Chaos, Solitons and Fractals 119 (2019) 118–125

Contents lists available at ScienceDirect

Chaos, Solitons and Fractals

Nonlinear Science, and Nonequilibrium and Complex Phenomena

journal homepage: www.elsevier.com/locate/chaos

Frontiers

Analysis of SIR epidemic model with information spreading of awareness

K.M. Ariful Kabir[a,b,*], Kazuki Kuga[a], Jun Tanimoto[c]

[a] Interdisciplinary Graduate School of Engineering Sciences, Kyushu University, Kasuga-koen, Kasuga-shi, Fukuoka 816-8580, Japan
[b] Department of Mathematics, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh
[c] Faculty of Engineering Sciences, Kyushu University, Kasuga-koen, Kasuga-shi, Fukuoka 816-8580, Japan

ARTICLE INFO

Article history:
Received 11 June 2018
Revised 12 September 2018
Accepted 20 December 2018
Available online 27 December 2018

Keywords:
Social dilemma
Epidemic
SIR model
Information spreading

ABSTRACT

The information spreading of awareness can prompt the manners of human to ease the infectious possibility and assist to recover swiftly. A dynamic system of Susceptible-Infected-Recovered (SIR) with Unaware-Aware (UA) process (SIR-UA) is newly developed by using compartment model through analytical approach with assumption of an infinite and well-mixed population. Moreover, individuals in a population can be classified into six states as unaware susceptible(S_U), aware susceptible(S_A), unaware infected(I_U), aware infected(I_A), unaware recovered(R_U), and aware recovered(R_A). Compared with previous models, the new dynamic set of equations described the more widespread situation and incorporated all possible states of Unaware-Aware (UA) with SIR process. The effect of awareness is explored carefully to show the significance on epidemic model with time steps. Consequently, the properties of parameters on the epidemic awareness model are studied to deliberate different physical situations. Finally, full phase diagrams are explored to show the epidemic sizes of susceptible and recovered individuals for various parameters.

1. Introduction

The word "awareness" seems to mean sending messages, getting consideration and making people chat about the issue. The effect of awareness has a great impact to reduce illness and help people to take prevention against diseases. Even, if the finest way of disease control is immunized, the practice of vaccination is expensive and sometimes protections are temporary and difficult to vaccinate all mass people. Furthermore, a number of fatal diseases like Dengue, Chikungunya, AIDS, Plague and Malaria have no vaccination, only consciousness can prevent the disease more effectively and efficiently. Beside vaccination, the awareness for a disease, meaning shared basic information about the disease to the people, makes the individuals familiar with the syndrome and suggests the required preventive practices as well. For example, usage of mosquito coils and mosquito nets help to prevent Dengue and Chikungunya [1,2], the practice of safe sex [3] reduce the possibility of AIDS and other self-awareness depending on the type of infectious disease. In view of awareness, with broader meaning 'information' spreading, the complex network plays a significant role that affects the dynamical functions of the embodied system in modeling epidemics. The contacts inside social networks, biological networks and technological networks are coexistence of multilayer types that has stimulated the statistical physics because it instinctively contains complex nature due to complexity of plural layers and intricate connectivity. Thus, the multilayer nature of complex systems has robust effect to explain and inspect the advent of physical properties of the spread of information about disease [4–9].

Meanwhile, a compartment model, where a population is separated into a set of distinct groups, is the base and also a powerful mathematical framework for understanding the complex dynamics of epidemics. Based on disease status, the simplest model, can be defined as SI epidemic model where S used for susceptible and I for infected. Furthermore, the SI model is also recognized as the SIS model [10] where once an individual is infected and afterward recovered, he/she becomes susceptible again. Subsequently, for three compartments: susceptible (S), infected (I), recovered (R), known as SIR model [11,12] has been widely applied in epidemiology. The SIR model is used by researchers and medical officials to compute the amount of susceptible, infected, and recovered people in a population to describe the needing amount of medical support and vaccination during an epidemic. As variant models from

* Corresponding author at: Department of Mathematics, Bangladesh University of Engineering and Technology, Dhaka, Bangladesh and Interdisciplinary Graduate School of Engineering Sciences, Kyushu University, Kasuga-koen, Kasuga-shi, Fukuoka 816-8580, Japan.

E-mail address: k.ariful@s.kyushu-u.ac.jp (K.M.A. Kabir).

https://doi.org/10.1016/j.chaos.2018.12.017
0960-0779/

SIR, there are also the SEIR model [13] (susceptible, exposed, infected, or recovered), MSIR (maternally derived immunity, susceptible, infected, and recovered) SEIS [14] and MSEIR [15] model that described the various situation of epidemiology for diseases [16–19].

Incidentally, human acts as medium for spreading disease as well as information. Hence, human behavior that is responsive and transmit of information have played an important role to control the disease. Moreover, the coexistence of the information awareness with spreading of infection in a multiplex networks depicts the physical as well as the virtual effect [20] on the epidemic. A number of researchers have studied the relationship between human awareness with epidemic model [21–28] to show the effect of spreading information and the role of media. Among them, notable studies are presented by, Funk et al. [29] for an epidemics awareness with small size of outbreak, Wu et al. [30] for the three types of the awareness model, Bu et al. [31] discussed the behavior changing according to social distancing, Meloni et al. [32] studied the effect of mobility patterns of individuals in spreading of infectious diseases and Byungjoon et al. [33] examined the layer-switching cost of different interaction layers for information spreading on multiplex networks. Recently, Granell et al. [34] and Yaphui et al. [35] explored the multiplex network with coexistence of awareness and epidemic, where the dynamics of susceptible-infected-susceptible (SIS) model is used with Aware - Unware (AU). Moreover, Microscopic Markov Chain Approach (MMCA) is used to present the spreading process with awareness. Additionally, Ting et al. [36] studied numerically the population size effect of the two-layer networks where a disease and information spread respectively. Whereas, in the current study, we introduce a more general model with all possible states of SIR-UA including intermediate defense measures to describe the spreading of awareness effect in an epidemic model. Additionally, by adding UA model to SIR will help us to explore how an intermediate protection measure such as wearing mask and taking protection so forth that is disseminated by the force of information (by personal interactions and public media) can oppress disease spreading. Very recently, Noinet et al. [37] discussed how a disease spreads on Active-Driven network that is one of the representing temporal networks with consideration of SIR model and the awareness effect. Their awareness model premises the disease transmittance decaying with increase of infected neighbors around a focal agent due to his large awareness about infection.

