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Multi-Agent Based Stochastic Dynamical Model to Measure Community Resilience

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Abstract: Emergency services and utilities need appropriate planning tools to analyze and improve infrastructure and community resilience to disasters. Recognized as a key metric of community resilience is the social well-being of a community during a disaster, which is made up of mental and physical social health. Other factors influencing community resilience directly or indirectly are emotional health, emergency services, and the availability of critical infrastructures services, such as food, agriculture, water, transportation, electric power, and communications system. It turns out that in computational social science literature dealing with community resilience, the role of these critical infrastructures along with some important social characteristics is not considered. To address these weaknesses, we develop a new multi-agent based stochastic dynamical model, standardized by overview, design concepts, details, and decision (ODD+D) protocol and derived from neuro-science, psychological and social sciences, to measure community resilience in terms of mental and physical well-being. Using this model, we analyze the micro-macro level dependence between the emergency services and power systems and social characteristics such as fear, risk perception, information-seeking behaviour, cooperation, flexibility, empathy, and experience, in an artificial society. Furthermore, we simulate this model in two case studies and show that a high level of flexibility, experience, and cooperation enhances community resilience. Implications for both theory and practice are discussed.

Key words: community resilience; collective behavior; emergency services; power systems; critical infrastructures; artificial society; overview, design concepts, details, and decision (ODD+D); cyber-physical-social system

1 Introduction

To improve preparedness and reduce death tolls and physical losses, government agencies, emergency services, and utilities need appropriate planning tools to analyze and enhance community resilience to disasters. Specifically, the planning tools will allow the planners to assess the level of resilience of the critical infrastructures together with the social community that they serve and, if that level is deemed to be insufficient, mitigation measures are predicted and passed to the critical infrastructure planning departments for implementation.

Resilience, for which a variety of definitions are given in the literature, is investigated in various domains such as sociology, policy implementation, decision-making, engineering, geography, and urban planning. In sociology, Cutter et al.[1], which is the most cited paper in community resilience, proposed the following definition: " resilience is the ability of a social system to respond and recover from disasters and

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includes those inherent conditions that allow the system to absorb impacts and cope with an event, as well as post-event, adaptive processes that facilitate the ability of the social system to re-organize, change, learn in response to a threat." This definition is the most comprehensive one found in the literature. Braden[2] highlighted other interesting features of community resilience, namely excess capacity, flexibility, confined failure, prompt rebound, and unswerving learning.

Community resilience is affected by critical infrastructures, mass media, and social features of the community. Critical infrastructures are of high importance for the well-being of a society[3]. Among them, power systems and the emergency services play a pivotal role during a disaster, whether being induced by natural, human, or economic stressors[4, 5]. Therefore, a power system must be resilient to extreme events. Indeed, the availability of electric energy has a physical and emotional impact on a society, which consists of residential, commercial, and industrial sectors. Its lack can diminish physical social health due to a decrease in economic welfare and in the availability of food, energy, water, transportation, and medical services, to cite a few. On-site electric generation can overcome power outages and hence, is desirable for long-term social well-being, especially during a disaster. Similar to power systems, emergency services are instrumental in mitigating the impact of a disaster on a society. When equipped with the highest level of alert communication, this critical infrastructure is able to decrease the physical and economic losses as well as the damage incurred by society during extreme events. Furthermore, emergency services can provide shelter, water, medication, food, sanitation, and treatment assessment to society during and after a disaster. The availability of these services has a positive impact on social physical health during a disaster[6]. Therefore, we propose the following definition of community resilience.

Definition: The resilience of a social community to a class of disasters is defined as its ability to (1) survive and reduce the death toll and the number of injured people and fear, by sharing the scarce resources and information still available, which is prompted by its flexibility, compassionate empathy, cooperation, and experience, and (2) initiate a rapid recovery by re-organizing itself and reconstructing the damaged or destroyed housing and infrastructures.

This definition is consistent with the one given by Mili et al.[6] for a critical infrastructure, which is viewed as a system of interconnected components or agents achieving a common goal. Modeling critical infrastructures along with their interdependencies and the behavior of the social community they serve are pivotal to disaster planning[7, 8]. Owing to the fact that the well-being of a society is entwined with the services provided by critical infrastructures, it is important to model social behavior together with critical infrastructures when studying community resilience.

