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SIS evolutionary game model and multi-agent simulation of an infectious disease emergency

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Abstract.
BACKGROUND: Susceptible-Infected-Susceptible (SIS) infectious disease outbreaks are hazardous events. However, if governments sectors do not adequately supervise such outbreaks, these infectious diseases could spread significantly, resulting in large economic losses and social issues.
OBJECTIVE: In this paper, an evolutionary game and simulation model based on the interactions between strategies and states was proposed, and the game between the public and government sectors and its impact on epidemic situations was discussed.
METHODS: Replicator dynamics equations and the multi-agent model simulation were used for analysis.
RESULTS: According to replicator dynamics equations as well as the multi-agent model simulation, the public all eventually adopted the mobility strategy. In addition, the supervision strength of the governmental sectors was equal to 0 after the strength fluctuated at a low level under the trigger strategy. Ultimately, the entire public shifted to the S state throughout the course of the emergency.
CONCLUSIONS: Social order was maintained and social loss was controlled to a certain extent in the final analysis.

Keywords: SIS evolution, evolutionarily stable strategy, evolution game, replicator dynamics equations, cellular automata, multi-agent simulation

1. Introduction

In recent years, numerous infectious disease emergencies have occurred, such as the Ebola virus, influenza A (H1N1), and H7N9 outbreaks. These emergencies cause tremendous physical and psychological damage. Thus, studies concerning how these emergencies can be supervised and controlled and how these measures can be taken during these incidents are highly important [1–3].

Some classical theory models for infectious disease emergencies include the Susceptible-Infected-Recovered (SIR) model, the Susceptible-Infected-Susceptible (SIS) model, and the Susceptible-Exposed-Infected-Recovered (SEIR) model [4–10]. The mathematical simulation models based on these classical theory models primarily use logistics or differential equations to analyze the ratio changes in different time dimensions for individuals in each state (S, I, E, or R) [11,12]. Xu et al. [13] used evolutionary game theory to analyze the role of information communication in public health emergencies

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using the SARS outbreak that occurred in 2003. In this model, the government sectors implemented compulsory intervention measures in the evolutionary game. The equilibrium of the game changed after the evolution, and a dynamic equation with a limited termination time, which included a diffused stage and a convergent stage, was deduced. Using a combination of a replicator dynamic equation of an evolutionary game and a logistic equation, Liu et al. [14] analyzed significant public health emergencies by implementing a scenario prediction and proposing prevention and control measures. Liu et al. believed that using cellular automata (CA) [15–17] to construct the model could compensate for the lack of differential equations when dealing with such a complex system. These automata had several advantage, including intuition, interaction, and dynamics. Using CA theory and the multi-agent technologies of complex systems to study the evolution of emergencies is a novel research idea. In addition, artificial societies and computing experiments have been used for this type of research more frequently in recent years [18,19]. Since the 1990s, scholars have begun to use CA models to study the evolutionary mechanisms of infectious disease emergencies. Fuentes et al. [20] proposed two types of CA models for SIR and SIRS models in order to characterize the propagation processes of diseases. The difference between the SIR and SIRS models is that, in the SIRS model, the individuals are capable of acquiring immunity after recovery. Sirakoulis et al. [21] proposed a CA model for SIR, and analyzed the effects of population movement and the existence of immune individuals on the spread of disease. Based on SIRS, Ahmed et al. [22], further subdivided the disease development process. According to Ahmed et al., between S and I and I and R, two types of individuals with different states exist: one that is infectious but not pathogenetic and another that is pathogenetic but is not infected and poses no danger to others. In addition, susceptible individuals were classified as either low or ordinary. Ahmed et al. [23] defined a class of infectious disease models based on CA, and discussed the influence of infection intensity and the classifications of the results. Other scholars have also proposed models related to the combination of classic models, game theory, and multi-agent CA simulations [24,25]. Yu et al. [26] proposed a model for public health emergencies based on evolutionary game theory. However, few studies have proposed combination models due to certain difficulties.