In this paper, we firstly introduce the model description with schematic diagram for couple multiplex SIR-UA epidemic model for different four cases. Secondly, we formulated the mathematical model by using compartmental model with mean field approach. It is because we have thought that an analytical approach presuming with an infinite and well-mixed population is still needed to elaborate fundamental characteristics of SIR-UA epidemic model. Thirdly, we present numerical simulations to show the effect of awareness in multiplex epidemic model and the full phase diagrams to display the influence of different parameters. Then, we investigate the comparison of four cases in different individual states by portraying 2D full phase diagram. Finally, we present some discussion and conclude the paper.

2. Model description

The coupled epidemic spreading dynamics with awareness by using the compartment model is explored, whereby the individuals in a population can be classified into unaware susceptible (S_U), aware susceptible (S_A), unaware infected (I_U), aware infected (I_A), unaware recovered (R_U), and aware recovered (R_A). The epidemic SIR model is used to compute the amount of susceptible, infected, recovered individuals in a population. In this model, we consider

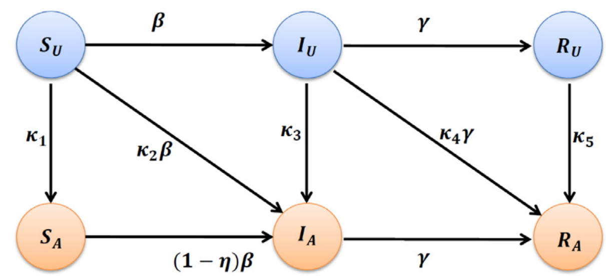

Fig. 1. Schematic of SIR-UA dynamics in multilayer networks. The upper layer presents the unware SIR and the lower layer corresponds to the aware SIR.

the assumptions about the fixed population, the probability of being diseased is independent of age, sex, social status and race, no inherited immunity, mixed homogeneously population and without death. We apply the two layer states denoted by subscripts; U and A, with a compartment method to model the awareness epidemic model which is depicted in Fig. 1.

From Fig. 1, it can be exposed that, the unaware susceptible individuals may become infected if he/ she is exposed to infectious individuals at the disease transmission rate β [per day per person]. On the other hand, aware susceptible individuals can reduce risk of infection by using intermediate defense measure and may also become infectious at the rate of $(1-\eta)\beta$. An infected individual recovers at the recovery rate γ [per day]. Unaware individuals may become aware if he/ she is encountered aware individuals at the various information transmission rates $\kappa_1, \kappa_2, \kappa_3, \kappa_4$ and κ_5 [per day per person]. Where, the information transmission rate κ_1 is used between unaware susceptible and aware susceptible, κ_2 in unaware susceptible and aware infected, κ_3 in unaware infected and aware infected, κ_4 in unaware infected and aware recovered and κ_5 in unaware recovered and aware recovered. For simplicity, we consider $\kappa_1 = \kappa_2 = \kappa_3 = \kappa_4 = \kappa_5 = \kappa$ as shown in Fig. 2, which is called Case 1 in the following text.

In this work, by incorporating the SIR model with unaware-aware (UA), a duel disease-information spreading model is established to explain the effect of awareness in widely spreading diseases. The upper and lower layers in Fig. 1 describe the physical interactions (disease spreading) for both unaware and aware situations and the each of arrows connecting the upper and lower layers indicates virtual interaction suggesting information spreading. Unaware people do not have information about disease, whereas aware individuals lessen their risk to be infected. Aware susceptible can only come from unaware susceptible with a probability $\kappa(\kappa_1)$. Consequently, aware infected individuals can come from three different states, such as: unaware susceptible at a rate of $\kappa\beta$ ($\kappa_2\beta$), aware susceptible with probability $(1-\eta)\beta$ and aware infected with probability $\kappa(\kappa_3)$. The intermediate defense measure rate η indicated that, how many individuals are getting susceptible from infected by themselves (self-protection) [38]. Similarly, the aware recovered is come from three sources, the communication with aware infected at the recovery rate γ, or unware infected with probability $\kappa\gamma$ ($\kappa_4\gamma$) and unware recovered at a rate of κ (κ_5). The unaware recovered propagates from unaware infected at a recovery rate γ. In the particular case of $\kappa = 0$, this model completely represents the SIR epidemic model with susceptible-infected-recovered.

To put it another way, we modify general UA-SIR model to reproduce three different scenarios to understand the effect of awareness transmission probability in all possible cases as shown Fig. 2. Namely in the Case 1, we consider a common information transmission rate κ. In the Case 2, only avoid two diagonal links between unware susceptible with aware susceptible and unaware susceptible with aware susceptible. Consequently, only unware re-

