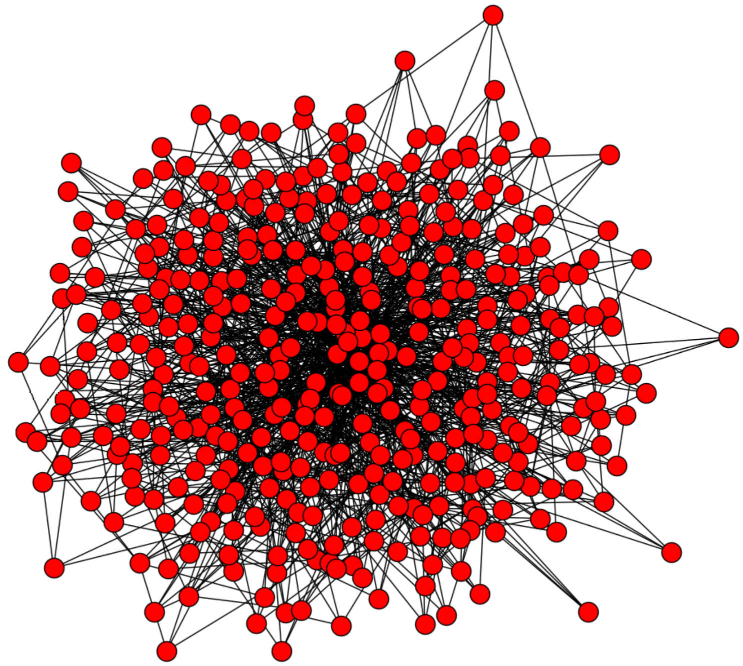


Figure 5.2 A scale free network with 400 nodes and average degree of 8

Table 5.1 Parameters of the model

Parameter	**Meaning**	**Value**
N	Population size of each node	100
N_{I0}	Number of initially infected individuals	5
N_{V0}	Number of initially vaccinated individuals	0
N_{R0}	Number of initially recovered individuals	0
C_I	Cost of infection	1000
C_V	Cost of vaccination	10 or variable
C_R	Cost of being recovered	0
g	recovery rate	0.1
β	Transmission rate of the disease	0.5 or variable
γ_0	Initial vaccination rate	0
W_{ij}	Communication weight from node i to j	2% or variable

t_p	Time steps between strategy updates	1
p	Probability of existence of infection in a node	5%
α	Willingness for keeping old strategy	0.5 or variable

5.2.1 Comparing public goods payoff with local payoff

In section 5.1.2, the payoff of a node is calculated based on the local payoff of the node itself and the local payoff of its neighbors considering its probable cost of infection and also its neighbors, probable cost of infection. Using such function, the effect of public goods in decision making is reflected. One may ask, why considering the public payoff and not just the local payoff of a node itself and its probable infection cost for decision making. As discussed in section 5.1.1, the public goods game based payoff function can take into account the health factor of a communication group and therefore can help the whole group to maintain a healthier society. In this section, an alternate model is developed in which the payoff of a node is calculated based on the local payoff and the risk of infection for that node, and the result is compared with the proposed model. In this alternate model, the payoff of each node is calculated using the following formula:

$$P_i = P_{local\ i} - C_I E(\lambda_i) N_{Si} \qquad 5.11$$

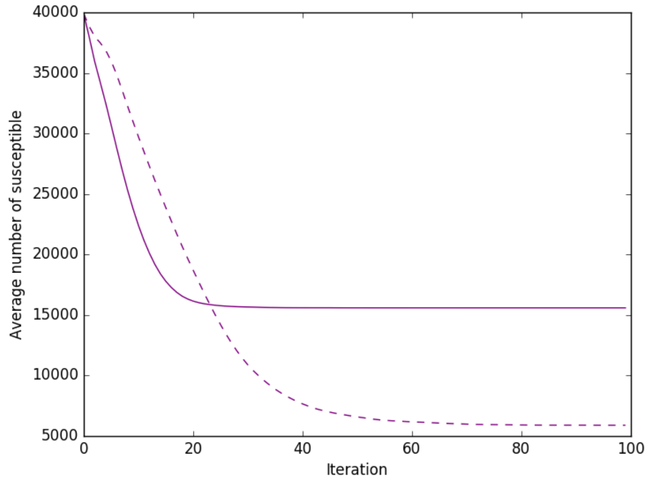
Where $P_{local\ i}$ is the local payoff of a node and calculated using Equation 5.5, and C_I is the cost of infection, $E(\lambda_i)$ is the estimated infection rate for the node i which is calculate using Equation 5.4, and i is the number of susceptible individuals in node i.

The following shows the average number of people in each stage of the disease for 20 different distributions of infected nodes in both a lattice and a scale-free network, which have the same ratio of initially infected nodes, for proposed model of this paper (solid lines) and the introduced alternate model (dashed lines).

Figure 5.3 shows the mean number of susceptible individuals in each iteration of the model or in the other words the mean of susceptible people at each time from the beginning to the end of the epidemic. It can be seen for both types of networks that, although in the first few iterations of the game the number of susceptible is higher for the model with the local payoff (alternate model), at the end the model with public payoff (proposed model) saved more people. Conversely, as it is illustrated in Figure 5.4 the mean number of vaccinated individuals is higher at the first stages of the epidemic for the proposed model but the total vaccination is lower at the end of the epidemic in comparison with the alternate model. Moreover, through the whole epidemic spread, the number of infected (recovered) people for proposed model is less than the alternate model (Figure 5.5). Thus, it can be concluded that the proposed model which is based on the public goods payoff can more efficiently control the epidemic spread with fewer vaccinations and more susceptible individual but at the same time less infection. This phenomenon can also be captured in Figure 5.6 which shows the cost of the epidemic throughout the epidemic period for each model since the cost of the proposed model is always less than the alternate one.

Comparing the lattice and a scale-free network we can observe that the difference between the public goods game model and the alternate model is much higher when a lattice is the network of interactions. This lower difference in the scale-free networks is the result of the existence of hubs in those networks which cause the epidemic to spread faster and be harder to control.

(a)



(b)

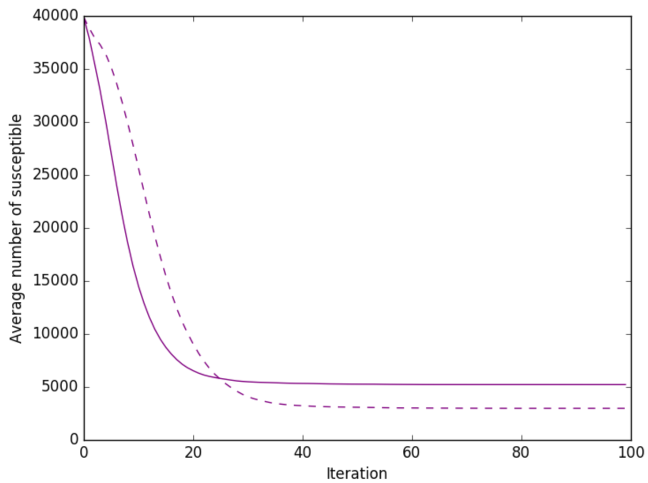
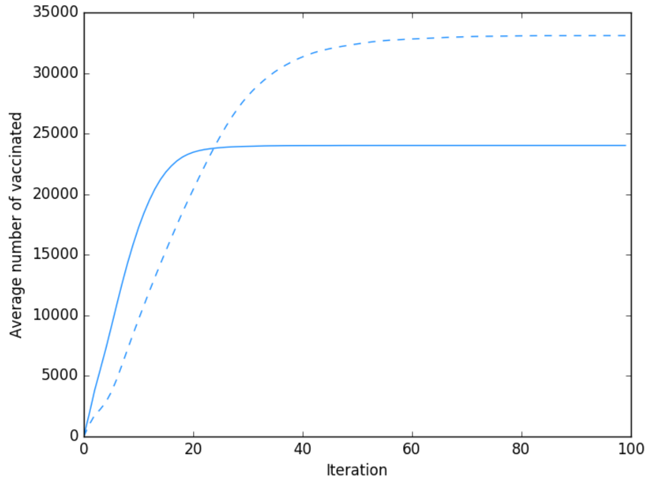