In short, classical theory models, such as SIR, SIS, and SEIR provide better frameworks for research. Most scholars have proposed differential equations or modified equations based on these theoretical models in order to thoroughly research the evolutionary principles of multiple individuals in different states. Replicator dynamic equations differ from these models in that they consider the evolutionary stability strategies for all of the parties in a game. From the micro level, the CA models allow for the discovery of the regularity which differential equations cannot express. Since classic models, evolutionary game theory, and multi-agent simulations each have their own advantages, they have been combined in some studies. However, actual infectious disease emergencies are complex systems influenced by various factors, such as more than two game parties, multi-stage dynamic evolution, and interactions among evolutionary strategies and individual states. Using one method or primitively combined methods could result in inadequacies. Differential equations, logistical models, and evolutionary games study these emergencies from a macro-perspective in order to analyze the evolution of individual states or party strategies. In addition, replicator dynamic equations seldom consider the different states of game parties even though changes in these states could influence the total number of individuals adopting a certain strategy and, thereby, change the evolutionary stability strategy of the game. Furthermore, the fusion degree of CA-based multi-agent simulation and evolutionary game is insufficient.

Only two public states (S and I) were considered by the model proposed in this paper; the evolutionary type was SIS. This model integrated the classical theoretical model for infectious diseases, evolutionary game CA, multi-agent simulations, and complex systems and networks in order to implement an SIS

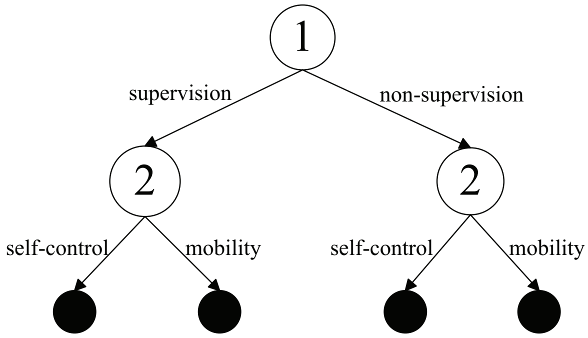

Fig. 1. Game extension form.

evolutionary game model with interactive states and strategies. In addition, the model concerned only two parties: the public and the government sectors. The public individuals interacted with the government sectors. The state S individuals became state I individuals when the diseases were diffused, and the state I individuals became state S individuals after the I individuals were cured. Most evolutionary game models do not consider this change in states. Moreover, unlike differential equation models, which only consider the evolutionary law on a macroscopic level, with CA, the proposed model was capable of fully analyzing the evolutionary law generated by the interactions among the strategies and states of the parties.

Thus, by combining multiple types of studies, a deeper understanding of the impact of the strategies and behaviors of the government and public on the spread of epidemics can be obtained, providing a reference for ways through which epidemics can be best controlled with governmental supervision.

2. The SIS evolutionary game model

Two types of agents, government department (game party 1) and social public (game party 2), were used in the proposed model. The social public was either S or I. The interaction process between two game parties is shown in Fig. 1.

The government strategy collection was equal to $\mathrm{S_z} = \{\mathrm{C}, \mathrm{N}\}$. C was used to indicate a ‘supervision’ strategy, and N was used to indicate a ‘non-supervision’ strategy. The social public strategy collection was equal to $\mathrm{S_g} = \{\mathrm{L}, \mathrm{Z}\}$. L was used to indicate a ‘mobility’ strategy, in which the people used vehicles freely and behaved casually while ignoring the infectious nature of the disease. In this strategy, the movement resulted in a change of state for the moving individual or someone else. Z was used to indicate a ‘self-control’ strategy, in which people sought appropriate medical care and isolation when infected; this selection did not expand the transmission range.

Two types of interactions were used in the model. The mutual supervision interactions occurred between the government sectors and the public, the latter of which could select the self-control or mobility strategy. The second type of interaction occurred among neighbors in the public. The S individuals were capable of becoming I individuals through contact with infected neighbors, and I individuals were capable of recovering or worsening. The states of I individuals who recovered were changed to S. These interactions are shown in Fig. 2.

The payoff matrix between the government and I individuals is shown in Table 1.

The payoff matrix of the game was based on the following assumptions.