The development of computational models of the collective behavior of humans is instrumental for a variety of disciplines such as psychology, security management, social science, and computer science among others[9, 10]. In this paper, we model an artificial society※ to evaluate community resilience. The history of agent-based modeling started from the cellular automata, checkerboard simulation, and game of life, and developed into artificial life and artificial societies in computational social science. Artificial society by constructing parallel simulations of agents (at the micro level) makes us be able to sociologically analyze the system (at the macro level) in the form of computational sociology and vice versa[11, 12]. Currently, there are three distinct types of agent models applied in artificial society: reactive, deliberative, and hybrid agents[13]. Agent characteristics involve both mental and physical aspects[13]. Important mental characteristics for the agents in our artificial society are: emotion, risk perception, information-seeking behavior, cooperation, empathy, flexibility, and personal characteristic such as optimism and experience[2, 14–16]. Additionally, physical characteristics include the sense of being safe and sheltered and having a hygienic lifestyle to carry out physical activities and perform social responsibilities[17, 18]. The dynamics of the agent behaviors are affected by individual psychological factors in addition to external events, i.e., power outages, the news from the emergency services, and the mass media[19]. A variety of dynamic agent based models of human behavior have been proposed in Refs. [10, 20]. Here, we propose an agent-based model of community

※Using multi-agent based model for computational social science and virtual experiments by means of computer simulation is referred to as an artificial society.

resilience, which consists of social physical and mental well-being. The dependence amongst the social physical and mental well-being and outside determinants in our artificial society is displayed in Fig. 1. Interestingly, neuroscientists have discovered the existence of a neural mechanism expressed by mirror neurons in the brain that stimulates the propagation of the same emotion, intentions, and beliefs among a group of people. This is accounted for by our proposed model, which makes it biologically plausible. Note that in Ref. [19], it is reported that a similar model has correctly predicted the behavior of people trapped in a building under fire.

In this paper, we address the following questions: (1) How do critical infrastructures and social characteristics influence community resilience, and (2) How to measure community resilience accordingly? To address these questions, we develop a new stochastic model by providing micro-macro level dependence in an artificial society to evaluate the impact of human mental and physical well-being characteristics and their effects on human responses to disasters.

The key contributions of this work are as follows:

(1) Due to the significance of critical infrastructures for achieving community resilience, we simulate emergency services alongside the electric utility, on-site generation, and distributed energy resources in an artificial society vulnerable to natural disasters.

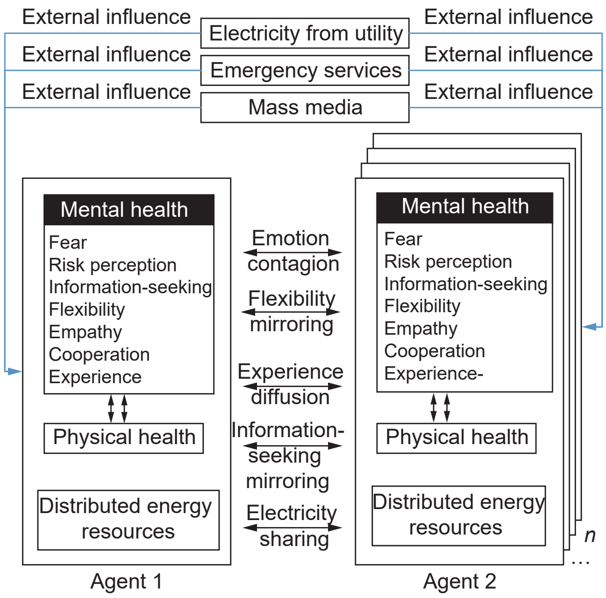

Fig. 1 Artificial society including agents and external factors, i.e., critical infrastructures, power systems, emergency services, and mass media. Critical infrastructures influence both mental and physical well-being while mass media only affects the mental well-being.

(2) We model and investigate significant social community characteristics, such as empathy, flexibility, experience, and cooperation for sharing electricity during disasters, that are not already covered in the computational social science and socio-technical systems literature.

(3) We create a mathematical description of the numerous societal and individual elements. In addition, by modeling each socio-technical element, we describe the dependency between these variables as well as their dynamical evolution.

(4) We model emotion contagion, flexibility mirroring, experience diffusion, and information-seeking behavior mirroring by integrating social science theories and computational social science in a multi-agent based model.