Figure 5.3 Average number of susceptible individual for 20 different starting configurations under two scenarios for a lattice structure (a) and a scale-free network (b)

(a)



(b)

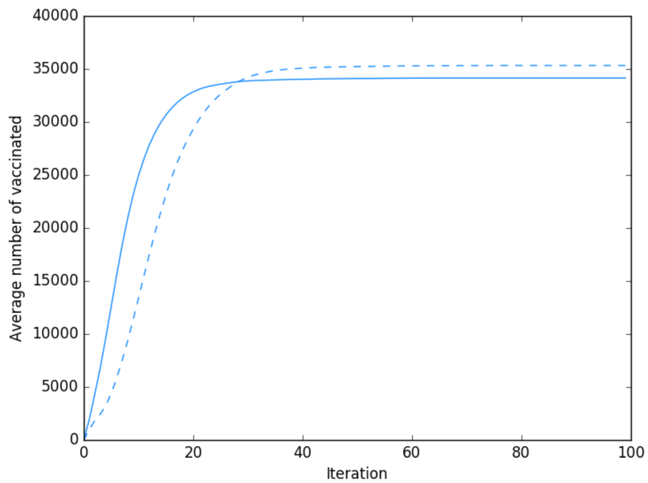
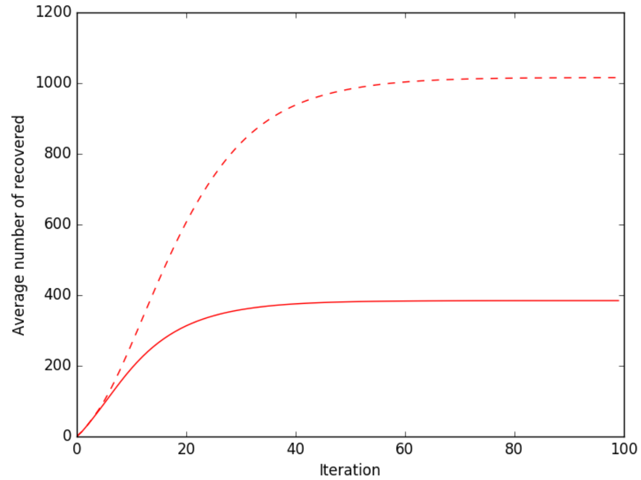


Figure 5.4 Average number of vaccinated individuals for 20 different starting configurations under two scenarios for a lattice structure (a) and a scale-free network (b)

(a)



(b)

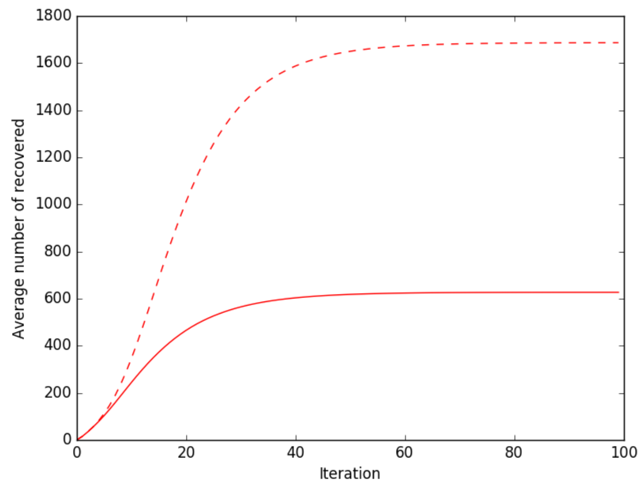
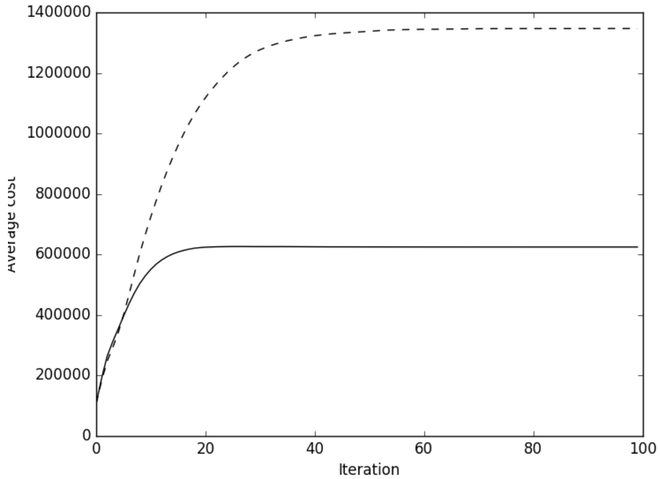


Figure 5.5 Average number of recovered individuals for 20 different starting configurations under two scenarios for a lattice structure (a) and a scale-free network (b)

(a)



(b)

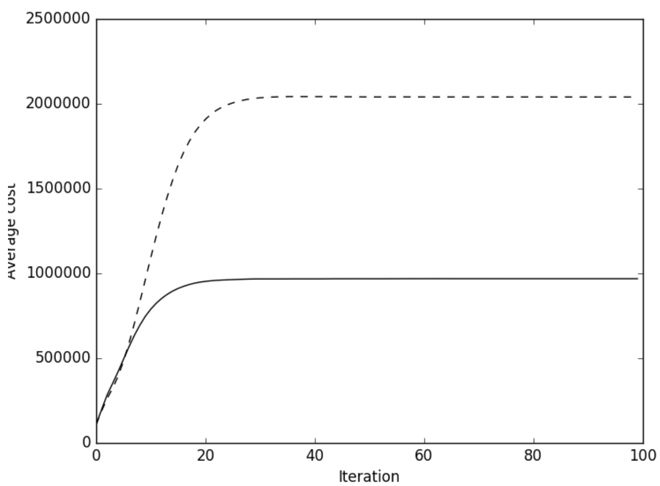


Figure 5.6 Average cost of epidemic for 20 different starting configurations under two scenarios for a lattice structure (a) and a scale-free network (b)

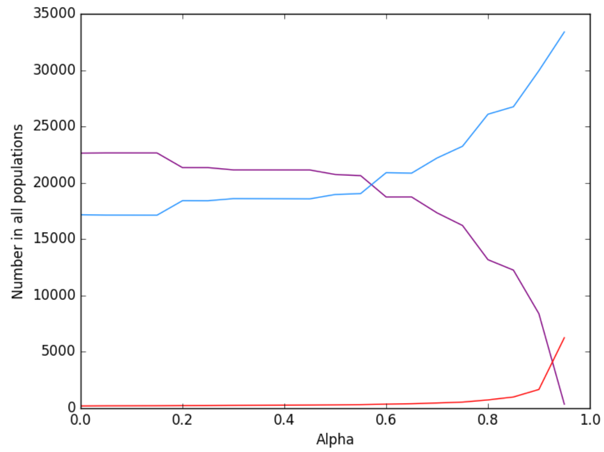
5.2.2 Effect of changing the value of α

One of the factors that can change the dynamic of the epidemic spread is the value of α. Since this value can show how willing is a population to change its vaccination rate, we can expect to see a better protection if the population is aware enough of the threat of the epidemic disease, meaning that it is willing to change its vaccination rate and consequently has a lower value of α

(1-α is high). To examine the effect of the value of α, a model was run for different values of α on both a lattice and a scale-free network in which the initially infected nodes are randomly distributed. Each model was run until it reaches the steady state situation and the result is used for evaluation. In Figure 5.7, the sum of number of susceptible, vaccinated, infected and recovered over all the nodes in the steady state situation for different values of α from 0 to 1 for a lattice and a scale-free network is represented.