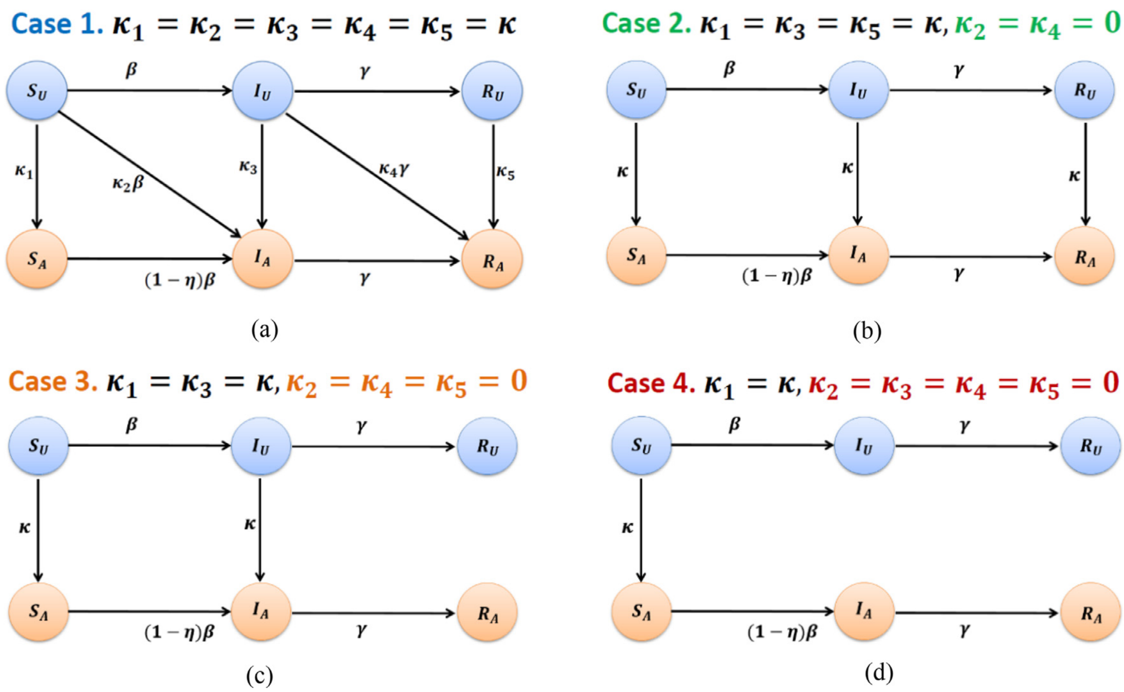

Fig. 2. UA-SIR model for different four cases: (a) Case 1 (b) Case 2 (c) Case 3 (d) Case 4.

covered and aware recovered is disconnected in Case 3. Finally, by following the previous consequences, the information transmission rate between unaware infected and aware infected is eliminated in Case 4. The four cases are expressed as follows,

Case 1. $\kappa_1 = \kappa_2 = \kappa_3 = \kappa_4 = \kappa_5 = \kappa,$

Case 2. $\kappa_1 = \kappa_3 = \kappa_5 = \kappa, \kappa_2 = \kappa_4 = 0$

Case 3. $\kappa_1 = \kappa_3 = \kappa, \kappa_2 = \kappa_4 = \kappa_5 = 0$

Case 4. $\kappa_1 = \kappa, \kappa_2 = \kappa_3 = \kappa_4 = \kappa_5 = 0$

2.1. Formulation of the model

In order to design the spreading of infectious disease with awareness, the mean field approximation approach is applied. Furthermore, two-layer states based on compartmental model is considered to define the SIR dynamics that portrayed in the previous section. At first, it is assumed that, the population is divided into three compartments, as susceptible (S), infected (I) and recovered (R). Next, based on spreading of information, population forms two new compartments namely unaware (U) and aware (A) with information transmission rate κ. According to the proposal model, at time t, each individual must have at least one state within the total six states: unaware susceptible($S_U(t)$), aware susceptible($S_A(t)$), unaware infected($I_U(t)$), aware infected($I_A(t)$), unaware recovered($R_U(t)$) and aware recovered($R_A(t)$). As constraint, we presume; $S_U(t)+S_A(t)+I_U(t)+I_A(t)+R_U(t)+R_A(t)=1$. It is also considered that the information spreading parameter κ is same for all circumferences from unaware to aware transition. With these assumptions the mean field approach is given by following system of ordinary differential equations (Case 1):

$$\begin{aligned}\frac{dS_U(t)}{dt} &= -\beta S_U(t)(I_U(t)+I_A(t))\{1-\kappa_3(S_A(t)+I_A(t)+R_A(t))\}\\ &\quad -\kappa_1 S_U(t)(S_A(t)+I_A(t)+R_A(t))\{1-\beta(I_U(t)+I_A(t))\}\\ &\quad -\beta\kappa_2 S_U(t)(I_U(t)+I_A(t))(S_A(t)+I_A(t)+R_A(t)), \quad (1)\end{aligned}$$

$$\begin{aligned}\frac{dS_A(t)}{dt} &= -(1-\eta)\beta S_A(t)(I_U(t)+I_A(t))+\kappa_1 S_U(t)(S_A(t)\\ &\quad +I_A(t)+R_A(t))\{1-\beta(I_U(t)+I_A(t))\}, \quad (2)\end{aligned}$$

$$\begin{aligned}\frac{dI_U(t)}{dt} &= \beta S_U(t)(I_U(t)+I_A(t))\{1-\kappa_3(S_A(t)+I_A(t)+R_A(t))\}\\ &\quad -\kappa_3 I_U(t)(S_A(t)+I_A(t)+R_A(t))(1-\gamma)\\ &\quad -\gamma I_U(t)\{1-\kappa_3(S_A(t)+I_A(t)+R_A(t))\}\\ &\quad -\gamma\kappa_4 I_U(t)(S_A(t)+I_A(t)+R_A(t)), \quad (3)\end{aligned}$$

$$\begin{aligned}\frac{dI_A(t)}{dt} &= \beta\kappa_2 S_U(t)(I_U(t)+I_A(t))(S_A(t)+I_A(t)+R_A(t))\\ &\quad +(1-\eta)\beta S_A(t)(I_U(t)+I_A(t))+\kappa_3 I_U(t)(S_A(t)\\ &\quad +I_A(t)+R_A(t))(1-\gamma)-\gamma I_A(t), \quad (4)\end{aligned}$$

$$\begin{aligned}\frac{dR_U(t)}{dt} &= \gamma I_U(t)\{1-\kappa_3\kappa(S_A(t)+I_A(t)+R_A(t))\}\\ &\quad -\kappa_5 R_U(t)(S_A(t)+I_A(t)+R_A(t)), \quad (5)\end{aligned}$$

$$\begin{aligned}\frac{dR_A(t)}{dt} &= \gamma\kappa_4 I_U(t)(S_A(t)+I_A(t)+R_A(t))\\ &\quad +\kappa_5 R_U(t)(S_A(t)+I_A(t)+R_A(t))+\gamma I_A(t), \quad (6)\end{aligned}$$

where, all the parameters: β, η, $\gamma, \kappa_1, \kappa_2, \kappa_3, \kappa_4, \kappa_5$ are positive constants and η, $0 \le \eta \le 1$, is the intermediate defense measure rate from aware susceptible to aware infected. Based on previous assumption for Case 1 to Case 4, we can easily modify the set of equations (1) – (6) for the zero (0) value of different $\kappa_1, \kappa_2, \kappa_3, \kappa_4, \kappa_5$. Such as, by using the values of $\kappa_2 = \kappa_3 = \kappa_4 = \kappa_5 = 0$ in Eq. (1) – (6), the modified set of equations should be implied Case 4 shown in Fig. 2(d).

