DIFFUSION MODEL OF MULTI-AGENT COLLABORATIVE BEHAVIOR IN PUBLIC CRISIS GOVERNANCE NETWORK BASED ON COMPLEX NETWORK EVOLUTIONARY GAME

Shao-Nan Shan[1],*, Zi-Cheng Zhang[2], Chun-Juan Wang[3] and Guo-Qiang Han[4]

Abstract. In order to explore the phenomenon of diffusion of group decision making formed by the emergence of decision-making behaviors of governance agents in public crisis governance systems, this research uses a complex network evolutionary game approach, considers BA scale-free networks as network vectors of public crisis governance systems, and develops a diffusion model of collaborative governance decision making behaviors. Simulation experiments are also conducted to show the macro-level impact of micro-subjects' decision-making behavior on group "Emergence-Diffusion". The results of this study show that the cost of collaborative governance has the most significant effect on the depth and breadth of the spread of collaborative behavior in governance networks. The size of the network determines the speed of network diffusion. The smaller the network size, the more sensitive it is to the spillover benefits of collaborative governance, and the larger the network size, the more sensitive it is to the penalties of non-compliance. The findings of the study have implications for the collaborative behavior of multiple agents in public crisis governance. The main findings are that (1) in order to ensure the stability of the collaborative governance system, decision making options should be selected according to the size of the network. (2) A reasonable penalty mechanism for breach of contract should be set up to avoid the phenomenon of "free-riding" in collaborative governance. (3) Reasonable allocation of collaboration benefits and maintenance of cooperative relationships between nodes in the neighborhood. (4) External regulators should ensure that information in the network is disseminated without barriers and reduce the phenomenon of information asymmetry.

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[1] School of Business, Shenyang University, Shenyang 110064, P.R. China.
[2] School of Information Management, Nanjing University, Nanjing 210023, P.R. China.
[3] Business Research Institute, Beijing College of Finance and Commerce, Beijing 101101, P.R. China.
[4] School of Business, Dongguk University, Seoul 04620, South Korea.
*Corresponding author: rose_1844100@cueb.edu.cn

Nomenclatu

Parameters

		$s_{-i}^j(T)$	vector matrix of governance strategies chosen by other agents in period T
G	diffusion initial network	λ	sensitivity of attractiveness parameters in strategic decision making
V	a collection of nodes in a network	$1/\lambda$	coefficient of noise
L	a collection of edges in a network	s_i	pure strategy computed by subject i based on the attractiveness index
a_{ij}	a direct connection between two nodes	r	game radius of nodes in a network
m_0	number of isolated nodes	h_{ij}^T	costs of adopting a collaborative governance strategy
m	the number of edges connected by a node	c_{ik}	spillover effect coefficients from different strategies
N_0	total number of nodes in the current system	C_{ij}^T	default penalties for breach of the concerted contract
S_i	strategy space	γ_{ij}	initial benefit
U	strategic gains	$p_{s_i}^{T+1}$	probability that subject i chooses governance strategy s_i at moment $T+1$
γ	own benefits before subject state transfer		
μ	discount factors	Acronyms	
δ	real income	EWA	a stochastic game learning model formed by mixing reinforcement learning and belief learning
$\emptyset$	depreciation rates for subject selection experience		
$A_j^i(T)$	attraction index of subject i to governance strategy j in period T		
s_i^j	the governance strategy chosen by subject i in period T		

1. Introduction

Today, the frequent occurrence of public crisis events has triggered a rapid increase in the international community's attention to public crisis governance and emergency management [19]. In particular, the outbreak of COVID-19 Risk in early 2020 has led countries around the world to consider the governance of public crisis events as an important part of national governance. Governments attach great importance to the ability and level of governance of public crisis events, taking the level of public crisis governance as a major factor in measuring the overall level of national governance [23,35]. In China, for example, more than 9 public crises occurred in the whole of 2021 alone, as shown in Table 1. Compared to 2020, public crises in China are increasingly characterized by frequent occurrences, increased intensity and complex compounding. These large-scale public crisis events generate a chain of critical incident disasters. This is a network of public crises formed by primary emergencies and one or more secondary crises arising from them. Primary emergencies result directly from human activities or abnormal changes in the environment. Secondary public crises are "collateral" or "extended" crisis events caused by the primary emergency, and the coupling of the two produces a "cascading failure effect" that can greatly spread the crisis in the form of a network. They have not only caused serious losses of people's lives and property, but also reflected the absence and inadequacy of China's public crisis governance approach at this stage. The high complexity, frequency and uncertainty of the development and evolution of public crisis

TABLE 1. Cases of Public Crisis Events in China 2021.

NO.	Type of event	Month and year	Place of occurrence	Name of event
1	Accidents & Disasters	2021.1	Yantai, Shandong Province	"1.10" Shandong Yantai gold mine major explosion accident
2	Social Security	2021.5	Dalian, Liaoning Province	"5.22" Dalian car hit-and-run incident
3	Accidents & Disasters	2021.5	Baiyin, Gansu Province	"5.22" Gansu Baiyin Yellow River Stone Forest Marathon Trail Running Accident
4	Accidents & Disasters	2021.6	Shiyan, Hubei Province	"6.13" Hubei Shiyan market major gas explosion accident
5	Accidents & Disasters	2021.7	Shangqiu, Henan Province	"6.25" Major Fire Accident at Shangaie Wushu Gymnasium in Henan Province
6	Accidents & Disasters	2021.7	Suzhou, Jiangsu Province	"7.12" Hotel collapse in Suzhou, Jiangsu
7	Natural hazards	2021.7	Zhengzhou, Henan Province	"7.20" Heavy Rainfall in Zhengzhou, Henan Province
8	Accidents & Disasters	2021.7	Changchun, Jilin Province	"7.24" Major fire accident at logistics warehouse in Changchun, Jilin
9	Accidents & Disasters	2021.10	Shenyang, Liaoning Province	"10.22" Gas explosion at Shenyang Hotel

events have aroused widespread concern from all walks of life and have become a major hidden danger affecting economic and social harmony and stability [39].

Faced with the increasing prominence of the destructive, dynamic, random and non-linear nature of public crisis events, a single government decision can no longer meet the needs of public crisis governance [35]. In response to complex and volatile public crisis events, the UN Global Crisis Response Team has worked with relevant agencies to revise disaster risk reduction policies, reports and share information to support national, regional and global disaster reduction efforts [38]. It also suggests that a social governance community should be established in the face of public crises to ensure that all groups in society can participate in governance activities. From this perspective, the public crisis governance model should be shifted from the traditional model of single government management to one in which the government, enterprises, social groups and citizens participate together. This is a collaborative model of public crisis governance that integrates online and offline, thus effectively enhancing the effectiveness of public crisis governance [22].

