A Resilience Control Method for Mitigating the Sudden Change in Online Group Opinion based on Q-Learning and PSO

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Abstract

In today's digital age, online group opinions are easily influenced by rapid and unpredictable changes caused by external stimuli, which poses a significant threat to social organizations. This paper introduces an innovative way to mitigate such sudden changes by regulating the hidden capacity of online group opinions to withstand external stimuli. The hidden capacity is quantified as the resilience of online group opinions, based on the catastrophe model that characterizes the transferring mechanism around the tipping point of group opinion. To construct the catastrophe model, we utilize textual data derived from group opinions. Subsequently, we devise a resilience control method aimed at lowering the possibility of sudden change by controlling independent variables related to resilience, which turns out to be an optimization problem for the complex social system. We develop a comprehensive approach by integrating Q-Learning (with nonlinear discretization for the states) and Particle Swarm Optimization, named QLPSOND. Our proposed method surpasses the most competitive state-of-the-art baseline, QLPSO, by demonstrating an impressive improvement of 37.59% and 7.98% in average fitness, 31.66% and 10.28% in best fitness on the Meituan and Xiaomi datasets, respectively. Furthermore, the resilience control strategies and managerial implications are explored. The works can extend the methodology of opinion dynamics in the online environment, and aid enterprises and governments in monitoring and managing online customers as well as online society.

Keywords

Sudden change; Resilience control; Online Group opinion; Reinforcement Learning; Particle Swarm Optimization.

1. Introduction

The polarization and reversal phenomena in the evolution of online group opinion happen more frequently than offline. The reasons can be explained as follows. First, the online network structure of an online group (i.e., the relation between members) is dynamic [1]. Second, online interaction between members is instant and convenient and does not be constrained by social customs and behavioral norms during offline face-to-face communication. Third, the group can instantly perceive the stimuli from the external environment through the network. With the hybrid effect of the above internal and external reasons, group opinion shows polarization and reversal phenomena more frequently than that in the traditional environment [2]. These phenomena in group opinion are also a major aspect in social cybersecurity studies. Based on the interaction between cyberspace and humans, social cybersecurity focuses on human behavior under online messaging and connecting. Mitigating social cybersecurity attacks and making online communities more resilient to internal and external stimuli are the related goals within the field of social cybersecurity [3, 4].

The frequent polarization and reversal of online group opinion are harmful to any social organization, e.g., a government may be overthrown during a short period, or an enterprise will go bankrupt overnight. Therefore, controlling the frequent polarization and reversal is very meaningful for the administrators of any social organization. In order to realize the control, the online group opinion is seen as a complex social system. The normal way is the system modeling method [5, 6, 7] which is obviously hard since it considers a great quantity of internal and external factors and the structure is dynamic, pluralistic, and multi-dimensional. Its controlling method is difficult to develop when facing such a complex system.

Thus, we try to avoid a comprehensive modeling of the group opinion system, that is, we do not consider the structure, components and external environmental factors of the entire group opinion system in detail, but only model the hidden capacity within the system. This hidden capacity is the underlying power of a system that defends external stimuli and constrains the behavior of the system, which is called resilience [8]. Once the resilience collapses, a sudden change in system state occurs, i.e., sudden transfer from a steady state to another steady state. This can be explained by catastrophe theory [9]. When the system suffers external stimuli, the structure of the system is compressed and deformed. We can use the hidden capacity (i.e., resilience) to measure the magnitude of the deformation degree. With the external stimuli increasing, the system's resilience approaches its threshold. Once the resilience arrives at its threshold, the hidden capacity of the system collapses and the sudden change in group opinion occurs. This process, i.e., the changes in system behavior around resilience critical value, can be characterized by the catastrophe model [10].

Therefore, we build the catastrophe model of the group opinion system. The catastrophe model avoids modeling the whole group opinion system in detail but models the underlying catastrophe mechanism within the group opinion system [11] The catastrophe model digs out the system's hidden capacity for defending external stimuli and derives the resilience model. Based on the resilience model, the controlling method can be designed. That is, we control the group opinion avoiding sudden change through controlling the resilience of the group opinion.

There are numerous factors influencing resilience, and conventional optimization algorithms prove inefficient for finding effective control strategies. Combining Q-learning (i.e., a type of reinforcement learning) with the evolutionary algorithm PSO (i.e., Particle Swarm Optimization) to develop the QLPSO algorithm is proved to be a more effective approach than the classical PSO to solve multi-modal problems [12]. The key elements of Q-learning (i.e., agent, action, state, etc.) are mapped to the key elements of PSO (i.e., Particle, parameters, fitness, etc.) to construct the QLPSO algorithm. By utilizing QLPSO, common issues encountered by conventional algorithms when dealing with complex multidimensional problems, e.g., getting trapped in local optima easily, inadequate solution precision, and slow convergence speed, can be solved [13]. However, QLPSO still has limitations when dealing the complex social context issues. Thus we make further development based on QLPSO and propose our QLPSOND algorithm.

In this work, we take the group opinion of two online forums as our experiment datasets and examples. One is the Meituan forum from a food delivery company in China, and it is a public forum where netizens can make speech freely; another is the Xiaomi forum from a smart manufacturing company of smartphones and smart hardware, and it is an official forum and there are certain restrictions on what netizens can say. In the Meituan forum, employees engage in discussions regarding work conditions and the environment. In the Xiaomi forum, customers join in evaluating Xiaomi's products. The group opinion easily leads to sudden fluctuation. To build a catastrophe model for the group opinion, we collected online textual data consisting of statements and comments made by employees and customers. The sentiment expressed in these statements and comments serves as a proxy for their opinions [14], representing the dependent variable in the catastrophe model. Various factors and elements that influence these opinions are considered independent variables. The resilience of group opinion is modeled using the catastrophe model. To effectively manage the resilience of the system and mitigate the possibility of sudden changes, we develop and implement a resilience control method based on QLPSOND.

2. Research objective

In this study, we aim to address the following research questions:

(1) How to quantify the possibility of the sudden change in online group opinion and its capacity to defend external stimuli?

(2) How to mitigate the sudden change phenomena in online group opinion most efficiently?

(3) How to identify the main factors related to the opinion sudden change control problems?

(4) What is the difference between the public forums and the official forums concerning their strategy to mitigate opinion sudden change?

By answering the above research questions, this study aims to contribute to the following aspects:

(1) We use the concept of resilience to describe the hidden capacity of an online group opinion system. To quantitatively measure the group opinion system's resilience, we introduce a resilience metric, resilience loss, based on catastrophe theory. The higher the resilience loss of the system, the higher the risk of system collapse, that is, when a sudden change happens.

(2) By quantifying the resilience, mitigating the sudden change in group opinion is transformed into a resilience control problem, which is essentially an optimization problem. Based on existing heuristic algorithms and machine learning techniques, we propose the QLPSOND algorithm combined with the characteristics of complex social systems, which has outstanding performance in finding the most effective approach to lower the system's resilience loss.

(3) We investigate the relation and reflections between the resilience control strategy (numerical data) provided by QLPSOND and practical variables. By inverse standardization and discretization of the original variables data, we find out the change degree of each variable in the resilience control strategy, thus identifying the most important factors in the resilience control.

(4) We apply the proposed resilience control method on the two types of datasets, Meituan from Baidu Tieba, which represents the public forum, and Xiaomi Forum, which represents the official forum, respectively. Then we compare the results and find out the similarities and differences in management strategies for mitigating group opinion sudden change.

The rest of this work is organized as follows. Section 3 introduces the related works. Section 4 introduces the methodology framework, including building the resilience model based on the catastrophe model and constructing the QLPSOND-based resilience control method. Section 5 conducts the experiments, presents the research datasets and analyzes the performance of the proposed control method. Section 6 further discusses the results of the study and compares the control strategies in two different datasets. Section 7 summarizes the theoretical and practical implications. Section 8 draws the conclusions.

3. Related works

3.1. Sudden change in group opinion

The phenomenon of sudden changes in group opinion has obtained substantial attention across various disciplines, especially in the fields of information science and computer science. Researchers have delved into this dynamic phenomenon, investigating the mechanisms and dynamics that underlie these rapid shifts [15, 16, 17]. Some studies have examined the root causes and far-reaching implications of sudden opinion shifts. For instance, Ng and Carley shed light on the influential role of bot agents in inducing users' stance flipping on Twitter, elucidating the intricate interplay between automation and opinion dynamics [18]. Additionally, De et al. have delved into the profound impact of social networks on opinion polarization, unraveling the complex web of connections that contribute to polarized group sentiments [19]. Most of the time, the sudden change or the polarization of group opinion can bring so much trouble to organizations and governments [20, 21]. These shifts can disrupt decision-making processes, challenge consensus-building efforts, and even sway public sentiment on critical matters.

Regarding the unpredictable, nonlinear and complex characteristics of the sudden changes in group opinion, it is a big challenge and necessary to take action to reduce such phenomena. Recent research conducted relevant field experiments to uncover effective strategies for mitigating opinion polarization and minimizing the impact of such sudden shifts [22, 23].

3.2. Catastrophe model

The catastrophe theory, originally proposed by Thom in the 1970s [9, 24], provides a framework for understanding discontinuous and sudden changes in dynamic nonlinear systems and has expanded significantly, encompassing various fields in social science such as psychology, business, investors and organization behavior [11, 25, 26, 27].

The cusp catastrophe model is one of the most commonly utilized models within catastrophe theory. The general expression of the cusp catastrophe model can be represented by Equation (1).

$$-f^{3}+u\cdot f+v=0 \qquad \textbf{(1)}$$

Consider the example of individual behavior. Here, the observed behavior f is also denoted as the system state, where the bifurcation factor u and the asymmetry factor v influence f. The continuous change of v can lead to the sudden change of the system's state, while u determines whether this change will happen.

The behavior surface *f*, depicted in the upper part of Figure 1, exhibits two stable states: normal behavior and abnormal behavior. The lower part of Figure 1 illustrates the control plane formed by the control variables u and v. When the behavior surface *f* is projected onto the control plane, it reveals a cusp-shaped region defined by two curves, known as the singularity set. The catastrophe phenomenon refers to when a sample arrives at an arbitrary position located in the singularity set, that is, the state of the system can transform from normal to abnormal.

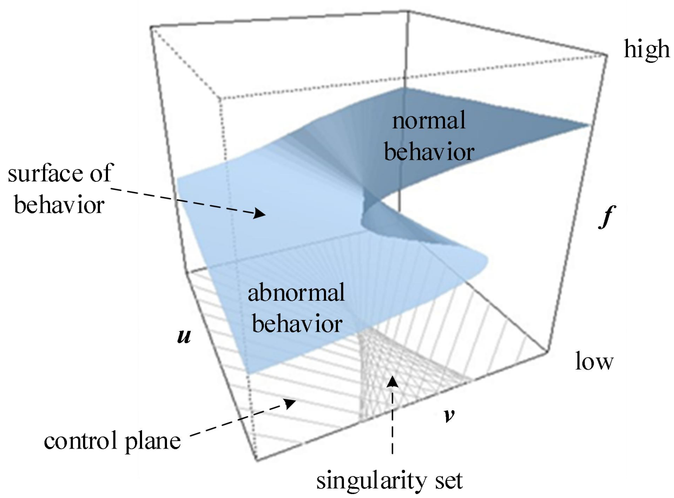


Figure 1. Cusp catastrophe model of changes and jumps in behavior

To make the model more accurate, more factors are necessary to be considered. Using Cobb's maximum likelihood method [27], the behavior variable f and the control variables u and v are formed by a series of dependent and independent variables. The expressions of f, u and v are provided in Equation (2).

$$\begin{cases} f=w_0+w_1y_1+w_2y_2+\ldots+w_my_m \\ u=a_0+a_1x_1+a_2x_2+\ldots+a_nx_n \\ v=b_0+b_1x_1+b_2x_2+\ldots+b_nx_n \end{cases} \qquad \textbf{(2)}$$

Where *f* in our study refers to the sentiments of group opinion, the coefficients w_i, a_i, b_i represent the polynomial approximation for the dependent and independent variables. To fit Equation (1) and Equation (2), we utilize the cusp function from the cusp package in R [28] based on the real data collected for the system variables.