Figure 5.7 shows that as the value of α increases and populations are less willing to change their policy for vaccination, the number of infected people increases (red line) although the total number of vaccinated people increases (blue line), which means that populations are less successful in controlling the epidemic. This can be due to inefficient reaction of the populations which are close to initial infection to epidemic, causing other populations to be in threat of being infected and in need of more vaccination to be able to control the epidemic in their communities. Consequently, as a result of more infection and vaccination, the number of susceptible people will decrease (purple line). Comparing the lattice structure and a scale-free network, it can be seen that in scale-free network the epidemic spreads faster, resulting in more infection, more vaccination and fewer susceptible individuals. Also, in the scale-free networks, if the value of α is too high, the number of infected individuals grows larger and there will be no more susceptible individual in the societies to get vaccinated, thus the number of vaccinated people decrease. Moreover, it can be seen in Figure 5.8 that if populations show more interest in changing their vaccination rate (decreasing α), not only less people will be infected at the end, but also more populations can remain not infected at all. However, the number of not infected nodes is fewer for scale-free networks. Additionally, the total cost of all the societies is lower with smaller values of α (Figure 5.9). The epidemic length will also decrease since fewer nodes are infected (Figure 5.10).

(a)



(b)

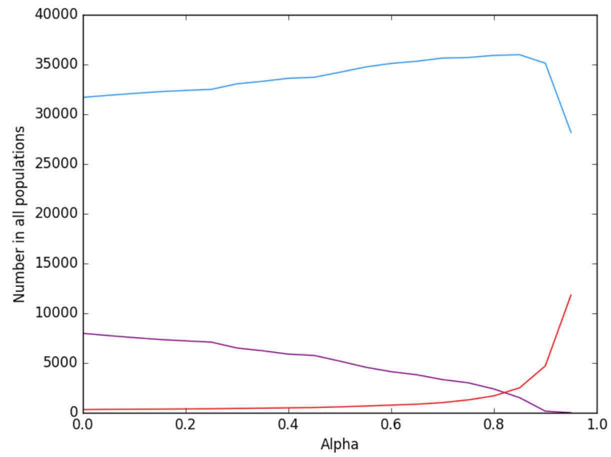
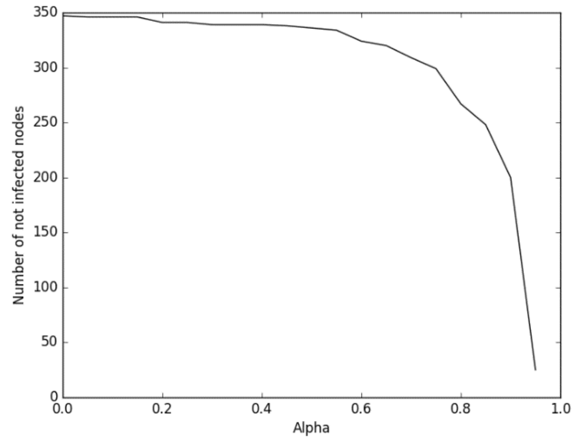


Figure 5.7 Number of total susceptible, vaccinated and infected for different values of α for a lattice structure (a) and a scale-free network (b)

(a)



(b)

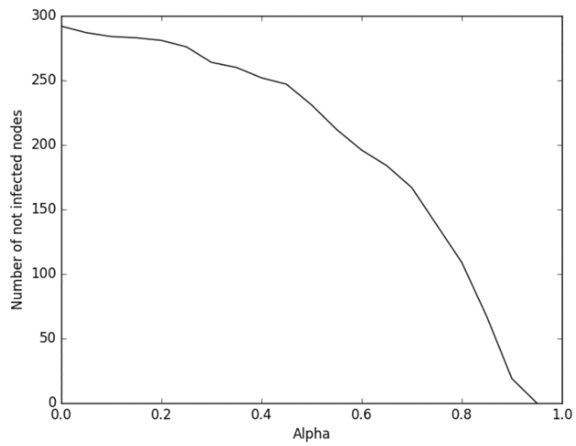
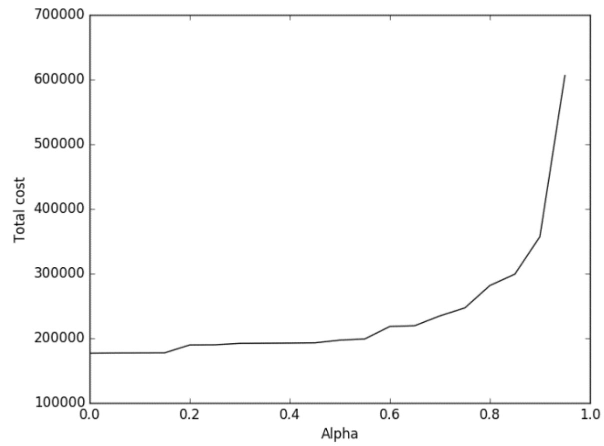


Figure 5.8 Number of not infected nodes for different values of α for a lattice structure (a) and a scale-free network (b)

(a)



(b)

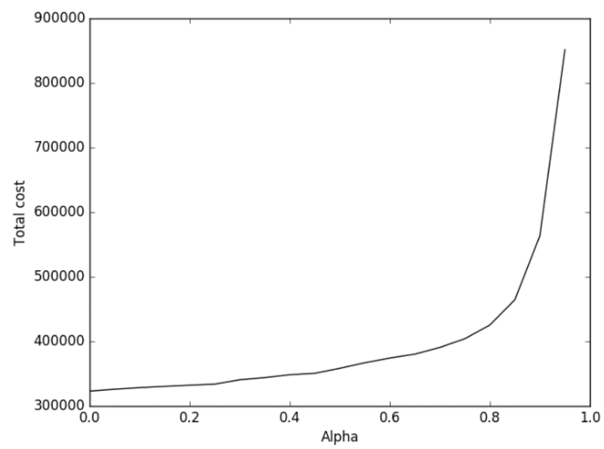
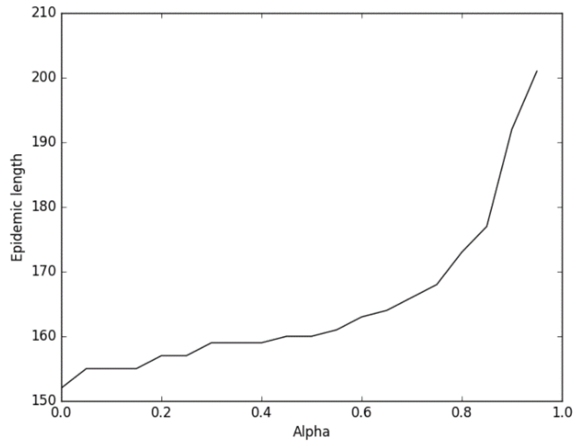