3. Results and discussion

Human behaviors, the awareness of diseases, can assist individuals to decrease their threat of being infected. In this study,

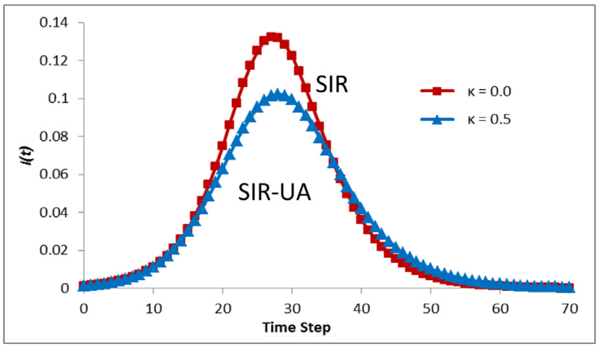

Fig. 3. Comparison of the total infected individuals $I(t) = I_U(t) + I_A(t)$ as a function of the time step t for awareness $\kappa = 0.5$ and without awareness $\kappa = 0.0$ for Case 1, where, $\eta = 0.6$ and $\gamma = 0.2$. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

we explore different properties of the model to understand the awareness effect of spreading epidemics. Numerical simulations with depth exploration of two-layer states are investigated to show the effect of the infection rate, recovery rate, intermediate defense measure rate and information spreading rate. The set of differential Eqs. (1)–(6) are nonlinear, with this in mind, it is very difficult to find the exact solution for above set of equations by using analytical method as well as equilibrium condition at steady state, because of very complex two layer mean field approximation is used with multiple variables. Finally, the effects of susceptible, recovered and infected are shown as full phase diagram for different parameters variation.

First off, let us presume Case 1. It is revealed from the results shown in Fig. 3, the effect of spreading information (awareness) is significant in multiplex network dynamics. Here, the infected individuals *I(t)* is taken as the sum of both unaware and aware infected ($I(t) = I_U(t) + I_A(t)$) at time step *t*. In particular, by comparing the SIR and SIR-UA model, it is worthwhile to confirm that there is a significant change on the peak of *I(t)* over time *t*. The value of *I(t)* is much higher in SIR model than in SIR-UA model (corresponding to the blue line) at the peak time. It is displayed from the figure that there have significant influence of awareness to lessen the spreading of infectious individuals in a population.

To establish the effects of awareness more comprehensively, the full phase diagrams of the epidemic spreading and awareness are shown in Figs 4–6 for Case 1. In Fig. 4, the susceptible and recovered incidences are shown with respect to the disease transmission rate β and the information spreading rate κ, at the equilibria under different recovery rate γ. For the small information transmission rate κ, the recovered size, implying the so-called final epidemic size, is increasing due to the increase of disease infection rate β which is depicted in the red area to the horizontal axis in panels (d)–(f). Moreover, if we increase the recovery rate γ consecutively, we observe the decrease of recovered population. As an illustration, if the awareness is spreading very slowly then the impact of disease transmission rate on the recovered individuals becomes significant. As a result, the effect of awareness can reduce the recovered individuals as well as infected population. Meanwhile, the increasing of recovery rate would be reduce the recovered population (panels (d)–(f)). At the same time, exactly opposite incidences occur on the susceptible population for the changes of different values of parameters β, κ and γ. Thus, it can be said that, from both susceptible and recovered phase diagrams, the susceptible individuals are opposite compared with the recovered individuals and the summation of both display the total number of population at equilibrium.

