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Modeling and Analysis of Rumor Control Strategies in Social Networks *

Research Article

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Abstract: Todays, although social networks are used for extensive information sharing, spreading rumors has also been accelerated and become a serious problem. Rumor control can be accomplished through either hard or soft control strategies. The former uses depriving actions like blocking rumor spreaders, while the latter tries to persuade people personally avoiding rumor propagation by increasing their knowledge and awareness. Although there are some proposals for rumor control in social networks, suitable frameworks for modeling and analysis of rumor control strategies and methods with proper consideration of the effective factors is still a need. This study introduces a rumor propagation model based on evolutionary game theory along with a number of soft and hard rumor control methods. Using the proposed model, we simulate and analyze rumor control methods considering different environmental, personal, and content-related factors that may influence people's decisions about rumors. The simulation is conducted on a Twitter graph according to various society conditions. One of the findings is that the soft rumor control strategy is generally more effective than the hard rumor control strategy. The proposed model itself and the conducted analysis can be adopted for developing and deploying effective rumor control mechanisms in social network systems.

Keywords: Evolutionary Game Theory, Rumor Spreading, Rumor Control, Social Network

1. Introduction

In recent decades, as social networks have grown significantly, smartphones have provided their users instant and real-time access from anywhere. With the advent of social media and various communication tools and technologies, any information is transmitted through social media faster than ever before. Rumor is unconfirmed information that is accompanied by ambiguity and uncertainty [9]. Rumors often originate from one or multiple users and are widely disseminated through social networks. Some believe that ambiguity of rumors is the main cause for the rumors to be spread widely [20]. Indeed, social networks are accelerating the spread of fake news and rumors that cause lots of social, economic, and psychological damages. For example, Coronavirus 2019 (COVID-19) has not only posed significant challenges to health systems around the world, but has also increased rumors and misinformation about the causes, prevention, and treatment of the disease. Such misinformation increases the prevalence of the virus and ultimately leads to serious psychological and physical harm to people [31].

Regarding the importance of the problems that rumor poses in recent years, there is a number of researches which addresses different rumor control approaches [5, 10, 11]. Rumor control in social networks can be classified into hard or soft control strategies [3]: Hard rumor control methods such as those proposed in [14, 33] rely on limiting or removing users who transmit rumors, or blocking the rumor messages on social networks. Hard rumor control can be considered a kind of legal/illegal censorship. For example, some social networks such as Instagram and Facebook block/suspend accounts that are reported by users or violate their policies/regulations. Soft rumor control strategy on the other hand, relies on increasing people's knowledge and awareness to persuade them personally avoid rumor propagation. The works are presented in [3, 35, 38] are examples of those who adopt the soft rumor control strategy.

Despite the above works, a suitable framework for modeling and analysis of different rumor control methods is a need. Indeed, regarding the complex nature of the social networks and absence of proper and comprehensive related datasets, using abstract models for analysis of different aspects of the rumor phenomena in social networks is a reliable solution. The models can be used as underlying parts of different analysis methods including simulation and verification.

A model is presented in this study that includes a way for modeling rumor diffusion along with different rumor control methods. In the proposed model, social network users are divided into two groups of rumor spreaders and anti-rumor spreaders. Anti-rumor is a message that with the help of correct and accurate evidence and news, shows that the rumor is false. To analyze the spread of rumors, we use an evolutionary game approach to model the battle space between rumor spreaders and anti-rumor spreaders. Using the proposed model, we study personal, environmental, and content-related parameters affecting the spread of rumor and anti-rumor in social networks. Besides, we propose two hard and two soft rumor control methods. Hard controls include punishment of the rumor spreader by other users (e.g., blocking him due to spreading fake or rumor messages), or punishment of the rumor spreader by the social network (e.g., removing or restricting capabilities of rumor spreaders due to publishing or massively distributing fake or rumor news). Soft rumor controls include systematic consultation of users

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with selected expert entities that we name social network leaders (such as news agencies, NGOs, and celebrities), as well as a complementary method for recommending leaders for consultation by users to their friends.

To analyze and compare the rumor control methods, we simulate the base evolutionary game model along with rumor control methods considering different society conditions on a sample of Twitter graph. We extensively analyze different control methods considering some environmental, personal, and content-related factors that influence people's decisions about rumors. The analysis results illuminate and compare the effectiveness of different hard and soft strategies in controlling rumor considering different related factors. A notable result of the conducted analysis is that soft rumor control methods are more effective than hard rumor control methods in general.

The rest of paper is organized as follows. A brief overview of the evolutionary game is provided in Section 2. In Section 3, the related works are reviewed. The proposed evolutionary game model for rumor diffusion along with four rumor control approaches are presented in Section 4. The simulation analysis of the models in different environments is presented in Section 5. Finally, the conclusion of the paper and the future works are discussed in Section 6.