Figure 5.9 Total cost for different values of α for a lattice structure (a) and a scale-free network (b)

(a)



(b)

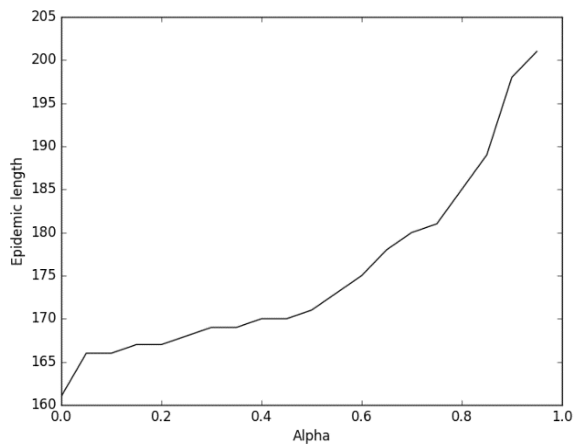


Figure 5.10 Epidemic length for different values of α for a lattice structure (a) and a scale-free network (b)

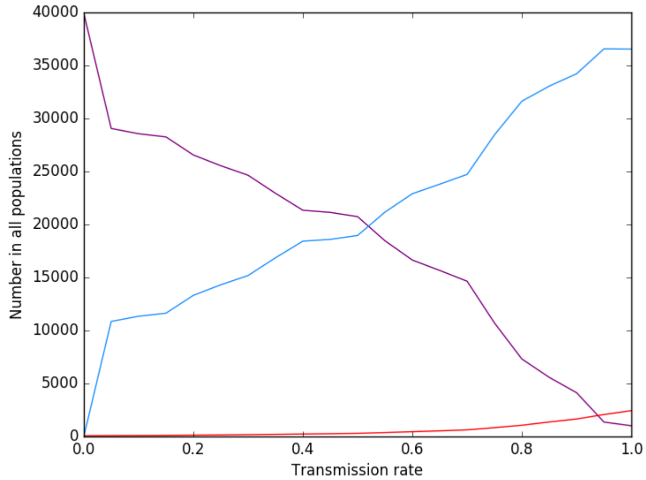
5.2.3 Effect of changing the transmission rate

The disease transmission rate is another variable which can affect the dynamic of an epidemic. This variable depends on the characteristics of the disease. To examine the effect of changing the value of β, considering that the recovery rate is constant, a model was run for different values of β on both a lattice and a scale-free network in which the initially infected nodes are randomly distributed. Each model was run until it reaches the steady state situation and the result is used for evaluation. In Figure 5.11, the sum of number of susceptible, vaccinated, infected and recovered over all the nodes in the steady state network for different values of β from 0 to 1 is represented.

Figure 5.11 shows that the increase of transmission rate will increase the number of vaccinated individuals (blue line) because vaccination is the only way to protect people in an infected node from being infected. As a result, the number of susceptible individuals will decrease (purple line). Moreover, the result shows that even with a high infection rate, the effective vaccination response to the disease spread can control the spread of the epidemic and result in just a small increase in number of infected (red line). Thus, the large group of vaccination is due to the fear of being infected which is associated with high transmission rate of the disease. Consequently, as the transmission rate increases, the cost of epidemic also increases because of higher vaccination and a few more infections (Figure 5.13). Also, the number of not infected nodes decreases with the increase of transmission rate, because the higher transmission rate will result in higher probability of becoming infected for the nodes (Figure 5.12). Thus, since higher vaccination rate cannot guarantee no infection in a population, although the vaccination rate in societies increases, the total number of not infected nodes decreases. Again, the scale-free network has more vaccination and infection and is more sensitive to increase of transmission rate.

Studying the total length of the epidemic we can observe that diseases with higher transmission rate have higher epidemic length while we expect it to be shorter due to the faster response of people considering its high threat (Figure 5.14). This unexpected observation is due to the fact that faster response of people to the epidemic is presented with larger vaccination rate, but larger vaccination rate cannot stope a node from being infected and any new infected node will increase the effort to stop the epidemic spread in form of more vaccination and time.

(a)



(b)

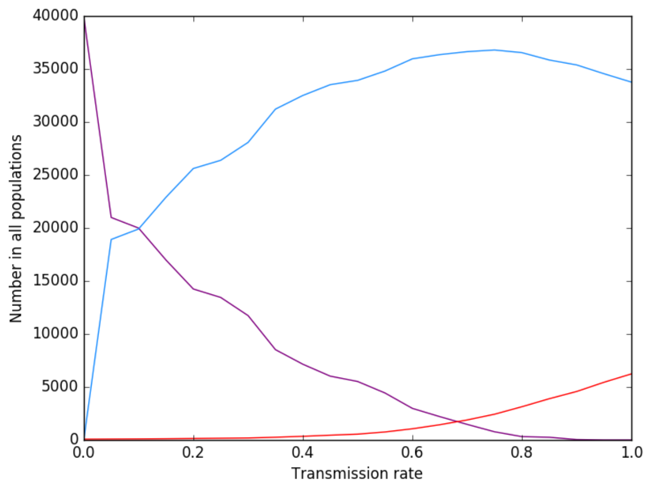
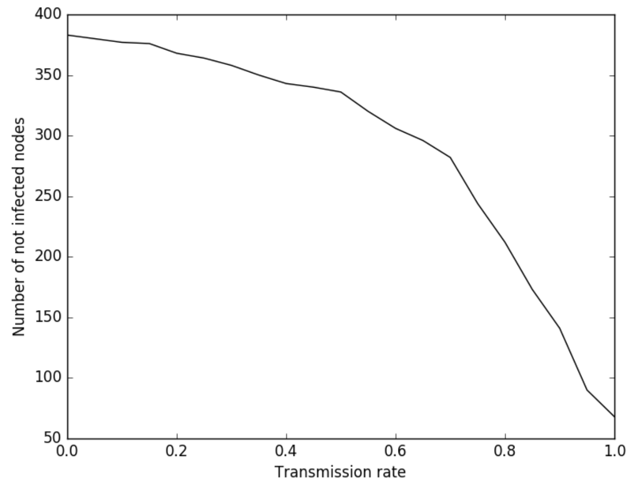


Figure 5.11 Number of total susceptible, vaccinated and infected for different values of transmission rate for a lattice structure (a) and a scale-free network (b)

(a)



(b)