There is a large amount of research on collaborative public crisis governance. Chen *et al.* [6] emphasized the importance of partnerships for disaster resilience, highlighting in particular that the stability of government, business, NGOs and community participation in the process is relevant to the effectiveness of disaster resilience governance. Christensen *et al.* [8] used the Norwegian government's response to the COVID-19 virus as an example to analyses how combining citizens' rights of popular legitimacy with the government's ability to govern is the key to effective management of public crisis events in the process of public crisis governance. Choi [7] explored the collaboration created by a public crisis governance system involving various sectors of the public and private sectors, using the Korean response to the COVID-19 virus as an example. Zhang [46] suggests that the governance of public crises, especially major public health crises, should form a "Stimulus-Response" chain model of governance, emphasizing the participation of different social agents in governance

and information sharing. Comfort *et al.* [9] suggest that collaborative management of cross-regional public crises by local governments is essentially a 'Cooperative-Transactional' behavior. The existing research findings focus on qualitative or quantitative analysis at the macro level, and lack attention to the micro basis of the evolutionary process in the collaborative governance system. Research methods are relatively homogeneous, research perspectives lack interdisciplinary research, and there is a lack of analysis of how to achieve the emergence of multi-agents group behavior within the public crisis governance system.

The agents of public crisis governance are constantly cooperating, competing, evolving and playing games with each other. It is a complex network of agents connected by functional, technical and information flows. The structural characteristics of complex networks have an important influence on the evolution of the agents within them. Koliba *et al.* [24] proposed a complex accountability governance network framework through the governance process of Hurricane Karina in 2005. Vanden Oordet *et al.* [36] constructed and simulated an evolutionary model of a community public crisis governance network based on COVID-19 outbreak prevention and control in Belgium. Boeke [2] used Provan and Kenis' model of network governance to analyze the potential role of multi-agent behavioral emergence in emergency response networks in four countries - the Netherlands, Denmark, Estonia and the Czech Republic - on the overall network. Yang *et al.* [41] found through entity-relationship network (E-R) analysis that neighbor-avoidance conflict agents can only adapt to environmental changes through continuous adaptive learning. Although the above studies have analyzed the evolutionary process of collaborative governance in public crises from the perspectives of complex network theory and evolutionary game theory respectively, they lack a comprehensive perspective that combines complex networks and evolutionary games. There is also little coverage in the research of issues such as diversity and uncertainty in the decision-making behavior of multiple agents involved in governance. If complex network evolutionary game theory is used to analyze the agents of collaborative public crisis governance and to explore the evolutionary game process among microscopic agents in complex networks, it can reveal the complex connections among the agents in complex systems. This is particularly useful for analyzing the diffusion process of multi-agent collaborative behavior and the emergence of multi-agent agglomerative behavior in macro systems.

On the other hand, public crisis governance systems are composed of a large number of heterogeneous micro-actors. Then the heterogeneous actors involved in governance can accept the concept and requirements of collaborative public crisis governance in terms of their preferences, capabilities, resources and behaviors. These directly determine whether the complex network can successfully achieve the proliferation of collaborative governance behaviors. De Balanzo *et al.* [11] studied the case of Barcelona, Spain, and found that the heterogeneity of agents in social networks facilitated learning, experimentation and social innovation, and had the flexibility that single agent dominated groups lacked. Freemark [12] argues that multi-agent public sector governance can create healthy and diverse communities, and McGuire *et al.* [27] develop a theoretical and analytical model of adaptive 'Polycentric-Collaborative governance' for heterogeneous agents, which is more likely to be self-driven, with a division of labor and synergistic mechanisms. Studies have shown that researchers have not paid much attention to heterogeneous agents in the public crisis governance system, especially on the behavioral decision-making patterns of heterogeneous agents and how self-learning and self-adaptation of heterogeneous agents lead to group macro-evolution. However, an analysis of the behavior of micro-heterogeneous agents in networks can fill this gap. By organically linking the micro-behavior of a single subject to the 'emergence' of a macro-system of multi-subject governance behavior, the 'micro-macro' operational mechanism for the emergence of collaborative public crisis governance can be revealed.

In summary, this paper applies the complex network evolutionary game research method, based on the perspective of micro-heterogeneous agents in the network, and considers their influence on the emergence of subjects' collaborative behaviors in the governance system, which are the expected benefits of heterogeneous agents' strategy choice, adaptive self-learning behavior, and inter-node game behavior in the neighborhood. And based on the EWA learning model to construct a diffusion model of collaborative governance behavior in public crises. This research models the diffusion system of multi-actor participation in public crisis governance in a complex network through a Matlab simulation platform. Simulation experiments are also conducted to investigate

the influence of the decision-making behavior of micro-heterogeneous agents, the complex network structure and network externalities on the diffusion mechanism of governance networks in public crisis governance systems.

The remainder of the paper is organized as follows. Section 2, presents a diffusion network for collaborative multi-agent governance behavior in public crises. Section 3, displays a learning model of heterogeneous agents in collaborative public crisis governance. Section 4, presents model and algorithm for collaborative behavioral diffusion. Section 5 simulation results and discussion. Section 6 summarizes the research findings and proposes corresponding policies.

2. A DIFFUSION NETWORK FOR COLLABORATIVE MULTI-AGENT GOVERNANCE BEHAVIOR IN PUBLIC CRISES

The public crisis governance system can be seen as a complex social network formed by the various agents involved in governance within the system as nodes and the existence of certain direct relationships between different agents as edges [31–34]. In this complex network, there is a certain heterogeneity of the agents involved in governance [21, 26, 28]. A large number of heterogeneous agents interact with each other and constantly play the game, allowing the equilibrium of the system to change constantly [43]. The individual behavior of nodes emerges through aggregation to form a macroscopic phenomenon of the complex system, which is ultimately reflected in the diffuse evolution of the whole network [16]. The above findings provide a theoretical basis and framework for the study of collaborative public crisis governance in complex networks [14]. Although in social networks, interconnected nodes have characteristics such as specificity and limitations. The vast majority of nodes are not adjacent to each other, but neighboring nodes of a node are likely to be adjacent to each other. Most arbitrary nodes can access other nodes with fewer steps or jumps, and the inter-node game behaviors are only linked and acted upon by nodes in their neighborhoods, presenting the characteristics of a small-world social network. Existing research has shown that in the real world, the degree distribution of many complex social networks obeys the properties of a power-law distribution [37]. In order to better explain the formation mechanism of the power-law distribution, we can adopt the BA scale-free degree model. Therefore, this research will use the BA scale-free model to portray the diffusion phenomenon of collaborative multi-agent governance behavior in public crises.

The governance approach to government decision-making suffers from hesitant emergency decision-making [30], poor communication of fragmented information [42], ineffective early warning response [10], and fragmented governance departments [13]. It is unable to cope with the demands of a dynamic, uncertain, complex and non-linear public crisis matter. Therefore, an important way to effectively respond to frequent and volatile public crisis events is to involve multiple governance agents. In the process of governance, participants imitate each other in choosing the optimal governance strategy behavior [3]. In a public crisis governance system, when one agent succeeds in achieving the greatest benefit from a governance strategy, through cooperation or other means, this decision prompts many agents in the system to imitate each other, and eventually this behavior spreads rapidly. The evolution of collaborative governance behavior among public crisis agents is also a process in which governance strategies emerge and are imitated and learned from each other. In a collaborative public crisis governance system, a lack of behavioral imitation and innovation in decision-making will lead to a rigid development of the system, making it difficult for efficient governance strategies to emerge. The act of maximum benefit governance strategy imitation is a process of governance strategy optimization [17]. It reflects the agent's rational trade-off between the costs and benefits of governance strategies, and the process of discovering and introducing more effective governance strategies. In a repetitive game, the players in a public crisis governance system maximize the benefits of their choice of governance strategy by imitating, learning and choosing the best.