2. Preliminaries

In this section, the required preliminaries are reviewed. We first review the traditional evolutionary game theory, then we introduce the basic concepts of the evolutionary game theory on graph.

2.1. Evolutionary game theory

The emergence of evolutionary game theory goes back to the application of game theory in biology which examines the evolving populations [27]. Moreover, evolutionary game theory was later used in economics, sociology, and computer science [16, 21, 30, 32]. The game theory for evolutionary biology first was used by R. C. Lewontin in 1961 [18]. Evolutionary game theory based on Darwin's theory expresses repetitive game among evolving populations. In evolutionary game, participants produce as many replicas of themselves as they can, and the units of fitness is their payoff. In 1972, Maynard Smith defined the concept of an evolutionarily stable strategy (ESS) [23, 28]. ESS is an environmentally fitted population that evolves and as a result, other populations die out. The traditional evolutionary game is defined for infinitely large and well-mixed populations. A well-mixed population means that users do not interact with each other in a particular structure, and users interact with each other equally likely.

2.2. Evolutionary game theory on graph

Evolutionary game theory on graph was first studied by Ohtsuki and Nowak [22]. They demonstrate how the frequency of strategies evolve in a structured graph. Since we aim to model the spread and control of rumor on social networks, we utilize the evolutionary game on graph. Ohtsuki and Nowak [22] discuss how players obtain a payoff from the interaction with their adjacent individuals. There are three update rules for the evolutionary dynamics: birth–death (BD), death–birth (DB), and imitation (IM) [18], which are described as follows:

- BD update rule: an individual is selected proportional to the fitness from the whole network and is replaced with one of its neighbors randomly;
- DB updating rule: an individual is selected randomly from the whole network and one of the neighbors is selected proportional to the fitness to take its place;
- IM updating rule: an individual is selected randomly and it will either keeps its current strategy or selects the neighbor's strategy proportional to the fitness.

These update rules describe three stochastic processes which represent how frequencies of strategies are changed on a graph. In this study, since we do not need to remove users during the game, we employ the IM update rule to implement the evolutionary game on graph.

3. Review of related works

Modeling rumor spreading has a deep history and literature. Epidemic models are the basis of rumor spreading models. The Susceptible-Infectious-Recovered (SIR) model has been studied to analyze the spread of disease. The Daley-Kendall (DK) model was presented based on the SIR model to analyze rumor spreading [7]. DK model divides individuals into three groups of Ignorants, Spreaders, and Stiflers. Ignorants are people who have never heard the rumor, spreaders are people who have heard the rumor and intend to spread it to others and they change their neighbors who are ignorants to spreaders. Stiflers are people who have heard the rumor, but do not intent to spread it. Several researches have been conducted on modeling the spread of rumors based on epidemic models [5, 12, 25, 40, 41, 42].

Regarding the rumor control methods, researchers use a variety of hard and soft rumor control methods. Hard rumor control strategies sometimes are realized via two methods of random immunization and targeted immunization [24]. Random immunization tries protecting a fraction of nodes, while targeted immunization considers the most highly connected individuals to immunize them against the rumor. Bao et al. suggest two hard rumor control methods of random immunization and targeted immunization, and one soft rumor control of an opinion guidance rumor control method [5]. They propose a rumor spreading model named SPNR, and study these rumor control methods on the proposed model. The results show that random immunization strategy requires immunizing a very large fraction of networks. However, since targeted immunization immunizes the most highly connected individuals, it is more effective for preventing rumor and in targeted immunization method, the total information of the social network graph is required. In the third method, some opinion guidance nodes are inserted in social network and make them connected to the whole network. The opinion guidance method tries to prevent rumor spreading by sending anti-rumors.

Some researches in hard rumor strategy side, focus on finding the optimal set of influential links or nodes to block misinformation diffusion. Kimura et al. proposed a greedy algorithm to find and remove the most influential links [17]. Yao et al. by blocking a limited number of rumor spreaders prevent rumor spreading. They studied two topic-aware heuristics based on betweenness and out-degree for finding influential rumor spreaders [39]. Tan et al. evaluate the importance of a nodes according to their activation increment

[29]. A node with more "activation increment", can activate more neighbors. They show that blocking nodes with high activation increment can prevent rumor spreading.

