International Journal of Industrial Engineering Computations 13 (2022) 319–328

Contents lists available at GrowingScience

International Journal of Industrial Engineering Computations

homepage: www.GrowingScience.com/ijiec

The effect of probabilistic incentives to promote cooperation during the pandemics using simulation of multi-agent evolutionary game

Parinaz Esmaeili[a], Ahmad Makui[a*], Seyed Mohammad Seyedhosseini[a] and Rouzbeh Ghousi[a]

[a]*Department of Industrial Engineering, School of Engineering, Iran University of Science and Technology, Tehran, Iran*

C H R O N I C L E

Article history:
Received November 1 2021
Received in Revised Format December 20 2021
Accepted March 6 2022
Available online March, 6 2022

Keywords:
Multi-Agent Simulation
Evolutionary Game
Catastrophe Theory
Reward and Punishment
Pandemic
Volunteer Dilemma

A B S T R A C T

Social dilemmas describe conflict situations between immediate self-interest and longer-term collective interests. In these situations, it is better that all players work together to attain a common goal, but individuals may threaten the best payoff of the group by free-riding. Human behavior in a pandemic is one example of a social dilemma but wait-and-see games and relying on herd immunity to get a free ride generates a threat of continuing the pandemic. This study aims to use probabilistic incentives given by a third party as a mechanism to inhibit free-riding behavior by promoting cooperation in the volunteer dilemma game. For more realistic human behavior simulation, we use an agent-based model of network topology. When the parameters of the problem change gradually, an abrupt jump in the cooperation rate may happen and lead to a significant shift in the outcome. Catastrophe theory is a valuable approach to survey these nonlinear changes. This study tries to give some managerial insights to the decision-makers to find the minimum level of necessary effort in which the cooperation dominates the defection.

1. Introduction

Social dilemmas are the result of the misalignment of individual and group motivations. Although the best outcome is attained when all the players work together for a common goal, individuals are likely to have free-riding; because they expect that the other players of society will make enough effort to achieve the common goal. Human behavior in a pandemic like COVID-19 is an example of a social dilemma problem because having a virus-free environment depends on people's collective responsibility toward safety efforts (Paakkari & Okan, 2020). However public health recommendations like wearing masks, being socially distanced, washing hands, staying at home, and vaccination will significantly reduce the risk of infection, it has costs, such as vaccines side effects and personal challenges with practicing social distancing (Jentsch et al., 2021). In pandemic situations, many people would rather play the wait-and-see games and rely on herd immunity to get a free ride by not contributing to public safety and get the benefits of reduced health risk from others' compliance. This behavior generates a threat of continuing the timing of the epidemic peak with a high rate of transmission (Bhattacharyya & Bauch, 2011). From this aspect, people who neglect safety procedures, such as wearing masks and maintaining social distance, are free-riders as they benefit from safety despite doing nothing (Cato et al., 2020). Many models reveal that cooperating at the beginning of the process will collapse by failure in excluding free-riders. Number if scholars have studied the mechanisms that could improve cooperation and discourage free-riding such as externally imposed incentives like reward and punishment, and have shown their positive effect in cooperative behavior (Yamagishi, 1992; Fehr & Gächter, 2002; Sefton et al., 2007; Gachter et al., 2008; Balliet et al., 2011). A great deal of theoretical (e.g., Sigmund et al., 2001; Sigmund, 2010) and experimental (e.g., Andreoni et al., 2003) research has examined the effectiveness of incentives in promoting human cooperative behavior. Rand et al. (2009) and Sutter et al. (2010) compared the effectiveness of punishment and reward in repeated public goods games.

* Corresponding author Tel.: +98-21-73225004
E-mail: amakui@iust.ac.ir (A. Makui)

2022 Growing Science Ltd.
doi: 10.5267/j.ijiec.2022.3.001

Nosenzo and Sefton reviewed the literature on the merits of incentives to show how diffused reward/punishment power across the members of a group affects cooperation (Nosenzo & Sefton, 2012). Some researchers discussed the role of voluntary punishment (Yamagishi, 1986; Ostrom et al., 1992; Fehr & Gächter, 2000). Choi and Ahn (2013) studied the effects and the motivations behind voluntary sanctions in a finitely repeated public goods game. By using a controlled field experiment, Noussair et al. (2015) investigated the performance of decentralized peer incentives in building up cooperation. Gao et al. (2015) discussed the effectiveness of collective punishment and reward as two potential mechanisms in the multiplayer evolutionary snowdrift game to explain the evolution of cooperation. Hiemstra (2017) modeled an extended public good game in a scale-free network with heterogeneous contributions and interactions by adding an incentive resources institution.

Wu et al. (2017) studied the role of probabilistic reward and punishment in developing cooperation. Qian et al. (2019) tried a static analysis and evolutionary simulation for monitoring the effect of the endogenous combination of rewards and punishments. Jiao and Chen (2020) studied the role of probabilistic altruistic incentives in promoting cooperation in social dilemmas. Although there are many studies about the benefits of punishment in promoting cooperation, some studies proposed that reward is a better mechanism in changing attitude than punishment is (Molm, 1990; Molm et al., 1993; Banks, 2002; Larsen & Tentis, 2003; Kim et al., 2006). Others showed that costly punishment does not always bring about cooperation and can sometimes lead to negative consequences in social dilemmas (Wu et al., 2009; Cressman et al., 2013; Kitakaji & Ohnuma, 2019). To date, numerous articles represented an impressive effort to enhance our awareness of human behavior during a pandemic social dilemma, such as COVID-19 (Cato et al., 2020; Porterfield, 2020). Collective cooperation is a crucial factor in defeating the pandemic, high incidence, mortality, and social and economic catastrophes. Pandemics Social dilemmas are complex systems with bounded rational players with the continuous decision-making process and dynamically changing strategies during the spread of the epidemic; so the simulation of the agent-based evolutionary game model is an effective solution in studying the evolution of people strategies (Piraveenan et al., 2020). Chang et al. (2020) surveyed the game-theoretic modeling of infectious disease dynamics as an effective method. Regarding the problem condition, they proposed the intervention mechanisms based on these classifications: 1) classical or network-based population modeling type, 2) repeated or non-repeated frequency of the game, 3) self-learning or imitation strategy.