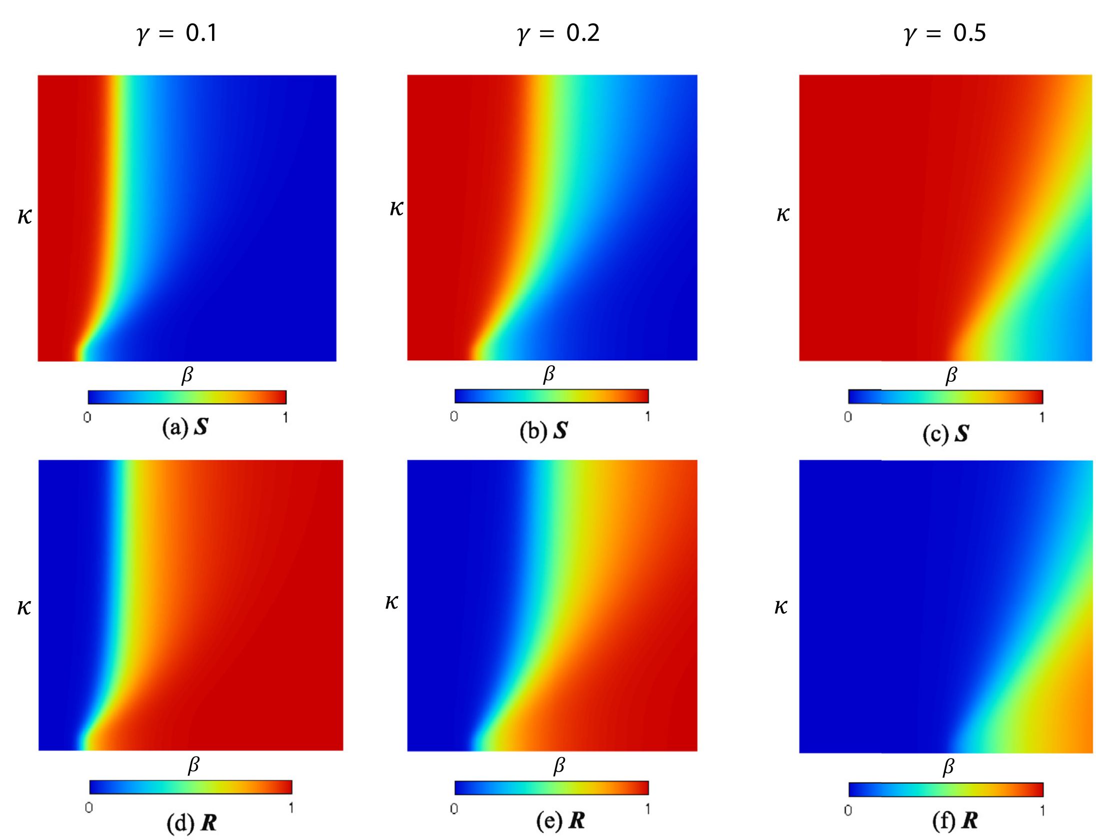

Fig. 4. The 2D phase diagrams of the individuals of susceptible (a), (b) & (c) and recovered (d), (e) & (f), with combinations of β and κ for $\gamma = 0.1, 0.2, 0.5$ (Case 1).

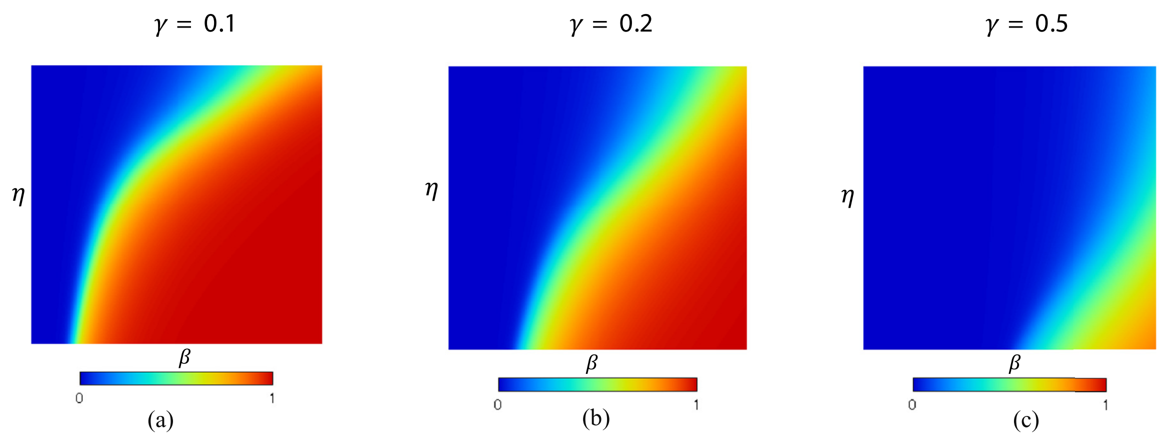

Fig. 5. Full phase diagrams β- η for the SIR-UA epidemic model of recovered individuals for recovery rates: (a) $\gamma = 0.1$, (b) $\gamma = 0.2$ and (c) $= 0.5$, where, only Case 1 is presumed.

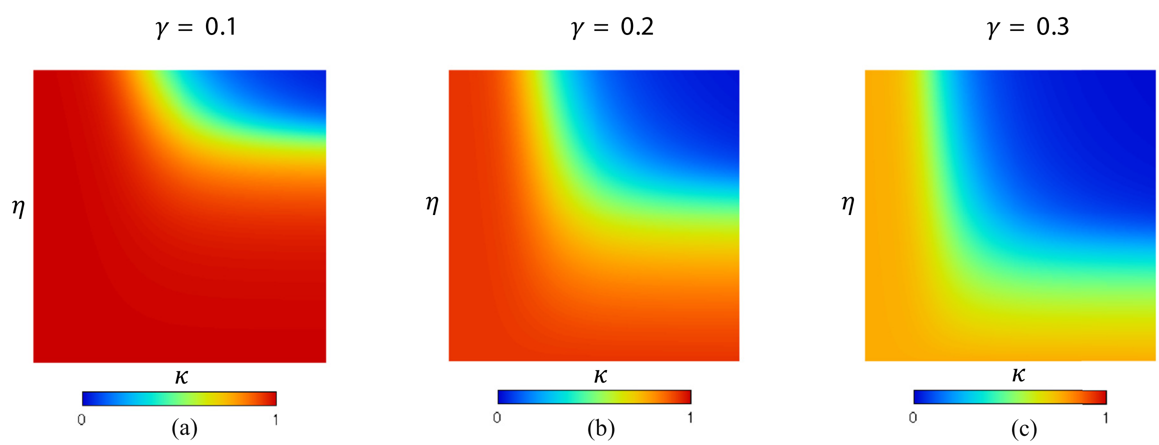

Fig. 6. The 2D phase diagrams of the individuals of recovered (a), (b) & (c), with combinations of information spreading rate κ and self-protection rate η for recovery rates, $\gamma = 0.1,\ 0.2,\ 0.3$ (Case 1).

Following, the influence of self-protection rate η is considered with respect to the disease spreading rate β for $\gamma = 0.1$, 0.2 and 0.5 in Fig. 5(a)–(c). In this comparison, the final recovered size would be maximum for the higher values of the disease transmission rate β and the lower intermediate defence measure rate η. On the other hand, the size of recovered individuals reduced for the increasing of η. If individuals can survive by taking self-protection against disease, it is obvious that the number of infected people decreased and recovered individuals also decreased. Finally, in Fig. 6(a)–(c), the phase diagram of κ- η is depicted to show the association between the information spreading rate and the self-protection rate for various recovery rate $\gamma = 0.1$, 0.2 and 0.3. For the lesser values of both κ and η, the recovered population size is large, but for the maximum values of both κ and η at each γ, the recovered individual size is declined. Because, after getting information about disease, individuals should take some protection against disease, which enlarges the size of susceptible population but decreases not only the recovered but also the infected individuals. Therefore, in a word, the large value of defence measure rate causes more people safe from diseases and the effect of awareness make individuals to aware about diseases and help to take protection measures, that reduced the recovered individuals.

