Chaos

Evolutionary multigame with conformists and profiteers based on dynamic complex networks

Cite as: Chaos **32**, 023117 (2022); https://doi.org/10.1063/5.0081954
Submitted: 11 December 2021 • Accepted: 25 January 2022 • Published Online: 16 February 2022

Bin Pi, Ziyan Zeng, Minyu Feng, et al.

Evolutionary multigame with conformists and profiteers based on dynamic complex networks

Cite as: Chaos **32**, 023117 (2022); doi: 10.1063/5.0081954
Submitted: 11 December 2021 · Accepted: 25 January 2022 ·
Published Online: 16 February 2022

View Online Export Citation CrossMark

Bin Pi,[1] Ziyan Zeng,[1] Minyu Feng,[1,a)] and Jürgen Kurths[2]

AFFILIATIONS

[1]College of Artificial Intelligence, Southwest University, Chongqing 400715, People's Republic of China
[2]Potsdam Institute for Climate Impact Research, 14437 Potsdam, Germany and Institute for Complex System and Mathematical Biology, University of Aberdeen, Aberdeen AB24 3UE, United Kingdom

[a)]**Author to whom correspondence should be addressed:** myfeng@swu.edu.cn

ABSTRACT

Evolutionary game on complex networks provides a new research framework for analyzing and predicting group decision-making behavior in an interactive environment, in which most researchers assumed players as profiteers. However, current studies have shown that players are sometimes conformists rather than profit-seeking in society, but most research has been discussed on a simple game without considering the impact of multiple games. In this paper, we study the influence of conformists and profiteers on the evolution of cooperation in multiple games and illustrate two different strategy-updating rules based on these conformists and profiteers. Different from previous studies, we introduce a similarity between players into strategy-updating rules and explore the evolutionary game process, including the strategy updating, the transformation of players' type, and the dynamic evolution of the network structure. In the simulation, we implement our model on scale-free and regular networks and provide some explanations from the perspective of strategy transition, type transition, and network topology properties to prove the validity of our model.

The study of network evolutionary games can provide a new perspective for explaining cooperation in society. Our task is to incorporate conformists and multigames into the traditional evolutionary game, which are more consistent with reality. Based on this model, this paper proposes two different strategy-updating rules and investigates their impact on the evolution of cooperation in the network. In addition, we make an interpretation of the simulation results in terms of strategy transition, type transition, and network topology properties. Our work may shed some new light on the study of network evolutionary games with conformists and multigames.

I. INTRODUCTION

In the whole development process of human civilization, although there are all kinds of conflicts and struggles, cooperative behavior is still ubiquitous in the real world and can be found in natural and social systems.[1] Cooperation is the motive force for the stable development and progress of human society, and its scope and depth are unmatched by any other animal. Using game theory, it has been tried to explain human cooperative behavior from various angles, and five basic theories have been formed, including kin selection, direct reciprocity, indirect reciprocity, network reciprocity, and group selection.[2] In addition, complex networks have also made rapid progress, and various novel network models have been proposed in recent years.[43–45] Meanwhile, numerous game models have been widely employed as paradigms to describe pairwise or group interactions. Among them, the most commonly mentioned ones are the prisoner's dilemma game (PDG)[3–5] and the snowdrift dilemma game (SDG).[6–8] In the classical PDG, two players simultaneously decide whether to cooperate (C) or defect (D) and will receive the reward R (punishment P) if both players choose cooperation (defection). While a player chooses cooperation and the other one chooses defection, the cooperator will get a sucker's payoff S and the defector will receive a temptation to defect T. These payoffs satisfy the ranking: $T > R > P > S$ and $2R > T + S$.[9–11] As is well known, for a rational individual, the defect is the best choice regardless of which strategy the opponent chooses, and only two sides choose to cooperate to maximize the collective income. Obviously, players will inevitably fall into the social dilemma of pursuing individual and collective benefits, and we note that different parameter values will lead to different social dilemmas. In the classical SDG, players interact and accumulate payoffs in the same way, but the order of payoffs changes to $T > R > S > P$. It is worth noting that (D, D) is the only Nash equilibrium for the PDG, while the SDG has two equilibriums comprising (C, D) and (D, C) strategy combinations; i.e., a player chooses the defection strategy when the opponent chooses cooperation strategy and chooses cooperation strategy when the opponent chooses defection strategy. In addition to the two classical game models introduced above, there are the public goods game (PGG),[12,13] the stag-hunt game (SHG),[14,15] and the ultimatum game (UG),[16,17] to name but a few.

In recent years, evolutionary multigame or hybrid game, which can use different payoff matrices in the field of social dilemmas, has attracted extensive attention and achieved fruitful results. For example, Huang *et al.* introduced multigame with the aspiration-driven updating rule and investigated the evolution of cooperation.[18] Li *et al.* proposed a multigame (composed of the prisoner's dilemma game and the snowdrift game) and its coevolution mechanism in networked populations.[19] Han *et al.* incorporated the aging property to evaluate the effect of age on cooperation in the investigated spatial multigame.[20] Liu *et al.* proposed the coevolution setup of strategy and multigame based on a memory step.[21] Deng *et al.* introduced the mechanism of multi-games on interdependent networks and explored the evolution of cooperation.[22] Recently, Szolnoki and Chen extended the prisoner's dilemma game and the public goods game by allowing players not simply change their strategies but also let them vary their attitudes for a higher individual income to reveal the possible advantage of a certain attitude.[39] Besides, players not only learn the most successful strategies, but also choose the most popular strategies.[23–29] We call this type of player conformist, and there are many conformists in real life. For example, we have noticed that when consumers shop online, they tend to buy mass-market goods. In fact, a person's point of view is often strongly influenced by most people around him or her. Furthermore, there are also researchers who have investigated the effect of different strategy-updating rules on cooperation. For example, Szolnoki and Danku studied that players may use two updating rules simultaneously, which are imitation and death–birth rule.[38] In addition, Szolnoki *et al.* first proposed the idea of changing strategy and interaction simultaneously.[41,42]

In previous works, the Fermi updating rule is the most widely used strategy-updating rule, which is based on the pairwise comparison by using a Fermi-function-like probability function.[30] Nevertheless, it does not consider the impact of similarity between players, which can play a significant role in real-life interactions. For instance, studies have shown that people who are from the same social class are often more similar in aspects, such as generosity toward others[31] or the willingness to take risks.[32] In this paper, we incorporate the similarity parameter into the strategy-updating rule and assume that individuals are more likely to adopt strategies similar to their counterparts. If a player tends to pursue the high payoff, we call him/her a profiteer and his/her rule payoff-driven strategy-updating rule. On the other hand, as we have mentioned above, a player might adopt the strategy more frequent in his neighborhood. In this case, we call him/her a conformist and his/her rule conformity-driven strategy-updating rule. In addition to the evolution of the strategy, we also allow for the evolution of the type, namely, the alternation of the player's type between profiteers and conformists with time, which will lead to the transformation of the strategy-updating rule between payoff-driven and conformity-driven rules. Moreover, in the process of evolution, individuals with lower income will be more likely to change their types and game opponents. Because for a player with low income, this is not only related to his/her strategy-updating rule, but it may also be relevant to his/her game opponents. In order to improve the income, he/she will try to change his/her game opponents and type to alter the strategy-updating rule. Therefore, it is worth noting that the whole concept used in this work belongs to the family of co-called coevolutionary models.[40]

The remainder of this paper is organized as follows. In Sec. II, we describe the model. Then, we show our numerical simulation results in Sec. III. Finally, we summarize the conclusion and show the outlook in Sec. IV.