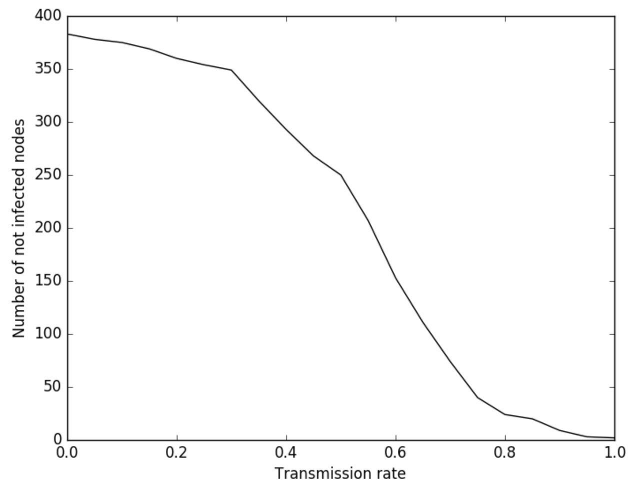
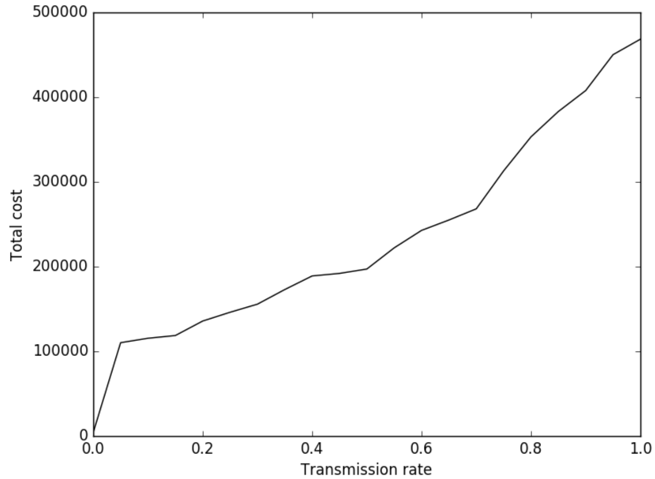


Figure 5.12 Number of not infected nodes for different transmission rates for a lattice structure (a) and a scale-free network (b)

(a)



(b)

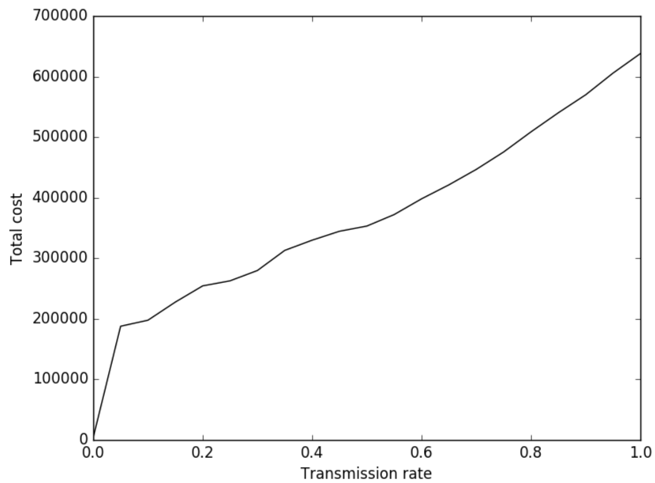
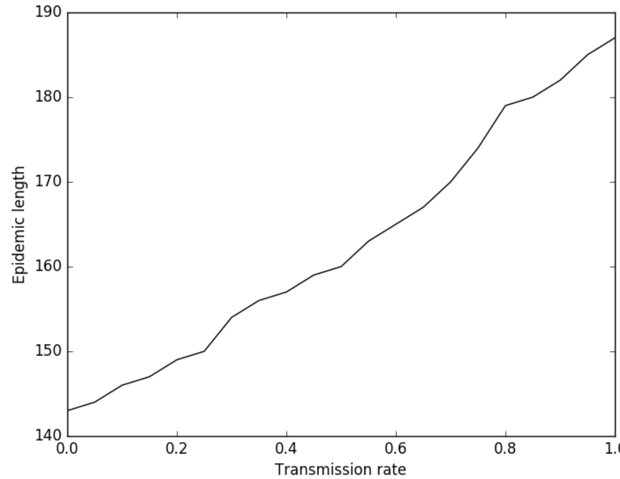


Figure 5.13 Total cost for different transmission rates for a lattice structure (a) and a scale-free network (b)

(a)



(b)

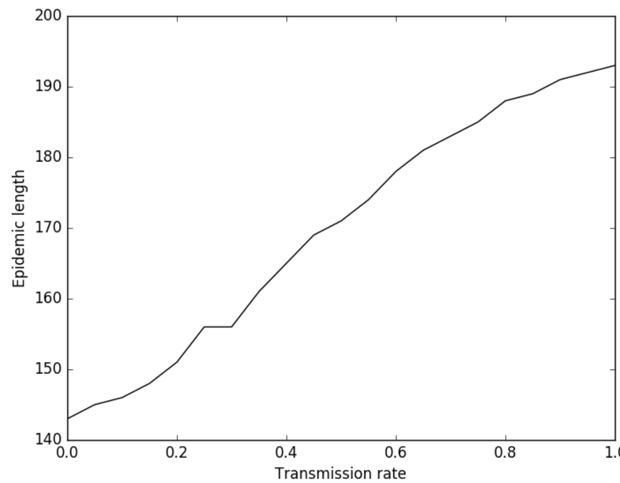


Figure 5.14 Epidemic length for different transmission rates for a lattice structure (a) and a scale-free network (b)

5.2.4 Effect of changing the communication weight

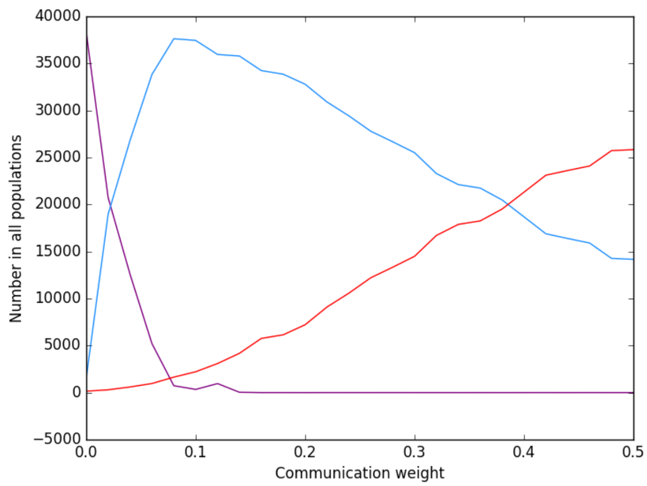
When modeling the epidemic spread among populations, another factor which has great importance in spread of the disease among populations is the rate of communications between populations. It is expected that as the rate of communication increases, the epidemic spreads wider. To examine the effect of changing the communication weight between nodes, a model was run on both a lattice and a scale-free network for different communication weights from 0 to 0.5 in which the initially infected nodes are randomly distributed. Each model was run until it reaches the steady state situation and the result is used for evaluation. In Figure 5.15, the sum of number of susceptible, vaccinated, infected and recovered over all the nodes in the steady state network for different values of W_{ij} for both the lattice and the scale-free network is represented. Here it is assumed that W_{ij} is the same for all i and j, but it can varied to match real patterns.

Figure 5.15 shows that the increase of communication weight between nodes, when communication weight is less than 0.1 for the lattice structure and less than 0.05 for the scale-free network, will increase the number of vaccinated individuals (blue line). This happens because vaccination is the only way to protect people in an infected node from being infected and increasing the communication weight increases the probability of existence of infection in a node, thus requires more vaccination. As a result of increase in vaccination, the number of (infected) individuals will not increase too high (red line) but the number of susceptible individual decreases (purple line). Consequently, as the communication weight increases up to less than the aforementioned values, the number of not infected nodes decrease because the higher communication weight will result in higher probability of becoming infected for the nodes (Figure 5.16). Also, the epidemic length increases (Figure 5.18).

We can see that the behavior of epidemic dynamics when increasing the communication weight is very similar to the behavior of epidemic dynamic when increasing the transmission rate of the disease. This is because these two factors are the ones which can increase the probability that an infection transfers to other nodes. However, when the communication weight grows two large, the spread of the disease is much faster than the vaccination and thus the population will be divided to vaccinated and infected with no susceptible people, and as the communication weight increases the infected portion becomes larger.