3.3. Resilience model

The concept of resilience was initially defined as the system's ability to recover to its original state after suffering from disturbances [29]. Since then, the definition of resilience has been widely applied in social science, especially in psychology and management science.

In the field of psychology, the resilience model is mainly employed to investigate the changes in individual behavior resulting from interactions between the environment and psychology [30, 31, 32]. In the field of management science, resilience-related research focuses on an enterprise or an organization's ability to effectively manage unexpected disruptions and swiftly restore normal operations [33, 34, 35, 36]. Both human psychology and organizations can be viewed as complex systems.

Resilience measurement encompasses qualitative and quantitative methods. Qualitative approaches involve analyzing the factors that influence system resilience, while quantitative methods focus on building mathematical models for resilience. A modeling approach for assessing resilience loss in a community due to an emergency is depicted in Figure 2 [37]. The disruption occurs at time t_0, after which the resilience of the community decreases significantly, and then the community gradually returns to its normal state (assumed to be 100) by time t_1.

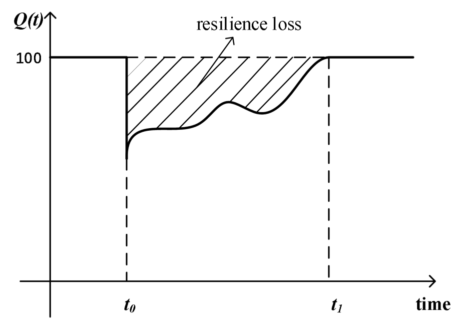


Figure 2. Measurement for resilience loss

In Figure 2, the resilience loss (*RL*) is represented by the shaded area. This assessment allows us to quantify the *RL* experienced by the community. A larger *RL* value indicates lower resilience. The calculation of resilience loss (*RL*) can be performed using Equation (3).

$$RL = \int_{t_0}^{t_1} \left[100 - Q(t)\right] dt \qquad \textbf{(3)}$$

Based on the *RL* illustration and its quantitative modeling approach presented in Equation (3), we develop a resilience model for group opinion.

According to resilience theory, the lower the resilience of the system, the higher the risk of system collapse [38]. In this way, we consider the connection between the sudden change of the system’s state in the catastrophe domain in catastrophe theory and the collapse of the system when its resilience returns to zero in resilience research.

3.4. Particle Swarm Optimization and its variants

The particle swarm algorithm (PSO) was initially proposed by Kennedy and Eberhart in 1995, inspired by bird foraging behavior [39], integrating concepts from evolutionary computation and swarm intelligence. Throughout the entire PSO search process, particles share their best position information and adjust their velocity and position based on the influence of their previous best solution.

Assuming a D-dimensional search space, the velocity and position update formulas for particles are shown in Equation (4) and Equation (5).

$$v_{id}^{t+1} = \omega v_{id}^{t} + c_1 r_1 (Pbest_{id}^{t} - x_{id}^{t}) + c_2 r_2 (Gbest_{id}^{t} - x_{id}^{t}) \quad \textbf{(4)}$$

$$x_{id}^{t+1} = x_{id}^{t} + v_{id}^{t+1} \quad \textbf{(5)}$$

Here, represents the velocity of the i-th particle in the d-th dimension in the t-th iteration. ω is the inertia weight. c_1, c_2 are the cognitive and social acceleration rates respectively. r_1, r_2 are random numbers with uniform distribution in the range of [0,1]. *Pbest* stands for the position of the specific particle ' s personal-best fitness in history, while *Gbest* stands for the global position among all particles.

Since it was put forward, the PSO algorithm has been widely used because of its simple method, fast convergence speed and strong searchability. However, PSO is easy to fall into local optimum in some complex multi-modal problems. Different improvement strategies for PSO were proposed. Since parameter control is very important to the performance of any evolutionary algorithm (EA) [12], the classic parameter control methods for PSO such as linear and nonlinear decreasing inertia weight [40,41], and linear time-varying cognition acceleration coefficients [42] were proposed first. Furthermore, some PSO variants equipped with adaptive parameter control that monitors performance dynamically were put forward [43, 44, 45, 46].

In recent years, Q-learning in Reinforcement Learning has been widely used to optimize the structure of PSOs to improve their performance [12, 13, 47, 48], leading to improved convergence and performance. For instance, particles can adaptively adjust their learning rate based on the feedback signals (reinforcement signals) obtained from the optimization process.

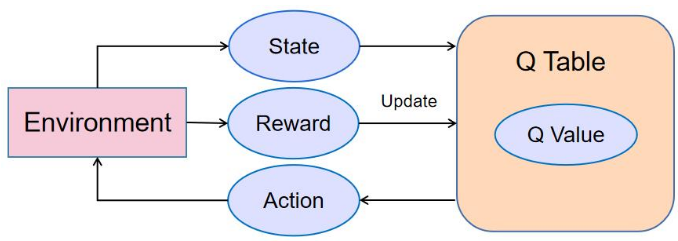


Figure 3. Structure diagram of Q-learning

Q-learning is a model-free reinforcement learning method proposed by Watkins and Dayan [49], which is used to solve the problem of sequential decision-making. Its main idea is to get the optimal strategy through the continuous interaction between agents and the environment and to accumulate the maximum return. Q-learning has four key elements: state, action, reward and Q table. In addition, the Q table needs to be updated during the training process. See the following Equation (6) for the update strategy:

$$Q(s_{t+1}, a_{t+1}) = (1-\alpha)Q(s_t, a_t) + \alpha[R(s_t, a_t) + \gamma \max_a Q(s_{t+1}, a)] \quad \textbf{(6)}$$

Where s_t, s_{t+1} are the states at period *t* and *t+1*, a_t, a_{t+1} are the actions at *t* and *t+1*; α is the learning rate and γ is the discount coefficient, and both of them are within [0,1]. The closer γ is to 0, the more the agent pursues immediate rewards, while the closer γ is to 1, the more the agent pursues long-term rewards in the future. $R(s_t, a_t)$ is the immediate reward obtained by the agent when it performs action α in state *s*, and $Q(s_t, a_t)$ is the expected Q value of the agent when he takes action α in state *s*.

Based on the methods mentioned above, this paper builds the cusp catastrophe model of the online group opinion first, then constructs the resilience model, after which the resilience control method QLPSOND is developed and implemented.

4. Methodology

This section presents the detailed process of construction of our whole resilience control method step-by-step. The catastrophe and resilience model is introduced first, to quantify the group opinion on sudden change phenomena. After that, the main control problem based on the resilience model is formulated and finally integrated with the QLPSOND algorithm. The methodology overview is shown in Figure 4.

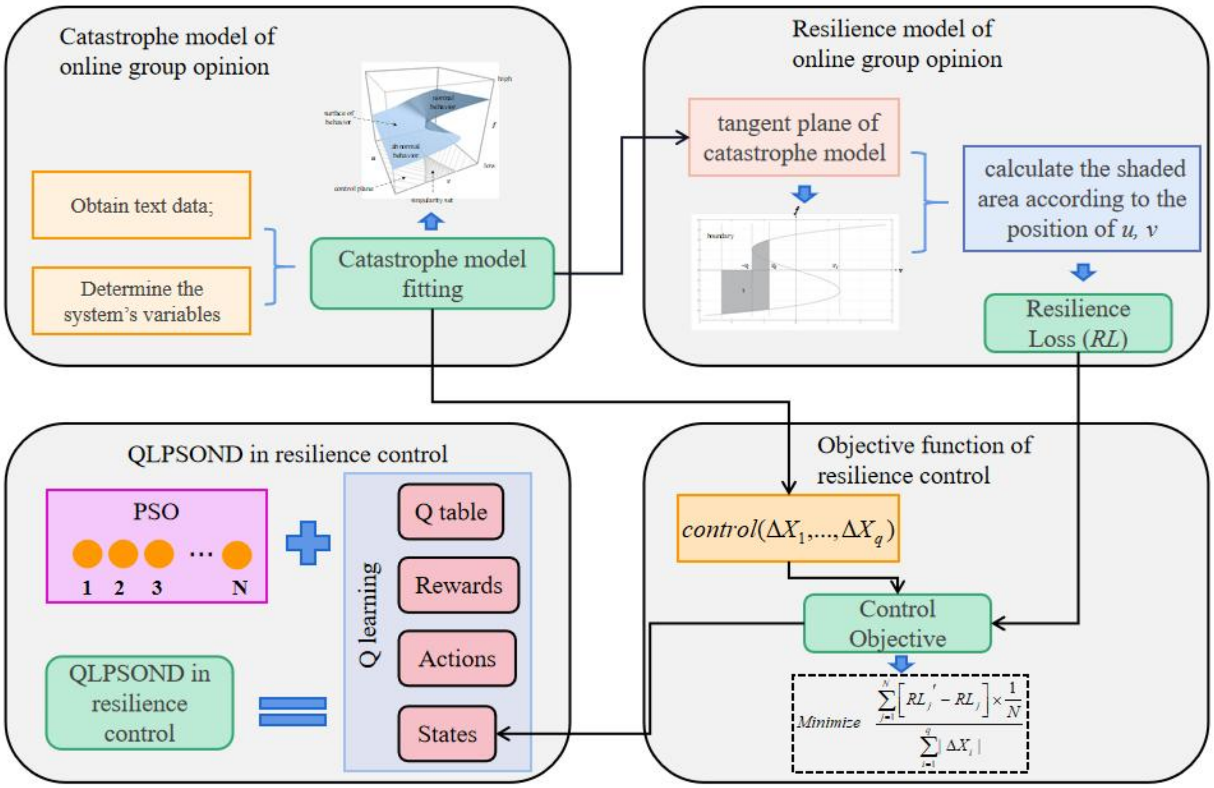


Figure 4. An overview of our methodology

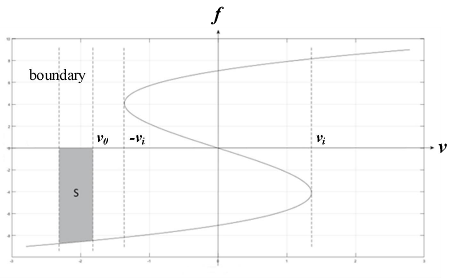
4.1. Catastrophe model of online group opinion

To construct the catastrophe model of the online group opinion evolution system, the text data from the online forum is initially obtained through a crawler. It is then transformed into quantitative data using SnowNLP and text mining techniques. The cusp function (i.e., Equation (1) & (2)) can be fitted by utilizing the cusp package in R. The fitting results are compared among the catastrophe model, logistic model, and linear model to select the most suitable one. The modeling process using real data is given in section 5.

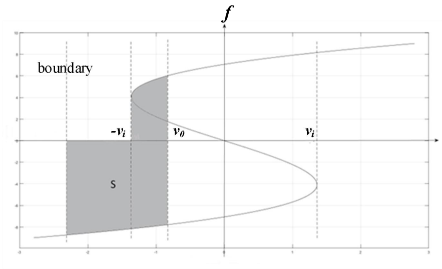
Due to the inclusion of linear and nonlinear relations in the fitting process, the R-square is inadequate for evaluating model performance. Therefore, AIC and BIC are primarily utilized to compare the performance of the cusp catastrophe model and other models (e.g., logistic model, linear model), with smaller values indicating superior performance [50, 51].

4.2. Resilience model of online group opinion

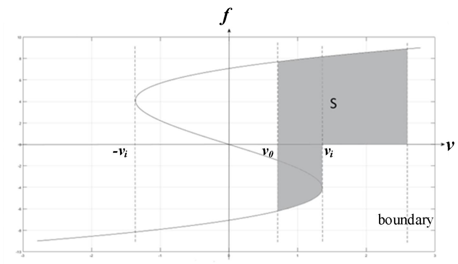
The resilience measurement model is based on the tangent of the equilibrium surface of the catastrophe model. In Figure 1, when $u > 0$, we can choose any point on the v-axis to determine the tangent plane, as illustrated in Figure 5. -v_i and v_i represent the two tipping points where the opinion undergoes a sudden jump. In order to construct the resilience model using the tangent plane, consider a specific point v_0 as an example. Along the v axis, we divide the region into four sections: $v_0 < -v_i$, $-v_i < v_0 < 0$, $0 < v_0 < v_i$, and $v_0 > v_i$.