This paper aims to introduce the incentives given by a third party as a mechanism to inhibit free-riding behavior and increase human collective cooperation in the context of pandemics using evolutionary game theory. In the traditional social dilemma games, players choose their strategies (cooperation or defection) simultaneously. If they both choose to cooperate, they will obtain the highest collective payoff. On the other hand, mutual defection yields the lowest profit. This game is called the prisoner dilemma. However, the prisoner dilemma game is the most employed game for studying social dilemmas; there are some social dilemmas related to altruistic behavior that could be modeled by other games more appropriately. In particular, the volunteer's dilemma game is an important paradigm for modeling the situation in which each player can either make a small sacrifice that helps everybody or instead wait in the hope of benefiting from others' sacrifice (Chen et al., 2013). In some problems, such as producing safeguard public good, a threshold number of volunteers is required. The process of small and continuous changes of the probability and value of incentives could lead to an abrupt jump in the cooperation rate so the fractions of cooperators increase considerably. Catastrophe theory is a helpful approach to survey these nonlinear events and find out if this threshold exists or not. These nonlinear models are analyzed by catastrophe theory. This theory was introduced by Thom (1972) and has many applications in human behavioral changes such as employees rebellions (Hu & Xia, 2015; Zhao & Hu, 2015; Makui et al., 2020), alliances collapse (Xu et al., 2014); opinion changes (Hu & Hu, 2018) and conflicts (Dimas et al., 2018).

In the past few years, many structures have been suggested to understand the origin and evolution of cooperation. Among these mechanisms, network reciprocity, where agents are arranged on the spatially structured topology and interact only with their direct neighbors, is a significant dynamical rule that favors the evolution of cooperation (Nowak & May, 1992; Nowak, 2006). Network-based models can show population clusters forming to protect the interior agents from the aggression of defectors, hence it can describe the possible interactions in the population as one of the factors that may promote cooperation among selfish individuals. Also, they do not have the limitations of replicator dynamics equations consists of an infinite, well-mixed population with no mutations (Roca et al., 2008). The other plus point is that networks simulate more realistic human behavior models. In network-based models, the link between players (nodes) is shown through edges. There are many homogeneous and heterogeneous empirically derived topologies for reflecting differences of various social systems such as Erdös-Rényi random networks, scale-free networks, small-world networks, square lattice, and others (Chang et al., 2020). The rest of this paper is structured as follows. In sections 2 and 3, problem modeling and result analysis are discussed. The conclusion is presented in section 4.

2. Model and Assumptions

To represent the evolution of the population in a pandemic, an agent-based evolutionary volunteer dilemma is modeled on a square lattice with periodic boundary conditions (Fig. 1). Players can choose the strategies of volunteer (cooperation) and ignore (defection). The public good is produced if the players decide to volunteer at the minimum level of k $(1 \leq k \leq N)$. In COVID-19, $k = 85\%$ because when we reduce contact by 75%, the peak epidemic cases drop by about 91%. If we reduce contact by 95%, we note 98% fewer cases (Matrajt & Leung, 2020).

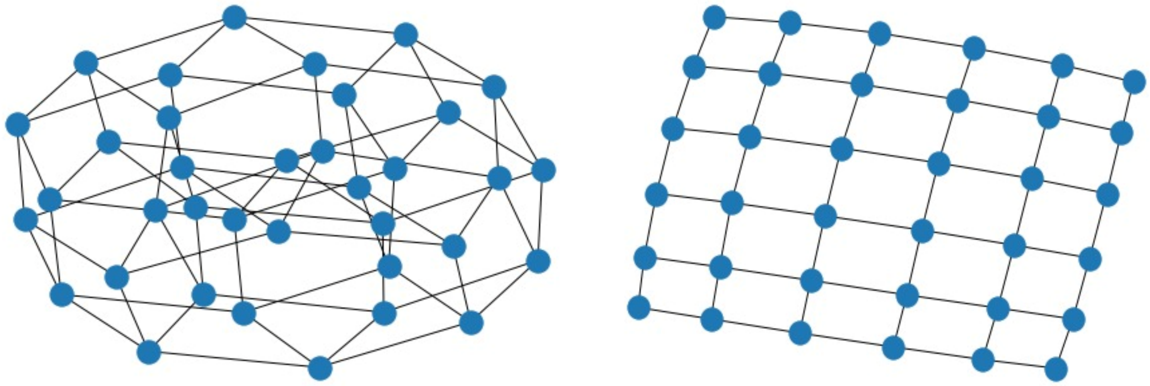

Fig 1. Square lattice with and without periodic boundary conditions, respectively

To reach the minimum acceptable level of cooperation, the third-party agent will give cooperators an incentive as a reward and charge the defectors a penalty as a punishment with the probability of p. In the beginning step of the simulation, both populations have the same likelihood of occupying the vertices of the lattice. The payoff (P_i) of player i at each step is the summation of all payoffs it gains from playing with all its neighbors. Next, all the finite population strategies update synchronously.