Consequently, as the communication weight increases, the cost of epidemic also increases (Figure 5.17). This is due the higher number of required vaccinations when the communication weight is small and also the higher number of infections when the communication weight is high.

(a)



(b)

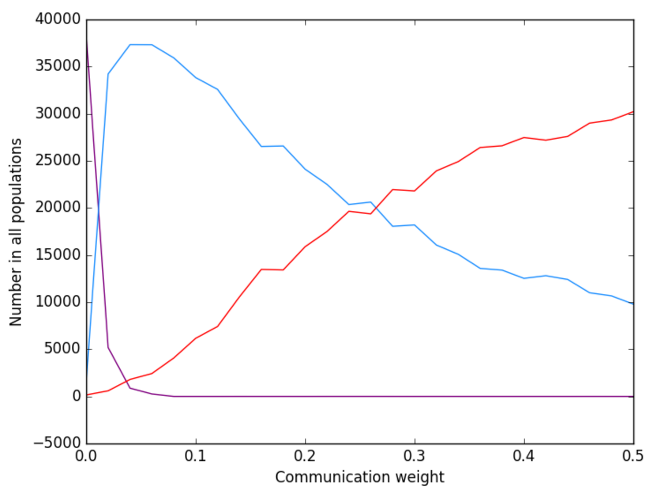
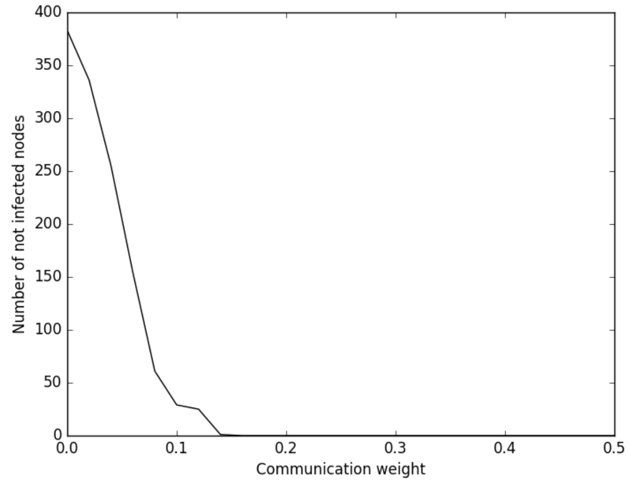


Figure 5.15 Number of total susceptible, vaccinated and infected for different values of communication weight for a lattice structure (a) and a scale-free network (b)

(a)



(b)

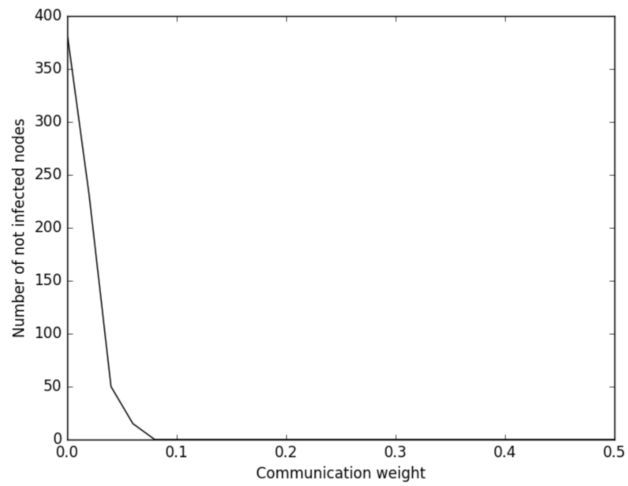
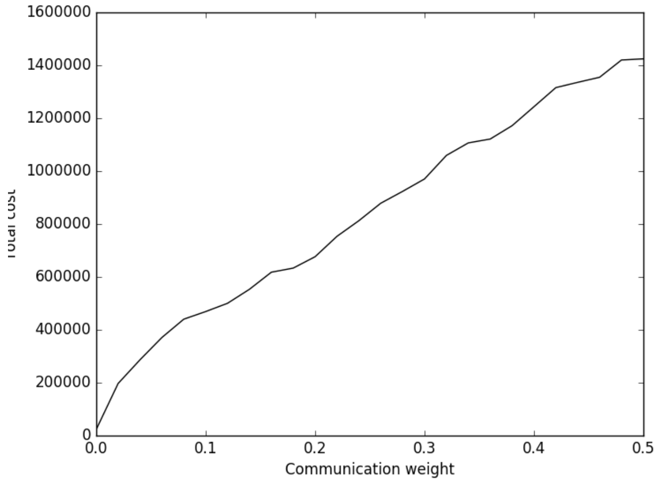


Figure 5.16 Number of not infected nodes for different communication weights for a lattice structure (a) and a scale-free network (b)

(a)



(b)

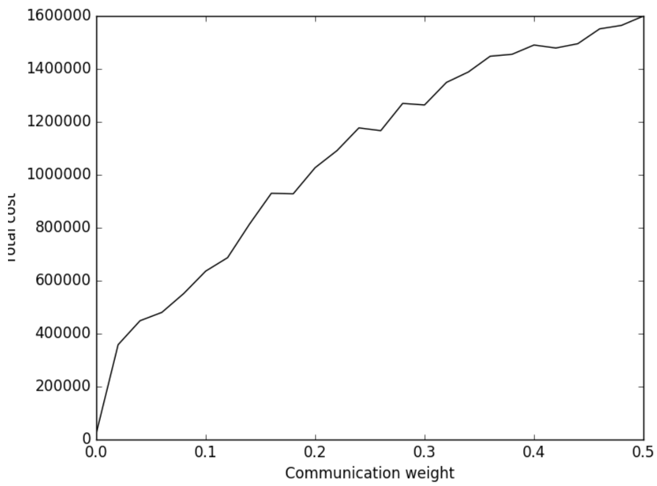
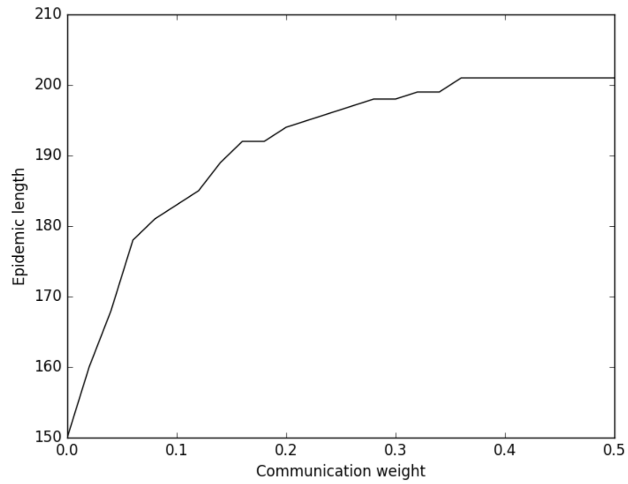


Figure 5.17 Total cost for different communication weights for a lattice structure (a) and a scale-free network (b)

(a)



(b)