II. MODEL

In this section, we study an evolutionary multigame in a population of N players sitting on a scale-free network proposed by Barabási–Albert (BA) and an $L \times L$ square lattice network (RE), in which each node or each lattice site denotes a game player. In our model, each individual will be divided into two categories, one-half of the players will participate in SDG and the other half will play PDG. All of them are randomly distributed on the network, which indicates that there randomly exists an interaction between different categories of players. The different payoff matrices for the SDG and PDG players can be described as M1 and M2, respectively,

$$M1 = \begin{pmatrix} 1 & \delta \\ b & 0 \end{pmatrix}, \quad M2 = \begin{pmatrix} 1 & -\delta \\ b & 0 \end{pmatrix}, \tag{1}$$

where $1 \leq b \leq 2$ represents the temptation to defect. In particular, there are two types of players in the network, including type C (rational conformists: players with rational conformity behavior) and type P (profit-seeking players). Additionally, we introduce a parameter $\rho \in [0, 1]$ that indicates the proportion of type C players, while the rest of the population are type P players. Obviously, when $\rho = 0$, all players belong to type P, it becomes the traditional prisoner's dilemma game or the snowdrift dilemma game. Besides, a larger value of ρ indicates a greater proportion of type C and more rational conformists in the group. In this model, we mainly consider two kinds of strategies: cooperation C and defection D, in which we assume that each player in the population holds only one single strategy at a certain step.

A. Strategy evolution

In this subsection, we illustrate the strategy-updating rules based on the different types of players. In the proposed model, we suppose that players asynchronously update their strategy; i.e., only one player's strategy will be updated at each round of the game. Besides, a player is randomly chosen and accumulates his/her payoffs by interacting with his/her own neighbors depending on his/her payoff matrix. Then, the payoff-driven players update strategies relying on the payoff difference, while the conformity-driven players

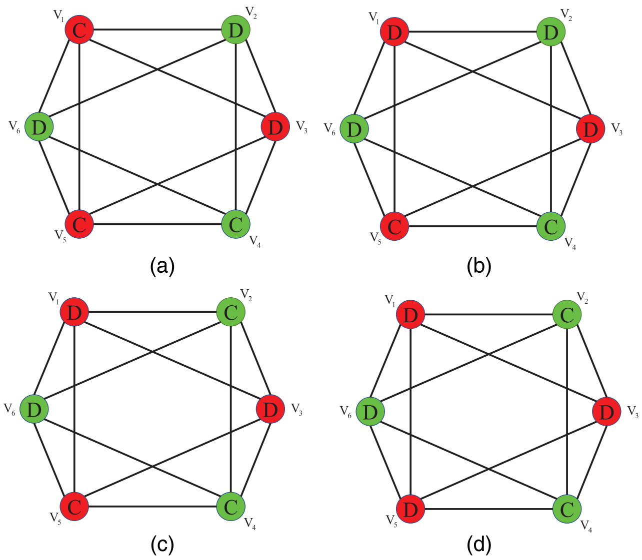

FIG. 1. An example for strategy evolution. (a) represents an initial status of a network, where green nodes are profiteers and red nodes are conformists, while C marks cooperators and D marks defectors. In (b), V_1 is randomly chosen and updates its strategy from C to D. In (c) and (d), V_2 and V_5 are following the same steps mentioned above.

choose the most popular strategy among their neighbors. Referred to the strategy evolution of the model, we illustrate the strategy evolution as an instant in Fig. 1. C corresponds to cooperators in the network and D corresponds to defectors, while green nodes represent profiteers and red nodes conformists. At each step, a player will be randomly selected and update his/her strategy according to his/her type. We note that if a player is a conformist, e.g., V_1, he/she is more likely to choose the most popular strategy among his/her neighbors. While if a player is a profiteer, he/she is more likely to choose the strategy of the player with the highest payoff among his/her neighbors.

First of all, according to the random sequential update protocol, a randomly selected player x acquires his/her payoff Π_x by playing the game with all his/her neighbors. Next, player x randomly chooses one neighbor y, who also acquires his/her payoff Π_y in the same way as previous player x. To avoid payoff-related effects that are due to heterogeneous interaction topologies, we normalize the payoff with the degree of the corresponding player; we, therefore, have $\overline{\Pi}_i = \Pi_i/k_i$, where k_i denotes the degree of player i.

After both players acquire their payoffs, if player x is a profiteer, then he/she adopts the strategy s_y from player y with a probability determined by the Fermi updating rule

$$P(s_x \leftarrow s_y) = \frac{1}{1 + e^{(\overline{\Pi}_x - \overline{\Pi}_y)/s_{xy}}}, \tag{2}$$

where s_{xy} quantifies the similarity between players x and y denoted as

$$s_{xy} = \frac{k_x k_y + c_x c_y}{\sqrt{k_x^2 + c_x^2}\sqrt{k_y^2 + c_y^2}}, \tag{3}$$

where k_i indicates the degree of player i and c_i represents his/her local clustering coefficient. In this proposed rule, we have the payoff-driven rule by Eq. (2). Different from the previous game strategy-updating rule, our model utilizes the similarity between two players instead of a noise factor κ. The reason is that, in the actual game process, each player should be affected by different external influences, and the constant κ is impracticable. Therefore, we employ the similarity s_{xy} to better express this feature.

On the other hand, if player x is a conformist, we use the Fermi updating rule

$$P(N_{s_x} - k_{h_x}) = \frac{1}{1 + e^{(N_{s_x} - k_{h_x})/s_{xy}}}, \tag{4}$$

where N_{s_x} is the number of players adopting strategy s_x within the interaction range of player x, while $k_{h_x} = k_x/2$, which indicates one-half of the degree of player x. Analogously, we propose the conformity-driven rule by Eq. (4). Through Eq. (4), player x is more likely to adopt the strategy more frequently in his neighborhood. It is worth noting that, in this study, a conformist obtains only local information. In particular, a conformity-driven player, namely, a conformist, simply tends to follow the majority in its local neighborhood.