2.1 Update rule

1- To apply the update rule for each player, first, one of its neighbors will be picked up randomly,
2- The focal player's payoff is compared with the selected neighbor.
3- The agent will keep its strategy if it is higher; else, its strategy will change into the neighbor's strategy with a probability that is dependent on the payoff difference; $W_{i\leftarrow j} = \frac{P_j - P_i}{max\{d_i, d_j\}L}$ where d_i represent the degrees of player (node) i, and L denotes the maximum possible distance between payoffs for each pair of individuals in the network.

2.2 The structure of the volunteer dilemma

The population of volunteers is shown by c. Each volunteer benefits the society with a fix amount of v ($v > 1$), while others invest nothing. The total contribution to the pool is the multiplication of c and v and distributed equally to the whole population (N). The cooperators have a cost of volunteering irrespective of the result (b), and everybody has a cost (a) in the case of failing to produce public good and $a > b$ (Chen et al., 2013). Relevant parameters and variables of our formulation are shown in Table 1.

Table 1
Relevant parameters and variables

parameters variables	Definitions
P_{Vol}	Volunteer payoff
P_{Ig}	Ignore payoff
Inc_i	Incentive for player i
d_i	Degree of node i
L	Maximum possible distance between payoffs for each pair of individuals
c	Volunteers population
v	The benefits that each volunteer adds to the society
a	The cost of pandemic continuation
b	The cost of volunteering
N	Population size
k	Minimum acceptable cooperation rate
α	Leverage of rewarding. The reward recipient's payoff is increased relative to the cost of implementing the reward.
β	Leverages of punishing. The punishment recipient's payoff is decreased relative to the cost of implementing the punishment.
w	Reward share of total incentive budget
σ	Third party incentive budget per individual
p	The probability that each player will get a reward or be punished

$$P_{Vol}(c) = \begin{cases} \frac{vc}{N} - b & c \geq k \\ \frac{vc}{N} - b - a & c < k \end{cases} \tag{1}$$

$$P_{Ig}(c) = \begin{cases} \frac{vc}{N} & c \geq k \\ \frac{vc}{N} - a & c < k \end{cases} \tag{2}$$

The average per capita incentive dedicated to each person is σ ($\sigma > 0$); so the total incentive budget is $N\sigma$. Based on relative weigh of reward share from total incentive budget ($w, 0 < w < 1$), $N\sigma$ is divided in to the parts of reward and punishment. The shared amount of cooperators (c) is equal to $wN\sigma$ so each one obtains a reward of $\frac{wN\sigma\alpha}{c}$. This amount for defectors is $-\frac{(1-w)N\sigma\beta}{c}$. The two factors of α and β mentioned here are leverages of rewarding and punishment. By assuming $w = 0$ or 1 the incentive changes to pure punishment or reward, respectively (Chen et al., 2015).

$$Inc_i = \begin{cases} +\frac{wN\sigma\alpha}{c} & ,if\ plyer\ i\ cooperates\ and\ chosed\ to\ be\ rewarded \\ -\frac{(1-w)N\sigma\beta}{N-c} & ,if\ plyer\ i\ defects\ and\ chosed\ to\ be\ punished \\ 0 & ,else \end{cases} \tag{3}$$

In the case $c \geq k$, L is the differences of $\frac{vc}{N} - b + \frac{wN\sigma\alpha}{c}$ and $\frac{vc}{N} - \frac{(1-w)N\sigma\beta}{N-c}$. In the case $c < k$, L is the differences of $\frac{vc}{N} - b - a + \frac{wN\sigma\alpha}{c}$ and $\frac{vc}{N} - a - \frac{(1-w)N\sigma\beta}{N-c}$. In both case, the result is same and as below:

$$L = \left| N\sigma\left(\frac{w\alpha}{c} + \frac{(1-w)\beta}{N-c}\right) - b \right| \tag{4}$$

3. Result and analysis

In the process of simulation, we assumed that the values of parameters as $\alpha = \beta = 1,\ v = 0.3, \sigma = 0.5, b = 0.2, a = 1, 0 \leq p \leq 1, w = 0,\ 0.5$ and 1; but they could change based on the circumstances of each specific model. The results are the average of 50 independent rounds, the network size is $N = 10^4$ nodes, and the degree for all nodes is $d = 4$. In Fig. 2 and Fig. 3, it is clear that the gradual increase of p has an influential role in promoting cooperation, and a sudden discrete jump occurs in the system's status means the defection mode turns to the cooperation mode.