Soft rumor control methods often include models that raise awareness about rumors by sending anti-rumors [26]. They study the spread of anti-rumor along with sending rumors [2, 15, 26]. Hong et al. believe that SIR is an inefficient model for spreading rumors and extend it to SCNDR model [12]. They divide infected users into three groups of credulous (C), neutrals (N), and deniers (D). Credulous are users who believe rumors and spread them. Neutrals are users who do not spread rumors, and deniers are users who do not believe rumors and recommend others not to believe them. In another work, the dynamic 8-states ICSAR model was developed to analyze rumor spreading [42]. They show that improving awareness of people, degree of trust to media information, and expert effects can stop rumor propagation. They also deploy official rumor controllers such as governments to stop rumor propagation. Jain et al. analyzed the effect of delay to influence thinkers [15]. Thinkers are people who hear the rumor but keep it into consideration. Moreover, Wang et al. propose a new model based on the SI model [36]. They study the transition of rumor and anti-rumor in both homogeneous and heterogeneous networks. They conclude that all authorities can effectively control rumor by improving their trust degree. Some researches have studied the influence of people behavior and social condition on rumor spreading [4, 6]. Chen et al. extend the SIR model, considering people personality, the correlation between rumors and people's lives and the rumor credibility [6]. They propose SEIsIrR model and show that the high correlation degree between a rumor and people's lives, and the credibility of the rumor cause rumors to spread more. Moreover, radical people are more likely to spread rumors.

Some soft rumor control strategies employ rumor control centers to send anti-rumors [37]. Tripathy et al. utilize rumor control centers in delayed-start model and beacon model [34, 35]. In these models, when local authorities receive a rumor, they send anti-rumors to prevent the rumor from spreading. In the beacon model, the control centers are presented as beacons on social networks to lookout for rumors and immediately after the rumor is spread, they start broadcasting anti-rumors. In the delayed start model, on the other hand, rumor control centers receive the rumors after a few days and then start sending anti-rumors. Askarizade et al. propose an evolutionary game model for rumor propagation along with two soft rumor control methods [3]. They suggest two methods of consulting trusted friends and asking reputable authorities about the received rumors. They deploy soft rumor control methods on an evolutionary game model. Although their proposed model can be used to analyze some soft rumor control methods, since they do not consider hard rumor controls as internal part of their model, it is not possible to comprehensively analyze hard rumor control methods and compare them with soft rumor control methods.

Evolutionary game theory is an appropriate tool for modeling decision-making situations. Since people's decision on sending rumor or anti-rumor is an important factor in rumor propagation, an evolutionary game model can properly model the rumor spreading and rumor control. Li et al. propose an evolutionary game framework for analyzing the user behavior in spreading rumors [19]. They conclude that by increasing judgment about the rumor and punishment cost, rumor is debunked. Moreover, Askarizade et al. in their other work analyzed the spread of rumor using an evolutionary game model [4]. They study factors affecting the users' decisions including social anxiety, people's attitude toward rumor/anti-rumor, strength of rumor/anti-rumor, influence of rumor control centers, and participation of people in discussions. They verify their model with real data from Twitter and examine the model by considering different society conditions and people characteristics. However, they only analyze the spread of rumors and do not provide any method for controlling rumors. Furthermore, Xiao et al. propose SKIR rumor propagation model based on the evolutionary game theory [38]. They study the effect of symbiosis of anti-rumor and rumor, as well as the user behavior and psychological factors.

Table 1. Comparison of some more related works together and to the proposed model

Work	Rumor control strategy	Rumor control method	Content-related parameters	Behavioral parameters
Bao [5]	Hard and Soft	Immunization and propagating anti-rumor by opinion guidance nodes	No	No
Kimura [15]	Hard	Removing influential links	No	No
Yao [37]	Hard	Limiting rumor spreaders	Y	No
Tan [27]	Hard	Blocking active nodes	No	No
Hong [12]	Soft	Propagating anti-rumor	No	No
Zhang [40]	Soft	Propagating anti-rumor	Yes	Yes
Tripathy [32, 33]	Soft	Receiving anti-rumor from rumor control centers	No	No
Askarizade [3]	Soft	Receiving anti-rumors from rumor control centers and consulting trusted friends	Yes	Yes
Askarizade [4]	Soft	No	Yes	Yes
Xiao [35]	Soft	Propagating anti-rumors	No	Yes
The proposed model	Soft and Hard	User punishment, System punishment, Consultation, and Recommendation	Yes	Yes

They demonstrate that their model reflects the propagation of rumor and anti-rumor in real social networks. Although existing evolutionary game models have examined some of the factors influencing rumor spreading, they have focused little on rumor control approaches.

Table 1 compares a number of more related works together. As shown in the table, the related works mostly consider only one of the hard or soft rumor control strategies. Moreover, they do not consider content-related and behavioral parameters that affect the people's decisions about spreading rumors. In this study, we try to propose a model for analysis and comparison of both soft and hard rumor control methods considering the impact of people's decisions. The effects of personal, environmental, and content-related parameters on soft and hard rumor control methods can be analyzed using the proposed model.