Based on the above analysis, the initial network G(V, L) for the diffusion of collaborative governance behavior of multiple agents in public crisis is constructed by combining the properties of BA scale-free networks [5], where V = $\{v_1, v_2, \cdots, v_N\}$ represents the set of all nodes in the public crisis governance network, representing the agents involved in governance; L = $\{l_1, l_2, \cdots, l_K\}$ represents the direct relationship between the agents involved
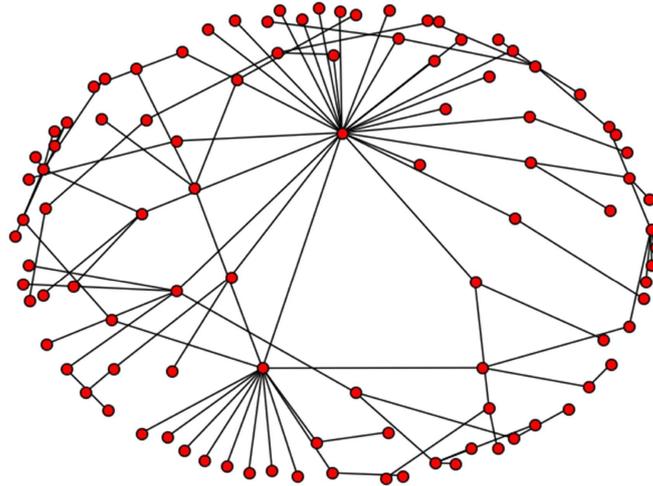
FIGURE 1. Scale-free network diagram for $N = 100$.

in public crisis governance, which may be either competitive or cooperative. It is assumed that all nodes in the network affect each other, meaning that the edges connecting nodes in the network are undirected edges and that there is at most one contiguous edge between two nodes. In the network, if there is a connecting edge between point v_i and point v_j, it means that there is a direct relationship between the two, denoted as $a_{ij} = 1$. Otherwise, it means that there is no direct relationship between the two then $a_{ij} = 0$. The diffusion network of collaborative behavioral governance of public crises is part of a complex social network and therefore also has the topological and statistical characteristics of a complex network [1]. In this paper, the network topology is characterized by the degree distribution, the average path length, and the aggregation factor.
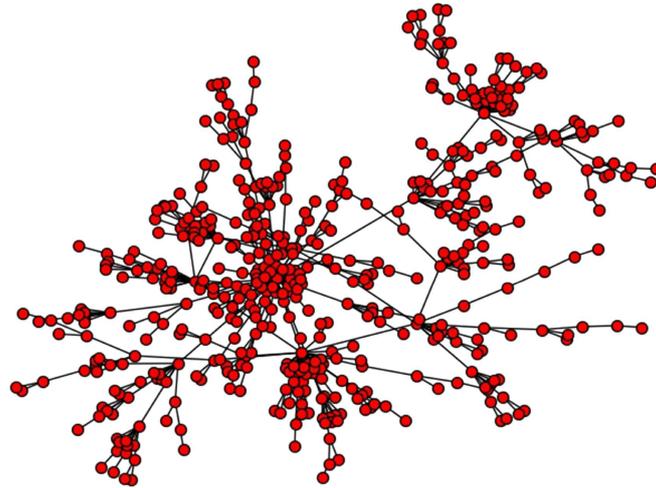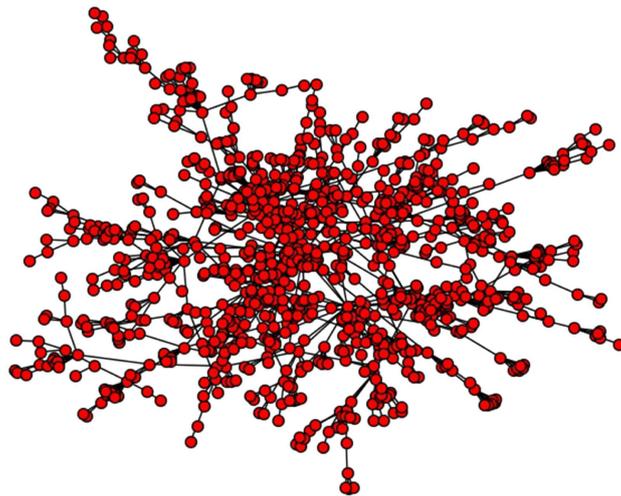
We calculate the degree distribution of the BA model analytically by means of a meanfield approach with the following algorithm:

(1) Initial condition $t = 0$, network consists of m_0 isolated nodes.
(2) Each time step t adds a new node into the network with m $(\mathrm{m} \leq m_0)$ edges.
(3) The probability of a newly joined node making a connection with an existing node i in the network is $\prod_i = \frac{k_i}{\sum_{j=1}^{N_0} k_j}$, where N_0 is the total number of nodes in the current system, and after a time interval of t produces a network of $\mathrm{N} = m_0 + mt$ nodes and mt edges, with a power-law distribution of degree.
(4) For any node i, the change in degree $k_i(t)$ satisfies the kinetic equation $\frac{\partial k_i(t)}{\partial t} = \Pi(k_i) = \frac{k_i}{\sum_j k_j}$. Python was used to simulate different network sizes, where Figures 1, 2 and 3 show the topological relationship of a randomly generated BA scale-free network of 100 nodes, 500 nodes and 1000 nodes in the initial state, respectively.

3. A LEARNING MODEL OF HETEROGENEOUS AGENTS IN COLLABORATIVE PUBLIC CRISIS GOVERNANCE

3.1. Self-learning behavior of heterogeneous agents in collaborative public crisis governance

The network of multi-agent collaborative governance behavior diffusion in public crises is composed of a large number of heterogeneous agents with limited rationality [44]. The agents belong to different group types, such as local governments, enterprises, NGOs, media, experts, the public, etc. There are agents in the same group

FIGURE 2. Scale-free network diagram for $N = 500$.

FIGURE 3. Scale-free network diagram for $N = 1000$.

with different personalities and behavioral traits. Even the same type of agents can be highly heterogeneous due to differences in group size, social attributes, productive capacity, public crisis management preferences, profitability, literacy, resource conditions and competitive strength [20, 25, 45]. The focus of this research is to explore the interactions between heterogeneous subjects in diffusion networks. This leads to a precise portrayal of the emergent scale effect of group behavior under the combined effect of single-agent self-learning and inter-agents interaction and cooperation. The heterogeneity of agents in complex networks plays an important role in the research on the proliferation of collaborative multi-agent governance behavior in public crises. As the agents involved in governance have different goals and different expectations for achieving them, this leads to a greater variability in the behavioral decisions and interactive cooperation of the agents. In the process of public crisis governance, the governing agent decides whether to adopt a particular governance behavior by comparing the governance strategies of other agents in the neighborhood in order to maximize the benefits of its governance

strategy. In complex networks, the evolution of multi-agent collaborative governance behavior is driven by the diffusion of optimal strategies, and ultimately the formation of multi-agent collaborative governance clusters in public crises.