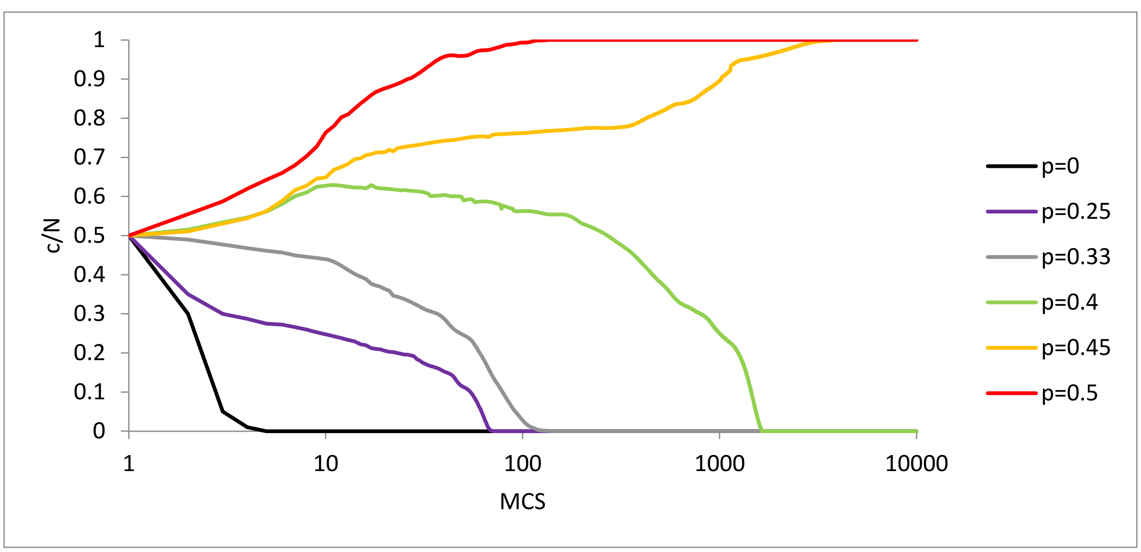

Fig. 2. Evolution of cooperation rate ($\frac{c}{N}$) in volunteer dilemma for different values of p ($w = 0$)

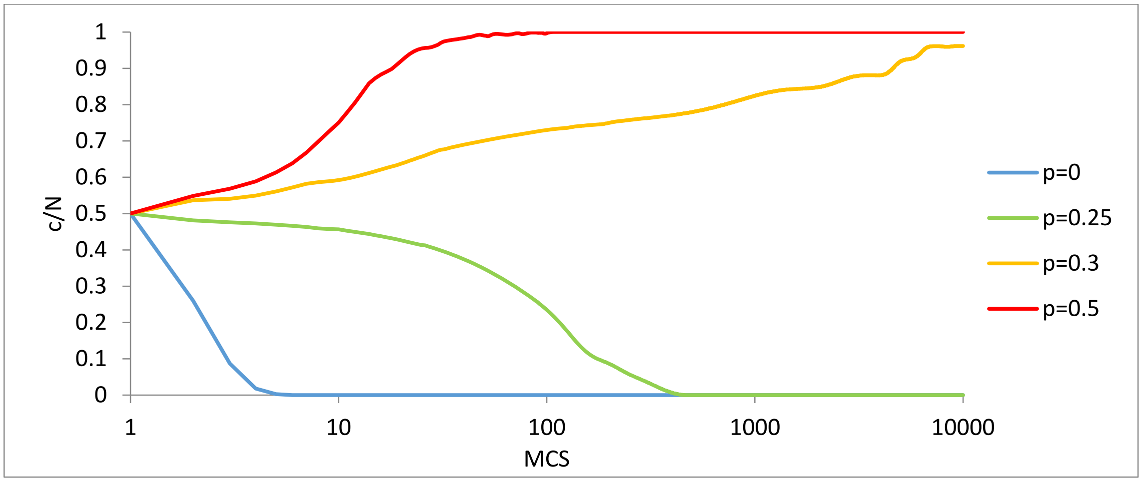

Fig. 3. Evolution of cooperation rate $(\frac{c}{N})$ in volunteer dilemma for different values of p $(w = 0.5)$

The catastrophe set for Fig. 2 is $0.4 < p < 0.45$, Fig. 3 is $0.25 < p < 3$ and for Fig. 4 is $0.4 < p < 0.45$. In Fig. 4 the cooperation rate after the jump is lower than the minimum acceptable rate for reaching the herd immunity. By comparing Fig. 2 and 4 it could be found that punishment is a better mechanism than reward and the hybrid one is the best strategy. As w indicates reward share from the total budget, it is important to know what probability of p for each value of w leads to a jump to the desired state. Lower values of p means lower monitoring costs. Because less probability of applying incentives means less cost of inspection and less social resistance against restrictions and applying incentive for everyone is not feasible in the real world condition. By comparing the catastrophe sets for different values of w, the decision makers can select the lowest value of p. In order to choose the best policy there are other essential factors to consider; such as the trade-off between social resistance and the monitoring cost. Regarding this set and the conditions of each specific model, third parties who try to facilitate cooperation can know how much extra effort is needed to reach their goal. Chen et al. (2013) surveyed the cusp catastrophe model in the volunteer dilemma with infinite well-mixed population size to find the critical reward that leads to cooperation.