In Fig. 7, the recovered individuals are depicted for four different cases, it is noticeable that all four cases show almost same pattern. Interestingly, in Case 4, although there is only one link between unaware susceptible to aware susceptible, the results shows in the Fig. 7(d) almost identical to those by other models. To understand clearly, the flux comparison between different connections respective states depicted in Fig. 2 are studied for Case 1 and Case 4 in Fig. 8, where the flux is defined as the amount of individuals passing through between two states. Again, Case 4 has only one connection between unaware susceptible to aware susceptible. On the other hand, Case 1 has five links as unaware susceptible to aware susceptible, unaware susceptible to aware infected, unaware infected to aware infected, unaware infected to aware recovered and unaware recovered to aware recovered. Moreover, the flux of the first link between unaware susceptible to aware susceptible indicates far more amount of transferred individuals vis-a-vis other connections. Thus, it can be concluded that Case 4 seems a sufficiently appropriate model to emulate the effect of spreading information on the epidemic model; SIR. This finding might be justified if we note that the information concerning self-protecting behavior is able to work effectively only when the information is given to people before infection, which can be qualitatively drawn from our common sense.

As we can confirm in Fig. 9(a), for the slight values of disease transmission rate and self-protection rate, the amount of recovered population is very trivial, but the rise of the infection

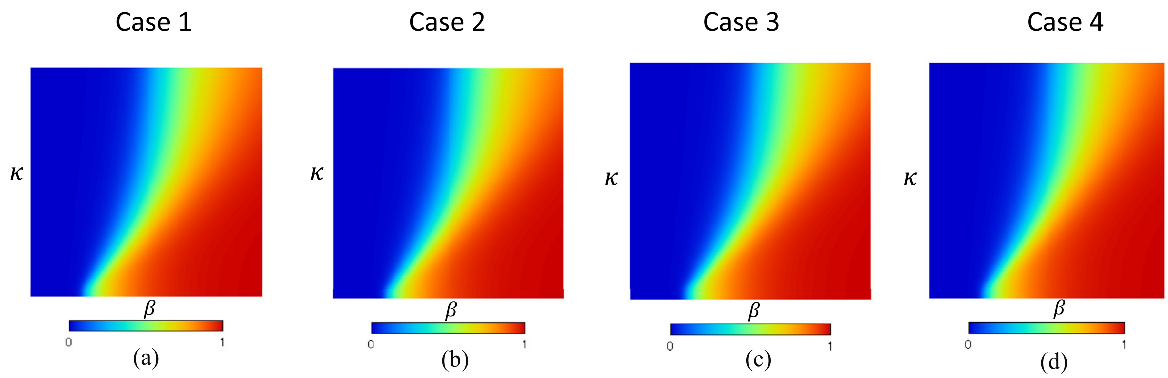

Fig. 7. The phase diagram of recovered individuals for four different cases are shown in (a) Case 1 (b) Case 2 (c) Case 3 and (d) Case 4.

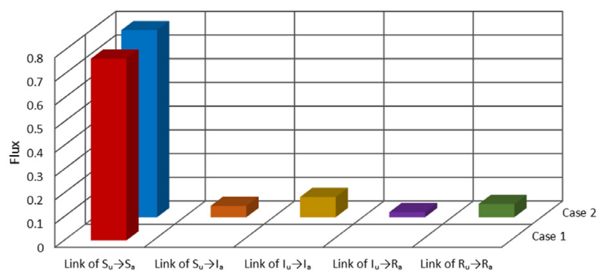

Fig. 8. Flux between different links for Case 1 and Case 4.

rate enhances the individuals of the recovered population because of increasing of infected individuals. However, it also well documented that the influence of self-protection rate η suppressed the recovered individuals that indicate the importance of taking action against disease. The impact of awareness does not work properly, if he/she is not taking any action after hearing the news about diseases. Fig. 9(b) implies the relation between the awareness and self-defense. If the rates of both information spreading and self-protection are kept at a comparably higher level, the population of recovered (say, the final epidemic size) will be minimized. Let alone, lower values of both κ and η, the recovered individuals will be utmost. One point to be noted is that both setting κ and η at a comparably higher level than only setting one of the two at an extremely higher value is needed to efficiently oppress the disease spreading. It might be justified by the fact that the processes of information spreading ($S_U \to S_A$) and self-protection ($S_A \to I_A$) are taken place in tandem (Fig. 2(d)). To get an insight scope behind this situation more clearly, we consider the maximum total ($I_U + I_A$) infected individuals at the peak in its time series as shown in Fig. 9(c). The range of η to confine disease spreading at the peak time shows wider than that of κ, which implies that a more efficient intermediate protection measure should be considered before realizing more efficiently diffused information.

To clarify the effect resulting from awareness in infected population more clearly, Fig. 10 provides the effect of disease transmission rate and information spreading rate influence on the maximum total infected individuals (panel (a)) as well as the maximum aware (panel (b)) and unaware (panel (c)) infected, respectively. Maximum infected individuals are greater when the disease transmission rate is high even if a small value of information transmission rate would be given (panel (a)). The color contour of panel (a) is split into twofold; aware and unaware infected people at the peak time as shown in panels (b) and (c). Most of the infected people are infected because of lack of information (panel (c)). However, aware people would be unavoidable for being infected only when both disease and information transmittances are high (panel (b)), which implies there is no way to avoid infection in such a situation. Fig. 9 can be drawn only when we presume Case 4. In fact, any other models; Case 1 to Case 3 allow, more or less, aware infected individuals not going through the path giving discounted disease transmittance; $(1-\eta)\beta$, thus which makes impossible any transparent discussions about the effect of information shown here.