4. The proposed rumor propagation and control model

In this section, we propose an evolutionary game model for rumor propagation along with a number of soft and hard rumor control methods. First, we model the rumor propagation in social network considering the related behavioral, environmental, and rumor content-related parameters as an evolutionary game. Then two hard rumor control methods and two soft rumor control methods are deployed in the proposed evolutionary game model.

A social network is modeled as a graph $G = (V, E)$, where V is the set of users and E is the set of relations between users in social networks. We consider any information transition such as posting, commenting, or sharing a post as relations between users. Rumors are usually originated from one or multiple users and spread through the network. When people hear rumor, they may accept the rumor and transmit it, or they may reject the rumor and spread anti-rumor. A rumor usually is a vague message during the publication period while an anti-rumor is a message that along with evidences, indicates that a rumor is false.

We assume that when a rumor is spread, a battlefield between those who believe in rumor and those who believe in anti-rumor is shaped. People's belief in rumor or anti-rumor is a critical parameter that affects rumor or anti-rumor propagation. Moreover, various parameters determine users' beliefs about the rumor or anti-rumor. In the following section, first we discuss the parameters affecting rumor and anti-rumor dissemination, and then define the battlefield between the entities as an evolutionary game model. Finally, we define the rumor control methods and incorporate them in the evolutionary game model.

4.1. Model parameters

Users in social networks are players in our game. Each user has two possible actions of spreading rumor or spreading anti-rumor. We consider two strategies of rumor spreading (RS) and anti-rumor spreading (AS).

$$\begin{cases} RS & Rumor\ Spreading \\ AS & Anti-rumor\ Spreading \end{cases}$$

Rumor spreaders are people who accept the rumor and spread it, while anti-rumor spreaders are people who reject the rumor and spread anti-rumor. The physical meaning of payoff in our evolutionary game model is the amount of users' belief in the news they receive. Therefore, each strategy tries to reduce the rival's belief. For instance, rumor spreaders try to persuade anti-rumor spreaders to believe and spread the rumor and vice versa [8].

Each node in a graph receives news from its neighbors, and if they decide to publish the news, their followers receive it. To decide whether to send a rumor or anti-rumor, the news received must convince the recipients and change their beliefs. Users' belief in rumor or anti-rumor depends on five parameters:

- Publisher's Reputation (PR): The reputation of the news publisher affects the beliefs of the recipients. If the news publisher has a high reputation, people more likely believe the rumor. For instance, opinions and endorsements of celebrities such as actors, politicians, and athletes about news influence their followers' opinions.
- Strength of Rumor (SR): The strength of rumor is the extent to which rumor affects users' beliefs. The strength of the rumor is influenced by the two factors, the importance of the rumor content and ambiguity in the text of the rumor [1]. The importance of a rumor depends on news novelty (NV) and news charm (CH). If there is no rumor about a topic before, the news novelty is high and the news is very attractive to users, therefore users are eager to spread the rumor. Conversely, after a while, users lose their interest in repetitive news [8]. In addition, trending news and news related to people's lives such as disasters, diseases, elections and wars are interesting to users and hence the news charm is high. Since users may think that they do not have access to the right news and because of their fear, they publish most of such news [8]. Therefore, the importance of news is calculated as $NV + CH$. In addition, if a rumor is ambiguate, people talk more about the rumor and the rumor spreads more. Hence, SR is calculated by importance (IM) and ambiguity (AM) of rumor.
- Strength of anti-rumor (SA): The strength of anti-rumor is the extent to which anti-rumor affects users' beliefs. Besides, news source credibility (CR) is an important factor of the anti-rumor strength. If the news is accompanied by evidences that shows the credibility and clarity of the news, it will be accepted by more recipients. In addition, same as rumor, the more important the anti-rumor content, the more it affects the beliefs of the users. Therefore, SA is obtained by CR multiplied by IM.
- News tendency (NT): users form their beliefs according to their insights about the subjects including their political, social, and religious viewpoints. Hence, users' beliefs affect rumor or anti-rumor acceptance and it is obtained by $\frac{B_r}{B_{max}}$, where B_r is the belief of rumor/anti-rumor receivers and B_{max} is the maximum beliefs of users in social networks.
- Lack of news tendency (LT): LT is the amount of resistance against opposing beliefs to change their belief. LT is calculated by $\frac{-B_r}{B_{max}}$.

Table 2 shows the abbreviations of the parameters, their equations, and their corresponding range of values. These parameters are used to define the payoff matrix of the proposed evolutionary game model.