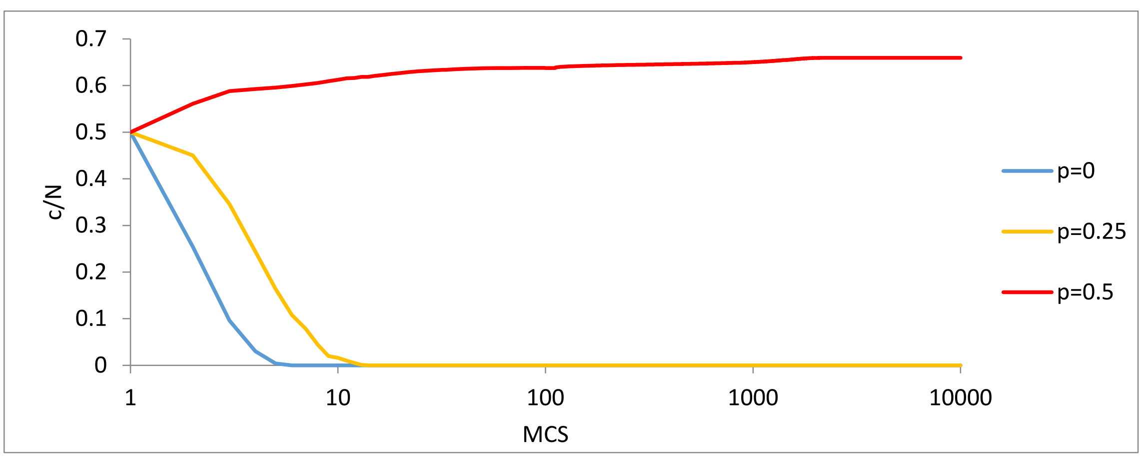

Fig. 4. Evolution of cooperation rate $(\frac{c}{N})$ in volunteer dilemma for different values of p $(w = 1)$

In Fig. 5 for $w = 0.25$ (as an example) collective cooperation is achieved in $0.35 < p < 0.4$. Compared to $w = 0.5$, the probability of applying incentives for each player should be higher in $w = 0.25$ to achieve cooperation. The cooperation rate $\frac{c}{N}$ in Fig 2 to Fig. 5 is determined by averaging the last 10% of the total 10^5 full Monte Carlo simulations. In Fig. 6 jump points from defection $(\frac{c}{N} = 0)$ to fully cooperating $(\frac{c}{N} = 1)$ mode in terms of p for all values of w are depicted. An important note is that the simultaneous existence of reward and punishment is more effective in reaching cooperation than implementing only one mechanism, because the cooperation rate may shift from 0 to 1 at lower levels of p. Lower levels of p mean lower monitoring costs; and higher levels of w mean less resistance against punishment policies in the society. In Fig. 6 the most effective value of reward share is $w = 0.7$ (70% of the budget should be assigned to rewarding the players). By considering the pure punishment or reward mechanisms, the punishment is more effective than the reward; because the maximum cooperation rate in $w = 1$ is 0.6 and it is not enough to have a virus-free environment.

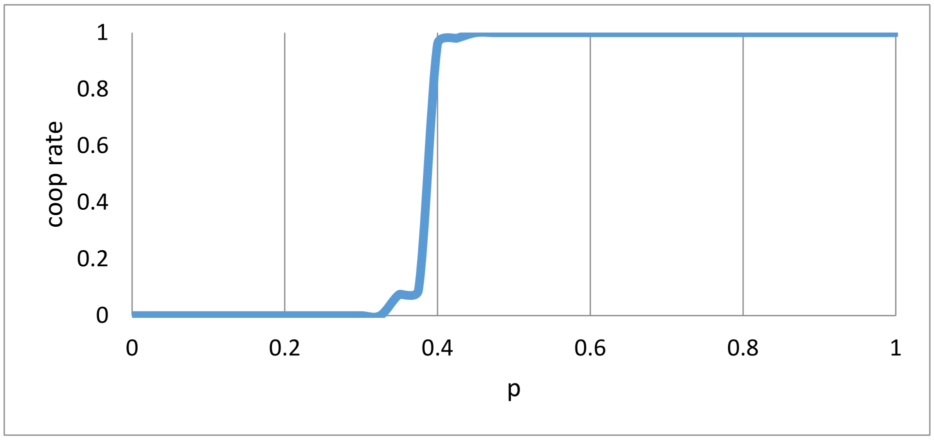

Fig. 5. Sudden jump in cooperation rate ($\frac{c}{N}$) due to gradual changes in p ($w = 0.25$)

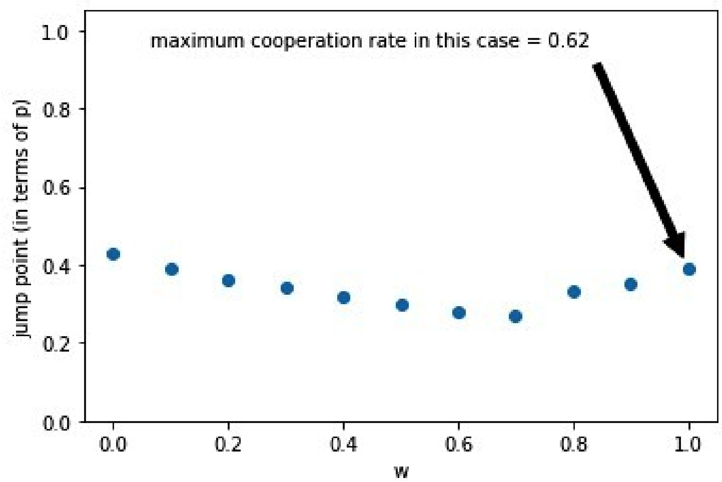

Fig. 6. Jump points in terms of p for different values of w

4. Proof of catastrophe existence in volunteer dilemma through replicator dynamics

Proof of catastrophe existence is possible in two ways. (1) Depicting the jump in the system's state surface. (2) Turning the model's equation to the catastrophe equation. The first approach is done in section 3. The second approach is possible by replicator dynamics equation if we assume that the population is infinite & well-mixed. The Replicator dynamics is a nonlinear approach to describe the system's evolution and it is equal to the difference between the average payoff of the strategy and the average payoff of the whole population (Esmaeili et al., 2018). As mentioned before there are two strategies; being a volunteer with the probability of x or ignore with the probability of $1 - \mathrm{x}$. The general volunteer dilemma payoff matrix is shown in Table 2 ($0 < f < g < 1$).