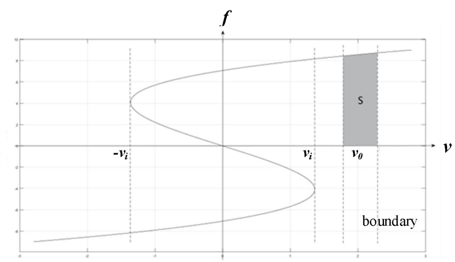
a. $v_0 < -v_i$



b. $-v_i < v_0 < 0$



c. $0 < v_0 < v_i$



d. $v_0 > v_i$

Figure 5. Tangent plane at any point of axis v when $u < 0$

Based on the metric introduced by Bruneau [37], the resilience loss of the system can be quantified by the area represented as S in Figure 5. The detailed modeling process of resilience loss is expressed in Equation (7).

$$resilience\ loss = \begin{cases} \int_{-boundary}^{v_0} -f(v)dv, v_0 \le -v_i \\ \int_{-boundary}^{-v_i} -f(v)dv + \int_{-v_i}^{v_0} \left[f_1(v) - f_3(v)\right]dv, -v_i < v_0 < 0 \\ \int_{v_0}^{v_i} \left[f_1(v) - f_3(v)\right]dv + \int_{v_i}^{boundary} f(v)dv, 0 < v_0 < v_i \\ \int_{v_0}^{boundary} f(v), v_0 \ge v_i \end{cases} \tag{7}$$

In the equation, $boundary$ determines the boundary of v within the system. Notably, $f(v)$ corresponds to the unique real solution of the equation $-f^3 + uf + v = 0$, while $f_1(v)$ and $f_3(v)$ represent the maximum and minimum real solutions for equation $-f^3 + uf + v = 0$, respectively. Additionally, the case when $u < 0$ in Figure 1 that is based on the logistic-shape curved surface is also displayed in Appendix A.1.

We then employ Rose's resilience ratio to standardize the resilience loss [52] and use the standardized resilience loss as the resilience metric in our study. This can be expressed by Equation (8).

$$\text{Standardized\_}RL = \frac{RL_0}{RL_{\max}} \tag{8}$$

Where RL_0 represents the current resilience loss, and RL_{max} is the maximum resilience loss within the system. This modified resilience loss is scaled between 0 and 1, providing a standardized measure. Unless otherwise specified, the term 'resilience loss' (RV) mentioned in the following text refers to the standardized resilience loss.

After introducing the whole resilience model of online group opinion, we are going to design the resilience control algorithm for group opinion resilience.

4.3. Objective function of resilience control

The resilience model mentioned above can measure the possibility of a sudden change of the system, with higher resilience loss (*RL)* indicating a greater possibility of such an event. As *RL* is a function of variables *u* and *v*, *RL* can be reduced by controlling the variables *u* and *v* to lower the possibility of catastrophe in the system.

(1) **Control Function.** As the control variables *u* and *v* are influenced by independent variables x_i, the *RL* of the system is finally controlled by adjusting the independent variables. The control function of the system is $control(\Delta X_1,...,\Delta X_q)$, and the value of each independent variable is adjusted through this interface to control the system state.

Taking the control variable *v* as an example, the adjusted v_1 can be expressed as:

$$\begin{aligned} v_1 &= c + c_1(X_1 + \Delta X_1) + c_2(X_2 + \Delta X_2) + ... + c_q(X_q + \Delta X_q) \\ &= c + c_1 X_1 + c_2 X_2 + ... + c_q X_q + c_1 \Delta X_1 + c_2 \Delta X_2 + ... + c_q \Delta X_q \\ &= v + c_1 \Delta X_1 + c_2 \Delta X_2 + ... + c_q \Delta X_q \end{aligned}$$

(2) **Objective Function.** The control objective is to minimize the *RL* of the system most effectively by adjusting the control variables, which means changing the unit control variables to make the average resilience loss decrease the most. Therefore, the objective function we construct is in the form of a ratio. The objective function is as follows in Equation (9):

$$Minimize \quad \frac{\sum_{j=1}^{N}\left[RL_j{}' - RL_j\right] \times \frac{1}{N}}{\sum_{i=1}^{q} |\Delta X_i|} \qquad \textbf{(9)}$$

Where RL_j and $RL_j{}'$ represent the resilience loss of sample *j* before and after the implementation of the resilience control strategy. *N* is the size of samples and *q* is the number of control variables.

4.4. QLPSOND algorithm strategy

QLPSOND algorithm is an improved PSO based on Q-learning which has four key elements: states, actions, Q table and reward. As shown in Figure 6, through a series of definitions, the QLPSOND algorithm can update the parameters of PSO through Q-learning, realizing online adaptive parameter control to improve the performance of the particle swarm optimization algorithm.

PSO	Defined as	Q-Learning
Particle		Agent
Particle's position and fitness		State
Particle's parameters		Action
Changes of particle's fitness		Reward

Figure 6. Definition in QLPSOND

(1) States. Considering the characteristics of the PSO, the state of each particle in QLPSOND is divided into the decision state and target state. The decision state represents the relative distance between the particle's position and the global optimal solution, while the target state reflects the relative difference between the particle's fitness and the global optimal fitness. Both states are essential for accurately measuring the difference between the current particle and the global optimal particle, in order to guide the particle to dynamically iterate its parameters to a more optimal solution.

Specifically, the decision state is denoted as $\Delta d/\Delta D$, where Δd is the Euclidean distance between the particle's position and the global optimal solution (i.e.. $\Delta d = \|x_{id} - Gbest\|$), and ΔD is the Euclidean distance between the upper and lower bounds of the decision space. The target state is denoted as $\Delta f/\Delta F$, where Δf is the difference between the particle's fitness and global best fitness (i.e., $\Delta f = |f(Gbest) - f(x_{id})|$), and ΔF is the difference between global best fitness and global worst fitness (i.e., $\Delta \mathrm{F} = |f(Gbest) - f(Gworst)|$).

In addition, since the values of the decision state and target state need to be stored in the Q table, it is necessary to discretize the states' space. Due to the complexity of the control problem addressed in this study, improvements are made to the state-of-the-art QLPSO algorithm proposed by Liu et al. (2019) [12]. Here, instead of using the linear discretization method employed by Liu et al., a nonlinear discretization approach is adopted for the states space of QLPSO, named QLPSOND. This approach aims to achieve the effect of making the relative distances more difficult to classify as 'near' and easier to be classified as 'far'. The purpose of this operation is to prevent premature convergence to local optima by using a larger relative distance threshold. It also helps to explore a wider search space and find potential solutions beyond the vicinity of the known optimum. We discretize both decision state and target state into six sub-states, defined as from the nearest to the farthest, and from the smallest to the largest. Specifically, they are defined as follows.

Table 1. Definition of States of QLPSOND

Decision Type	Relative Distance	Decision State
1	$0 \le \Delta d/\Delta D \le 0.05$	Nearest
2	$0.05 < \Delta d/\Delta D \le 0.15$	↓
3	$0.15 < \Delta d/\Delta D \le 0.3$	
4	$0.3 < \Delta d/\Delta D \le 0.5$	
5	$0.5 < \Delta d/\Delta D \le 0.75$	
6	$0.75 < \Delta d/\Delta D \le 1$	Farthest

a. Definition of Decision State

Target Type	Relative Difference	Target State
1	$0 \le \Delta f/\Delta F \le 0.05$	Smallest
2	$0.05 \le \Delta f/\Delta F \le 0.15$	↓
3	$0.15 \le \Delta f/\Delta F \le 0.3$	
4	$0.3 \le \Delta f/\Delta F \le 0.5$	
5	$0.5 \le \Delta f/\Delta F \le 0.75$	
6	$0.75 \le \Delta f/\Delta F \le 1$	Largest

b. Definition of Target State

(3) **Actions.** In QLPSOND, each particle's action set contains four actions, {Rough Exploration, Fine Exploration, Slow Convergence, Fast Convergence}, each corresponding to different values of the inertia weight ω , and acceleration coefficients c_1, c_2 . Different parameter values can affect the particle's exploration and convergence performance. For example, according to Equation (4), a larger inertia weight ω implies faster particle velocity and stronger global exploration ability, while a smaller ω implies stronger local search ability, with a decrease in particle velocity, resulting in improved solution accuracy. Moreover, larger values of c_1 and smaller values of c_2 indicate a stronger global search ability of the particle, whereas smaller c_1 and larger c_2 values imply a faster convergence rate of the particle. Specifically, the set of four actions is defined in Table 2.

Table 2. Parameter setting of the actions

Action Type	Parameters	Particle's velocity	Impact from *Gbest*

	ω	c_1	c_2		
Rough Exploration	1	2.5	0.5	Largest	Smallest
Fine Exploration	0.8	2	1	Large	Small
Slow Convergence	0.6	1	2	Small	Large
Fast Convergence	0.4	0.5	2.5	Smallest	Largest

(3) Q table. Based on the above definition, a Q table needs to be designed to determine the actions taken by each particle based on its current states. Both the decision state and target state are vital, leading to a three-dimensional Q table in QLPSOND (instead of the two-dimensional Q table in Q-learning). With six types in the decision and target space, and four types in the action set, the Q table is a **6*6*4** three-dimensional table (Figure 7). The particle's action selection based on its states using the Q-table is explained below.

First, a specific location in the state plane is determined by the calculation of the particle's current decision state and target state, $\{0.15 < \Delta d/\Delta D \leq 0.3,\ \ 0.5 < \Delta f/\Delta F \leq 0.75\}$, for instance. Next, the Q column corresponding to the specific state location in the Q table is selected. Finally, the action with the maximum Q value in the selected Q column is chosen for the particle.

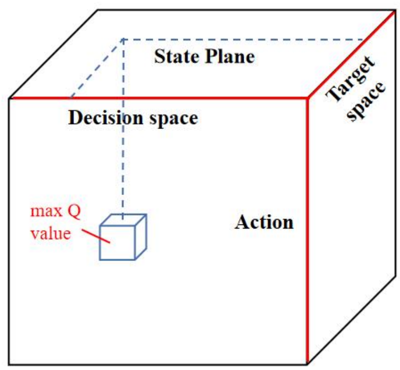


Figure 7. 3-dimension Q table

(4) Rewards. In QLPSOND, each particle shares the same Q table constructed as described above, and each particle can update the Q table. The update of the Q-table depends on specific reward and penalty mechanisms. After a particle performs a certain action, if its fitness is better than the global best fitness, a positive reward is given to the action, i.e., the Q-value corresponding to this action should increase. Conversely, if the fitness of the particle is equal to or worse than the global best fitness, a penalty will be given to the action, and the corresponding Q value should decrease. Additionally, to achieve particles' sufficient exploration in the early stages to avoid falling into local optima, and encourage particles to speed up convergence in the later stages, the reward mechanism should be set as a function dynamically changing with the iteration times, as shown in Figure 8.

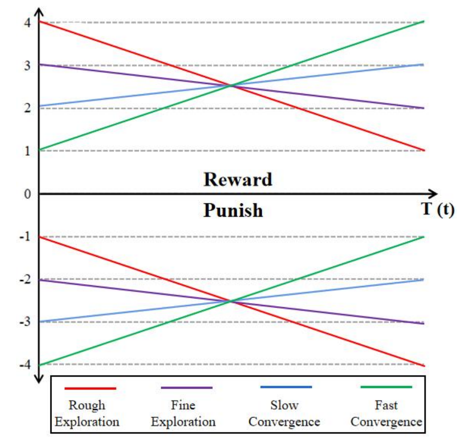


Figure 8. Reward Function Design

The pseudocode of QLSPOND is presented as follows, where *num_particles* represents the number of particles in the swarm, *max_Iter* is the maximum number of iterations, and *dim* is the dimension of the solution.