Table 1
Payoff matrix of I individuals and government sectors

		Government sectors	
The public (I)		Supervision (C)	Non-supervision (N)
	Self-control (Z)	$-a$, $-dt$	$-dt$, 0
	Mobility (L)	0, $-dt$	$-dt$, 0

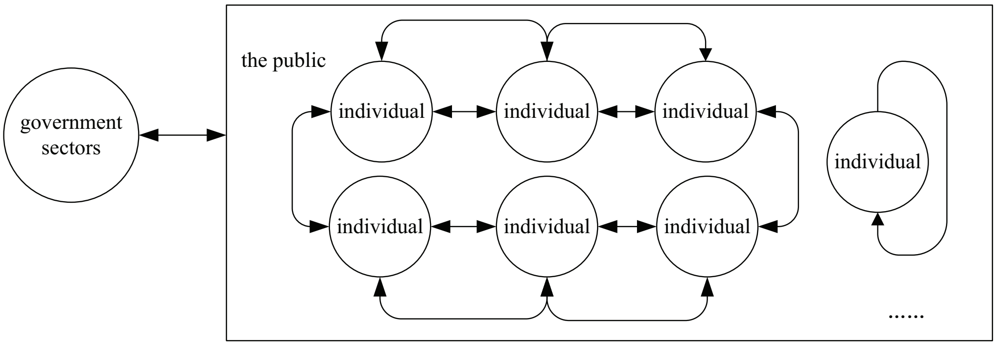

Fig. 2. Interaction.

(1) After the emergency occurred, if the government sectors implemented a supervision strategy, they were required to afford various fees, such as fees for the isolation and treatment of I individuals. In contrast, if the government sectors adopted a non-supervision strategy, the public afforded various fees. This was based on the strategies that many countries have adopted.
(2) In Table 1, the government sectors' payoff is the cost of supervising and treating a single individual after the game. Thus, this game matrix is a cost matrix rather than an income matrix.
(3) Suppose the evolutionary trajectory an infectious disease is S to I to S. This disease would not cause infected individuals die and continuously cure individuals that could be infected. The infected individuals would have to be treated after changing into state S. The required treatment time was available during the epidemic period. This was based on the current SIS model.
(4) No punishment mechanism was implemented. Thus, the government sectors did not punish public individuals who adopted the mobility strategy and, thereby, caused the epidemic to spread. This was due to the non-fatal nature of the simulated disease. When the government sectors implemented the supervision strategy, the individuals experienced a loss ($-a$) due to their limited freedom when adopting the self-control strategy. Meanwhile, the government sectors afforded the fees ($-dt(t < T)$) for the treatment of the I individual. T was used to denote the duration of the disease from onset to cure. t was used to represent an already infected cycle. When individuals adopted the mobility strategy, they experienced no loss due to the lack of supervision and punishment. However, the government sectors were still required to treat those individuals and afford their treatment fees ($-dt$).

When the government sectors implemented the non-supervision strategy the individuals either adopted the self-control or mobility strategy, but had to afford their own treatment fees ($-dt$) regardless. The government sectors afforded no costs.

3. Replicator dynamics equations

As shown in Fig. 1, the ratio of the selection of the self-control strategy by the public was denoted as

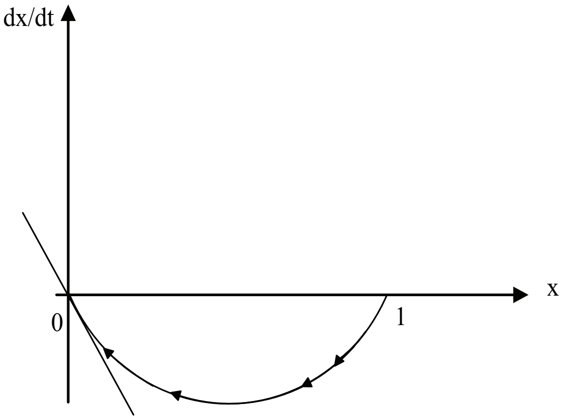

Fig. 3. $\boldsymbol{y} \neq 1$.