Table 2
The players' payoff

		Player2	
		Vol (x)	Ig $(1-x)$
Player 1	Vol (x)	$1-f, 1-f$	$1-g, 1$
	Ig $(1-x)$	$1, 1-g$	$0,0$

The respective expectation values of "Vol" and "Ig" strategies are $\mathrm{U_{Vol}}$ and $\mathrm{U_{Ig}}$ and average value is $\overline{\mathrm{U}}$, $F(x)$ describes the system's evolution.

$$U_{Vol} = x(1-f) + (1-x)(1-g) \tag{5}$$

$$U_{Ig} = x \tag{6}$$

$$\bar{U} = x(x(1-f) + (1-x)(1-g)) + (1-x)x \tag{7}$$

$$F(x) = \frac{dx}{dt} = x(U_{Vol} - \bar{U}) \tag{8}$$

In the next section after presenting a brief background of catastrophe theory, it will be proved that F(x) is an example of the cusp catastrophe equation.

4.1 A brief background of catastrophe theory

Catastrophe theory defines that slight changes in the specific parameters of a nonlinear system can cause the equilibrium to appear or disappear leading to a major abrupt jump in the system status (Zeeman, 1976). The equation of the classic catastrophe theory for deterministic systems is as below:

$$dx(t) = \frac{-\partial V(x(t), \vec{c})}{\partial x(t)} \tag{9}$$

The Potential function, state variable and control variable vector are $V(x(t), \vec{c})$, $x(t)$ and $\vec{c}$, respectively. Cusp catastrophe (Fig. 7) is one of the seven elementary catastrophes and it is bimodal (before and after sudden transition). It consists of one behavior variable (Z) and two control variables (α, β); the potential function, equilibrium surface and the catastrophe set are represented in Eq. 10-12.

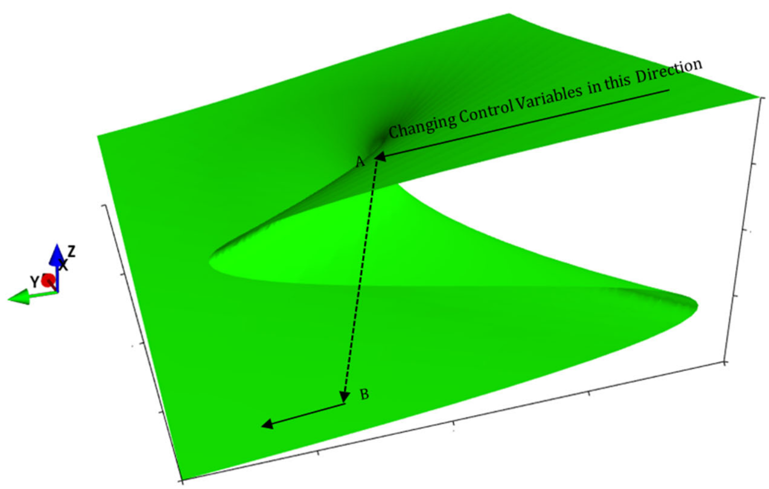

Fig. 7. The cusp catastrophe

$$F(Z, \alpha, \beta) = \frac{1}{4}Z^4 + \frac{1}{2}\alpha Z^2 + \beta Z \tag{10}$$

$$\frac{\partial F}{\partial x} = Z^3 + \alpha Z + \beta = 0 \tag{11}$$

$$27\alpha^2 = 4\beta^3 \tag{12}$$

4.2 The existence of the cusp catastrophe

As mentioned in section 4 the replicator dynamics equation for the strategy of being volunteer is presented in Eq. (13). In Eq. (14) the Eq. (13) is expanded.

$$dx(t) = x(t).(U_{Vol} - \bar{U}).dt = x(1-x)(x(1-f) + (1-x)(1-g) - x) \tag{13}$$

$$dx(t) = \left(x^3(f-g+1) + x^2(2g-2-f) + x(1-g)\right).dt = (Ex^3 + Fx^2 + Gx).dt \tag{14}$$

$$E = f-g+1 \qquad F = 2g-2-f \qquad G = 1-g$$

We assume α, β and Z as below and rewrite the replicator dynamics equation as Eq. 15. Eq. (15) is the equation of cusp catastrophe.

$$x = Z - \frac{F}{3E} \qquad \alpha = \left(G - \frac{F^2}{3E^2}\right) \qquad \beta = \left(\frac{2}{27}\frac{F^3}{E^3} - \frac{1}{3}\frac{GF}{E^2}\right)$$

$$dx(t) = E(Z^3 + \alpha Z + \beta).dt \rightarrow dx(t) = 0 \rightarrow Z^3 + \alpha Z + \beta = 0 \tag{15}$$

By replacing the variables in Eq. (12), the boundary in which the cooperation rate experiences a discrete increase or decrease abruptly will be identified (Eq. 16).

$$27\alpha^2 = 4\beta^3 \rightarrow 27\left(G - \frac{1}{3}\left(\frac{F}{E}\right)^2\right)^2 = 4\left(\frac{2}{27}\left(\frac{F}{E}\right)^3 - \frac{1}{3}\frac{GF}{E^2}\right)^3 \rightarrow$$
$$27\left(1-g-\frac{1}{3}\left(\frac{2g-2-f}{f-g+1}\right)^2\right)^2 = 4\left(\frac{2}{27}\left(\frac{2g-2-f}{f-g+1}\right)^3 - \frac{1}{3}\frac{(1-g)(2g-2-f)}{(f-g+1)^2}\right)^3 \tag{16}$$

4. Conclusion

This paper studied the pandemic social dilemma in which free-riding may lead to a failure in forming a cooperative alliance. The structure of the payoffs is based on a volunteer dilemma which is helpful in modeling the situation in which each player can either make a small sacrifice that helps everybody or instead wait in the hope of benefiting from others' sacrifice. The paper's method was the agent-based network simulation for its ability in modeling the finite-size population and reflecting various social systems' differences.