Algorithm 1: Pseudo code of QLPSOND

Input: *num_particles, max_Iter, dim*, lower bound, higher bound
Output: optimal resilience control strategy

```
initialize PSO population and Q
while t <= max_Iter do
    while p <= num_particles do
        decide decision state and target state
        select the action (parameters w, c1, c2) based on Q table
        update velocity and position
        calculate fitness
        update Pbest and Gbest
        calculate reward
        get the next states
        update Q table
        p++
    end
  t++
end
```

It should be noted that in the PSO, inertial weight ω and acceleration coefficients c_1 and c_2 are shared by all particles as algorithmic properties. However, in QLPSOND, these parameters become properties of each individual particle. In each iteration, each particle can choose an optimal action (parameter) based on its current states to achieve adaptive parameter updates. The whole QLPSOND framework is shown in Figure 9.

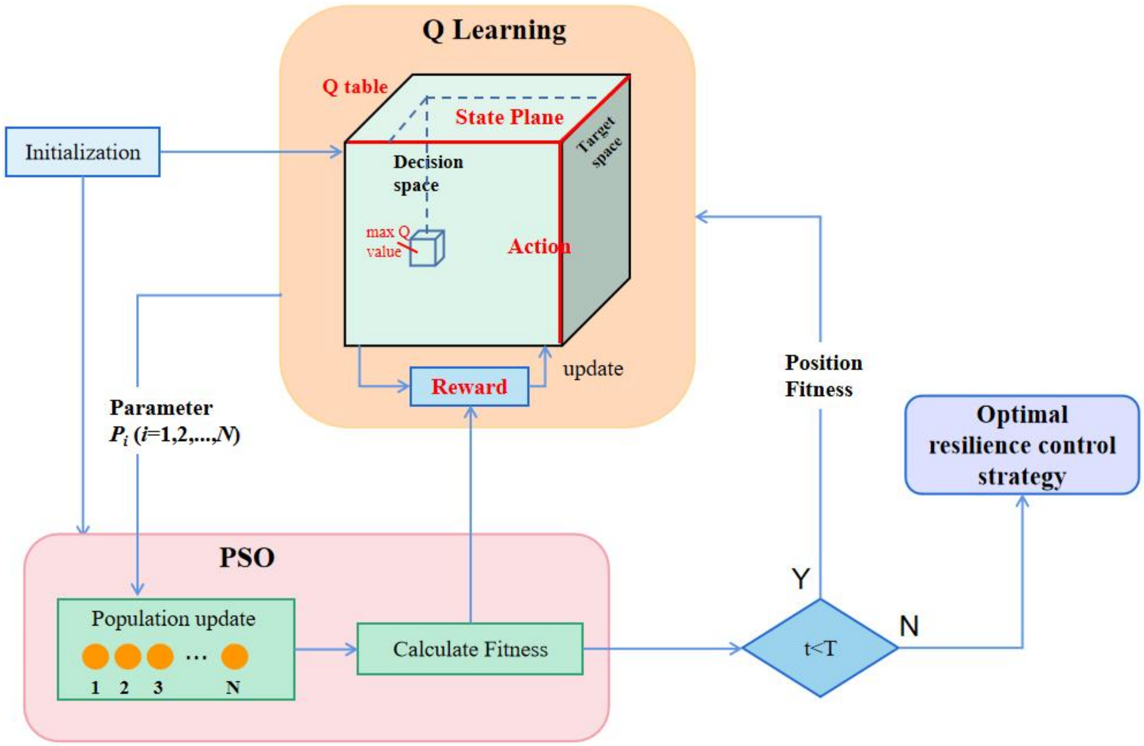


Figure 9. QLPSOND framework

Moving forward, we will apply the resilience model and resilience control strategy based on QLPSOND to two online forum datasets to examine the performance of QLPSOND and investigate the effect of the resilience control implementation.

5. Experiments

In this section, we apply the above methods to two datasets, Meituan forum (a public forum) and Xiaomi forum (an official forum), respectively. We first provide a detailed introduction to the datasets as well as the reasons for studying them. Then, we collect and process relevant text data. Next, we construct the variables and provide a detailed explanation of each variable. After that, we build the catastrophe-resilience model of the system based on the datasets. Finally, QLPSOND is designed to control the resilience loss to lower the possibility of a sudden change in the online group and different methods used for comparative analysis are discussed.

5.1. Datasets

5.1.1. Cases introduction

We select these two datasets for the following reasons. First, group opinions in these two forums are likely to have sudden change. In the Meituan forum, employees are engaged in topics primarily involving work-related matters and emotional changes due to inadequate legal and social protection, as well as insufficient professional and personalized management of delivery workers. In the Xiaomi forum, consumers are more likely to have a serious polarization in Xiaomi's products' evaluation due to issues such as their processor performance and battery life. The group opinion easily leads to sudden fluctuation in these two cases.

Second, since Meituan Forum and Xiaomi Forum are two different types of online communities (Meituan is a public forum while Xiaomi is an official forum), by applying the resilience control method to them we can examine if our proposed method is universal in different cases. What is more, we can deeply investigate what the differences and similarities of the resilience control strategies are between the public forums and official forums.

5.1.2. Summarization of datasets

(1) *Meituan*: We take the Meituan-related posts in Baidu Tieba as the main source of text data. The Meituan dataset has about 25,204 human-annotated comments. A total of 6,301 posts related to Meituan were collected from Baidu Tieba, each of which contains basic elements such as title, time, poster's statement and follower's comment. Each post is an independent sample, while the 6,301 posts as a whole reflect the changes in group opinion.

(2) *Xiaomi*: We select text data from the Xiaomi Community Forum (MIUI Forum) for analysis. The Xiaomi dataset has about 26,875 human-annotated comments and a total of 6,000 discussion posts. The composition of the dataset is similar to *Meituan*, as shown in Table 3.

Table 3. Detailed descriptions of the two experimental datasets (original)

Dataset	Sum of the data	Time scope	Content included in the dataset
Meituan	25,204	29th May. 2021~ 20th Mar. 2023	title, time, poster's statement, follower's comment
Xiaomi	26,875	15th Feb. 2021~ 7th Jan. 2023	title, time, poster's statement, follower's comment, number of likes, number of views, poster's level

To perform catastrophe fitting and resilience computing, the text data needs to be quantified. This paper uses Natural Language Processing (NLP) and text mining techniques to extract useful information from the text data [53] and to form the independent and dependent variables required for fitting the catastrophe model. In addition, we also construct a semantic network for the text data of each post to explore the correlations between different textual vocabulary. After quantifying the text data, each variable is standardized using the Z-score method to unify the data dimensions. The variables analysis is shown as follows.

5.1.3. Variables analysis

As we quantify textual data of group opinions into the sentiment of the opinion, the dependent variable is the mean sentiment of follower comments. The selection of independent variables is shown below.

(1) **Meituan.** It is well-established that opinion leaders in social networks can influence users' behavior [54], which means that key nodes usually have a significant impact on the structure and function of the entire network [55]. Based on this, we consider that ***the sentiment of the original poster's statement*** is an independent variable that can influence the sentiment of follower comments. Additionally, ***the absolute value of the sentiment difference between the original poster's statement and follower comments*** indicates the degree of difference in their attitudes, which can be considered as another independent variable. These two factors reveal the impact that the posters' statement has on the followers.

The standard deviation of the sentiment of follower comments can reflect the emotional fluctuations of the followers' comments; ***the frequency of the three highest-frequency words of follower comments*** shows us the concentration of followers' comments, while ***the average sentiment of the three highest-frequency words of follower comments*** indicates the general opinion of follower comments keywords. These three factors represent the characteristics and correlation among all comments in a post, so they are selected as independent variables.

The study of sudden changes in complex systems can be effectively conducted through the network model, which is a nonlinear method that closely approximates the complete structure of the complex system [56, 57]. We assume that all follower comments in the same post can form a complex network and each comment is a node in this network. The formation of connections between two nodes is based on the co-occurrence of keywords, resulting in the creation of a complex network. Thus, ***the number of nodes, the number of edges, density and transitivity*** are taken as the independent variables that are added in the model fitting.

The specific variables notation and definitions are detailed in Table 4, where x_1 to x_5 are the commonly used indicators in text sentiment analysis, and x_6 to x_9 are the commonly used indicators in complex network analysis [57].

Table 4. Variables Notation and Definition of Meituan Dataset

Variables Notation	Variables Name	Variables Meaning
x_1	Statement sentiment	the sentiment of the original poster statement
x_2	Comment variance	the absolute value of the difference between the sentiment of the poster statement and follower comments
x_3	Std. sentiment	the standard deviation of the sentiment of follower comments
x_4	Frequency	the frequency of the three highest-frequency words of follower comments
x_5	Top word sentiment	the average sentiment of the three highest-frequency words of follower comments
x_6	Number of nodes	the number of nodes for the semantic network from the follower comments
x_7	Number of edges	the number of edges for the semantic network from the follower comments
x_8	Density	the density for the semantic network from the follower comments
x_9	Transitivity	the transitivity for the semantic network from the follower comments

(2) Xiaomi. In terms of variables selection, the variables selected by Xiaomi Forum and Meituan Forum are generally consistent. However, due to the characteristics of the case and the differences in text data available for crawling in different forums, the variables selected by Xiaomi Community also vary in some cases. Specifically, Xiaomi Forum has two more significant variables related to post characteristics than Meituan Forum: the number of *Views* and *Likes* on posts, and one variable that reflects the owner's level: *Posters' level*; Missing variable *number of edges*. Other variables are consistent with Meituan Forum. Overall, there are eleven independent variables in the Xiaomi Forum.

5.2. Catastrophe-Resilience modeling

Taking the Meituan dataset as an example, according to the model presented in section 4, the catastrophe model is fitted using the data from the case study by R. Estimates for the parameters of each independent variable and their significance are obtained. According to the fitting results (displayed in Appendix B.1), the mathematical expressions of the two control variables *u*, *v* are shown in Equation (10).

$$\begin{cases} v = -2.1152 + 0.2142x_1 - 0.0450x_2 + 0.3165x_3 + 0.2207x_4 + 0.9418x_5 \\ \quad -1.0985x_6 + 0.5686x_7 - 0.1384x_8 - 0.2002x_9 \\ u = -1.3343 - 1.5246x_2 - 0.2334x_3 - 0.5849x_4 - 0.9330x_6 + 0.5133x_7 \\ \quad + 0.5009x_8 + 0.1402x_9 \end{cases} \tag{10}$$

Based on the resilience model presented in section 4, we draw the surface of the system resilience using real data (Figure 10). We also display the group opinion sentiment surface to observe the sentiment fluctuations corresponding to the resilience surface of the system in Figure 10 directly. Figure 11 shows that in the area where u>0, the sentiment fluctuation of group opinion is relatively large, leading to a sudden change phenomenon, while the sentiment fluctuation of the u<0 part is relatively small.