B. Network evolution

Along with the above strategy evolution, the scale-free and the $L \times L$ square lattice networks also keep evolving over time. In the last stage of each step, on the basis of the payoff of all players in the network, we randomly choose a player according to the payoff of anti-selection; i.e., the lower payoff is the higher probability of the player being selected. The probability that a profiteer (conformist) is selected is as follows:

$$W_i = \frac{(\Pi_i - \Pi_{min} + \alpha)^{-1}}{\sum_{j\in\Omega}(\Pi_j - \Pi_{min} + \alpha)^{-1}}, \tag{5}$$

where Π_i represents the payoff of player i, Π_{min} is the minimum payoff of the network in the current step, Ω indicates the player set of the network, and α is a smoothing coefficient. Although the player's payoff may be negative, we can still guarantee that the probability W_i is positive through Eq. (5). After that, the selected player will disconnect all the existing edges from his/her neighbors and then randomly choose players to reconnect from the network. Thus, the number of connected players equals the number of edges before disconnection. Furthermore, the selected player will change his/her type; namely, if he/she is a conformist in the current step, he/she will become a profiteer in the next step and vice versa. We hereby illustrate the network evolution as an instant in Fig. 2 to better describe the network evolutionary steps. C corresponds to cooperators in the network and D corresponds to defectors, while green nodes represent profiteers and red nodes conformists. At each step, a player will be selected by anti-preference and then change his/her type and reconnect existing edges.

In brief, we first introduce our multiple game model, including PDG and SDG, then propose two different strategy-updating rules based on conformists and profiteers, and finally explain the evolution rules of the network and the type-updating of a player to perfect the shortcomings of some previous studies.

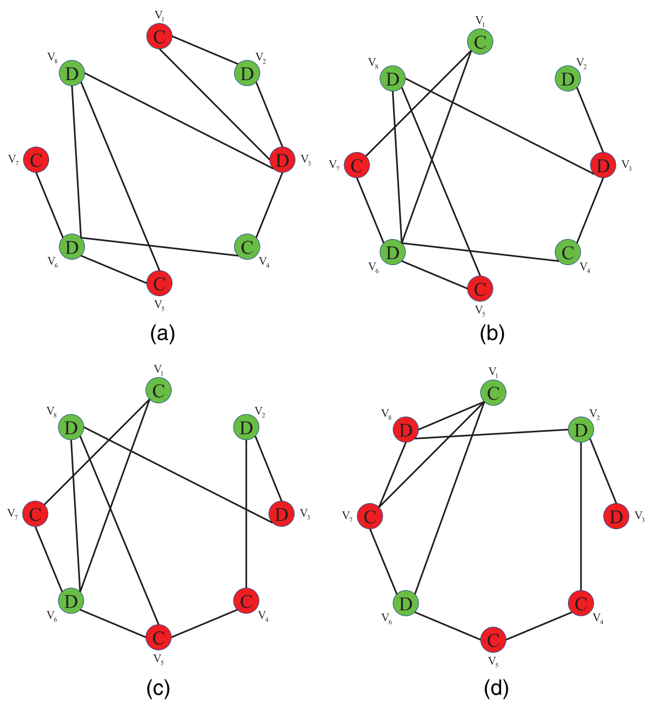

FIG. 2. An example for network evolution. (a) represents an initial status of a network, where green nodes are profiteers and red nodes are conformists, while C marks cooperators and D marks defectors. In (b), V_1 is chosen by an anti-preference law; hence, type transition occurs; this makes V_1 becoming a profiteer from a conformist and its connections are reconnected to V_6 and V_7. In (c) and (d), V_4 and V_8 are following the same steps mentioned above.

III. SIMULATION RESULTS AND DISCUSSIONS

In this section, with the purpose of confirming the previous theory, we hereby provide the simulation method and also present the simulation results along with their analyses. Specifically, we analyze the changes of the topological structure before and after network evolution through degree distribution first and then observe the influence of b and δ on the fraction of network cooperators f_c. Next, we study the strategy and type distribution on the regular square lattice network at the micro-level and finally discuss the quantitative evolution of conformist cooperators (CCs), conformist defectors (CDs), profiteer cooperators (PCs), and profiteer defectors (PDs) in the evolution process.

A. Method

The simulation is carried out in Python. At the beginning of each simulation, unless otherwise specified, $N = 900$ players are embedded into a BA network or a 30×30 square lattice network. BA is generated by growth and preferential attachment, as proposed by Barabási and Albert in 1999. When a node is newly added to the network, it connects to $m = 3$ existing nodes with the probability defined by $\Pi_i = \frac{k_i}{\sum_j k_j}$. The initial strategies, types, and games of the players are randomly selected from the spaces S = {C, D}, T = {P, C}, and G = {PDG, SDG} respectively, which is implemented by the roulette algorithm. Specifically, we first generate a random number that obeys a (0, 1) uniform distribution and then let it compare to the threshold 0.5. If it is larger than 0.5, we let the player choose to cooperate; otherwise, we let the player choose to defect. For the state space T and G, we use the same method to carry out. Subsequently, a player is randomly selected from non-isolated players in the network to evolve his strategy. If his type is P, he updates the strategy by Eq. (2). On the contrary, he updates the strategy with Eq. (4). Next, another player is chosen by an anti-preference law denoted by Eq. (5) to reconnect his edges and change his type. In this paper, we have a constant smoothing coefficient $\alpha = 1$ for Eq. (5). We implement the evolution of cooperation in a simulation with length $T = 7000$ steps. Moreover, to avoid additional disturbances, the final results were averaged over up to ten independent realizations for each set of parameter values to assure suitable accuracy.

B. Structural properties

In this simulation, we present the degree distribution, the most significant topological property of the network, to analyze the following conclusions. We use the two networks mentioned above (BA and RE) and then record the degree distribution at the beginning and end of their evolution, respectively. As a result, Fig. 3 shows the degree distribution before and after the evolution of the BA network and the regular network, respectively. From Figs. 3(a) and 3(c), it is obvious that the degree distribution obeys the power-law characteristics of BA networks and the uniformity characteristics of regular networks. Since there will be random reconnection of player at each step, the degree distribution shown in Figs. 3(b) and 3(d) has changed into a near normal distribution, which means that the network at this time is no longer a BA network or a regular network. Moreover, we can see that the degree distributions of the two evolved networks are very similar.

C. Cooperative behaviors

For a population, the cooperation level is one of the most concerning indicators to people and is commonly characterized by the cooperation frequency f_c, denoting the fraction of cooperators to a population. Hereby, we mainly investigate the fluctuation of f_c in various scenarios.