To decrease the free-riders ratio and promote cooperation, third-party judges reward cooperators and punish defectors. These incentives are assumed to be probabilistic. When the probability of applying incentives increases gradually, an abrupt jump in the cooperation rate may happen. In another word, slight changes in the input parameters could shift the outcome of the game from social failure to successful collective cooperation. These discrete jumps are called catastrophe, and it is valuable to provide the authorities with useful insights about the minimum level of efforts and the best combinations of reward and punishment strategies needed to ally people to defeat pandemics.

It is a good idea to consider the frequency of the game, types of strategy adoption such as self-learning or imitation in further studies. Carrot and stick policy in setting incentives, the proportionality of incentives to cooperation rate, and other approaches to reduce free-riding problem are other interesting points of view.

References

Andreoni, J., Harbaugh, W., & Vesterlund, L. (2003). The carrot or the stick: Rewards, punishments, and cooperation. *American Economic Review*, *93*(3), 893-902.

Balliet, D., Mulder, L. B., & Van Lange, P. A. (2011). Reward, punishment, and cooperation: a meta-analysis. *Psychological bulletin*, *137*(4), 594.

Banks, J. A. (2008). An introduction to multicultural education.

Bhattacharyya, S., & Bauch, C. T. (2011). "Wait and see" vaccinating behaviour during a pandemic: a game theoretic analysis. *Vaccine*, *29*(33), 5519-5525.

Cato, S., Iida, T., Ishida, K., Ito, A., McElwain, K. M., & Shoji, M. (2020). Social distancing as a public good under the COVID-19 pandemic. *Public health*, *188*, 51-53.

Chang, S. L., Piraveenan, M., Pattison, P., & Prokopenko, M. (2020). Game theoretic modelling of infectious disease dynamics and intervention methods: a review. *Journal of biological dynamics*, *14*(1), 57-89.

Chen, X., Gross, T., & Dieckmann, U. (2013). Shared rewarding overcomes defection traps in generalized volunteer's dilemmas. *Journal of theoretical biology*, *335*, 13-21.

Chen, X., Sasaki, T., Brännström, Å., & Dieckmann, U. (2015). First carrot, then stick: how the adaptive hybridization of incentives promotes cooperation. *Journal of the royal society interface*, *12*(102), 20140935.

Choi, J. K., & Ahn, T. K. (2013). Strategic reward and altruistic punishment support cooperation in a public goods game experiment. *Journal of Economic Psychology*, *35*, 17-30.

Cressman, R., Wu, J. J., Li, C., & Tao, Y. (2013). Game experiments on cooperation through reward and punishment. *Biological Theory*, *8*(2), 158-166.

Dimas, I. D., Rebelo, T., Lourenço, P. R., & Rocha, H. (2018, May). A cusp catastrophe model for satisfaction, conflict, and conflict management in teams. In *International Conference on Computational Science and Its Applications* (pp. 335-350). Springer, Cham.

Esmaeili, A., Ghorrati, Z., & Matson, E. (2018, January). Multi-agent cooperation using snow-drift evolutionary game model: Case study in foraging task. In *2018 Second IEEE International Conference on Robotic Computing (IRC)* (pp. 308-312). IEEE.

Fehr, E., & Gächter, S. (2000). Cooperation and punishment in public goods experiments. *American Economic Review*, *90*(4), 980-994.

Fehr, E., & Gächter, S. (2002). Altruistic punishment in humans. *Nature*, *415*(6868), 137-140.

Gachter, S., Renner, E., & Sefton, M. (2008). The long-run benefits of punishment. *Science*, *322*(5907), 1510-1510.

Gao, L., Wang, Z., Pansini, R., Li, Y. T., & Wang, R. W. (2015). Collective punishment is more effective than collective reward for promoting cooperation. *Scientific reports*, *5*(1), 1-12.

Hiemstra, D. A. (2017). *Facilitating cooperation by selective institutional reward and punishment'* (Doctoral dissertation, Faculty of Science and Engineering).

Hu, B., & Hu, X. (2018). Qualitative modeling of catastrophe in group opinion. *Soft Computing*, *22*(14), 4661-4684.

Hu, B., & Xia, N. (2015). Cusp catastrophe model for sudden changes in a person's behavior. *Information Sciences*, *294*, 489-512.

Jentsch, P. C., Anand, M., & Bauch, C. T. (2021). Prioritising COVID-19 vaccination in changing social and epidemiological landscapes: a mathematical modelling study. *The Lancet Infectious Diseases*, *21*(8), 1097-1106.

Jiao, Y., Chen, T., & Chen, Q. (2020). Probabilistic punishment and reward under rule of trust-based decision-making in continuous public goods game. *Journal of Theoretical Biology*, *486*, 110103.