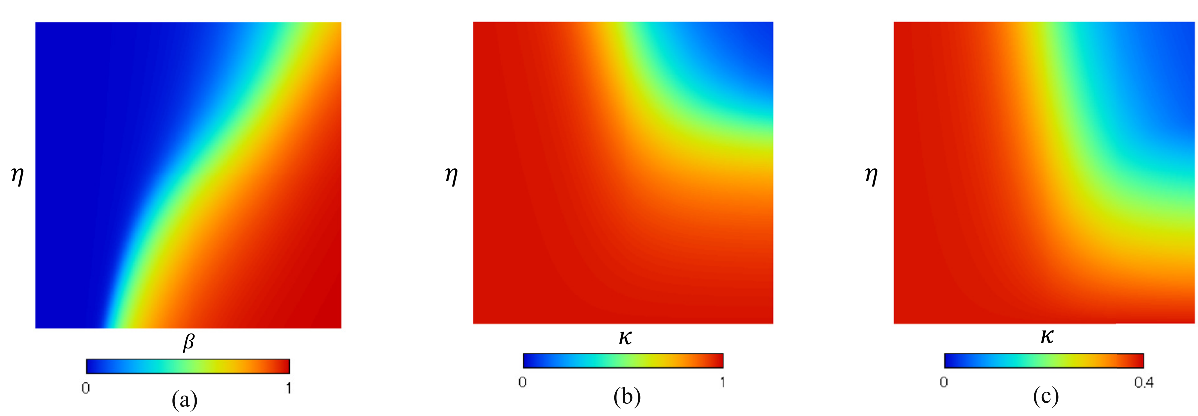

Fig. 9. Recovered individuals for Case 4: (a) the disease transmission rate and the self protection rate and (b) the information spreading rate and the self protection rate. (c) The information spreading rate and the self protection rate for maximum of total infected individuals ($I_U + I_A$) at the peak in its time-series.

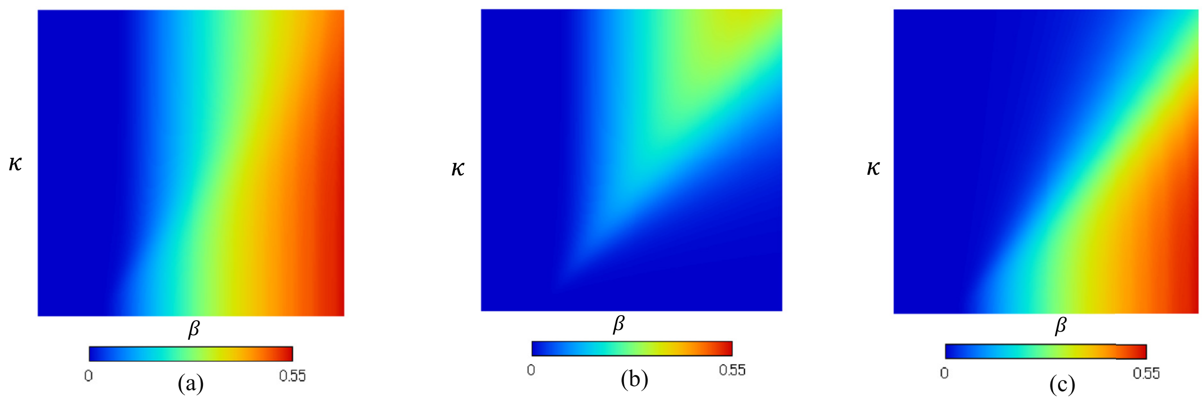

Fig. 10. The 2D phase diagram for the disease transmission rate and the information spreading rate at peak for Case 4 (a) maximum of total infected individuals ($I_U + I_A$) and (b) the maximum of aware infected (I_A) (c) the maximum of unaware infected (I_U).

4. Conclusion

The intension of present work is to develop a new coupled multiplex epidemic model with information spreading called awareness to reduce the diffusion of diseases. The study presents a comparative investigation on SIR-UA model to display the relationships among the variables and the parameters for a couple of variant models. Throughout this work, mean field approximation is used to present the mathematical and theoretical investigation, and we carried out numerical simulations to validate the model. Thus, in this work, four variant models are adopted to investigate the information spreading influence on epidemic SIR model that is different from so called spatial epidemics with disease-behavior dynamics on complex network [39,40].

As indicated by the obtained results, Case 4, which has only one connection between unaware susceptible and aware susceptible is enough to feature SIR-UA model. The effect of awareness, disease and self-protection are shown clearly by portraying full phase diagrams. Our results indicate that the information about the disease before illness can reduce the number of infected individuals phenomenally. This is because the information about disease; awareness promotes people to take protection, after taking shelter against illness individuals can stay safe from diseases. The effect of awareness have wide range of application to minimize the infectious diseases as well as other field like computer virus and natural disaster. As for example, chikungunya and Dengue like diseases have no vaccination, but self-protection and taking preventive measure only can reduce the risk of diseases. To extend this approach in wide field, computer virus also can be avoided by using alert for upcoming virus. In future, the effects of vaccination on the SIR-UA model will be considered implying the SIR-UA we established in the present work will be extended to the so-called vaccination game [41].

Acknowledgments

Ajaya Ketana Nayak significantly input to improve the final manuscript.