3.2. EWA model of heterogeneous agents

In evolutionary games, determining the self-learning behavior of the players and the way in which strategies are optimized is a central issue for research. Heterogeneous agents involved in public crisis governance are adaptive and self-learning. They are able to adjust their current governance strategies through game learning, based on their own governance strategies and objective functions, the strategies of other subjects in their neighborhood and their expectations for the future. In the evolutionary process, although the past experiences of heterogeneous agents play a role in the proliferation of collaborative governance behaviors in the network, the key driving force behind the proliferation of collaborative multi-agent governance behaviors in public crises comes from the self-learning and adaptive capacity of heterogeneous agents and their inter-agent interaction behaviors. This is also an important feature of evolutionary game models of complex systems. Therefore, this article introduces the experience-weighted attraction (EWA) learning model to construct a learning model for heterogeneous agents involved in public crisis governance, taking into account the self-learning ability of heterogeneous agents [4].

The EWA model is a stochastic game learning model formed by mixing reinforcement learning with belief learning. It is a finite-state discrete Markov process. We assume that a regular game with n players has m_i choices of strategy s_i for player i with a strategy space $S_i = s_i^1, s_i^2, \cdots, s_i^{m_i}, s_i \in S_i$, where $S = S_1 S_2 S_3 \cdots S_n$ is a Cartesian product of independent strategy spaces; the payoff $\pi_i(s_i, s_{-i})$ for player i. When the state of the environment is probability P and the state transitions from e to e', then,

$$\mathrm{Prob}\left(e = e'/e, m_i\right) = P\left(e, m_i, e'\right). \tag{1}$$

At this point, the group gain is U as:

$$\mathrm{U}(e) = \gamma + \mu \sum P\left(e, m_i, e'\right) v\left(e'\right) \tag{2}$$

where γ is the subject's own gain before the state shift; μ is the discount factor; and $v\left(e'\right)$ is the gain under state e'. $\longleftrightarrow$

According to complex network theory, heterogeneous agents involved in public crisis governance are capable of self-learning, able to assess the benefits of the strategies chosen by other agents in their neighborhood, and to engage in imitative behavior if the benefits are greater than the benefits of their own decisions at the moment. The utility function of a body at this point is related to the number of other bodies in the neighborhood that prefer the same strategy, which means that collaborative governance decisions in diffusion networks have significant network externalities. Since the players in an evolutionary game select only the agents in their neighborhood, only direct network effects are considered for the externalities of the diffusion network.

In summary, this study considers the direct externalities of diffusion networks and the possible compatibility between different governance strategies. We construct the learning model by considering the effect of heterogeneity of participating governance agents and combining it with the network externality utility function of Holland [15, 18]. In period T, the expected payoff function U_{ij}^T for heterogeneous agent i choosing governance strategy j is

$$\mathrm{U}_{ij}^T = \gamma_{ij} + v\left(g_{ij}^T\right) + \sum_{k \neq j} v\left(c_{ik} g_{ij}^T\right), 0 \leq c_{ik} \leq 1 \tag{3}$$

where γ_{ij} is the initial gain from strategy j for heterogeneous agent i, indicating the agent's initial preference for governance decisions. This gain is the heterogeneous agent's initial estimate of the gain from adopting governance strategy j based on its own assessment of the resources, information and learning capacity it possesses. It is fixed and does not change over time nor is it subject to external influences. Due to the heterogeneity characteristic of agent i, it is assumed that γ_{ij} obeys the distribution of the random function $\gamma_{ij} = \mathrm{rand}[0, 1](i =$

$1, 2, \cdots, n), \mathrm{v}\left(g_{ij}^T\right)$ denotes the gain from the positive externality of the network; e_{ij}^T is the number of agents in the neighborhood of agent i who choose governance strategy j at moment t; c_{ik} denotes the coefficient of the spillover effect arising from the choice of different strategies.

In the EWA model, the attractiveness index determines the probability of a governance strategy being selected at random, so the higher the attractiveness index the higher the probability of a governance strategy being selected. The formula for the attractiveness index is shown below.

$$A_i^j(T) = \frac{\emptyset N(T-1)A_i^j(T-1) + \left[\delta + (1-\delta) * I\left(s_i^j, s_i(T)\right)\right] * \pi_i\left(s_i^j, s_{-i}(T)\right)}{N(T)}. \tag{4}$$

In the above equation, $A_i^j(T)$ denotes the index of agent i 's attraction to governance strategy j in period T. δ denotes the weight of the expected gain for a heterogeneous agent relative to the actual gain. a larger δ indicates that the higher the expected gain for the agent for this decision, the more likely the agent is to choose the strategy. $\emptyset$ denotes the depreciation rate of the agent's choice of experience, combined with equation (3.4) denoting the weighting rule for the subject's experience of attraction; s_i^j denotes the governance strategy chosen by agent i in period $T, I\left(s_i^j, s_i(T)\right)$ denotes the actual benefit of subject i 's choice of governance strategy s_i^j when subject i chooses governance strategy $s_i(T)$ in period T. $s_{-i}^j(T)$ denotes the vector matrix of other agents in the complex network choosing governance strategies in period $T.\pi_i\left(s_i^j, s_{-i}(T)\right)$ denotes the actual payoff of agent i 's choice of governance strategy s_i^j when other subjects choose governance strategy $s_{-i}(T)$ in period T. With the probability μ^T of other agents' governance strategy choices in the complex network, agent i calculates its expected return $\pi\left(s_i/\mu^T\right)$ for choosing each governance strategy s_i (pure strategy) based on the attractiveness index. Based on the magnitude of the expected return to decide the strategy choice in period $T + 1$, the probability that subject i chooses the governance strategy s_i at the moment of $T + 1$ is $p_{s_i}^{T+1}$ [47], where $s_i \epsilon A, \lambda$ denotes that can be measured the sensitivity of the attractiveness parameter in the strategy decision, and $1/\lambda$ can be interpreted as the noise as shown in equation (5).

In order to increase the subjectivity of the evolution rule, this paper chooses the reconnection mechanism with preference to determine the connection point j of node i. Let d be the preference tendency, the larger d is, the more obvious the preference tendency is, and the probability formula of reconnection of the broken edge is shown in (6).

$$p_{s_i}^{T+1} = \frac{\exp\left(\lambda\pi\left(s_i/\mu^T\right)\right)}{\sum_{s_i \in A} \exp\left(\lambda\pi\left(s_i/\mu^T\right)\right)} \tag{5}$$

(λ is the degree to which the agent values self-selection)

$$f_{ij} = \sum_{i \in G} U_j^d/U_i^d. \tag{6}$$

4. MODEL AND ALGORITHM FOR COLLABORATIVE BEHAVIORAL DIFFUSION IN PUBLIC CRISIS GOVERNANCE

Complex network evolutionary game theory consists of three elements: the network structure, the game model and the update rules. Based on the modeling of BA scale-free networks, this research will model the diffusion mechanism of collaborative public crisis governance behavior based on Santos *et al.*'s two-player two-strategy game behavior on BA scale-free networks [29].