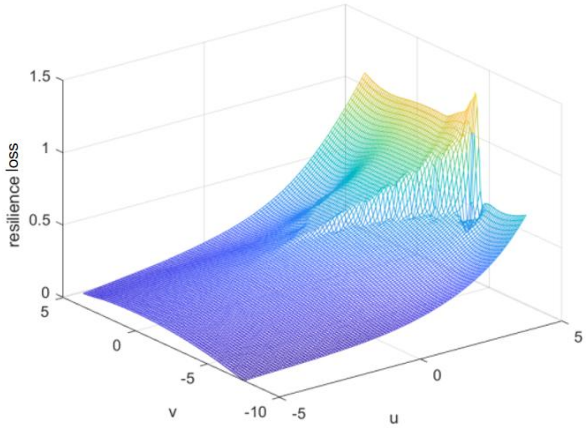


Figure 10. System Resilience Surface

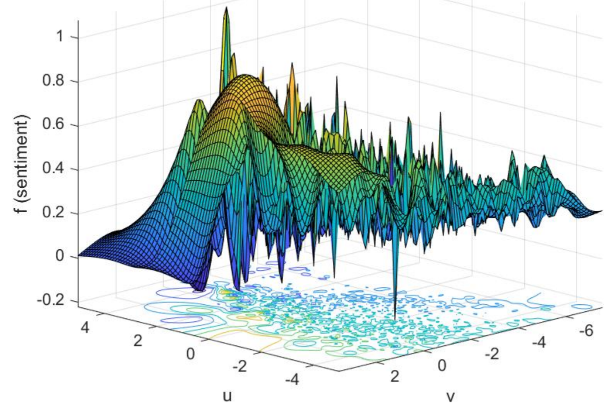


Figure 11. Group Opinion Sentiment Surface

It should be noted that there is an obvious protruding area on the surface in Figure 10. This is the region where the catastrophe phenomenon in the set of divergence points is significant. The higher resilience loss in this region indicates that the individual emotions in this region are more likely to undergo a sudden change. The significant fluctuation in sentiment in the corresponding area in Figure 11 confirms this viewpoint. Our goal is to reduce the overall resilience loss in Figure 10 since once this metric reaches a certain threshold, the system may be prone to catastrophe.

5.3. Experimental settings

5.3.1. Compared methods

We perform a comparative analysis to evaluate the performance of our model. For this purpose, we compare the results of our model QLPSOND with the following baseline methods:

- SPSO [39] is the standard PSO with constant learning rates and inertia weight, which means that the particles' convergent speed remains the same during the iterations.
- LPSO [40] is the linearly decreasing inertia weight PSO, in which particles converge from a global search to a local search during the iterative process.
- QLPSO [12, 58] is the state-of-the-art in the combination of PSO and reinforcement learning, in which the particles realize adaptively change their convergence speed and research ability according to their current states.

5.3.2. Parameters settings

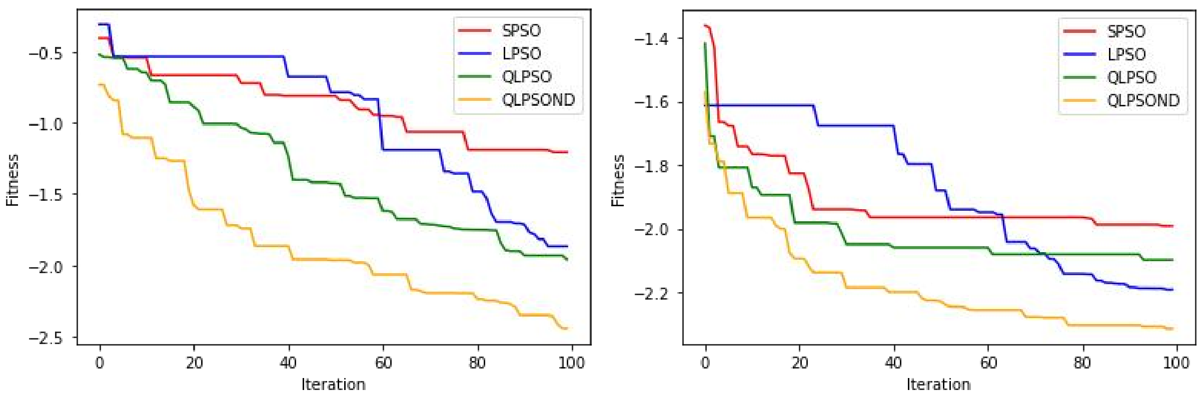
The experiment parameter settings are shown in Table 5. In LPSO, the algorithm always performs better when the inertia weight *w* is within the range of 0.4-0.9 [59], while in SPSO, *w* is usually set to 0.729 [60].

Table 5. Parameters setting of the algorithms

Parameter setting	SPSO	LPSO	QLPSO	QLPSOND
Inertia wright	0.729	[0.4, 0.9]	/	/
Population size	20			
Iteration	100			
Dimension	9 for Meituan; 11 for Xiaomi			

5.4. Experimental results and discussions

Since our goal is to minimize the resilience loss of the group opinion system by making minimal adjustments to control variables, the objective function introduced in Section 4.3 serves as the fitness function during the algorithm execution process. The smaller the fitness, the better the control strategy found by the algorithms. The convergence curves and experiment results of the four algorithms applied to Meituan and Xiaomi are shown in Figure 12 and Table 6, respectively.



(a) Meituan **(b) Xiaomi**

Figure 12. Convergence curves of the algorithms in two datasets

(1) **Meituan.** Figure 12(a) shows the iteration and convergence of each algorithm in the resilience control of Meituan dataset. We can see the convergence rate of the solutions for all four algorithms is relatively slow, mainly due to the complex property of the objective function, which is a multi-modal and nonperiodic function. Furthermore, among the algorithms, QLSPOND consistently outperforms QLPSO, SPSO and LPSO in 100 iterations, indicating the superior performance of the QLPSOND algorithm, which incorporates adaptive parameter adjustment and nonlinear discretization for states space. SPSO performs the worst, as it often gets stuck in a "plateau stagnation" state for long periods and is easily trapped in local optima when solving this multi-modal complex problem and LPSO has a similar problem, while the fitness of QLPSOND and QLPSO decreases steadily, showing QLPSOs' great searchability.

In addition, compared to the original QLPSO, the proposed QLPSOND has a faster convergence speed. It not only has a faster descent rate of the convergence curve in the early stage but also has a certain optimal searching ability and higher accuracy in the later stage.

(2) **Xiaomi.** Figure 12(b) shows that the performance of QLPSOND in Xiaomi is always better than the other three algorithms, with the fastest convergence speed and the highest fitness accuracy, which is consistent with the performance of QLPSOND in the Meituan case.

Table 6. Comparison with baseline methods on two datasets.

Methods	Time Complexity	Meituan		Xiaomi	
		Average Fitness	Best Fitness	Average Fitness	Best Fitness
QLPSOND	O(*max_Iter* * *num_particles*)	-1.85613	-2.46510	-2.17493	-2.31545
QLPSO		-1.34905	-1.87236	-2.01410	-2.09958
LPSO		-0.95427	-1.79834	-1.908560	-2.19237
SPSO		-0.87708	-1.23754	-1.87417	-1.99178

Table 6 shows the average fitness and the best fitness of the four algorithms in the resilience control example of the two datasets. The *average fitness* refers to the mean fitness during 100 iterations of the algorithm, and the *best fitness* is the global best fitness of 100 iterations of the algorithm. It can be seen that the QLPSOND algorithm proposed in this study has obtained the optimal average fitness and best fitness value in both two datasets. Proposed QLPSOND outperforms the most competitive state-of-the-art baseline method QLPSO by 37.59% and 7.98% in average fitness, 31.66% and 10.28% in best fitness on Meituan and Xiaomi datasets, respectively (calculated via Equation (11)).

$$\textbf{Performance improved}=\left|\frac{\text{QLPSOND}_{\text{average(best)\_fitness}}-\text{QLPSO}_{\text{average(best)\_fitness}}}{\text{QLPSO}_{\text{average(best)\_fitness}}}\right| \quad (11)$$

The application of the QLPSOND algorithm in the Meituan Forum and Xiaomi Forum demonstrates its superiority over the state-of-the-art QLPSO algorithm and other baseline methods in addressing the resilience control problem.

6. Further analysis and discussions

6.1. Validation of resilience control strategy

Although the experiments have verified our proposed resilience control method is efficient in lowering the resilience loss, there are still some questions to ask: (1) When should we implement the resilience control method for the system? (2) How to verify that this method indeed achieves our expected effect, that is, reduces the possibility of sudden change in group opinion? To solve these two problems, we introduce the resilience threshold.

6.1.1. Resilience threshold

Under external stimuli, the extent of group opinion change varies with the resilience loss. When the resilience loss increases to a certain degree, there is a sudden increase in opinion sentiment change, defined as the resilience threshold here. We consider the resilience threshold as a warning signal for sudden shifts in group opinion, that is when we need to implement the resilience control strategy in the system. By associating the sentiment changes with corresponding resilience loss, we can obtain the correspondence between the resilience loss and the change in group opinion sentiment, as shown in Figure 13.

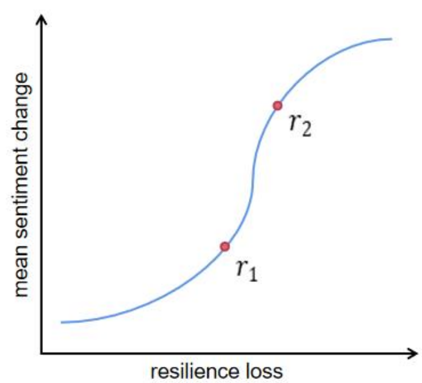


Figure 13. Sentiment change curve

The two threshold points r_1 and r_2 in Figure 13 are determined using the threshold point search method. The mathematical definition of this method is presented as Equation (12).

$$threshold=\begin{cases} r_1, \max\left\{\frac{\partial^2 s(r)}{\partial r^2}\right\} \\ r_2, \min\left\{\frac{\partial^2 s(r)}{\partial r^2}\right\} \end{cases} \quad s.t.\ r_2 > r_1 \qquad \textbf{(12)}$$

Here, r_1 and r_2 denote the two threshold points, and $s(r)$ represents the abstract function describing the change in group opinion sentiment concerning the system's resilience loss r. When the group's resilience loss arrives at r_1, the group opinion undergoes a sudden and rapid change, where even small disturbances can cause significant jumps in group opinion. Once beyond r_2, the change in group opinion stabilizes at a relatively high and stable value. At this stage, substantial intervention and effort are required to restore stability to the group's state.

6.1.2. The change of resilience threshold before and after control

Taking Meituan dataset as an example, the sentiment change curve before and after implementing the resilience control strategy is shown in Figure 14, along with the position of the two resilience thresholds. It can be observed that after implementing the control method, there are changes in the overall pattern and the position of the two thresholds.

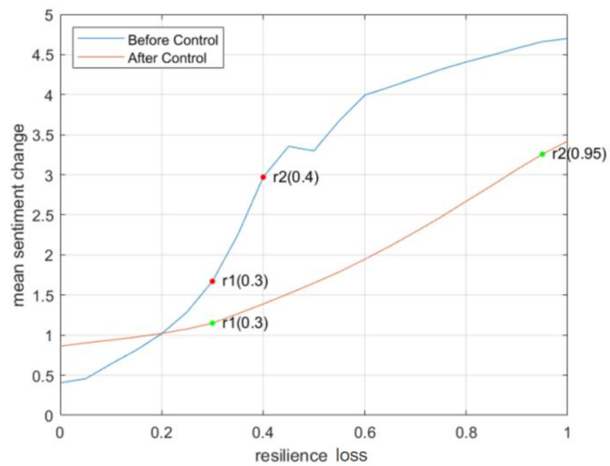


Figure 14. Sentiment change curve before and after resilience control

(1) **The sentiment change curve** shifts downwards and becomes flatter in the overall pattern after implementing the control method. This implies that with the increase in resilience, compared to the sentiment fluctuations before the implementation of the control method, the overall magnitude of the community's opinion changes decreases after using this control method. The amplitude of change becomes slower, and the entire system becomes more stable.

(2) ***The first threshold point*** moves lower after implementing the control method, indicating that the warning of rapid sentiment changes arrives earlier. Compared to that before the implementation of the control method, the system after control is more likely to reach the first warning, but the magnitude of sentiment change is relatively more gentle after reaching this threshold.

(3) ***The second resilience threshold*** represents the warning when sentiment fluctuation reaches its peak. After the control method, the second threshold moves toward the right side. This means that in the online community under the control method, it becomes more challenging to reach the critical threshold for intense sentiment fluctuations, indicating a higher threshold and a lower possibility of experiencing sudden changes.