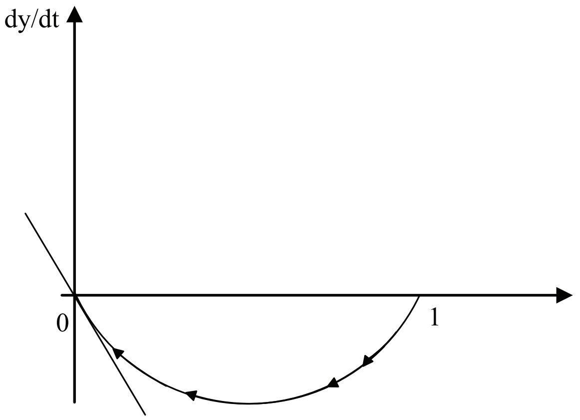

Fig. 4. $\boldsymbol{x} \neq 1$.

x. In addition, the ratio of the selection of the mobility strategy was denoted as $1 - x$. The possibility of governmental supervision was denoted as y, and $1-y$ was used to denote non-supervision. The expected returns of the public that selected the mobility and self-control strategies are, respectively, equal to

$$u_{1\mathrm{z}} = -a * y + (-dt) * (1 - y) = -ay - dt\,(1 - y) \tag{1}$$

$$u_{1\mathrm{L}} = 0 + (-dt) * (1 - y) = -dt\,(1 - y) \tag{2}$$

Thus, the expected return of the public is equal to

$$u_1 = x * u_{1\mathrm{z}} + (1 - x) * u_{1\mathrm{L}} = -x\,(ay + dt\,(1 - y)) - dt\,(1 - x)\,(1 - y) \tag{3}$$

The expected returns of the government sectors that selected the supervision and non-supervision strategies are, respectively, equal to

$$u_{2\mathrm{C}} = -dt * x + (-dt) * (1 - x) = -dt \tag{4}$$

$$u_{2\mathrm{N}} = 0 * x + 0 * (1 - x) = 0 \tag{5}$$

Thus, the expected return of the government sectors is equal to

$$u_2 = y * u_{2\mathrm{C}} + (1 - y) * u_{2\mathrm{N}} = -dty \tag{6}$$

Next, substitute this formula into the following replicator dynamics equations.

$$\frac{d_x}{d_t} = x\,[u_{1\mathrm{z}} - u_1] = x\,(x - 1)\,[ay + (1 - y)\,(dt - 1)] \tag{7}$$

$$\frac{d_y}{d_t} = y\,[u_{2\mathrm{c}} - u_2] = dty\,(y - 1) \tag{8}$$

Given:

$$0 \leqslant x \leqslant 1, 0 \leqslant y \leqslant 1, d > 1, t > 1$$

Thus, according to formulas (7) and (8), $\frac{d_x}{d_t} \leqslant 0$, $\frac{d_y}{d_t} \leqslant 0$, and the evolutionarily stable strategy can be obtained for $x = 0$ and $y = 0$, as shown in Figs 3 and 4. This indicates that the government sectors

Table 2
Neighborhood table

$A_3(x_i-1, y_i+1)$	$A_2(x_i, y_i+1)$	$A_1(x_i+1, y_i+1)$
$A_3(x_i-1, y_i)$	$A_i(x_i, y_i)$	$A_1(x_i+1, y_i)$
$A_3(x_i-1, y_i-1)$	$A_4(x_i, y_i-1)$	$A_1(x_i+1, y_i-1)$

selected non-supervision as the final stable strategy and that all of the public individuals eventually selected the mobility strategy.

This result could change if the trigger strategy was considered. Some strategies are usually triggered during evolution, which can consequently change the result. However, with dynamic games, they are not taken into account, and therefore, the confidence in the final stable strategy is not ensured. The government sectors could prevent the spread of infectious diseases without considering cost after a rapid increase in the social cost and a gradual decline in credibility.

4. CA evolutionary game model and multi-agent simulation

After analyzing the evolutionary game model replicator dynamics equations, a model was proposed for constructing the cellular levels of the public and government sectors at a micro level using CA and multi-agent simulations. The influence of the trigger strategy and the possibility of state changes between I and S were considered. Then, the change process of the governmental supervision strength, the total social cost of each cycle, the public selection ratio, the mobility strategy, and the proportion of I individuals in each cycle were observed.

4.1. Network and neighborhood evolution

Due to the influence of neighbors, S individuals became I individuals if they had adopted the mobility strategy and a high proportion of their neighbors were I individuals.

The proposed model used a spherical network without borders, in which eight neighbors surround each cell. According to complex network theory, network structures can be one-dimensional, two-dimensional, or multi-dimensional (difficult to realize). A one-dimensional network node is a linear structure with only two neighbors. A two-dimensional structure is more complex, and includes either a polygon boundary network, no boundary spherical network, a tree network, or a distributed network. The number of neighbors in a two-dimensional structure can be equal to four or eight, and the collection of neighbors is referred to as a neighborhood. An example of eight neighbors without a spherical network boundary is shown in Table 2.