1. f_c vs b

For the purpose of exploring the relationship between the fraction of cooperators f_c and b, we proceed by examining the impact of the value of temptation to defect b under different values of δ, which measures the payoff of a sucker to PDG and SDG. The results are shown in Fig. 4, from which we can clearly see how the frequency of cooperators f_c varies in dependence on b for different values of δ on the BA network and the regular network, respectively. First, it can be observed that when the value of b is small, the number of cooperators is slightly lower than the number of defectors. Then, f_c will decline with the increase of b. However, cooperators are not extinct when the value of b is large enough, and there still exist a few cooperators in the network. In particular, as simulation, it also shows that the fraction of cooperators f_c is independent of the value of δ (Fig. 4).

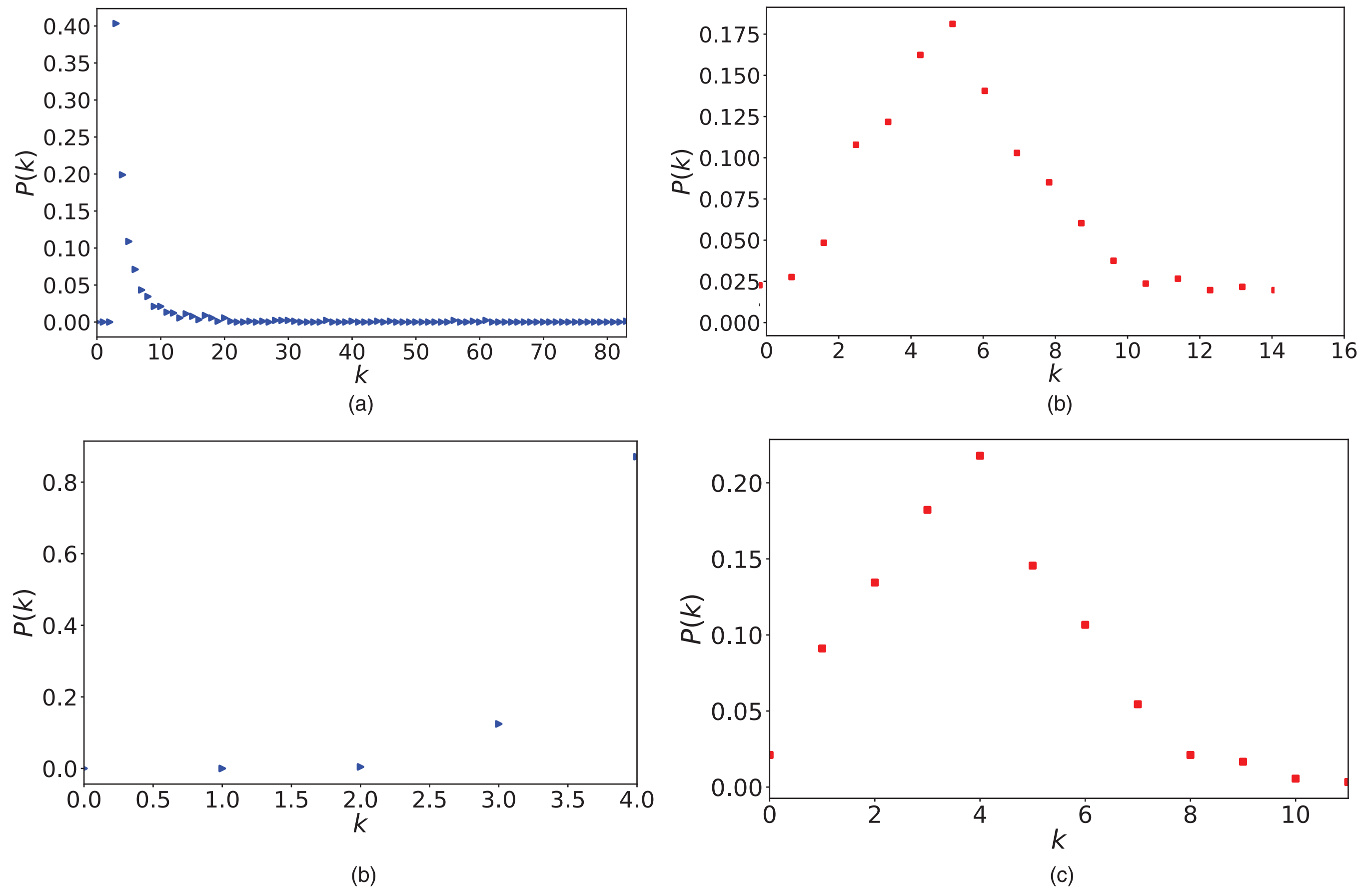

FIG. 3. Degree distribution of networks before and after evolution. BA is generated by the growth and preferential attachment, where the parameters are set as $N = 900$ and $m = 3$. RE is generated by a square lattice network with 900 nodes. In the game model, we set $b = 1.1$ and $\delta = 0.8$. Subplots (a) and (b) show the degree distribution before and after the evolution of the BA network, respectively. Subplots (c) and (d) show the degree distribution before and after the evolution of the regular network, respectively.

In addition, we can see that the changing trend of f_c in the BA and the regular network is similar from Figs. 4(a) and 4(b); i.e., the change of the network will not lead to too much variation in the number of network cooperators.

2. f_c vs δ

In order to better observe the relationship between the fraction of cooperators f_c and δ, we let the cooperation frequency f_c be a function of the independent variable δ for different values of b, where both the BA and the regular network size $N = 900$. The experimental results are shown in Fig. 5. From both Figs. 5(a) and 5(b), we can see that f_c has slight fluctuations with the increase of δ, and f_c is always stable around 0.3. Besides, it can be observed that f_c will be inhibited with the increase of b when δ is moderate, e.g., $0.70 < \delta < 0.90$, which proves the correctness of our above experiment indirectly.

To summarize, we study the fluctuation of the fraction of cooperators f_c under different values of b and δ on the scale-free and regular network and find that f_c decreases with the increase of b and is independent of the transformation of δ.

D. Snapshots on the regular network

A question worthy of consideration has emerged, i.e., why did the above results appear? As is well known, cooperation can survive by means of forming clusters, which is known as network reciprocity. Therefore, we subsequently concentrate on snapshots that describe the evolution of the strategy and type at the micro-level. For the sake of clarity, cooperators and profiteers are colored by green, defectors and conformists are colored by red, and isolated players are colored by black. From top to bottom, the parameter pairs (b, δ) are set as (1.2, 0.7), (1.3, 0.8), and (1.5, 0.8), while the time steps from left to right are equal to 0, 2500, and 7000, respectively.