Table 2. Summary of the parameters of payoff matrix

Parameter	Abbreviation	Equation	Range
News Novelty	NV	-	$0 \le NV \le 1$
News Charm	CH	-	$0 \le CH \le 1$
News Credibility	CR	-	$0 \le CR \le 1$
News Importance	IM	$CH + NV$	$0 \le IM \le 2$
News Ambiguity	AM	$1 - CR$	$0 \le AM \le 1$
Lack of News Tendency	LT	$\frac{-B_r}{B_{max}}$	$-1 \le LT \le 0$
News Tendency	NT	$\frac{B_r}{B_{max}}$	$0 \le NT \le 1$
Strength of Anti-rumor	SA	$CR * IM$	$0 \le SA \le 2$
Strength of Rumor	SR	$AM * IM$	$0 \le SR \le 2$
Publisher Reputation	PR	-	$0 \le PR \le 1$

4.2. Payoff matrix

In this section, we discuss the battlefield between RS and AS strategy, and then present the payoff matrix of our evolutionary game model. The physical meaning of payoff is people's belief in rumor or anti-rumor. Therefore, in the payoff matrix we demonstrate how people's beliefs change during this game. The confrontation between RS and AS strategies is defined as follows:

- If a rumor spreader receives a rumor from another rumor spreader, his belief in the rumor increases and he gains a payoff;
- If an anti-rumor spreader receives an anti-rumor from another anti-rumor spreader, his belief in the anti-rumor increases and he gains a payoff;
- If a rumor spreader receives an anti-rumor from an anti-rumor spreader, his belief will decrease in proportion to SA, PR, and LT;
- If an anti-rumor spreader receives a rumor from a rumor spreader, his belief will decrease in proportion to SR, PR and LT.

Table 3 presents the payoff matrix of the evolutionary game model. The columns of the table show the sender of the rumor/anti-rumor and the rows of the table show the recipients of the rumor/anti-rumor. In this model, the beliefs of rumor/anti-rumor receivers change. In other word, rumor/anti-rumor senders gain payoff, if their opposite strategy lose payoff, and they lose payoff if their opposite strategy gain payoff.

Table 3. The payoff matrix of our evolutionary game model

	RS	AS
RS	$(PR_{sender} + NT)\,SR$	$-(PR_{sender} + LT)\,SA$
AS	$-(PR_{sender} + LT)\,SR$	$(PR_{sender} + NT)\,SA$

The payoff matrix shows that if similar strategies encounter, the recipient strategy gains payoff. Hence, anti-rumor spreaders gain payoff from encountering another anti-rumor spreader in proportion to strength of anti-rumor multiplied by publisher's reputation and news tendency, and rumor spreaders gain payoff from encountering another rumor spreader in proportion to strength of rumor multiplied by publisher reputation and news tendency. Moreover, if different strategies encounter, the receiver will lose the payoff. Hence, anti-rumor spreaders lose payoff from encountering a rumor spreader in proportion to SR multiplied by PR and lack of news tendency, and rumor spreaders lose payoff from encountering an anti-rumor spreader in proportion to SA multiplied by PR and LT.

4.3. Rumor control methods

In the previous subsections, rumor and anti-rumor propagation were modeled using an evolutionary game model considering behavioral, content-related, and environmental parameters, which we call the base model. Along with the base model, two hard rumor control methods and two soft rumor control methods are used on the base model to compare and analyze different rumor control methods. In the following, we discuss four rumor control methods:

- Users punishment: Punishment of the rumor spreader by other users;
- System punishment: Punishment of the rumor spreader by the social network;
- Consultation: Consulting users with social network leaders when receiving rumor;
- Recommendation: Recommending social network leaders by the users to each other.

In the following, we explain the proposed rumor control methods in detail.

A. Users punishment

In this approach, when users frequently receive news that is contrary to their beliefs, as a hard control method, they cut off or reduce their relation with the news spreaders. Users in social networks can block or unfollow users to cut off or reduce their relations. To implement this approach, since the relations between users is in the real world have changed, the graph structure must change. Therefore, if a user receives news from users who have the opposite strategy, it will cut off their relationship with a probability p. The probability p is calculated as Equation 1:

$$p = \frac{B_r}{B_{max}} * (1 - PR_{sender}) \quad (1)$$

As Equation 1 indicates, B_{max} is maximum belief of users in the social network and B_r is the belief of receiver which is contrary to the sender's belief, therefore the probability of cutting off the relationship is proportional to the ratio of his belief to B_{max}, whereas the reputation of the sender is inversely related to the probability of cut off.

B. System punishment

In this approach, when users receive news that is contrary to their beliefs, according to the previous method, they punish the sender with a probability p as shown in Equation 1. In this method, in addition to the previous punishment, the social network itself deprives users who have been penalized (with probability p) from participating in the social network for a period of time. In our model, users are penalized with probability p and are deprived from the evolutionary game for one game iteration.