4.2. State switch and strategy update rules

4.2.1. States switch r rules

In the proposed model, state switches only occurred within the public and were divided into two types. In one state switch, S became I due to contact with mobile I individuals under the implementation of the mobility strategy. In the other state switch, I became S after the self-control strategy was applied, supervision had been implemented, or the disease had evolved to a final stage where treatment was accepted compulsively. Regardless of whether the I individuals were in the last stage, they were required to accept treatment immediately when the self-control strategy was adopted or supervision has been implemented.

Assume that the probability of the S individuals becoming infected is equal to

$$p_{sc} = p * (m_l/m_1) * (m_i/m_2) * (s_0 - 1) * ((T - t)/T) \tag{9}$$

where p represents the contagiousness of the infectious disease, m_l/m_1 represents the proportion of neighbors adopting the mobility strategy, m_i/m_2 represents the proportion of I neighbors, s_0 represents the strategy value, T represents the total infectious period of the disease, and the initial value of t is equal to the value of T. The value of t is reduced by one every cycle until it reaches zero. Then, the state of the individuals cured at moment t could be changed from I to S, and $T - t$ is equal to the time interval of the illness.

When the states of individuals were changed from S to I, the following assumptions were made.

(1) The probability of infection is directly proportional to the contagiousness of the diseases, the proportion of neighbors adopting the mobility strategy, and the proportion of I individual neighbors. This was based on realistic infectious situations and the known SIS model.

(2) The probability of infection for an individual is relative to the strategy he or she adopts. When the self-control strategy ($s_0 = 1$) is adopted, the state is not changed from S to I. In contrast, when the mobility strategy ($s_0 = 1$) is adopted, this state transition could occur. This is consistent the reality.

(3) Since state S is the susceptible state, only S individuals could be infected at $t = 0$. However, a special case could occur for $t > 0$ in S individuals that had just recovered from an I state due to the implementation of a self-control strategy or supervision before the final stage of the disease. For such a case, the state of the individual would be S, and $T - t > 0$. Based on the assumption that the earlier treatment begins, the stronger an immunity becomes, the probability of re-infection decreases as t increases. The probability of infection is directly proportional to the value of $(T - t)/T$. Namely, as the value of $T - t$ decreases, the probability of infection also decreases.

4.2.2. Strategy update rules

The government, as a single entity in the model, its strategy update rule should take into account of its own profit as well as the trigger strategy during the evolution. The update rule was also influenced by the total social profit in that two factors generated opposite effects. When the current profit was higher than the previous, the supervision strength was reduced. In order to strengthen the supervision, the current total social profit had to be reduced and vice versa.

The public as a group used pair comparison for their strategy update rules. Namely, the individuals randomly selected one of their neighbors for income comparison. A strategy under a calculated probability can transit into one of its selected neighbor's. The probability was a function of the difference in income between two individuals.

Each node (the corresponding player was assumed to be P_1) randomly selected one of his or her neighbor nodes (the corresponding player was assumed to be P_2), and P_1 imitated the strategy of P_2 with a certain probability (W); the evolution rules were

$$W(p_1 \to p_2) = \frac{1}{1 + e^{(u_1 - u_2)/k}} \tag{10}$$

Where u_i represents the accumulated return for P_i, the parameter $k(> 0)$ represents noise, namely the possibility of irrational behavior. It is a very small value, usually equal to 0.1. When $k \to \infty$, all of the information is drowned by noise, and a completely random update strategy could be used. When $k \to 0$, imitation rules are implemented. Namely, if the accumulated return of P_2 is higher than P_1, P_1 adopts the strategy of P_2.