Kim, H., Shimojo, S., & O'Doherty, J. P. (2006). Is avoiding an aversive outcome rewarding? Neural substrates of avoidance learning in the human brain. *PLoS biology*, *4*(8), e233.

Kitakaji, Y., & Ohnuma, S. (2019). The detrimental effects of punishment and reward on cooperation in the Industrial Waste Illegal Dumping Game. *Simulation & Gaming*, *50*(5), 509-531.

Larsen, M. A., & Tentis, E. (2003). The art and science of disciplining children. *Pediatric Clinics*, *50*(4), 817-840.

Makui, A., Seyedhosseini, S. M., Sadjadi, S. J., & Esmaeili, P. (2020). Analysis of labor strike based on evolutionary game and catastrophe theory. *EURO Journal on Decision Processes*, *8*(1), 79-88.

Matrajt, L., & Leung, T. (2020). Evaluating the effectiveness of social distancing interventions to delay or flatten the epidemic curve of coronavirus disease. *Emerging infectious diseases*, *26*(8), 1740.

Molm, L. D. (1990). Structure, action, and outcomes: The dynamics of power in social exchange. *American Sociological Review*, 427-447.

Molm, L. D., Quist, T. M., & Wiseley, P. A. (1993). Reciprocal justice and strategies of exchange. *Social Forces*, *72*(1), 19-44.

Nosenzo, D., & Sefton, M. (2012). *Promoting cooperation: the distribution of reward and punishment power* (No. 2012-08). CeDEx Discussion Paper Series.

Noussair, C. N., van Soest, D., & Stoop, J. (2015). Punishment, reward, and cooperation in a framed field experiment. *Social Choice and Welfare*, *45*(3), 537-559.

Nowak, M. A., & May, R. M. (1992). Evolutionary games and spatial chaos. *Nature*, *359*(6398), 826-829.

Nowak, M. A. (2006). Five rules for the evolution of cooperation. *science*, *314*(5805), 1560-1563.

Ostrom, E., Walker, J., & Gardner, R. (1992). Covenants with and without a sword: Self-governance is possible. *American political science Review*, *86*(2), 404-417.

Paakkari, L., & Okan, O. (2020). COVID-19: health literacy is an underestimated problem. *The Lancet. Public Health*, *5*(5), e249.

Piraveenan, M., Sawleshwarkar, S., Walsh, M., Zablotska, I., Bhattacharyya, S., Farooqui, H. H., . & Perc, M. (2021). Optimal governance and implementation of vaccination programmes to contain the COVID-19 pandemic. *Royal Society open science*, *8*(6), 210429.

Porterfield, C. (2020). No-mask attacks: nationwide, employees face violence for enforcing mask mandates. Forbes.

Qian, J., Sun, X., Chai, Y., & Liu, Y. (2019, October). Endogenous Combination of Reward and Punishment Promotes Cooperation. In *Proceedings of the 4th International Conference on Crowd Science and Engineering* (pp. 1-5).

Rand, D. G., Dreber, A., Ellingsen, T., Fudenberg, D., & Nowak, M. A. (2009). Positive interactions promote public cooperation. *Science*, *325*(5945), 1272-1275.

Roca, C. P., Cuesta, J. A., & Sánchez, A. (2009). Evolutionary game theory: Temporal and spatial effects beyond replicator dynamics. *Physics of life reviews*, *6*(4), 208-249.

Sefton, M., Shupp, R., & Walker, J. M. (2007). The effect of rewards and sanctions in provision of public goods. *Economic inquiry*, *45*(4), 671-690.

Sigmund, K. (2010). *The calculus of selfishness*. Princeton University Press.

Sigmund, K., Hauert, C., & Nowak, M. A. (2001). Reward and punishment. *Proceedings of the National Academy of Sciences*, *98*(19), 10757-10762.

Sutter, M., Haigner, S., & Kocher, M. G. (2010). Choosing the carrot or the stick? Endogenous institutional choice in social dilemma situations. *The Review of Economic Studies*, *77*(4), 1540-1566.

Thom, R., (1972). *Structural Stability and Morphogenesis an Outline of a General Theory of Models*. Addison-Wesley, Reading, Ma.

Wu, J. J., Zhang, B. Y., Zhou, Z. X., He, Q. Q., Zheng, X. D., Cressman, R., & Tao, Y. (2009). Costly punishment does not always increase cooperation. *Proceedings of the National Academy of Sciences*, *106*(41), 17448-17451.

Wu, Y. E., Zhang, B., & Zhang, S. (2017). Probabilistic reward or punishment promotes cooperation in evolutionary games. *Chaos, Solitons & Fractals*, *103*, 289-293.

Xu, Y., Hu, B., Wu, J., & Zhang, J. (2014). Nonlinear analysis of the cooperation of strategic alliances through stochastic catastrophe theory. *Physica A: Statistical Mechanics and its Applications*, *400*, 100-108.

Yamagishi, T. (1986). The provision of a sanctioning system as a public good. *Journal of Personality and social Psychology*, *51*(1), 110.

Yamagishi, T., 1992. Group size and the provision of a sanctioning system in a social dilemma.

Zeeman, E. C. (1976). Catastrophe theory. *Scientific American*, *234*(4), 65-83.

Zhao, X., & Hu, B. (2015). Modeling and simulation of voluntary employee turnover using catastrophe theory: A case study on a manufacturing enterprise in China. *International Journal of Modeling, Simulation, and Scientific Computing*, *6*(04), 1550036.