C. Consultation

We divide anti-rumor spreaders into two groups of leaders and general users. Leaders are governmental or personal authorizations who are responsible for publishing the correct news, such as news agencies, political celebrities, NGOs, etc., and others are general users. Consulting with social leaders is a soft rumor control method, which raises users' awareness by receiving anti-rumors sent by leaders. For example, when the user hears that a flood will come to the city tomorrow, he can check the city's newsletter and if the newsletter has warned about the flood, he will be informed in this way. This approach in contrary to previous rumor control methods, does not change the network graph, but changes the payoff matrix of the base model. Table 4 illustrates the payoff matrix for the consultation method.

Table 4. The payoff matrix of the consultation method General Leader

	Leader	General	
	AS	AS	RS
RS	$-(PR_{sender}+LT)\,SA$	$-(PR_{sender}+LT)\,SA$	$(PR_{sender}+NT)\,SR$
AS	$(PR_{sender}+NT)\,SA$	$(PR_{sender}+NT)\,SA$	$-(PR_{sender}+LT)\,SR$

As we discussed earlier, the amount of belief of rumor/anti-rumor receivers changes during the game. We assume that leaders are anti-rumor spreaders who don't change their beliefs, therefore, they don't appear in the rows of the table, and also the leaders have only AS strategy. Apparently, the number of leaders does not change during the game. Therefore, the column general users in Table 4 is the same as in Table 3, while the payoffs of the leader users are payoff of AS strategy.

D. Recommendation

This method reinforces the previous consultation method. In this method, an anti-rumor spreader who follow a leader, proposes the leader with probability p1 to his friend to follow. Then, the friend follows the leader with probability p2. Therefore, a user who knows and follows a leader, recommends the leader to other users. In this way, more users follow the leaders and public awareness about the rumors increases. p1 and p2 are calculated as follows:

$$p_1 = \frac{B_S}{B_{MAX}} \tag{2}$$

$$p_2 = \begin{cases} \frac{B_r}{B_{MAX}}\, PR_{sender} & \mathit{if\ user\ has\ AS\ strategy} \\ \frac{B_{MAX}-B_r}{B_{MAX}}\, PR_{sender} & \mathit{if\ user\ has\ RS\ strategy} \end{cases} \tag{3}$$

In Equation 2, B_S is the belief of the user who proposes a leader, and indicates if the user has high beliefs, he is more eager to recommend the leader to his friend. Equation 3 shows that the probability of the friend to follow a leader is proportional to the reputation of the user who proposes the leader and the belief of his friend if he has an AS strategy. Nevertheless, if he has an RS strategy, this probability is proportional to the difference between maximum belief of the users and the belief of the friend. In this method, although the payoff matrix of the base model has not changed, the structure of the graph changes due to the addition of edges for new relations.

5. Experiments and analysis

To analyze the model, we simulate the evolutionary game using the IM update rule on a social network graph. We use a subgraph of Twitter social network to investigate the spread and control of rumors in the real-world. The dataset is a network of Twitter follower relationships in 2010, where an edge from i to j indicates that j is a follower of i [13]. The properties of the used Twitter subgraph have been shown in Table 5, where N is the number of nodes and N_E is the number of edges in the graph.

We divide users in social networks into active and passive users. Active users are those who post and share contents regularly, or comment on other users' content and like them. The belief of active users is higher than the belief threshold T. Passive users are usually spectators of other people's activities. We randomly assign 30% of users to active users, which includes rumor and anti-rumor users, and 70% of users to passive users.

To analyze different control methods, we divide the conditions of society into three groups: critical, potentially critical, and normal conditions, which are described as follows:

- Critical condition: In situations where people's lives are endangered or affected, such as disasters, wars, elections, diseases, etc., people anxiety is high. Therefore, users are more active on social networks and publish rumor or anti-rumor messages more than normal conditions [8]. Under these conditions, the belief threshold (T) of users is much higher than normal. For example, when Covid-19 started, because people were scared and had little knowledge about the disease, they spread thousands of rumors about Covid-19, and most of them were wrong news.
- Normal condition: A situation where authorities always publish credible news. In addition, entertainment news is published more than news about endangering people's lives, therefore people are less anxious. Moreover, since anti-rumor is always accompanied by evidence, the strength of anti-rumor is more than rumor. Also, in this situation, the user belief threshold is high.
- Potentially critical condition: This situation occurs at a time before the critical situation. For example, when

Covid-19 was released from China, other countries predicted the epidemic in their own countries and started rumors about the epidemic. In this situation, people are less anxious than in critical situations, so along with the rumor, anti-rumor is also spread on social networks. In addition, the users' belief threshold in these conditions is lower than the users' belief threshold in critical conditions and higher than that in normal conditions.