Snapshots visualize the evolutionary game in network and are more understandable and demonstrate the evolution of the strategies and types of players with different parameter pairs (b, δ) intuitively. The simulation results are shown in Fig. 6. In the beginning,

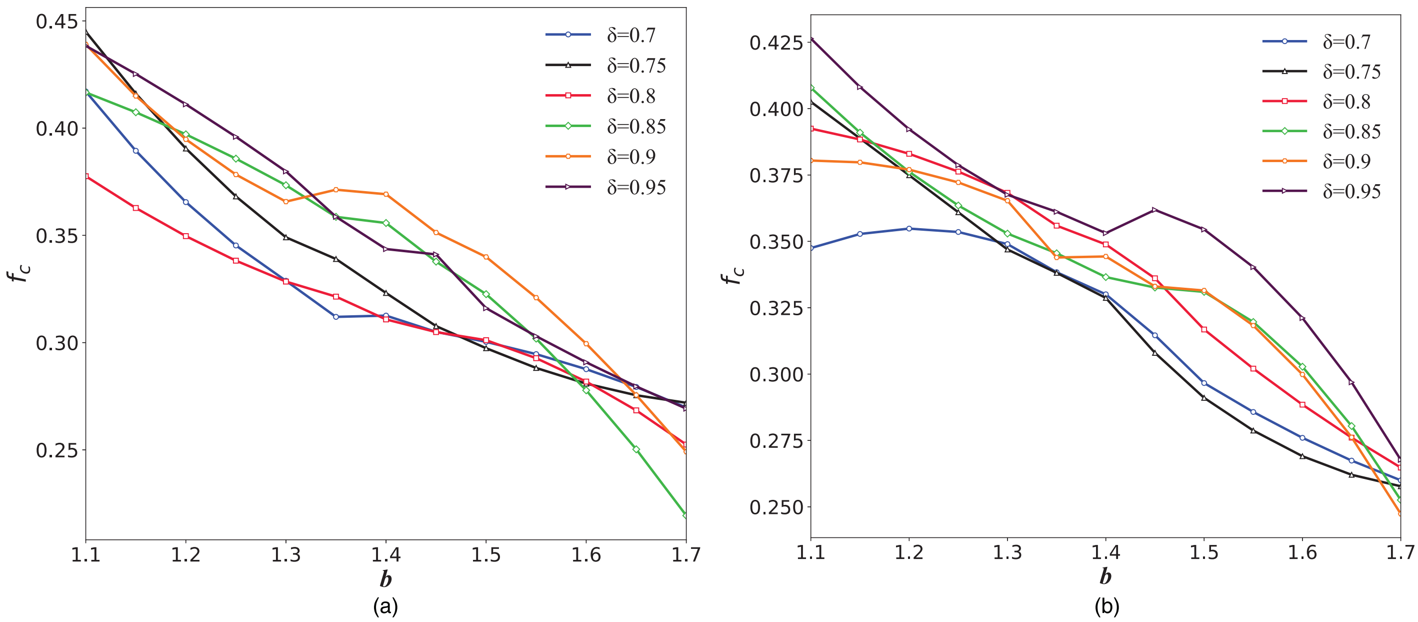

FIG. 4. Plots of cooperator fraction against defection temptation. BA is generated by the growth and preferential attachment, where the parameters are set as $N = 900$ and $m = 3$. RE is generated by a square lattice network with 900 nodes. We set $\delta = [0.7, 0.75, 0.8, 0.85, 0.9, 0.95]$, and the defection temptation b is set from 1.1 to 1.7. Subplots (a) and (b) show the cooperator fraction against defection temptation on the BA and regular network, respectively.

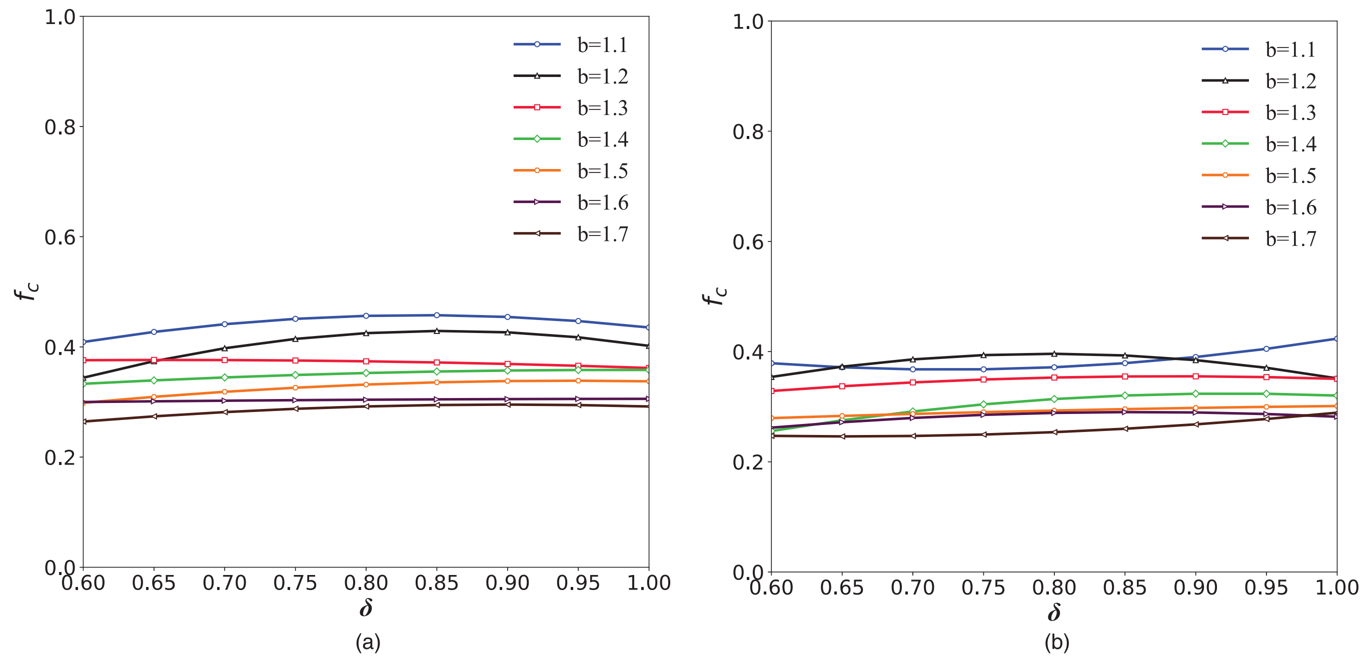

FIG. 5. Plots of cooperator fraction against sucker's payoff. BA is generated by the growth and preferential attachment, where the parameters are set as $N = 900$ and $m = 3$. RE is generated by a square lattice network with 900 nodes. We set $b = [1.1, 1.2, 1.3, 1.4, 1.5, 1.6, 1.7]$, and the sucker's payoff δ is set from 0.6 to 1. Subplots (a) and (b) show the cooperator fraction against sucker's payoff on the BA and regular network, respectively.