4.1. Hypothetical conditions

Based on the structural characteristics of the diffusion network of collaborative public crisis governance behaviors and the realistic need for game model construction, several hypotheses are given as follows.

H1: Heterogeneous agents in a complex network play the game by focusing only on other nodal agents playing the game in a certain neighborhood, which means that the game radius of node i is $r(r = 1)$. This corresponds to the actual situation. Due to constraints in terms of information, resources and geographical location, agents involved in collaborative public crisis governance are unable to establish links with all agents in the economy and society. Therefore, it is more realistic to assume a game between agents in the neighborhood.

H2: Only consider direct network effects in complex network externalities. Because the game is set up between agents in the neighborhood, interactions between agents are restricted to within the neighborhood and the gains are only related to the number of nodes in the neighborhood that adopt the same governance strategy.

H3: Heterogeneous agents in complex networks are finitely rational. The probability of their choice of a strategy depends on the expected payoff of that strategy. However, the possibility of a lapse in judgement and not choosing the optimal payoff solution cannot be ruled out.

H4: Heterogeneous agents adopt the same governance strategy evolutionary update rule. The agent's strategy is updated by determining the strategy to be chosen for the next period based on the outcome of this game only, that is, the memory length $L = 1$.

4.2. Model construction

Based on the framework of White *et al.* [40].'s research, the empirically weighted attraction (EWA) learning model is added to it for improving its evolutionary update rules. In the network of diffusion of collaborative governance behavior in public crises, each agent has two strategies: choosing collaborative governance and rejecting it. The decision-making behavior of heterogeneous agents in the network in choosing or rejecting collaborative governance strategies is influenced by the following factors:

(1) The initial expected return of a heterogeneous agent is γ_{ij}.
(2) The combined benefits from direct network effects in complex network externalities (see Eq. (3)).
(3) The cost of adopting a collaborative governance strategy is h_{ij}^T.
(4) The coefficient of the spillover effect from choosing different strategies is c_{ik}.
(5) When a collaborative governance relationship is entered into, if an agent breaches the collaborative contract, it is subject to a penalty for breach of contract of C_{ij}^T.

When there are network externality benefits, the agents in the network will inevitably assess the expected benefits to themselves from the choice of collaborative governance strategy, and the expected benefits will change as other factors change. Because of the variability of the expected equilibrium, this means that the choice of complex network strategy may be a situation in which one strategy dominates or two strategies exist side by side. As heterogeneous subjects constantly change their strategic choices, this paper analyses the diffusion behavior of collaborative governance of public crises from the perspective of acceptance or rejection of collaborative governance by agents in the network. Heterogeneous agents in complex networks make different choice strategies with different payoffs, as follows. ←

Strategy 1: If the agent does not make any strategic choices at moment T, then no strategic choices will be made in subsequent time periods either: $U_{ij}^T = \gamma_{ij}$.
Strategy 2: Reject the co-governance strategy at moment T, but will choose the cogovernance strategy at moment $T + 1 : \mathrm{U}_{ij}^T = \gamma_{ij} + v\left(g_{ij}^T\right) + \sum_{k \neq j} v\left(c_{ik} g_{ij}^T\right) - h_{ij}^T$.
Strategy 3: The co-governance strategy is chosen at moment T and the co-governance strategy will be rejected at moment $T + 1$ in violation of the co-governance contract: $U_{ij}^T = \gamma_{ij} - C_{ij}^T \leftarrow$
Strategy 4: Having chosen a collaborative governance strategy at moment T, it will continue to choose to adopt a collaborative governance strategy at moment $T + 1 : \mathrm{U}_{ij}^T = \gamma_{ij} + v\left(g_{ij}^T\right) + \sum_{k \neq j} v\left(c_{ik} g_{ij}^T\right)$

4.3. Diffusion algorithm

Based on the BA scale-free network, the algorithm of the public crisis collaborative governance behavioral diffusion model in this study is shown in Figure 4.
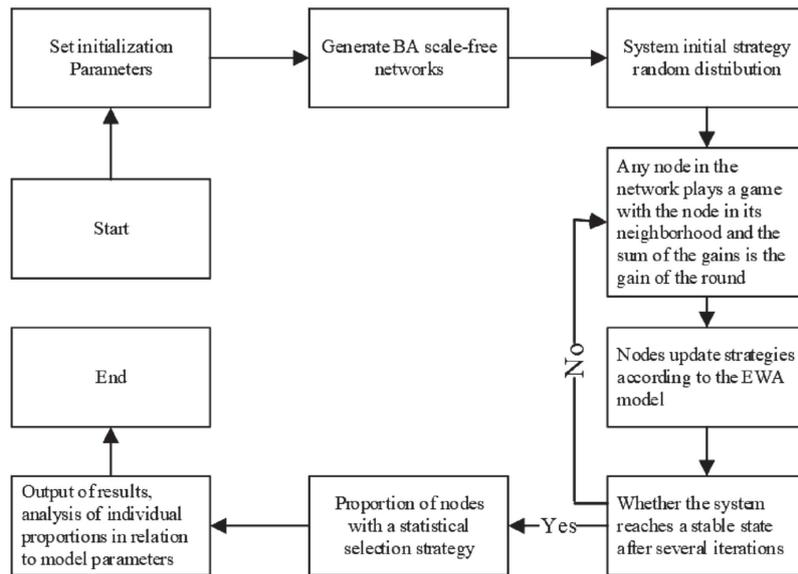
FIGURE 4. Evolutionary game flow on BA scale-free networks.

Step 1, the BA scale-free network is constructed and initialized with parameters.

Step 2, determine the rules of the evolutionary game between heterogeneous agents in the network. In each evolutionary cycle T, heterogeneous agents choose to play with other agents in the neighborhood (game radius r) to obtain the corresponding gains according to four strategies, and the gain of each agent is the sum of the gains obtained from playing with other agents in the neighborhood. If there are no other nodes in the neighborhood (radius r of the game) then no game is played.

Step 3, set up policy update rules. Agents in the network update the collaborative governance policy according to the set policy update rules. In each evolutionary cycle T, the probability p of making different policy choices is calculated according to the EWA learning model, and the policy update is randomly chosen to adopt or reject the collaborative governance policy according to the magnitude of p. In the network, any node i is reconnected to other nodes j with probability f_{ij}

Step 4, executed cyclically until the end of the predetermined time step.

5. SIMULATION RESULTS AND DISCUSSION

This paper considers two main situations in which public crisis governance collaborates with the decision-making behavior of governance agents. On the one hand, when faced to a public crisis event, agents can choose to accept collaborative governance or reject it. They both try to have their choice accepted by a larger number of subjects in the governance network. This results in an analysis of the behavioral emergence and diffuse evolution of complex systems. On the other hand, when a strategy has been accepted by the majority of agents, but it emerges that an agent has updated the strategy, analyses how and whether other agents in the system follow them to move to the new strategy. Thus, the key factors influencing the switch in the behavioral strategies of agents in the network are investigated. For the convenience of the study, it is assumed that there are two strategy choices within the system accepting co-governance as 1 and rejecting co-governance as 0. Heterogeneous agents can choose either strategy, but cannot adopt both strategies at the same time.