Table 5. Network parameters of a Twitter subgraph

Name	Type	N	N_E	Avg. degree	Connected components	Avg. clustering coefficient	Avg. path length
Twitter	Directed	90908	443399	4.8	1370	0.15	21.42

Table 6. Values of model parameters in critical, potentially critical, and normal conditions

Society condition	T	CH	NV	CR	SR	SA
Critical	1	0.84	0.73	0.3	1.1	0.47
Potential Critical	1.5	0.70	0.53	0.49	0.62	0.6
Normal	2	0.50	0.33	0.71	0.24	0.59

To analyze the model, we simulate the evolutionary game model on a sample of Twitter graph. We initialize the user strategies according to Table 6, and then the competition between RS and AS strategy begins. The competition finishes when one of the strategies becomes the ESS. To study the game results, we compare the frequency of strategies at the ESS point. Besides, we define the Mechanism Impact Measure (MIM) for analyzing the results as follows:

$$MIM = f_{AS} - f_{RS} \quad (4)$$

Equation 4 indicates the difference between f_{AS} and f_{RS}, where f_{AS} is the frequency of AS strategy at the ESS point and f_{RS} is the frequency of the RS strategy at the ESS point. We have conducted experiments to evaluate the influence of the initial frequency of strategies on different rumor control methods. For each society condition (critical, potentially critical, and normal), we increase the initial frequency of the anti-rumor strategy from 3% to 27%, and for each experiment, we obtain the MIM at the ESS point. We repeat the experiments for all rumor control methods and the base evolutionary game model. Figure 1 shows the MIM variations using different percentages of initial populations of anti-rumor spreaders for critical condition, Figure 2 shows the experiment result for potentially critical condition, and Figure 3 shows the experiment result for normal condition.

Equation 3 shows that the higher the MIM, the better the rumor is controlled. Therefore, any rumor control methods whose curve crosses the zero MIM line sooner, will perform better. The results show that as the initial anti-rumor spreaders increase to 18%, all rumor control methods perform better. Moreover, the results reveal that consultation and recommendation methods (i.e., soft control methods) can control rumor well in all society conditions. However, rumor spreading in critical condition using system punishment and users' punishment methods (i.e., hard control methods) are similar to the base model while in potentially critical and normal conditions it is even more than the base model. Besides, the spread of rumor in normal condition and potentially critical condition is better controlled using hard control methods than base model, while initial anti-rumor spreaders are less than 10%.

In another experience, different rumor control methods are compared with the base model. The MIMs for the various rumor control methods in potentially critical condition over a series of iterations are shown in Figure 4. For this experiment, we assign initial percentage of rumor spreader and anti-rumor spreader 0.27 and 0.3, respectively. Moreover, we also considered 8% of the anti-rumor spreaders as leaders. The results show rumor control methods control rumor better than the base model. Besides, soft rumor control methods (consultation and recommendation) outperform hard rumor control methods (user punishment and system punishment). Moreover, the results demonstrate system punishment method can control rumor better than user punishment, because in users' punishment method only the relation between the user and his penalized friend is cut off, but in system punishment method the penalized user is deprived of participation in the social network for a period of time, and all their relations with other users are ignored. In addition, the recommendation method slightly outperforms the consultation method.