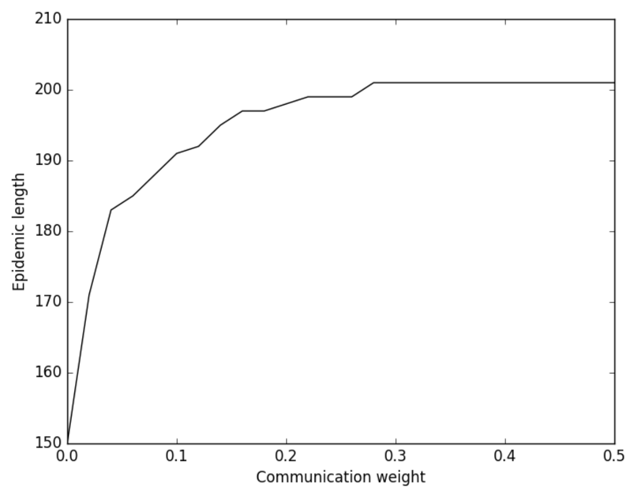


Figure 5.18 Epidemic length for different communication weights for a lattice structure (a) and a scale-free network (b)

5.2.5 Effect of changing the cost of vaccination

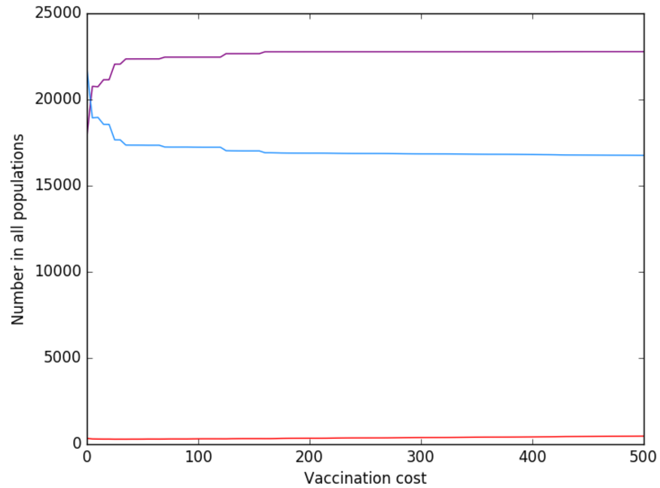
Cost of vaccination is another variable which can affect the dynamic of an epidemic. It is reasonable for the cost of vaccination to be much less than the infection cost otherwise people may prefer not to vaccinate and accept the risk of infection. To examine the effect of changing the cost of vaccination, the model was run for different values of C_V on both a lattice and a scale-free network in which the initially infected nodes are randomly distributed. Each model was run until it reaches the steady state situation and the result is used for evaluation. In Figure 5.19, the sum of number of susceptible, vaccinated, infected and recovered over all the nodes in the steady state networks for different values of C_V from 0 to 500 (half of the infection cost) for the lattice and the scale-free network is represented.

We can see in Figure 5.19 that as it was predicted, increasing the cost of vaccination will decrease the total number of vaccinations when the cost of vaccinations is low, but as the cost of vaccination increases the model will not decrease total number of vaccination more than a certain limit (blue line). As a result, the number of infected individuals is kept very low (red line). This behavior is due to the fact that vaccination and infection both have cost for societies and since the cost of vaccination is still lower than the cost of infection, infected nodes still prefer to vaccinate to protect their communities.

Interestingly, the number of not infected nodes will slightly increase as the cost of vaccination increases (Figure 5.20), because a high cost of vaccination is also a threat for populations and it causes the populations which are close to the infection source to vaccinate more. Since transmission rate is similar for both models with high vaccination cost and low vaccination cost, the higher vaccination close to the infection. source can protect more nodes from being infected.

Comparing the lattice structure and the scale-free network it can be seen that the epidemic spreads much faster in the scale-free network, resulting in fewer not infected nodes, more total vaccinations and infections, and fewer susceptible individuals.

(a)



(b)

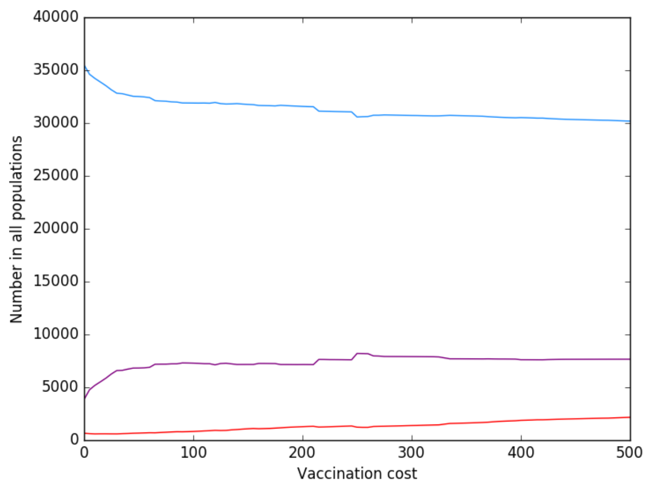
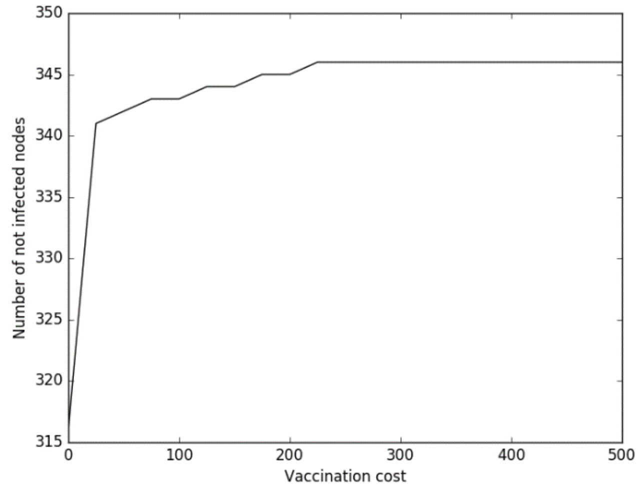


Figure 5.19 Number of total susceptible, vaccinated and infected for different vaccination costs for a lattice structure (a) and a scale-free network (b)

(a)



(b)

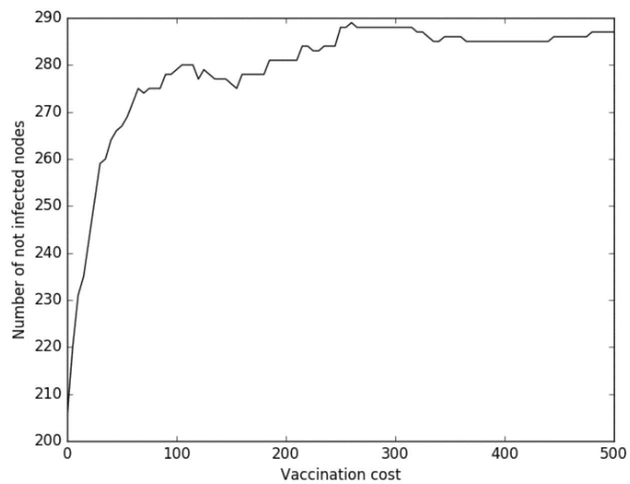


Figure 5.20 Number of not infected nodes for different vaccination costs for a lattice structure (a) and a scale-free network (b)

5.3 Conclusion

In this study, a model based on evolutionary spatial game under public goods game is presented to show the choice of populations which are interacting with each other when facing an epidemic. In this model, the payoff of each population is calculated based on its local payoff of vaccination and infection and also its share of global payoff considering the public goods effect.

The global payoff results from the local payoffs of the community of interactions of a node and the threat of infection in the community that a population is a member of. Based on the calculated payoffs, each population changes its vaccination rate to contribute in controlling the epidemic. It is also assumed that populations can have different willingness in changing their vaccination rate.