Table 3
Basic system parameters

Parameters	Illustration
M	System space, determines the maximum number of cases
T	The duration from onset to cure
p	The infectiousness of infectious diseases
a, d, t	The related parameters of the game matrix
State	S and I of individuals
s_0	The strategy selected by the public; S takes 1 or 2, namely, self-control or mobility
Totalz	The current government return
Total	The current total social return; an observation
p_z	The proportion of the mobility strategy; an observation
p_i	The proportion of I in the current system; its initial value can be set; an observation
p_k	Supervision strength of the government sectors at current time; an observation

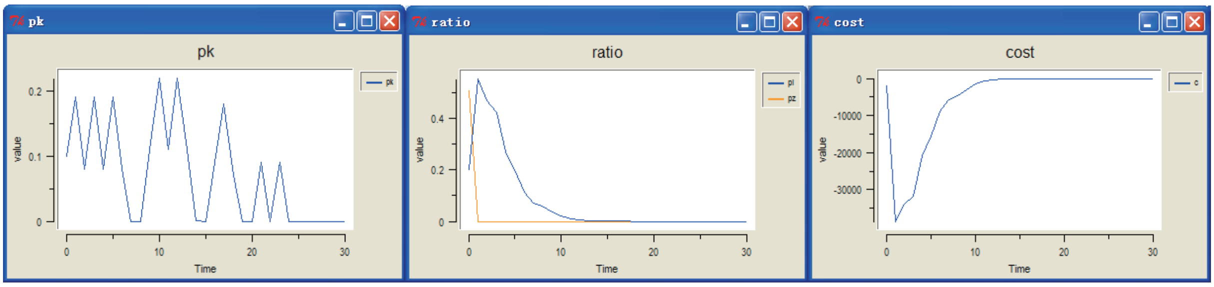

Fig. 5. Evolution process with strategy and state interactions (1).

4.3. Model parameters and simulation process

The basic parameters of the model are shown in Table 3.

Simulation flow:

Step 1: Initialize; create the S individuals and I individuals according to a certain probability, and the government sectors with a low supervision strength. The S individuals and I individuals select the self-control strategy or the mobility strategy according to a certain probability; more S individuals select the mobility strategy. I individuals currently are in the 0-th cycle of infection.

Step 2: Calculate and display the observation values.

Step 3: Subtract 1 from t for the I individuals.

Step 4: I individuals are supervised by the government sectors according to the current supervision; the individuals obtain the return according to the game matrix (shown in Table 1). Calculate the current return of the government sectors and the total social return.

Step 5: The game parties update their strategies for the next game according to the strategy update rules.

Step 6: The public update their states according to the state update rules. The new I individuals are currently in the 0-th cycle of infection.

Step 7: Determine whether there an evolutionarily stable strategy exists or the state ratio is stable; if so, then stop the evolution; otherwise, return to Step 2.

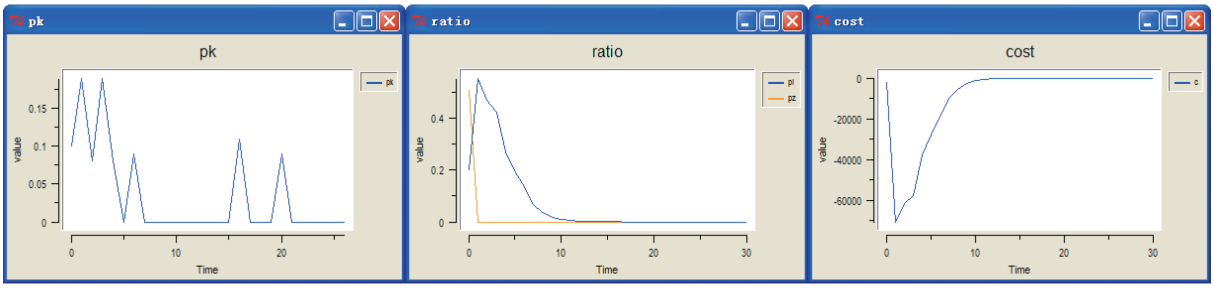

Fig. 6. Evolution process with strategy and state interactions (2).

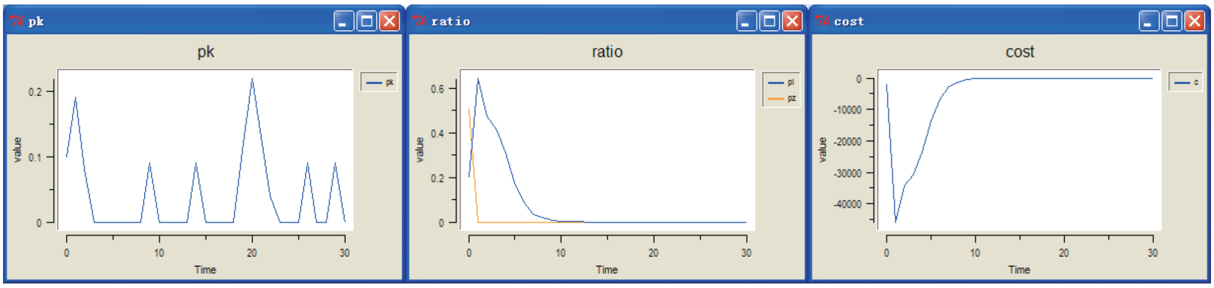

Fig. 7. Evolution process with strategy and state interactions (3).