TABLE 2. Public Crisis Collaborative Governance Behavioral Simulation Parameter Setting.

Parm Code	Initial benefit γ_{ij}	Collaborative costs h_{ij}^T	Spillover benefit factor c_{ik}	Penalties for breach C_{ij}^T
N_{11}, N_{12}, N_{13}	3	8	0.8	2
$N_{21}, N_{22}, N_{23}+$	3	6	0.6	3
N_{31}, N_{32}, N_{33}	3	4	0.4	4
N_{41}, N_{42}, N_{43}	3	3	0.2	5

5.1. Initial parameter setting

As the agents involved in public crisis governance are mostly clustered agents such as local governments, enterprises, NGOs and the public, in order to match the characteristics of the number of agents in different situations, the three scaled scale-free networks set up in this article are the vehicles. The diffusion process of collaborative public crisis governance behavior is explored with 100,500 and 1000 nodes respectively (see Tab. 2). N_{ij} is used as the diffusion curve, i represents the four types of parameter settings and j represents the three sizes of networks. Based on the above model setup, the following simulation of the scenario was carried out based on the Matlab simulation platform, where the x-axis is the number of network nodes and the y-axis is the collaborator density $f_c(t)$.

5.2. The impact of collaboration costs on evolution

According to the above parameter settings, the number of tests is Times $= 100$, the number of cycles runs Ticount $= 20$, the initial benefit $\gamma_{ij} = 3$, and the fixed spillover benefit coefficient c_{ik}, and the default penalty cost C_{ij}^T, take the values 0.4 and 5 respectively. On the basis of this, the cost of collaboration h_{ij}^T is changed to the following values: $8, 6, 4$ and 3 , respectively, to examine the diffusion of the choice of collaborative governance behavior of the agents involved in public crisis governance in a scale-free network of 100 nodes, 500 nodes and 1000 nodes, and the diffusion results are shown in Figure 5. In a network with node 100, the cost for agents to accept collaborative governance is greater than the penalty for breach, and the coefficient of collaborative spillover benefit is smaller, the collaborative governance behavior is not compensated accordingly, the level of cooperator density $f_c(t)$ in the network decreases monotonically, and the participating governing agents refuse to collaborate in governance. As shown in the N_{11} curve in Figure 5(a), the combined public crisis governance benefits for some of the agents involved in governance are lower than the expected value when the cost of the agents' decision to opt for collaborative governance behavior is greater than the penalty for breach of contract. This results in the sum of synergy costs and group synergy spillover benefits being greater than the sum of default penalties and synergistic governance benefits. Participating governance agents will not choose a collaborative governance strategy when faced with a loss of their own benefits, which leads to a decrease in the density of collaborators $f_c(t)$.

As shown in the N_{41} curve in Figure 5(a), when the cost of an agent's decision to choose to accept collaborative governance behavior is less than the penalty for default, the combined benefits of the agents involved in the governance component are higher than the expected value. At this time more agents are willing to choose to accept the collaborative governance strategy, resulting in a monotonic increase in the level of cooperator density $f_c(t)$. Similarly, examining Figures 5(b) and (c), the evolution of the N_{41} curve accelerates when the number of network nodes increases. Due to the combined gains increasing the nodes in the network are rapidly self-learning and adapting, adjusting their strategy choices during the game, such that the N_{41} curve converges quickly to 1 . This shows that the agents in the network that obtain higher game gains change from low-connected to high-connected collaborators, and the whole network evolves in the direction of collaborative governance diffusion.
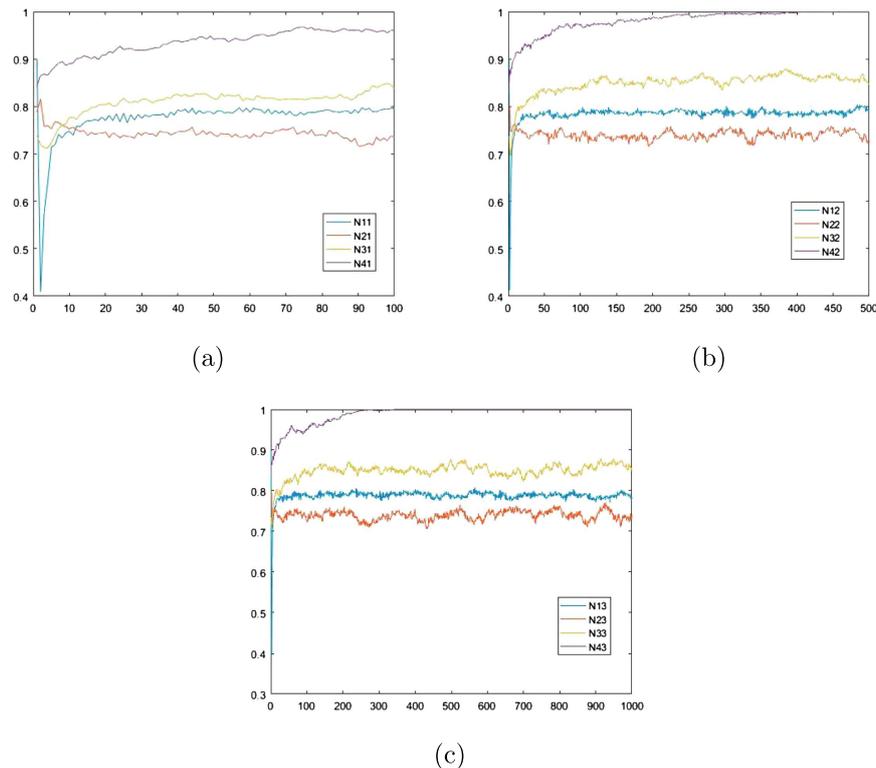
(a)

(b)

(c)

FIGURE 5. Results of the impact of collaborative costs on network diffusion. (a) $N = 100$. (b) $N = 500$. (c) $N = 1000$.

It is worth stating that the results of the above study use a cumulative utility function to measure the individual game payoffs, which is consistent with the results for the overall game behavior on scale-free networks. This is because the cost of synergy, h_{ij}^T is not related to increasing benefit differentials and individual network relationships, but only to the agents' own behavioral decisions. The increased game gain of highly connected nodes due to the increased spillover benefits of collaborative governance is only related to the heterogeneity of scale-free network nodes and not to the agglomeration of scale-free networks. Therefore, the effect of the initial setting of the scale-free network agglomeration parameter ($q = 0$ or $q = 0.9$) on the evolution of the diffusion of collaborative network governance behavior remains consistent regardless of whether it is high or low.

5.3. The impact of spillover benefits on evolution

The impact of collaborative governance spillover benefits on the diffusion of collaborative governance behaviors chosen by agents in the governance network is further discussed. According to the parameter settings in Table 1, the initial benefit $\gamma_{ij} = 3$. The fixed cost of collaboration h_{ij}^T and the penalty cost of default C_{ij}^T take values of 4 and 5 , respectively. On this basis, the spillover benefit coefficient c_{ik} is varied to take values of: 0.8, 0.6, 0.4 and 0.2 . Scale-free network participation at 100 nodes, 500 nodes and 1000 nodes are examined, respectively. The diffusion of the choice of collaborative governance behavior by public crisis governance agents. The simulation results are shown in Figures 6(a), (b) and (c).