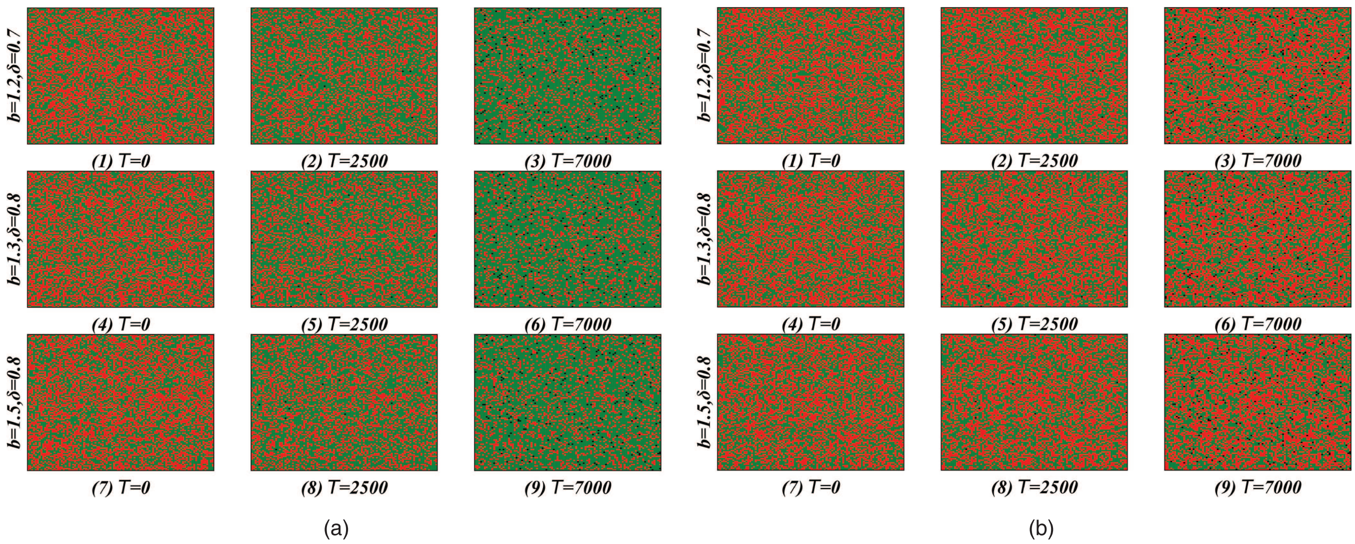

FIG. 6. Characteristic snapshots for different parameter pairs (b, δ). From top to bottom, the parameter pairs (b, δ) are set as (1.2, 0.7), (1.3, 0.8), and (1.5, 0.8), respectively. From left to right, the time step is fixed to be T = 0, 2500, and 7000. Here, green denotes profiteers and cooperators, red denotes conformists and defectors, and black denotes isolated players. Other parameters include the scale of the lattice network $N = 100 \times 100$ and the smoothing coefficient $\alpha = 1$. As evolution proceeds, the profiteers eventually dominate the network, with slightly more defectors than cooperators and a small number of isolated players emerging in the network.

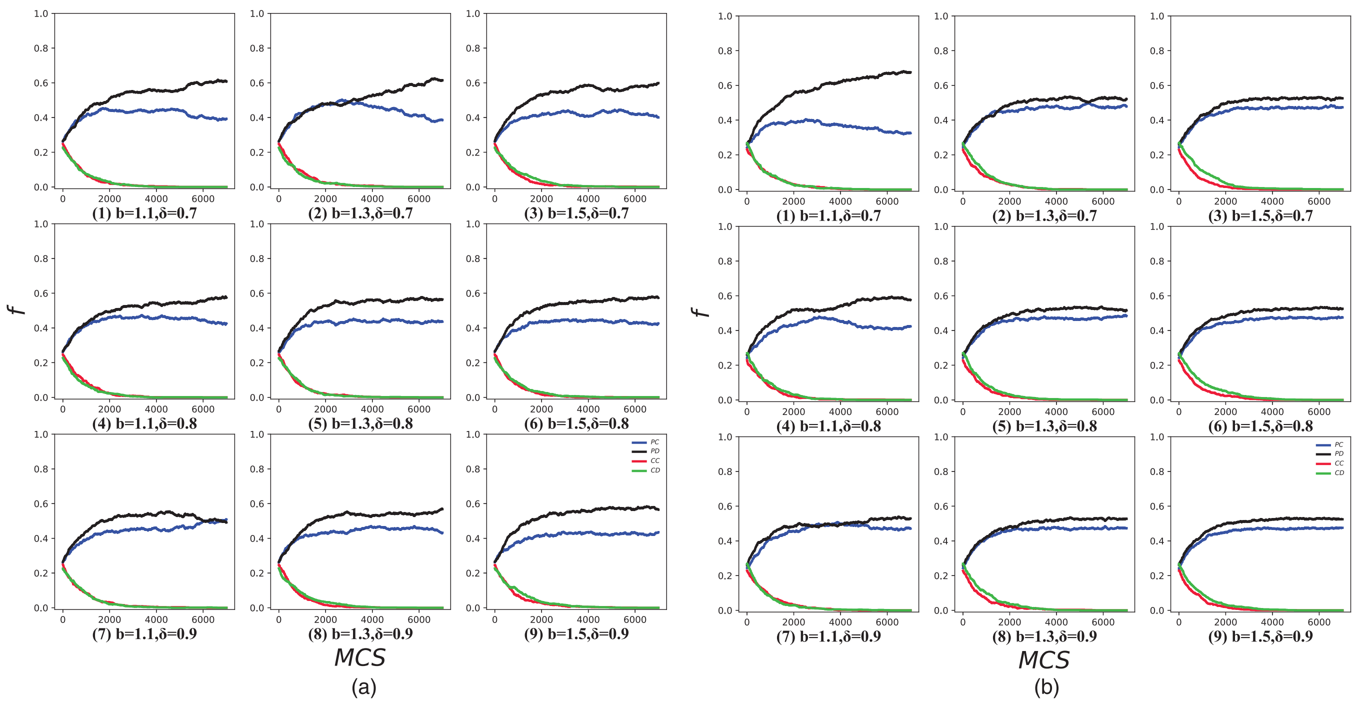

FIG. 7. Plots of fractions of conformist cooperators (CCs), conformist defectors (CDs), profiteer cooperators (PCs), and profiteer defectors (PDs) against MCS. BA is generated by the growth and preferential attachment, where the parameters are set as $N = 900$ and $m = 3$. RE is generated by a square lattice network with 900 nodes. In the game model, $b = [1.1, 1.3, 1.5]$ and $\delta = [0.7, 0.8, 0.9]$ are set for cross experiments. Subplots (a) and (b) show the network evolutionary game with conformists and profiteers on the BA and regular network, respectively.

the same number of cooperators and defectors and profiteers and conformists is located on the lattice randomly, and there exist no isolated players in the network at this time. We observe that several isolated players appear on the network when time reaches 2500. Moreover, we see from Fig. 6(a) that with the evolution of the network game, profiteers are gradually increasing and eventually dominate the whole network. Figure 6(b) shows that the number of defectors slowly increases along with the evolution proceeding. Ultimately, the cooperators are not annihilated, and the fraction of cooperators f_c is stable at about 0.3.