(4) ***The distance between the two threshold points*** widens, indicating that the system has sufficient time and buffer space to respond and take relevant measures after the first threshold warning. This allows the system to avoid reaching a high-stable state of emotional fluctuations.

In conclusion, after implementing the resilience control method, although it appears that the system is more likely to reach the first threshold point, the subsequent increase in sentiment fluctuations becomes slower and it becomes more difficult to reach the critical threshold for intense sentiment fluctuations (i.e., the second threshold). The resilience control method weakens the sudden and rapid changes in group opinion and enhances the stability of the system.

6.2. Identify the main factors in the resilience control strategy

The QLPSOND algorithm provides the optimal control strategy for reducing the system's resilience loss by adjusting the independent variables of the cusp model. In this section, we identify the main variables in the strategy and explain the practical implications of them. First, we need to rescale the independent variables from the normalized data to their original scale, since the aforementioned optimization variables are standardized. Subsequently, as the original data consists of continuous numerical values that are difficult to define and interpret, we discretize the raw data of the variables in datasets into specific groups to enhance the interpretability of the data.

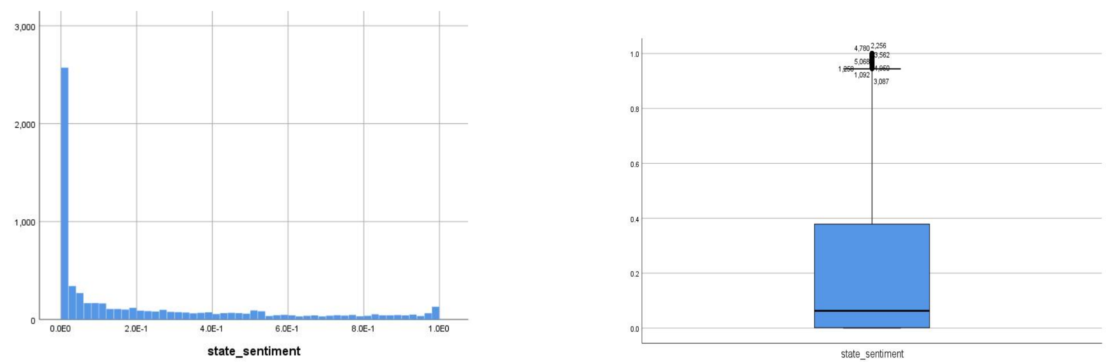
6.2.1. Inverse standardization

In the data preprocessing, the independent variables of each sample were standardized using the z-score method ($x_i^* = (x_i - x_{mean})/x_{std}$) and the obtained control strategy solution represents the change in each standardized independent variable. To restore these changes to the original scale, we multiply the change by the standard deviation of the corresponding independent variable before standardization across all samples.

6.2.2. Grouping and discretization of the original Data

After restoring the values of changes in variables to the original scale, it is necessary to consider the extent of variables' changes based on the distribution of the original data of the variables, which facilitates better interpretation and provides practical insights for resilience control suggestions.

However, due to uneven distributions and the presence of outliers or extreme values in each variable's original data, the judgment of the magnitude of the changes in variables can be affected. Take the distribution of variables in the Meituan dataset as an example, as shown in Figure 15 (charts of other variables' data distributions are displayed in Appendix B.2). One solution to address this issue is to discretize the original data of each independent variable. Here, we employ quartile-based grouping to divide the data, with equal frequency in each interval, which better captures the overall distribution of the data and mitigates the impact of outliers on group statistics [61].



(a) histogram **(b) boxplot**

Figure 15. Distribution of x_1 in Meituan dataset

The three percentiles (25%, 50%, and 75%) divide the data into four groups, which we label as {Very small, Small, Large, Very large} in ascending order. The grouping of variables is shown in Table 7 (for the grouping of other variables, please refer to Appendix B.3). For example, the change in x_1 (i.e., Δx_1) after inverse standardization is -0.0021272, whose absolute value falls within the range [0.001364, 0.062893] in Table 8. Therefore, Δx_1 belongs to the {Small} group.

Table 7. Grouping of x_1

Group	Dividing site	Upper limit of group	Lower limit of group
Very small	25%	0	0.001364
Small	50%	0.001364	0.062893

Large	75%	0.062893	0.378735
Very large	100%	0.378735	1

6.2.3. Grouping results and interpretation

By following the same procedure as described above, all variables in the resilience control strategy can be grouped and discretized. This allows us to derive the numerical implications of the resilience control strategies. Table 8 and 9 present the results of this grouping for all control variables in Meituan and Xiaomi datasets, respectively.

(1) **As for Meituan**, it can be observed from Table 9 that variables Δx_2 , Δx_3 , Δx_4 , Δx_5 , Δx_8 all belong to the {very small} group. Therefore, these variables are not the main focus of management in practical settings. On the contrary, Δx_1 , Δx_6 , Δx_7 , Δx_9 are more significant control variables in the resilience control strategy and require attention in real-world scenarios. Among these significant variables, x_1 represents *the sentiment of the original poster's statement*, while x_6, x_7 and x_9 represent key features of social networks, namely *the number of nodes (followers), number of edges, and transitivity* of the posts. These variables are all manageable and monitorable in real-world network communities. By managing these variables, the sentiment changes in the online community will tend to be stable, so as to reduce the possibility of sudden changes in the community's opinion. Hence, we can say that the derived resilience control strategy is feasible for management in real-world network communities.

Table 8. Grouping for control variables in Meituan

Variables Notation	Variables Meaning	Change value (Δx_i)	Change value after recovery ($\Delta x_i'$)	Change Extent
x_1	the sentiment of the original poster statement	-0.0072	-0.0021272	**Small**
x_2	the absolute value of the difference between the sentiment of the original poster statement and follower comments	-0.0094	-0.0007771	Very small
x_3	the standard deviation of the sentiment of follower comments	0.0087	0.0013974	Very small
x_4	the frequency of the three highest-frequency words of follower	-0.0102	-0.0013954	Very small
x_5	the average sentiment of the three highest-frequency words of follower	0.0027	0.0003836	Very small
x_6	the number of nodes for the semantic network from the follower comments	1.9012	59.3263802	**Very large**
x_7	the number of edges for the semantic network from the follower comments	-0.2561	-218.3074600	**Very large**
x_8	the density for the semantic network from the follower comments	-0.0049	-0.0009091	Very small
x_9	the transitivity for the semantic network from the follower comments	-0.0147	-0.0054154	**Small**

(2) In terms of **Xiaomi** dataset from Table 9, Δx_2 , Δx_8 are more significant control variables in the resilience control strategy and require attention in real-world scenarios. It suggests that to effectively reduce the possibility of sudden changes occurring in the Xiaomi forum, two actions can be taken: 1）Increasing the view count of each post, and 2）Decreasing the sentiment value of high-frequency words within the posts.

Table 9. Grouping for control variables in Xiaomi

Variables Notation	Variables Meaning	Change value (Δx_i)	Change value after recovery ($\Delta x_i'$)	Change Extent
x_1	the sentiment of the original poster statement	-0.0142	-0.0047130	Very Small
x_2	Number of views of the post	1.1367	1480.8033017	**Very Large**
x_3	Number of *likes* of the post	-0.0473	-0.9313275	Very small
x_4	Power of the original poster	-0.0003	-0.0003060	Very small
x_5	the standard deviation of the sentiment of follower comments	0.0118	0.0006525	Very small
x_6	the absolute value of the difference between the sentiment of the original poster statement and follower comments	0.0387	0.0062191	Very small
x_7	the frequency of the three highest-frequency words of follower	0.0248	0.0024378	Very small
x_8	the average sentiment of the three highest-frequency words of follower	-3.0000	-0.4419000	**Small**
x_9	the number of nodes for the semantic network from the follower comments	0.0143	0.2345214	Very Small
x_{10}	the density for the semantic network from the follower comments	-0.3644	-0.0411772	Very Small
x_{11}	The global efficiency for the semantic network from the follower comments	-0.0108	-0.0016254	Very Small

6.3. Comparison of resilience control strategy between two different forums

Since Meituan and Xiaomi represent two different types of online interactive communities, it is necessary to compare the similarities and differences in their control strategies in order to find management insights that are more applicable in reality.

6.3.1. The common ground of the resilience control strategies of the two forums

Here we discuss the commonalities in the resilience control strategies of two different types of forums. It is observed that four control variables share the same directional change. Specifically, the variables ***the sentiment of the original poster's statement*** and ***the density of the semantic network from the follower comments*** both exhibit negative changes. Conversely, the variables ***the standard deviation of the sentiment of follower comments*** and ***the number of nodes for the semantic network from the follower comments*** both show positive changes.

In conclusion, for both types of online communities, the most effective approach to reducing their resilience is to increase the diversity of the posts. This involves encouraging the existence of various opinions while diminishing the degree of interconnectedness and susceptibility of opinions among different users. By enhancing the system's stability, it becomes less prone to sudden disruptions.

6.3.2. The differences in resilience control strategies between the two forums

Due to the difference in availability and significance of variables, the variables of the two cases are not all the same, so here we only discuss the variables that both forums have.

For the change of ***the absolute value of the difference between the sentiment of the original poster statement and follower comments***, ***the frequency of the three highest-frequency words of follower comments***, Meituan is negative while Xiaomi is positive; for the change of ***the average sentiment of the three highest-frequency words of follower comments***, Meituan is positive and Xiaomi is negative.

(1) As for Meituan, an unofficial public forum, ***the absolute value of the difference between the sentiment of the original poster's statement and follower comments*** reveals the impact that the poster's statement has on the followers. The larger the values, the more likely the followers' opinions are influenced by the poster and transform. Therefore, reducing the indicator appropriately contributes to improving the stability of the system. ***The frequency of the three highest-frequency words in follower comments*** reflects the concentration of the followers' comments, the smaller of which, the greater the dispersion, and the less likely the system is to experience sudden change. A larger t***he average sentiment value of the three most frequent words*** value suggests that the followers' sentiments are more inclined toward positive sentiments. In our discussion, the occurrence of sudden change is primarily driven by extremely negative sentiments. Therefore, increasing this indicator aligns with our traditional understanding of the theory of catastrophe and resilience.

(2) As for Xiaomi, an official forum, the direction of changes in these three variables on Xiaomi Forum is opposite to that of Meituan. This is because, for Tieba Forum, the participants are individual users, while for Xiaomi Forum, the participants of the forum are not only Xiaomi consumers but also officials. Here, for Xiaomi consumers, the official is a potential and significant external influence factor, and the official sentiment value is a constant with a definite and high positive value (as the direct stakeholders of interests). Therefore, increasing the frequency of high-frequency words in a single post, the difference between the sentiment value of the poster and the followers, and reducing the positive sentiment of the post (and then forming a certain contrast with the official sentiment orientation) are ways to increase the diversity of opinions for the posts in the official forum.

7. Implications

7.1. Theoretical implications

This paper makes significant theoretical contributions in several ways. First, it proposes an innovation control approach to the complex system. Most control research for complex systems often focuses on the system's structure or data characteristics [6, 7, 62]. These methods belong to the surface-level control method in the context of the physical system, rather than the socio-political-cultural context. The social system has a sophisticated operation mechanism due to human beings as the main component of the system. Thus, the control method in this paper proposed a novel way. We avoid modeling the whole group opinion system with the structure, all components and external environmental factors, but dig out the resilience of the group opinion system. Resilience delegates the hidden capacity, the underlying power of a system that defends the external attack and constrains the behavior of the system. We control the resilience so as to reach the aim of controlling the behavior of the group opinion system, which is the bottom-level control method. By providing an effective way to make the online communities become more resilient to the internal and external stimuli.

Second, our study contributes to the existing literature on the limitations of the QLPSO by expanding its availability to complex social problems. The existing literature about QLPSO only tests the algorithm performance on common benchmark functions [12, 58], or uses QLPSO to solve some engineering structural problems [13], lacking research on using QLPSO to study social problems or complex systems that characterized by nonlinear, multi-modal and complex properties. Our paper improves the original QLPSO algorithm proposed by Liu [12] and proposes QLPSOND through the nonlinear discretization of its states space. Applying the developed QLPSOND algorithm to real online community cases, the algorithm shows outstanding performance in dealing with the complex system control problem (i.e., resilience control of group opinion evolution). We achieve in broadening the application scope of related research on the combination of Reinforcement learning and heuristic algorithms in solving practical complex social problems.