Observing Figure 6(a), it can be seen that in a network with 100 nodes, when the coefficient of collaborative governance spillover benefit is 0.2 , the result of the cooperator density $f_c(t)$ of the scale-free network after 100 games is relatively stable at 0.25 . Because the cost of collaboration and the penalty for default make
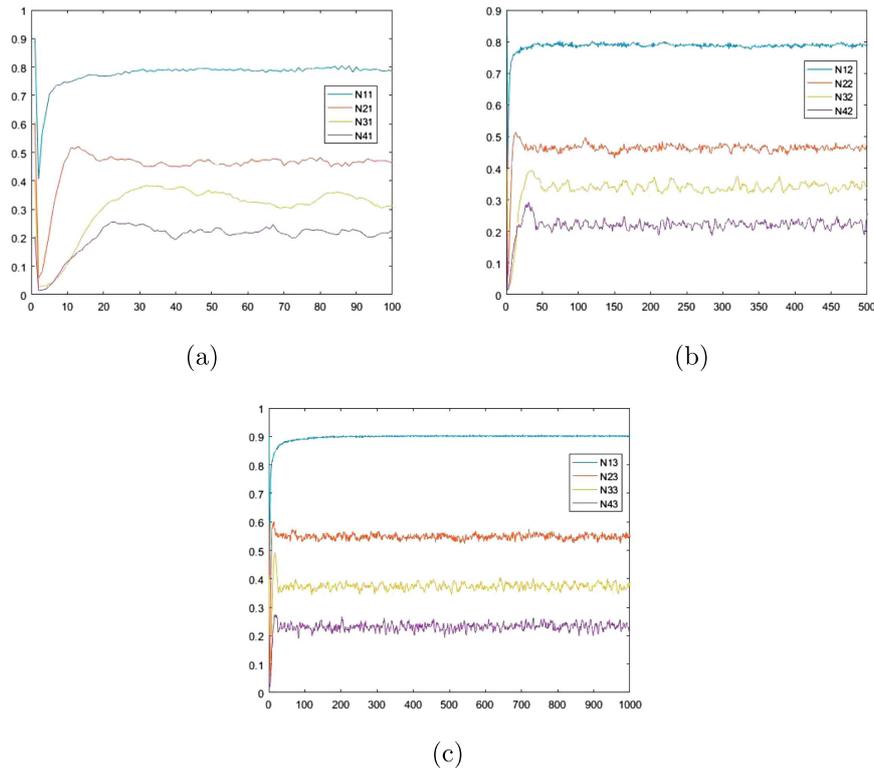
(a)

(b)

(c)

FIGURE 6. Results of the impact of spillover benefits on network diffusion. (a) $N = 100$. (b) $N = 500$. (c) $N = 1000$.

heterogeneous agents in smaller networks make the next game decision after comparing the cumulative benefits of T with $T + 1$ games, governance agents are reluctant to choose collaborative governance behavior for less cumulative benefits, so the cooperator density $f_c(t)$ stabilizes at a low level. When the coefficient of collaborative governance spillover benefits is 0.8 , the result for the density of collaborators in the governance network $f_c(t)$ is relatively stable at 0.75 . This indicates that the diffusion breadth of the network increases as the spillover benefits increase. This is attributed to the fact that heterogeneous agents in the network, after assessing the benefits of the game, imitate the high-yield decision-making behavior in their neighborhoods and thus accept collaborative governance. Similarly, observing Figures 6(b) and (c), it can be seen that in networks with 500 and 1000 nodes, when the collaborative governance spillover gain is 0.8 , the results of the cooperator density $f_c(t)$ in the governance network are relatively stable at 0.8 and 0.9 after 100 games. It can be seen that when the size of the scale-free network increases, the self-learning and adaptive behavior of heterogeneous agents in different neighborhoods of the network becomes more significant, making them choose behavioral decisions that are more beneficial to their own interests. In addition to the "herd effect" on the network, most agents also tend to keep pace with the network evolution trend, and eventually the network diffusion of collaborative governance behavior reaches a stable state of 0.9 . In particular, the larger the network, the faster the spread of acceptance of collaborative governance in the network, and the closer to 1 the final evolutionary outcome.

5.4. The impact of penalties for breach on evolution

According to the parameter settings in Table 1, the initial benefit $\gamma_{ij} = 3$. The fixed cost of collaboration h_{ij}^T and the spillover benefit coefficient c_{ik} take values of 4 and 0.4 respectively. On this basis, the default penalty
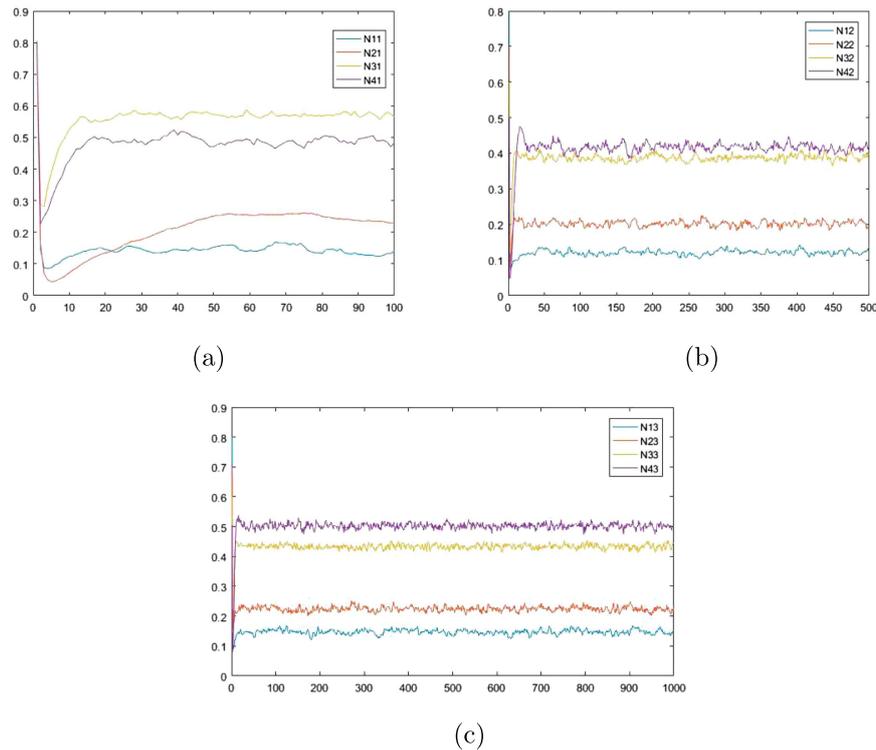
FIGURE 7. Results of the impact of penalties for breach on network diffusion. (a) $N = 100$. (b) $N = 500$. (c) $N = 1000$.