Next, we analyze the reasons for the results in Figs. 4 and 5 based on the degree distribution in Fig. 3 and snapshots in Fig. 6. Due to the existence of network reciprocity, the BA network will promote the evolution of cooperation. However, previous research has also shown that when we normalize payoffs on a heterogeneous interaction network, we destroy the heterogeneity among players and drastically weaken the positive impact of the enhanced network reciprocity.[33–35] In addition, there will be random reconnection of players in the network at each step, which further reduces the degree of heterogeneity between the players. As we have shown in Fig. 3(b), the degree distribution of the evolved BA network not following the power-law distribution means that it is no longer a BA network. Therefore, it does not promote the emergence of cooperation in our model. From Fig. 3, we know that although there are great differences in the degree distribution between the BA network and the regular network at the beginning, the degree distributions of them are very similar after the evolution, and the evolution of the fraction of cooperators f_c will consequently have similar results on the BA and regular network. As demonstrated in Fig. 6(a), there are only a few conformists in the network at the end of the evolution of the network game. Previous studies have shown that appropriate conformists in the network can promote the emergence of cooperation.[36,37] Since the number of conformists is too small, it does not promote the emergence of network cooperation. On the other hand, it is the existence of these conformists that makes the network cooperators not annihilated.

E. Evolution of the number of different categories

Eventually, we present the number of conformist cooperators (CCs), conformist defectors (CDs), profiteer cooperators (PCs), and profiteer defectors (PDs) to be dependent on the Monte Carlo Step (MCS) with different parameter pairs (b, δ) on the BA and regular network, respectively. The simulation results are shown in Fig. 7. In each subplot, despite the network type, the number of conformist defectors and conformist cooperators converges to zero after MCS = 4000, while the quantity of profiteer cooperators and profiteer defectors gradually increases as time goes by and finally reaches a steady value. It is observed that there is little difference in the number of conformist cooperators and conformist defectors, while the quantity of profiteer defectors is always greater than profiteer cooperators in the process of evolution, which shows that the phenomenon demonstrated in Fig. 7 is consistent with our previous analysis. It is worth noting that although our model has more defectors than cooperators in the network when the evolution reaches a steady state, defection does not dominate the network. Besides, in contrast to previous studies, when the temptation to defection b is large, the number of cooperators in the network is not extinct in our model and just slightly lower than the number of defectors. Therefore, our model still has a positive effect in preventing the annihilation of cooperative behavior.

Then, we analyze the causes of the phenomenon in Fig. 7. As shown in Figs. 3(b) and 3(d), players have random reconnection at each step, and the degree distribution of the BA and regular network after evolution is similar and is no longer the same as the initial degree distribution; i.e., the topology of both networks is changing in the evolution process and becomes more and more similar. Therefore, we find that the network has had little effect on the evolution of the quantity of CC, CD, PC, and PD. In addition, as is mentioned in the model, a player will be selected to change his type at each step, and when the type transition occurs, players with lower payoff are more likely to change their strategy-updating rules. Concretely, when a profiteer is chosen by the anti-preference law in Eq. (5), he obtains a relatively low payoff than other players; namely, defectors account for a large proportion in his neighbors. Thus, the chosen player will become a conformist at the next step and may become a defector with a higher probability than a cooperator according to Eq. (4). Otherwise, when a player changes his type from a conformist to a profiteer, its major neighbors are more likely to be defectors as well. In spite of the fact that defectors are still dominant in the chosen player's neighbors, its next strategy totally depends on neighbors' payoff.

IV. CONCLUSION AND OUTLOOK

In this paper, we propose a multigame model with transformations between conformists and profiteers on dynamic networks. The multigame evolution process is introduced, including strategy evolution and network evolution. In the simulation, we analyze the changes of the topological structure before and after the network evolution through degree distribution, additionally study the cooperation sensitivity to the parameters b and δ, and then observe the strategy and type distribution on the square lattice network at the micro-level. Moreover, we show the evolution process of conformist cooperators (CCs), conformist defectors (CDs), profiteer cooperators (PCs), and profiteer defectors (PDs) with different parameter pairs (b, δ). Finally, we provide some explanations from the perspective of strategy transition, type transition, and network topology properties for the simulation results.

In our work, the similarity is only conducted based on the cosine similarity of the players' degree and clustering coefficient. Different similarity rules, however, may lead to different results. In addition, players' choice of game opponents for reconnection is random in this paper. Different results may also appear when we give players a certain rule for selecting game opponents. Eventually, we hope that our work will stimulate further research in the multigame in structured populations to address the social dilemmas, especially from the perspective of empirical experiments.

ACKNOWLEDGMENTS

This work was supported in part by the Ministry of Education in China (MOE) Project of Humanities and Social Sciences under Grant No. 21YJCZH028 and in part by the Ministry of Science and

Higher Education of the Russian Federation within the framework of state support for the creation and development of World-Class Research Center's Digital Biodesign and Personalized Healthcare under Grant No. 075-15-2020-926.