4.4. Simulation scene analysis

The simulation results for certain conditions, including no punishment, no death, and no immune state, are shown in Figs 5–7.

(1) Given $M = 10000$, $T = 7$, $p = 4$, $a = d = -1$
Figure 5 indicates that, for the public state analysis, the value of p_i increased rapidly to 0.58 during the initial period due to the strength of the infection, and decreased until fluctuating around zero due to the government sector's supervision and the increasing population of individuals that adopted the self-control strategy. This change coincided with the improvement in condition of the I individuals due to the curability of the illness.

(2) Given $M = 10000$, $T = 14$, $p = 4$, $a = d = -1$
After the value of T increased to 14, the values of p_k and *cost* exhibited few changes. p_k fluctuated within a smaller range than before, the fluctuation times decreased slightly, and its peak value decreased to less than 0.2. The peak value of cost decreased to greater than 7000. The results indicated that as the duration of the illness from onset to cure increased, the ratio of I individuals did not change under low supervision, but the total social cost increased significantly.

(3) Given $M = 10000$, $T = 7$, $p = 8$, $a = d = -1$
When the value of p doubled, the infection strength increased. Accordingly, the peak value of p_i increased to greater than 0.6, but the increased value was smaller than it was previously. In addition, p_k fluctuated within a smaller range than in Fig. 5, and a peak value greater than 0.2 only occurred once. The value of *cost* fluctuated the same as it did in Fig. 6. The results indicated that the ratio of I individuals and the total social cost could increase after the infection strength increased. However, the supervision strength of the government sectors would hinder this.

Figures 6 and 7 display the results of the increase of the values of T and p, respectively. However, the conclusion was almost identical to that of Fig. 5.

For the evolutionary game method, p_k first fluctuated within a small range. The main influential element was the total social cost, and p_k reached 0 when the cost was equal to zero. Meanwhile, p_z decreased very soon after the beginning of the simulation. The two final values illustrated that the evolutionarily stable strategy of the government sectors was the non-supervision strategy and the evolutionarily stable strategy of the public was the mobility strategy. This result was identical to that of the replicator dynamics equation, illustrating that, although the government sectors were influenced by the trigger strategy and the supervision strength could fluctuate with non-zero social cost, the fluctuation range was limited, and the maximum was small. Thus, the non-supervision strategy was adopted. In addition, the public usually selected the mobility strategy under low strength supervision. This simulation model considered the interactions among states and strategies. The main conclusions were essentially consistent with those of the SIS model and the replicator dynamics equations. This model illustrated some of the detailed characteristics well.

5. Conclusions

The SIS evolutionary game and simulation model integrates classical theoretical models, evolutionary game CAs, and multi-agent simulations and is based on the interactions among states and strategies. This model could be used to adequately simulate the evolutionary processes of these events.

(1) Since no “death” state was used, these disease outbreaks eventually improved. However, since there were no immunities, none of them were cured. The supervision strength of the government sectors was capable of controlling the diseases to a certain extent.
(2) After considering the total social cost, the government sector evolutionary game indicated that the supervision strength became zero after the influence of the trigger strategy.
(3) The total number of infected increased significantly in the initial stage of the event, but disease was not fatal. The evolution results indicated that an increasing number, and eventually all, of the public chose the mobility strategy.

Overall, the government sectors and public did impact the spread of the epidemic to a certain extent. The mobility strategy chosen by the public resulted in epidemic spread. The number of the public that chose the mobility strategy did not change when government implemented a low level of supervision and the disease was non-fatal in nature. However, under the influence of a low level of supervision by the government and the implementation of the trigger strategy, social order was maintained and social loss was controlled to a certain extent.

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