cost C_{ij}^T is varied to take values of 2, 3, 4 and 5, in that order. Scale-free network governance agents at 100,500 and 1000 nodes, respectively, are examined in terms of their choice of collaborative diffusion of governance behavior. Looking at Figures 7(a), (b) and (c), the effect of default penalty strength on the choice of collaborative governance behavior by governing agents at different network sizes. In a comparative analysis of N_{11}, N_{21}, N_{31} and N_{41} in a network of size 100 nodes (Fig. 7(a)), the collaborator density $f_c(t)$ evolves significantly faster when the default penalty is 5 than when the default penalty is 2 . The effect of the default penalty is most evident in the size network with 1000 nodes (Fig. 7(c)). The evolutionary stability of the cooperator density $f_c(t)$ is positively correlated with the amount of default penalty, which means that the higher the penalty amount the greater the value of evolutionary stability of the cooperator density $f_c(t)$. In other words, a well-developed penalty mechanism can facilitate the spread of collaborative governance behavior among nodes in a scale-free network and reach an evolutionary steady state of cooperator density $f_c(t)$ more quickly. The higher the penalty for breach the more likely it is that heterogeneous agents in the neighborhood will be motivated to perform collaborative governance behaviors. In the governance process, this largely discourages midcourse defaults due to the high cost of collaboration, thus safeguarding the smooth implementation of the collaborative public crisis governance process.

Continuing to compare Figures 7(a), (b) and (c), when the cost of collaborative governance is less than the penalty for breach, it influences some agents to reject collaborative governance behavior. This leads to a change in the combined benefits under agents' choice of collaborative governance behavior and a change in the evolutionary steady state of the diffusion breadth of the governance network and the density of collaborators $f_c(t)$. Comparing N_{41} with N_{31} in Figure 7(a), although the default penalty for the former is 5 greater than 4 for the latter, the cost of collaborative governance is less than the default penalty at this point, and the N_{41}
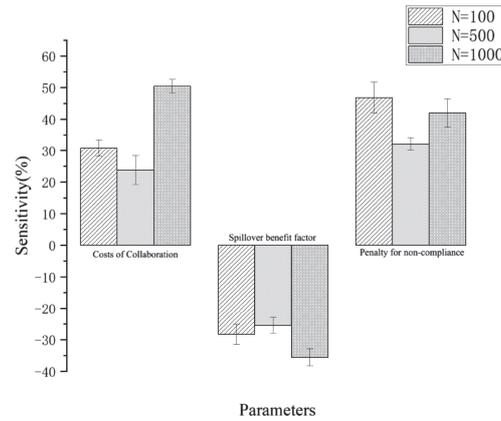
FIGURE 8. Parameter sensitivity analysis at different network sizes.

curve cooperator density $f_c(t)$ converges at a lower steady point of 0.45 than the N_{31} curve of 0.55 . Comparing different network sizes, it can be found that in small-scale networks ($N = 100$), the promotion effect of default penalties on the diffusion of collaborative governance behaviors is more significant. In particular, the rate of diffusion (reflected in the collaborator density $f_c(t)$) gradually increases as the network size increases. It can be seen that a well-developed penalty mechanism can promote collaborative governance behavior in large-scale networks. The twoway complementarity of collaborative spillover benefits and default penalties is a key factor in promoting network diffusion. When heterogeneous agents in a network have high collaborative capacity, they can compensate part of the cost of collaborative governance, allowing for collaborative governance spillover benefits between agents in the neighborhood, thus enhancing the diffusion capacity of the network. In networks of different sizes, the larger the network size, the more pronounced the effect of default penalties on the rate of upward diffusion.

5.5. Sensitivity analysis

In order to prove that the parameters are not affected by distortions of outliers or special events, the paper performs sensitivity analyses of each parameter that affects the degree of emergence and diffusion of complex networks. According to the above model the sensitivity analysis is performed in STATA software, if the result is positive, it means that it is positively correlated with the collaborator density $f_c(t)$, and the larger the result is the higher the sensitivity of the parameter. If the result is negative, it means negative correlation and the larger the absolute value of the result the higher the parameter sensitivity.

Determine the distribution function of the random variables in the diffusion modelling algorithm, that is, collaborative costs h_{ij}^T, spillover benefit factor c_{ik} and penalties for breach C_{ij}^T. Random values were taken for the variables in STATA and replaced in the diffusion model to do a model Carlo simulation, the number of content simulations was 5000, and the results after the simulation are shown in Figure 8. In the collaborative governance behavior network for public crisis governance with nodes 100&500, the high impact of the collaborator density $f_c(t)$ is penalties for breach C_{ij}^T. In a network of 1000 nodes for collaborative governance behaviors in public crisis governance, the high impact of the collaborator density $f_c(t)$ is collaborative costs h_{ij}^T. Spillover benefit factor c_{ik} are negatively but sensitively related to the collaborator density $f_c(t)$. Therefore, among the various factors affecting the degree of emergence and diffusion of complex networks, the sensitivity of collaborative costs h_{ij}^T, spillover benefit factor c_{ik}, and penalties for breach C_{ij}^T are strong, and the parameters are not affected by factors such as outliers or distortions from special events.

6. Conclusions

The findings of this paper have implications for optimizing the diffusion of collaborative behavior of agents in public crisis governance networks. Firstly, in order to ensure the stability of the diffusion network, attention should be paid to the variability in the choice of optimization solutions for different network sizes. Secondly, a reasonable penalty mechanism for non-compliance should be set up to avoid the risk of destabilization of the network caused by the phenomenon of "Free-riding" in the process of collaborative governance. Thirdly, it attaches importance to the reasonable distribution of collaborative benefits and the maintenance of cooperative relationships between nodes in the neighborhood to ensure the long-term stable development of the whole network cooperation. Finally, the central government, as the external manager of the governance network for public crisis management, should focus on ensuring the accessibility of information in the network, improving the quality of collaborative governance, and promoting cooperation and communication among the various agents, while reducing situations such as ineffective public crisis governance due to information asymmetry.

There are still some limitations to this research. Firstly, this paper only considers penalties for breach of contract, but not rewards for cooperation. In order to make agents in the network more willing to choose collaborative governance decisions, the reward and punishment mechanism should be improved in future studies may get richer results. Secondly, following existing research, model simulations were carried out in BA scale-free networks, but realistic complex networks are often more variable and further exploration of topologies suitable for collaborative public crisis governance networks would be more meaningful.

Conflict of Interest

The author declares no conflicts of interest.

Data availability statement

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

Author contribution statement

All authors were involved in preparing the manuscript. Conceptualization, Shao-nan S., Chun-juan W and Zi-cheng Z; methodology, Shao-nan S.; software, Guo-qiang H; validation, Zi-cheng Z, Guo-qiang H and Chun-juan W; formal analysis, Shao-nan S. and Guo-qiang H; investigation, Chun-juan W and Zi-cheng Z.; resources, Chun-juan W and Shao-nan S.; data curation, Zi-cheng Z; writing-original draft preparation, Guo-qiang H and Shao-nan S.; writing-review and editing, Guo-qiang H., Zi-cheng Z., Chun-juan W. and Shao-nan S.; visualization, Zi-cheng Z.; supervision, Zi-cheng Z and Shao-nan S.; project administration, Shao-nan S. and Zi-cheng Z.; funding acquisition, Shao-nan S.

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