Using this model, we can show that considering vaccination choice of populations as a public good and caring about the health of a larger community rather than a single population can help in controlling the epidemic with fewer required vaccinations. Moreover, increasing the willingness of population to contribute in getting sufficient vaccinations at the right time will result in fewer vaccinations and also fewer infections at the end of the epidemic. Additionally, the model tests the effect of increasing transmission rate of the disease and communication weight between populations. Both show a significant increase in the number of vaccinations and infections due to the higher probability of infection associated with them. Also, the effect of changing the cost of vaccination is examined, which shows that since the vaccination cost is less than infection cost, populations try to maintain a level of vaccination in their societies to control the epidemic.

Also, the comparison of the results of the model for a lattice structure and a scale-free network shows a very similar behavior for both structures. However, in scale-free networks the epidemic spreads much faster than lattice as a result of the existence of hubs in scale-free network. Those hubs are causing the epidemic to spread faster because they are connected to many nodes and therefore have a higher probability to become infected and also to transfer infection to other nodes.

Chapter 6 - Conclusions and Future Research

This dissertation introduced a public goods game modeling approach to model the behavior of individuals and populations in response to an epidemic. The models are built based on spatial evolutionary game theory on a network of interactions. It can be seen from the results that this approach can show a similar result to what we can expect to see in the real-world situation and can be used in controlling the epidemic spread. In the following we summarize the main contributions of this work, and follow with remarks on directions and avenues of future research and extensions of these contributions.

6.1 Conclusions

In chapter 3 of this dissertation, a public goods game model for modeling the behavior of population of individuals in response to an epidemic is illustrated in which the payoff of each player is calculated using a group related payoff function. In this function, other than the cost of vaccination for vaccinated people and the cost of infection for infected people, the actual and probable cost of all individuals in a 3 by 3 group is divided between the members of that group. Using this payoff for each player, individuals try to imitate the behavior of the people who are in the groups with the lowest cost or highest payoff based on their sensitivity. This sensitivity factor shows the risk tolerance of players encouraging switching to the strategy of their neighbors. The sensitivity factor can show the number of neighbors with highest payoffs in the candidate list of a players, so, if any vaccinated individual is in this candidate list the player will be encouraged to get vaccinated. Using this model, we can show that if the cost of vaccination is increased, players have less tendency to get vaccinated, which is a representative behavior to a real-world situation.

However, increasing the sensitivity of individuals can result in more vaccination in the same situation. This behavior is very similar to the effect of fear of being infected in real-world epidemics. Moreover, increasing the sensitivity can be beneficial for the society as individuals react to the epidemic sooner and decide faster to get vaccine in order to save themselves and their community, but increasing the sensitivity factor too much does not lead to an optimal cost for the society. The results show that increasing the sensitivity factor to more than 5 does reduce cost while the number of free-riders dose not increase, and the number of vaccinated and infected individuals does not change. This behavior is the result of dissuasive effect of selecting the strategy of the neighbors who have a higher payoff than the payoff of the player itself on the candidate list.

Additionally, the model tests the effect of the infection transmission rate, and surprisingly, the epidemic length is lower when facing a disease with high transmission rate. This is explained by the fact that individuals respond sooner to the disease spread when there is a higher probability of being infected (represented as a strategy with a higher potential cost).

We also examined the effect of the number of initially vaccinated individuals on the epidemic which shows that mandatory vaccination can be beneficial when it does not force too many individuals to get the vaccine. Also, the distribution of vaccinated players in the lattice can affect the final result, when the players are distributed evenly in the lattice, more people are in contact with vaccinated individuals and this can cause them to get vaccine sooner when facing an epidemic and can result a better control of epidemic compared to the same number of vaccinated individuals who are randomly distributed.

Also, it is shown in that considering community based payoff function in modeling the spread of infectious diseases can better capture the dynamic of epidemic sand therefore it is recommended to be used when modeling the epidemic outbreaks to study the behavior of populations and when such models are used for decision making for public health.

In chapter 4 we studied the effect of an incubation period on the spread of infectious diseases. It is assumed that during an incubation period, individuals are infectious, but they and their contacts are not aware of their threat of transmitting the disease. This changes the response of people to an epidemic and consequently can result in different epidemic dynamics. Considering the time delay in responding to an epidemic requires different public health management strategies.

This study analyzes the factors that can affect the epidemic spread. These factors are the cost of vaccination, initial vaccination rate, transmission rate and sensitivity of individuals to the threat of a disease. The results show that in comparison with the same model without considering the incubation period, time delay results in fewer vaccinated individuals, fewer free-riders and more infected individuals. However, this effect is more pronounced when the cost of vaccination is relatively low, transmission rate is high and mandatory initial vaccination is low. When considering the effect of the sensitivity factor s to the threat of a disease the analysis shows that an increase of the sensitivity s results in fewer infected individuals and more free-riders but may not affect the number of vaccinated individuals. Moreover, the results show that increasing the length of the incubation period in comparison to the total time of an infection results in more infected individuals and fewer vaccinated and free-riders.

In chapter 5, a model based on evolutionary spatial game under public goods game is presented to show the choice of populations which are interacting with each other when facing an epidemic. In this model, the payoff of each population is calculated based on its local payoff of vaccination and infection and also its share of global payoff considering the public goods effect. The global payoff results from the local payoffs of the community of interactions of a node and the threat of infection in the community that a population is a member of. Based on the calculated payoffs, each population changes its vaccination rate to contribute in controlling the epidemic. It is also assumed that populations can have different willingness in changing their vaccination rate.

Using this model, we show that considering vaccination choice of populations as a public good and caring about the health of a larger community rather than a single population can help in controlling the epidemic with lower required number of vaccinations. Moreover, increasing the willingness of population to contribute in getting enough number of vaccinations at the right time, will result in fewer vaccination and also fewer infection at the end of the epidemic. Additionally, the model tests the effect of increasing transmission rate of the disease and communication weight between populations. Both show a significant increase in the number of vaccinations and infections due to the higher probability of infection associated with them. Also, the effect of changing the cost of vaccination is examined, which shows that since the vaccination cost is less than infection cost, populations try to maintain a level of vaccination in their societies to control the epidemic.

Also, the comparison of the results of the model for a lattice structure and a scale-free network shows a very similar behavior for both structures. However, in scale-free networks the epidemic spreads much faster than lattice as a result of the existence of hubs in scale-free network. Those hubs are causing the epidemic to spread faster because they are connected to many nodes and therefore have a higher probability to become infected and also to transfer infection to other nodes.

6.2 Future research

In this dissertation, two methods for modeling epidemic spread in individual level and population level are proposed. In the individual level model, for simplicity and better visual illustration, it is assumed that individuals are interacting on a lattice form structure. However, different network structures such as small world networks can be used as the network of interactions. Also, it can be considered that the network for decision making and information spread is different from the network of epidemic spread. Moreover, in our model, the sensitivity factor is not varying among players while the result of having different sensitivities can be studied. It can also be assumed that the sensitivity factor is a function of the fear factor. More importantly, this model can be applied in real-world networks, and the in-hand data of a disease can be compared with the result of the model to validating the model and also adjusting the parameters.

When studying the effect of time delay, in our model just the time delay between infection and emergence of syndromes has taken into account while as introduces in chapter 2.2.4, several types of delay exists in the disease transmission that can be taken into account.

In the population-based model, the real network of travels can be used as the network instead of the scale-free networks and also the result can be compared with some real data for validation. Also, death and birth rate can be taken into account in modeling.

Additionally, machine learning techniques can be used to derive optimal model parameters for given epidemic conditions.

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