Third, the study also makes significant theoretical contributions to the emerging field of the social cybersecurity field. Social cybersecurity has gained prominence in recent years, yet it remains in need of further development and refinement [3]. Existing research primarily revolves around topics such as misinformation, social media privacy concerns and cyberbullying [63, 64, 65]. However, there is still a notable research gap in studying the mitigation of sudden opinion changes in this domain. Our paper proposes a way to understand how a social cybersecurity crisis (i.e., group opinion catastrophe phenomena) be mitigated. We introduce a resilience control method for online forums, aimed at enhancing their ability to withstand and recover from such attacks. The proposed resilience loss, modeled using catastrophe theory, can serve as a reliable measures of the online forums' resilience. The metric, in turn, facilitates further research in maintaining the security of the whole online society.

7.2. Managerial implications

The contributions also have practical significance for the administrators of the online communities. Utilizing the methods proposed in our paper, when administrators identify that the resilience loss of an online community is approaching the threshold, they can trigger the QLPSOND resilience control algorithm. The algorithm helps identify a set of control variables that lead to most efficiently mitigate the sudden change. Based on the above analysis, online community administrators can consider the following detailed measures.

For **public forums** (e.g., the Meituan forum from Baidu Tieba), administrators can intervene promptly to promote balance and diversity in discussions, preventing excessive focus on a single opinion. Attract more users to participate in the discussions by increasing the visibility of comments; strengthen monitoring and handling of malicious behavior and hate speech to maintain a friendly and harmonious environment within the community.

For **official organization forums** (e.g., Xiaomi forum), organizations should avoid excessive promotion of their products and instead encourage users to provide constructive criticism and improvement suggestions. Enhance users' focus on specific subjects by categorizing posts based on the topics discussed by users, thereby further increasing the frequency of high-frequency words within the posts; encourage higher levels of engagement and interaction, such as likes, comments, and shares, to increase the visibility of each post, which may contribute to a more stable and controlled environment.

8. Conclusions

Complex systems exhibit characteristics such as suddenness and instability, and the evolution of online group opinion serves as a quintessential example of such complexity. To control sudden changes in group opinion, catastrophe modeling and resilience modeling are integrated to gauge the hidden capacity, i.e., resilience, within the group opinion system. It avoids modeling the whole group opinion system considering the structure, all components and external environmental factors.

Since the traditional control methods, e.g., QLPSO, are oriented to the physical system and demonstrate inadequate performance when addressing complex nonlinear problems, reinforcement learning is integrated into the optimization algorithms to yield the QLPSOND algorithm. It takes into account the characteristics of textual data and variables in the online community within the field of group opinion and enhances the existing QLPSO proposed by Liu, via employing a nonlinear discretization technique for its states space.

The above-proposed methods are applied to the Meituan and Xiaomi forums. The effectiveness of QLPSOND is verified. Based on the control strategy identified by QLPSOND, an analysis of its implementation effect is conducted through the comparison of the opinion sentiment fluctuation. The implications of the control strategy are interpreted from various perspectives, taking into consideration real-world circumstances. This comprehensive discussion of resilience control strategy provides practical recommendations for managing group opinions of online communities. Furthermore, this study provides a method for identifying key control variables. By regulating these key variables, it is possible to effectively reduce the resilience of the system, achieving the most efficient control.

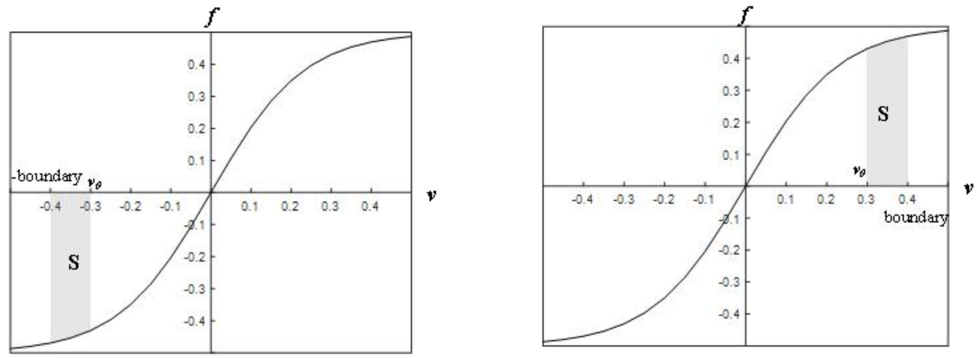
The study also has some limitations. Firstly, the study focused on static resilience control, studying the implementation of resilience control strategy as a one-time event. Besides, some independent variables are difficult to control in reality. In the future, it would be valuable to validate our proposed resilience control strategies by considering the practical application and developing a dynamic resilience control strategy.

Appendix

Appendix A. Resilience Model

A.1 Resilience model based on the logistic-shape curved surface

For the case when $u<0$ in Figure 2, we can select any point on the axis v to obtain the corresponding tangent plane, as depicted in Figure 8. Similarly, we consider a specific point v_0 on the axis v as an example. In this scenario, we can divide it into two parts: when $v_0<0$ and when $v_0>0$.



a. $v_0 < 0$ **b.** $v_0 > 0$

Figure A1. Tangent plane at any point of axis u when $u<0$

The resilience loss in the two parts depicted in Figure 8a and b, represented by the area *S*, is quantified to construct the resilience model. Therefore, we can formulate the resilience model as shown in Equation (A1).

$$resilience\ loss = \begin{cases} \int_{-boundary}^{v_0} (0.5 - \frac{1}{1+e^{-v/u_0^2}}) dv, v_0 < 0 \\ \int_{v_0}^{boundary} (\frac{1}{1+e^{-v/u_0^2}} - 0.5) dv, v_0 \geq 0 \end{cases} \quad \textbf{(A1)}$$

In the equation, u_0 and v_0 represent arbitrary points on the axis u,v. The parameter *boundary* determines the boundary of v within the system.

By considering values of u=3, $v_0 \in [-5, 5]$ and *boundary* = 0.5 , we can calculate the resilience loss over the range , as illustrated in Figure 9.

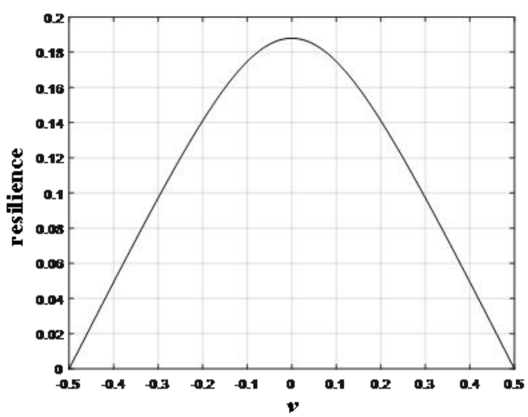


Figure A2. Resilience loss when $u=0.3$

A.2 Resilience Threshold

A second-order derivative-based approach is employed to locate the threshold point. The first derivative of this relationship reflects the slope of the sentiment change with respect to the resilience value, indicating the magnitude of the group opinion change rate. The second derivative reflects the rate of change of the first derivative. When the second derivative is maximized, it indicates the maximum rate of change of the dependent variable on the vertical axis. Conversely, when the second derivative is minimized, it indicates the minimum rate of change of the dependent variable. Therefore, the first threshold point is defined as the maximum value of the second derivative, while the second threshold point is defined as the minimum value of the second derivative. This can be mathematically represented as shown in Equation (12).

Appendix B. The Case Study: Meituan

B.1 The fitting results for Meituan

The cusp model fitting results for Meituan using R is shown as below.