AUTHOR DECLARATIONS

Conflict of Interest

The authors have no conflicts of interest to disclose.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] A. Colman, *Game Theory and Its Application* (Butterworth-Heinemann, Oxford, 1995).
[2] M. A. Nowak, "Five rules for the evolution of cooperation," Science **314**(5805), 1560–1563 (2006).
[3] M. A. Nowak and K. Sigmund, "A strategy of win-stay, lose-shift that outperforms tit-for-tat in the prisoner's dilemma game," Nature **364**, 56–58 (1993).
[4] Z. Wang and M. Perc, "Aspiring to the fittest and promotion of cooperation in the prisoner's dilemma game," Phys. Rev. E **82**, 021115 (2010).
[5] Q. Jin, Z. Wang, and Y. Wang, "Strategy changing penalty promotes cooperation in spatial prisoner's dilemma game," Chaos, Solitons Fractals **45**, 395–401 (2012).
[6] C. Hauert and M. Doebeli, "Spatial structure often inhibits the evolution of cooperation in the snowdrift game," Nature **428**, 643–646 (2004).
[7] W. B. Du, X. B. Cao, M. B. Hu, and W. X. Wang, "Asymmetric cost in snowdrift game on scale-free networks," Europhys. Lett. **87**, 60004 (2009).
[8] M. Doebeli and C. Hauert, "Models of cooperation based on prisoner's dilemma and snowdrift game," Ecol. Lett. **8**, 748–766 (2005).
[9] M. Perc and P. Grigolini, "Collective behavior and evolutionary games—An introduction," Chaos, Solitons Fractals **56**, 1–5 (2013).
[10] M. A. Nowak and R. M. May, "Evolutionary games and spatial chaos," Nature **359**(6398), 826–829 (1992).
[11] J. Hofbauer and K. Sigmund, *Evolutionary Games and Population Dynamics* (Cambridge University Press, Cambridge, UK, 1998).
[12] J. Gómez-Gardeñes, M. Romance, R. Criado, D. Vilone, and A. Sánchez, "Evolutionary games defined at the network mesoscale: The public goods game," Chaos **21**, 016113 (2011).
[13] M. Duh, M. Gosak, and M. Perc, "Public goods games on random hyperbolic graphs with mixing," Chaos, Solitons Fractals **144**, 110720 (2021).
[14] C. P. Roca, J. A. Cuesta, and A. Sánchez, "Time scales in evolutionary dynamics," Phys. Rev. Lett. **97**, 158701 (2006).
[15] A. Vukov, J. Szolnoki, and G. Szabó, "Selection of noise level in strategy adoption for spatial social dilemmas," Phys. Rev. E **80**, 056112 (2009).
[16] A. Szolnoki, M. Perc, and G. Szabá, "Defense mechanisms of empathetic players in the spatial ultimatum game," Phys. Rev. Lett. **109**, 078701 (2012).
[17] Y. Zhang, X. Chen, A. Liu, and C. Sun, "The effect of the stake size on the evolution of fairness," Appl. Math. Comput. **321**, 53–70 (2018).
[18] Y. J. Huang, Z.-H. Deng, Q. Song, T. Wu, Z. Deng, and M. Y. Gao, "The evolution of cooperation in multi-games with aspiration-driven updating rule," Chaos, Solitons Fractals **128**, 313–317 (2019).
[19] Z. Li, D. Jia, H. Guo, Y. Geng, C. Shen, Z. Wang, and X. Li, "The effect of multigame on cooperation in spatial network," Appl. Math. Comput. **351**, 162–167 (2019).
[20] Y. Han, Z. Song, J. Sun, J.-Z. Ma, Y. Guo, and P. Zhu, "Investing the effect of age and cooperation in spatial multigame," Physica A **541**, 123269 (2020).
[21] C. Liu, H. Guo, Z. Li, X. Gao, and S. Li, "Coevolution of multi-game resolves social dilemma in network population," Appl. Math. Comput. **341**, 402–407 (2019).
[22] Z.-H. Deng, H. Yi-Jie, G. Zhi-Yang, D. Liu, and L. Gao, "Multi-games on interdependent networks and the evolution of cooperation," Physica A **510**, 83–90 (2018).
[23] M. Wooders, E. Cartwright, and R. Selten, "Behavioral conformity in games with many players," Games Econ. Behav. **57**, 347–360 (2006).
[24] X. Wang, Z. Zhu, and X. Ren, "Evolutionary prisoner's dilemma game on complex networks with conformist mentality strategy," Sci. China Phys. Mech. **55**, 1225–1228 (2012).
[25] P. B. Cui and Z. X. Wu, "Impact of conformity on the evolution of cooperation in the prisoner's dilemma game," Physica A **392**, 1500–1509 (2013).
[26] A. Szolnoki and M. Perc, "Conformity enhances network reciprocity in evolutionary social dilemmas," J. R. Soc. Interface **12**, 20141299 (2015).
[27] A. Szolnoki and M. Perc, "Leaders should not be conformists in evolutionary social dilemmas," Sci. Rep. **6**, 23633 (2016).
[28] L. Eckmann, T. Nebelsiek *et al.*, "Opposing functions of IKKβ during acute and chronic intestinal inflammation," Proc. Natl. Acad. Sci. U.S.A. **105**, 15058–15063 (2008).
[29] A. Szolnoki, Z. Wang, and M. Perc, "Wisdom of groups promotes cooperation in evolutionary social dilemmas," Sci. Rep. **2**, 576 (2012).
[30] G. Szabó and C. Töke, "Evolutionary prisoners dilemma game on a square lattice," Phys. Rev. E **58**, 69 (1998).
[31] P. Piff, M. W. Kraus, S. Côté, B. Cheng, and D. Keltner, "Having less, giving more: The influence of social class on prosocial behavior," J. Pers. Soc. Psychol. **99**(5), 771–784 (2010).
[32] S. Côté, "How social class shapes thoughts and actions in organizations," Res. Org. Behav. **31**, 43–71 (2011).
[33] N. Masuda, "Participation costs dismiss the advantage of heterogeneous networks in evolution of cooperation," Proc. R. Soc. B **274**, 1815–1821 (2007).
[34] M. Tomassini, L. Luthi, and E. Pestelacci, "Social dilemmas and cooperation in complex networks," Int. J. Mod. Phys. C **18**, 1173–1185 (2007).
[35] A. Szolnoki, "Towards effective payoffs in the prisoner's dilemma game on scale-free networks," Physica A **387**, 2075–2082 (2008).
[36] Z. Niu, J. Xu, D. Dai, T. Liang, D. Mao, and D. Zhao, "Rational conformity behavior can promote cooperation in the prisoner's dilemma game," Chaos, Solitons Fractals **112**, 92–96 (2018).
[37] Z. Wang, A. Szolnoki, and M. Perc, "Different perceptions of social dilemmas: Evolutionary multigames in structured populations," Phys. Rev. E **90**, 185–198 (2014).
[38] A. Szolnoki and Z. Danku, "Dynamic-sensitive cooperation in the presence of multiple strategy updating rules," Physica A **511**, 371–377 (2018).
[39] A. Szolnoki and X. Chen, "Cooperation and competition between pair and multi-player social games in spatial populations," Sci. Rep. **11**(1), 12101 (2021).
[40] M. Perc and A. Szolnoki, "Coevolutionary games—A mini review," BioSystems **99**(2), 109–125 (2010).
[41] A. Szolnoki, M. Perc, and Z. Danku, "Making new connections towards cooperation in the prisoner's dilemma game," Europhys. Lett. **84**(5), 50007 (2008).
[42] A. Szolnoki and M. Perc, "Resolving social dilemmas on evolving random networks," Europhys. Lett. **86**(3), 30007 (2009).
[43] M. Feng, J. L. Deng, F. Chen *et al.*, "The accumulative law and its probability model: An extension of the Pareto distribution and the log-normal distribution," Proc. R. Soc. A **476**(2237), 20200019 (2020).
[44] M. Feng, L. Deng, and J. Kurths, "Evolving networks based on birth and death process regarding the scale stationarity," Chaos **28**(8), 083118 (2018).
[45] M. Feng, H. Qu, Z. Yi *et al.*, "Evolving scale-free networks by Poisson process: Modeling and degree distribution," IEEE Trans. Cybern. **46**(5), 1144–1155 (2015).