References

[1] Pandit N, Patel YBB. Awareness and practice about preventive method against mosquito bite in Gujarat. Healthline 2010;1:16–20.
[2] Faiz MA, Alamgir A. Chikungunya Outbreak in Dhaka: Lessons for Bangladesh. J Bangladesh Coll Phys Surg 2017;35(3).
[3] Ahituv A, Hotz VJ, Philipson T. The responsiveness of the demand for condoms to the local prevalence of AIDS. J Hum Resour 1996;31:869–97.
[4] Goffman W, Newill VA. Generalization of epidemic theory: an application to the transmission of ideas. Nature 1964;204:225–8.
[5] Barrat A, Barthélemy M, Vespignani A. Dynamical processes on complex networks. Cambridge University Press; 2008.
[6] Gross T, D'Lima CJD, Blasius B. Epidemic dynamics on an adaptive network. Phys Rev Lett 2006;96:208701.
[7] Fu X, Small M, Chen G. Epidemic control and awareness. Propagation dynamics on complex networks: models, methods and stability analysis. John Wiley & Sons, Ltd; 2014.
[8] Salathe M, Bonhoeffer S. The effect of opinion clustering on disease outbreaks. J Soc Interface 2008;5:1505–8.
[9] Havlin S, Cohen R. Complex networks: structure, robustness and function. Cambridge: Cambridge University Press; 2010.
[10] Liu T, Li P, Chen Y, Zhang J. Community size effects on epidemic spreading in multiplex social networks. Plos One 2016;11(3).
[11] Colizza V, Vespignani A. Invasion threshold in heterogeneous Meta population networks. Phys Rev Lett 2007;99:148701.
[12] Dickison M, Havlin S, Stanley H E. Epidemics on interconnected networks. Phys Rev E 2012;85:066109.
[13] Joan LA. Seasonality and Period-doubling Bifurcations in an Epidemic Model. J Theory Biol 1984;110:665–79.
[14] Li M.Y., Muldowney J.S., Global stability for the SEIR model in epidemiology, Math Biosci, vol. 125, no. 2, pp. 155–164 (1995).
[15] Asfour H.A., Ibrahim M., On the differential fractional transformation method of MSEIR epidemic model, Int J Comput Appl, 0975–8887 Volume 113 No. 3, 2015.
[16] Dantas E, Tosin M, Cunha AJ. Calibration of a SEIR–SEI epidemic model to describe the Zika virus outbreak in Brazil. Appl Math Comput 2018;338:249–59.
[17] Li L, Wang C, Wang S, Li MT, Yakob L, Cazelles B, Jin Z, Zhang WY. Hemorrhagic fever with renal syndrome in China: mechanisms on two distinct annual peaks and control measures. Int J Biomath 2018;11:1850030.
[18] Suna GQ, Xiea JH, Huang SH, Jina Z, Li MT, Liud L. Transmission dynamics of cholera: mathematical modeling and control strategies. Commun Nonlinear Sci Numer Simul 2017;45:235–44.
[19] Liu X, Stechlinski P. Application of control strategies to a seasonal model of Chikungunya disease. Appl Math Model 2015;39:3194–220.
[20] Scata M, Alessandro, Stefano D, Lio P, Corte AL. The impact of heterogeneity and awareness in modeling epidemic spreading on multiplex networks. Sci Rep 2016;6:37105.
[21] Soc JR. Modelling the influence of human behavior on the spread of infectious diseases: a review. Interface 2010;7(50):1247–56.
[22] Granell C, Gómez S, Arenas A. Competing spreading processes on multiplex networks: awareness and epidemics. Phys Rev E 2014;90:012808.
[23] Guo Q, Jiang X, Lei Y, Li M, Ma Y, Zheng Z. Two-stage effects of awareness cascade on epidemic spreading in multiplex networks. Phys Rev E 2010;91(1):012822 2015.
[24] Kamp C. Untangling the interplay between epidemic spread and transmission network dynamics. PloS Comput Biol 2010;6(11).
[25] Wang W, Liu QH, Cai S, Tang M, Lidia A, Braunstein, Stanley HE. Suppressing disease spreading by using information diffusion on multiplex networks. Sci Rep 2016;6.
[26] Huo L, Song N. Dynamical interplay between the dissemination of scientific knowledge and rumor spreading in emergency. Physica A 2016;461:73–84.
[27] Fan CJ, Jin Y, Huo LA, Liu C, Yun-peng Yang YP, Wang YQ. Effect of individual behavior on the interplay between awareness and disease spreading in multiplex networks. Physica A 2016;61:523–30.
[28] Gao B, Deng Z, Zhao D. Competing spreading processes and immunization in multiplex networks. Chaos Solitons Fract 2016;93:175–81.
[29] Funk S, Gilad E, Watkins C, Vincent A, Jansen A. The spread of awareness and its impact on epidemic outbreaks. PNAS 2009;106(16):6872–7.
[30] Wu Q, Fu X, Small M, Xu XJ. The impact of awareness on epidemic spreading in networks. Chaos 2012;22:013101.
[31] Bu Y, Gregory S, Mills HL. Efficient local behavioral-change strategies to reduce the spread of epidemics in networks. Phys Rev E. 2013;88(4):042801.

[32] Meloni S, Perra N, Arenas A, G ómez S, Moreno Y, Vespignani A. Modeling human mobility responses to the large-scale spreading of infectious diseases. Sci Rep 2011;1.

[33] Min B., Gwak SH., Lee N., Goh K.I., Layer-switching cost and optimality in information spreading on multiplex networks, arXiv: 1307.2967v2, 2016.

[34] Granell C, Gómez S, Arenas A. On the dynamical interplay between awareness and epidemic spreading in multiplex networks. Phys Rev Lett 2013;111:12870.

[35] Pan Y, Yan Z. The impact of multiple information on coupled awareness-epidemic dynamics in multiplex networks. Physica A 2018;491:45–54.

[36] Liu T, Li P, Chen Y, Zhang J. Community size effects on epidemic spreading in multiplex social networks. PLOS One 2016:0152021.

[37] Noinet A, Pastor-Satorras R, Barrat A. Effect of risk perception on epidemic spreading in temporal networks. Phys Rev E 2018;97:012313 37.

[38] Kuga K, Tanimoto J. Which is more effective for suppressing an infectious disease: imperfect vaccination or defense against contagion? J Stat Mech Theory Exp 2018;023407. doi:10.1088/1742-5468/aaac3c.

[39] Sun GQ, Jusup M, Jin Z, Wang Y, Wang Z. Pattern transitions in spatial epidemics: mechanisms and emergent properties. Phys Life Rev 2016;19:43–73.

[40] Wang Z, Andrews MA, Wu ZX, Wang L, Bauch CT. Coupled disease–behavior dynamics on complex networks: a review. Phys Life Rev 2015;15:1–29.

[41] Tanimoto J. Fundamentals of evolutionary game theory and its applications. Springer; 2015.