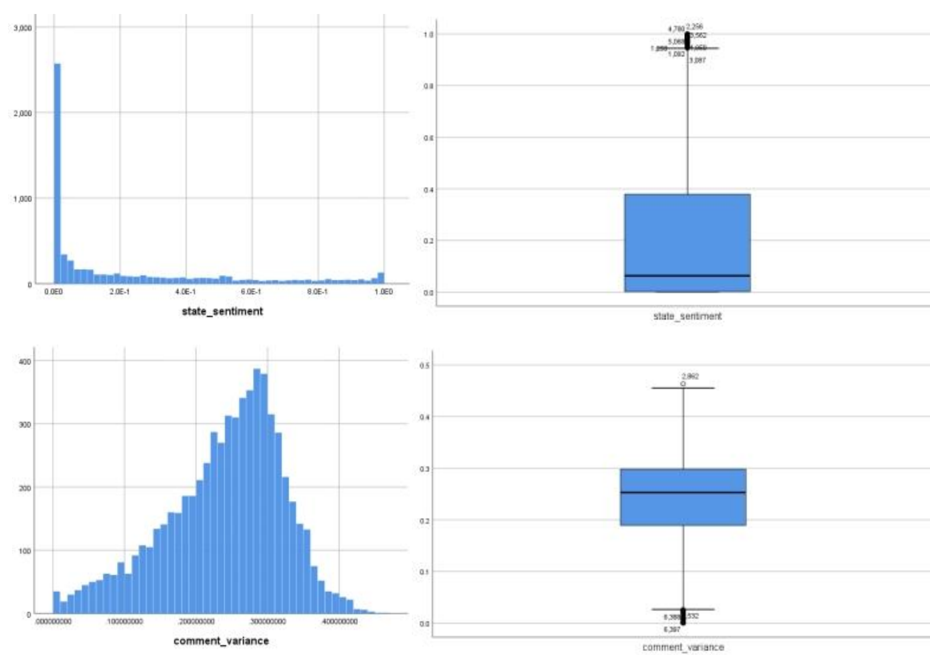
```
Call:
cusp(formula = y ~ f, alpha = formula(a), beta = formula(b),
    data = data)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-3.93890  -0.23342   0.05894   0.41420   3.44265

Coefficients:
                      Estimate Std. Error z value Pr(>|z|)
a[(Intercept)]       -2.115209   0.004385 -482.40  < 2e-16 ***
a[state_sentiment]    0.214185   0.015001   14.28  < 2e-16 ***
a[comment_variance]  -0.044977   0.008392   -5.36 8.34e-08 ***
a[minus_sentiment]    0.316514   0.007341   43.12  < 2e-16 ***
a[frequency]          0.220720   0.009296   23.75  < 2e-16 ***
a[topword_sentiment]  0.941855   0.006836  137.78  < 2e-16 ***
a[num_nodes]         -1.098496   0.010302 -106.63  < 2e-16 ***
a[num_edges]          0.568649   0.005636  100.90  < 2e-16 ***
a[density]           -0.138462   0.002707  -51.15  < 2e-16 ***
a[transitivity]      -0.200183   0.018120  -11.05  < 2e-16 ***
b[(Intercept)]       -1.334308   0.014398  -92.67  < 2e-16 ***
b[comment_variance]  -1.524665         NA      NA       NA
b[minus_sentiment]   -0.233435   0.003989  -58.52  < 2e-16 ***
b[frequency]         -0.584979   0.017046  -34.32  < 2e-16 ***
b[num_nodes]         -0.933042   0.027445  -34.00  < 2e-16 ***
b[num_edges]          0.513362   0.040034   12.82  < 2e-16 ***
b[density]            0.500968         NA      NA       NA
b[transitivity]       0.140243         NA      NA       NA
w[(Intercept)]       -0.775980   0.007498 -103.49  < 2e-16 ***
w[f]                  0.761025   0.004667  163.06  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

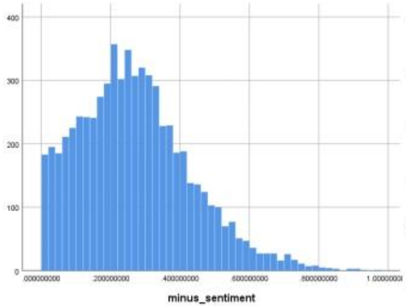
	R.Squared	logLik	npar	AIC	AICc	BIC
Linear model	0.4540939	-7173.243	11	14368.49	14368.53	14442.94
Logist model	0.5001236	-6890.222	19	13818.44	13818.56	13947.04
Cusp model	0.4619964	-6352.339	20	12744.68	12744.81	12880.04

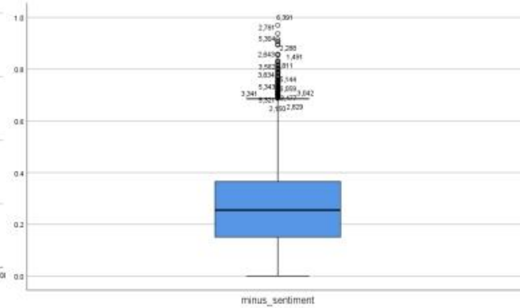
Figure B1. Catastrophe (cusp) model fitting result for Meituan

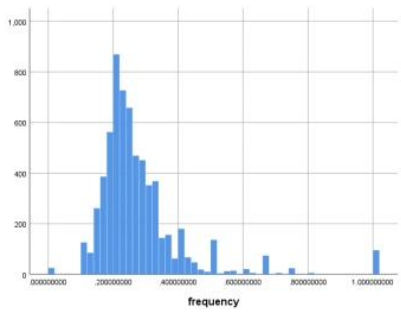
The AIC and BIC of Cusp model are both the smallest among the three models, which means that the Cusp model is the most suitable model for this case.

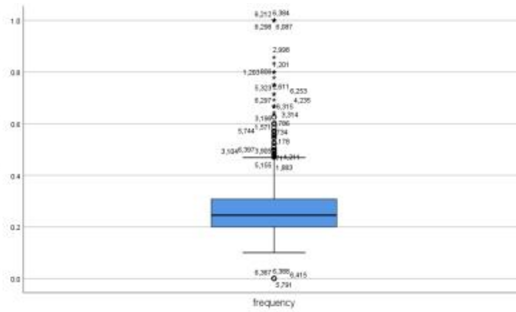
B.2 Data distribution of raw data for each variable

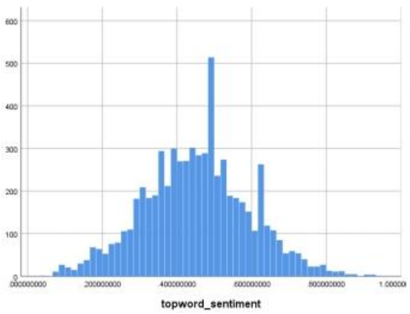


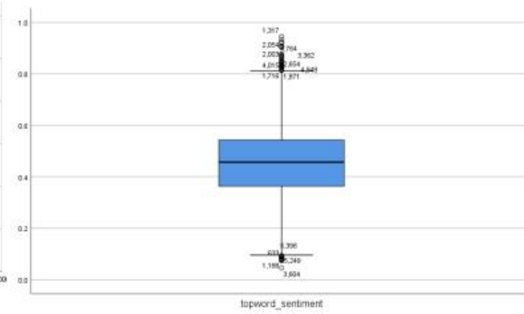

minus_sentiment

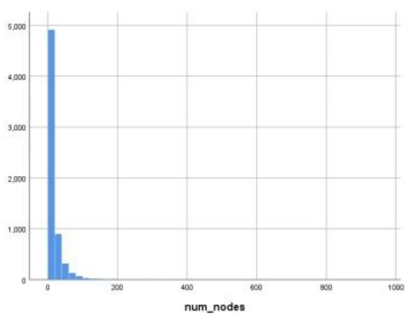

minus_sentiment

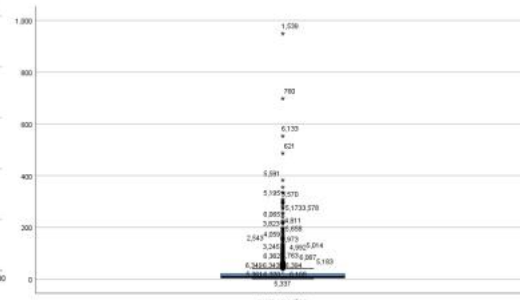

frequency

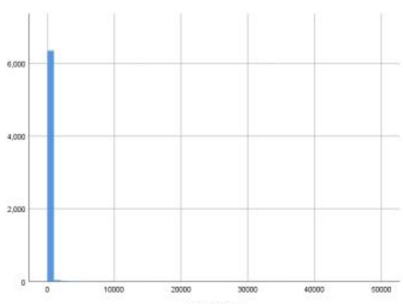

frequency

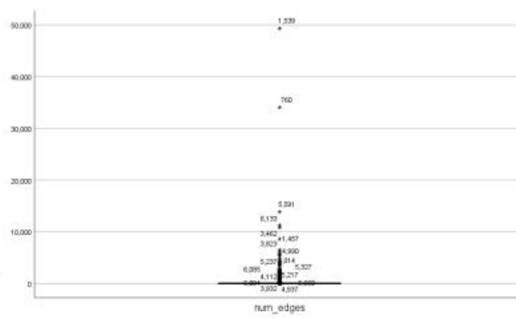

topword_sentiment

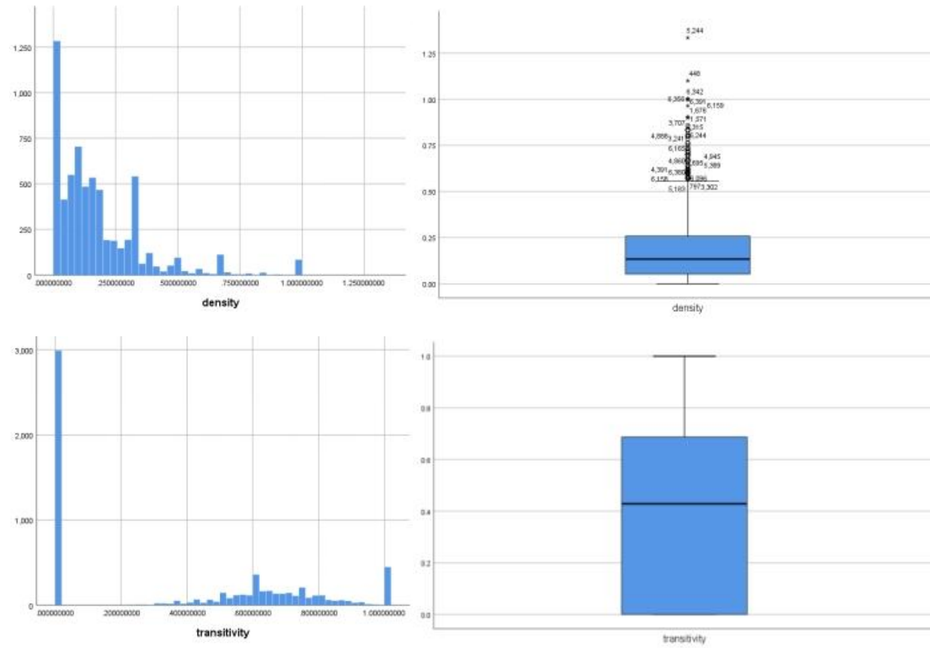

topword_sentiment


num_nodes


num_nodes


num_edges


num_edges



B.3. Quantile-based grouping results for each variable

Table B1. Grouping of x_1

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	0.001364
small	50%	0.001364	0.062893
large	75%	0.062893	0.378735
Very large	100%	0.378735	1

Table B2. Grouping of x_2

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	0.189242
small	50%	0.189242	0.252930
large	75%	0.252930	0.297918
Very large	100%	0.297918	0.463275

Table B3. Grouping of x_3

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0.000161	0.150600
small	50%	0.150600	0.254666
large	75%	0.254666	0.364963
Very large	100%	0.364963	0.969894

Table B4. Grouping of x_4

Group	Dividing site	Lower limit of group	Upper limit of group

Very small	25%	0	0.200000
small	50%	0.200000	0.245283
large	75%	0.245283	0.307692
Very large	100%	0.307692	1

Table B5. Grouping of x_5

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0.045463	0.363101
small	50%	0.363101	0.456653
large	75%	0.456653	0.542818
Very large	100%	0.542818	0.945175

Table B6. Grouping of x_6

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	1	4
small	4.000000	4	8
large	75%	8	19
Very large	100%	19	949

Table B7. Grouping of x_7

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	1
small	50%	1	4
large	75%	4	22
Very large	100%	22	49332

Table B8. Grouping of x_8

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	0.052358
small	50%	0.052358	0.133333
large	75%	0.133333	0.257576
Very large	100%	0.257576	1.333333

Table B9. Grouping of x_9

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	0
small	50%	0	0.428571
large	75%	0.428571	0.687338
Very large	100%	0.687338	1

Appendix C. The Case Study: Xiaomi

C1. Inverse Standardization of Xiaomi

Table C1. Inverse Standardization of Control Strategy

Variables	Change value before	Standard deviation of	Change value after recovery
x_1	-0.0142	0.3319	-0.0047130
x_2	1.1367	1302.7213	1480.8033017
x_3	-0.0473	19.6898	-0.9313275
x_4	-0.0003	1.0199	-0.0003060
x_5	0.0118	0.0553	0.0006525
x_6	0.0387	0.1607	0.0062191
x_7	0.0248	0.0983	0.0024378
x_8	-3.0000	0.1473	-0.4419000
x_9	0.0143	16.4001	0.2345214
x_{10}	-0.3644	0.1130	-0.0411772
x_{11}	-0.0108	0.1505	-0.0016254

C2. Quantile-based grouping results for each variable

Table C2.1. Grouping of x_1

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	0.051571
small	50%	0.051571	0.281178
large	75%	0.281178	0.654622
Very large	100%	0.654622	1

Table C2.2. Grouping of x_2

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	35	384
small	50%	384	663
large	75%	663	1238
Very large	100%	1238	18306

Table C2.3. Grouping of x_3

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	6
small	50%	6	11
large	75%	11	20
Very large	100%	20	231

Table C2.4. Grouping of x_4

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	1	3
small	50%	3	3
large	75%	3	5
Very large	100%	5	7

Table C2.5. Grouping of x_5

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0.028733	0.206529
small	50%	0.206529	0.248123
large	75%	0.248123	0.281425
Very large	100%	0.281425	0.450950

Table C2.6. Grouping of x_6

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0.001148	0.152751
small	4.000000	0.152751	0.268297
large	75%	0.268297	0.381190
Very large	100%	0.381190	0.880808

Table C2.7. Grouping of x_7

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0.1	0.200000
small	50%	0.200000	0.250000
large	75%	0.250000	0.304461
Very large	100%	0.304461	1

Table C2.8. Grouping of x_8

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0.114398	0.371795
small	50%	0.371795	0.461479
large	75%	0.461479	0.590735
Very large	100%	0.590735	0.923295

Table C2.9. Grouping of x_9

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	3	7
small	50%	7	10
large	75%	10	17
Very large	100%	17	217

Table C2.10. Grouping of x_{10}

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	0.057190
small	50%	0.057190	0.101197
large	75%	0.101197	0.190476
Very large	100%	0.190476	0.809524

Table C2.11. Grouping of x_{11}

Group	Dividing site	Lower limit of group	Upper limit of group
Very small	25%	0	0.066667
small	50%	0.066667	0.131109
large	75%	0.131109	0.255952
Very large	100%	0.255952	0.904762

CRediT authorship contribution statement

Di Wu: Conceptualization, Validation, Data curation, Methodology, Formal analysis, Visualization, Writing – original draft, Writing – review & editing.

Bin Hu: Conceptualization, Validation, Data curation, Methodology, Software, Writing – review & editing, Supervision, Funding acquisition

Xiaomeng Ma: Conceptualization, Validation, Funding acquisition, Resources, Writing – review & editing.

Zhichao Wang: Conceptualization, Data curation, Methodology, Software, Resources

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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