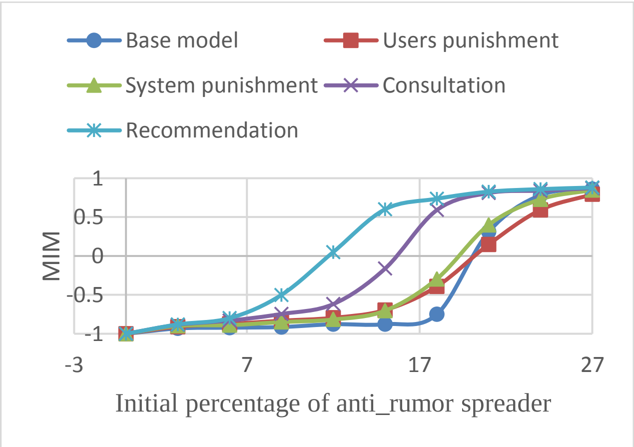

Figure 1. Rumor control in critical condition

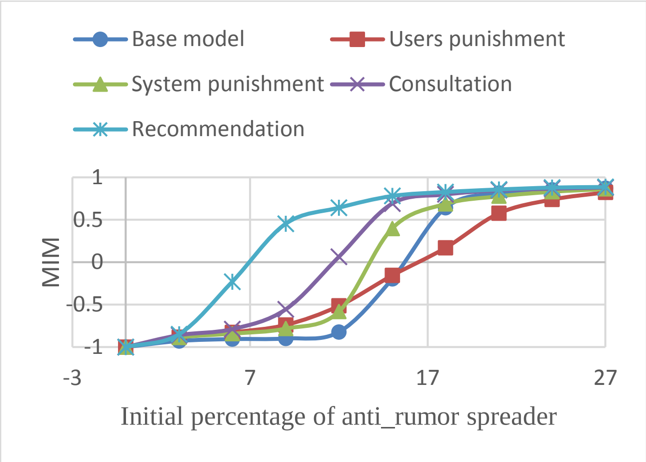

Figure 2. Rumor control in potentially critical condition

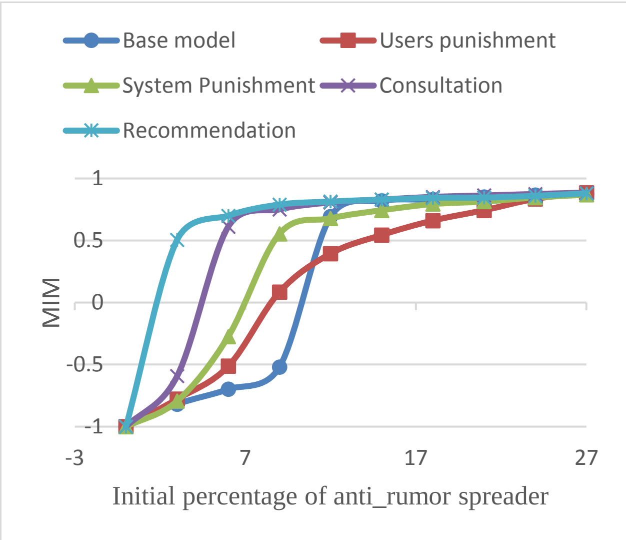

Figure 3. Rumor control in normal condition

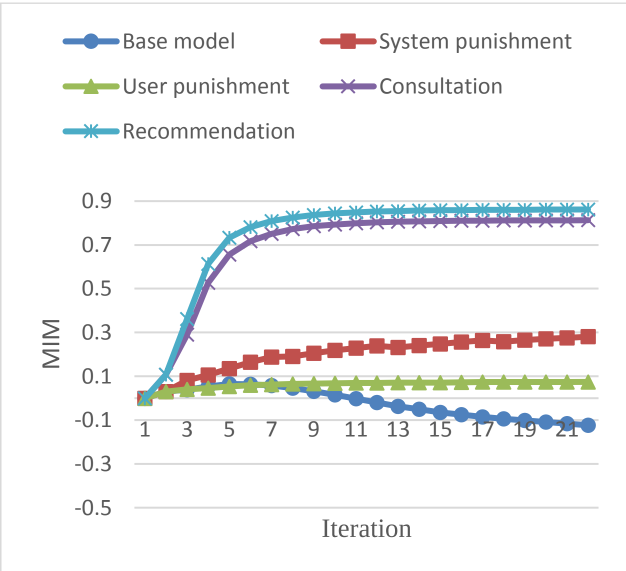

Figure 4. Comparison of different rumor control methods with the base model in potential critical condition

6. Conclusion

In this study, we proposed an evolutionary game model for analyzing the parameters affecting the spread of rumor and anti-rumor along with different hard and soft rumor control methods. We suggested four methods including two hard and two soft rumor control methods. To analyze the model and rumor control methods, we simulated the evolutionary game model on a subgraph of Twitter as an instance of a real social network. We studied the model on three society conditions of normal, potentially critical, and critical conditions and corresponding to each society condition, we initialized the parameters of the model. The results show that all rumor control methods can better perform when the initial population of anti-rumor spreaders increases, or when society condition is normal. In other words, If the users of social networks are reasonable and impartial enough and the published news is insignificant and even repetitive, then the first reaction of users to the rumors will be sending anti-rumors and the rumors will be controlled faster. Therefore, in societies where authorities warn people about the consequences of rumors and inform about new rumors, people get less excited and their first reaction is probably sending anti-rumors. Furthermore, we compared different rumor control methods with the base model over different iterations. The results demonstrate that soft rumor control methods control rumor better than hard rumor control methods. That is to say, the leader users such as news agencies, NGOs, and celebrities have a great impact on the formation of public opinion, therefore if leaders inform people about rumors, they can quickly control rumors. Generally, punishing multiple rumor spreaders cannot stop rumor. In conclusion, conventional hard rumor control methods such as removing or blocking rumor spreaders used by social networks to control rumors are less effective, and they should instead use soft control methods, including informing users about rumors and spreading anti-rumors through the social network leaders.

This research can be extended, which we will describe as future works as follows:

- We considered only one rumor on social network. However, in real social networks, several rumors are spread simultaneously and the user beliefs in each of them are different;
- We assumed that rumors are spread on social networks such as Twitter that the rumors are transmitted through direct relationships. However, on messaging platforms such as WhatsApp and Telegram, rumors are widely spread through channels and groups [22, 26];
- Using real rumor-spreading data, we can analyze the model more accurately.

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