The proposed model is standardized by the overview, design concepts, details, and decision (ODD+D) protocol. In the appendix, an online link provides a standardized form of the ODD+D protocol[19, 21] for the multi-agent based stochastic dynamical model to measure community resilience. The proposed model is useful for social behavior analysis and prediction and for testing different scenarios that can occur in real-world situations. The model provides the option of modeling many different effects, which would be costly and difficult to do with only experiments or surveys. Finally, we simulate this model in two case studies to understand (1) individual effects on community resilience and (2) the effects of emergency services and electric energy availability on community resilience. Specifically, in the first case study, a community of nine persons facing a hurricane is simulated to analyze the social effect of human characteristics and critical infrastructures on community resilience. In the second case study, a society of six separate communities is simulated to analyze the social effect of different community characteristics on mental well-being, physical well-being, and community resilience.

The remainder of this paper is organized as follows. Section 2 explains which community resilience metrics were included in the model and on which scientific evidence they are based. Section 3 proposes the formal dynamic relations between the community resilience metrics, the modeling choices, and assumptions. Section 4 discusses the simulation results associated with case study 1. In Section 5, the simulation results for a society with six different communities—each with different population sizes and social characteristics—are discussed. Section 6 provides a summary and discussion of this work.

The annotations used in the paper are as follows:

M_{ti}^{E}: The level of fear of an individual *i* at the time *t*;

M_{ti}^{R}: The level of risk perception of an individual *i* at the time *t*;

M_{ti}^{B}: The level of information-seeking behavior of an individual *i* at the time *t*;

M_{ti}^{F}: The level of flexibility of an individual *i* at the time *t*;

M_{ti}^{L}: The level of experience of an individual *i* at the time *t*;

M_{ti}^{C}: The level of cooperation of an individual *i* at the time *t*;

M_{ti}^{O}: The level of optimism of an individual *i*, which is a personal characteristic, at the time *t*;

γ_{ij}^{E}: The level of compassionate empathy between two individuals *i* and *j* at the time *t*;

γ_{ij}^{B}: The level of information-seeking behavior contagion between two individuals *i* and *j* at the time *t*;

γ_{ij}^{F}: The level of flexibility mirroring between two individuals *i* and *j* at the time *t*;

γ_{ij}^{L}: The level of experience diffusion between two individuals *i* and *j* at the time *t*;

P_{ti}: The level of physical health of an individual *i* at the time *t*;

S_t: The level of social well-being of a community at the time *t*;

Z_{ti}: The level of severity of the injury incurred by an individual *i* facing a given disaster at the time *t*;

N_t: The fraction of the event-related information of the public news provided by the mass media (e.g., television, newspapers, and social networks) at the time *t*;

N_t^{+}: The fraction of the information conveyed by the mass media that are positive at the time *t*;

Q_{ti}^{e}: The fraction of electricity that is available from utilities to a costumer *i* at the time *t*;

Q_{ti}^{DER}: The fraction of electricity that is available from DERs to an individual *i* at the time *t*;

W^{DER}: The fraction of the total amount of electricity consumed by an individual *i* that comes from DERs at the time *t*;

Q_t^{s}: The degree of help that an individual *i* gets from emergency services during and after a disaster at the time *t*.

2 Community Resilience Metrics

We model macro-micro linkages and dependencies between critical infrastructure and social characteristics to examine community resilience. We follow the generative social science approach of examining this with artificial life[12]. We created our conceptual model, as shown in Fig. 1, for our multi-agent based stochastic dynamical model based on studying the literature from neuroscience, psychological, and social science via discussions with our colleagues in these fields. We will have a detailed look at the dependencies between infrastructure and social characteristics of communities. In addition, in the simulation results, we will look for emergent patterns that cannot be explained by the individual rules of the agents. These aggregated effects will help us to understand community resilience better. By creating a model from the bottom up, we allow ourselves to create more understanding of these aggregated impacts.

Society is made of a set of communities, each of which has a distinct population, geographic exposure to a specific disaster, inter- and intra-community behavior diffusion, and social well-being characteristics. From studying the literature, we have found the following social well-being characteristics to have an important effect on community resilience: the level of fear, information-seeking behavior, risk perception, flexibility, cooperation, experience, willingness to share electricity during disaster, and physical health[2, 4, 14–18, 22–31]. Disasters may strike a community, both concurrently or at different times. When a hazard occurs, it may affect more or less the emergency services and the availability of electricity, depending on its severity[6]. It also may raise the level of fear and, in turn, it affects the risk perception of the individuals of that community[15]. The model of the mental and physical well-being of an individual during a hazard accounts for their interdependence, the inter- and intra-community diffusion, the mass media, and the severity of the disaster[15]. It allows us to measure the level of the social well-being of each community and of the whole society, that is, the degree of resilience of that society. We propose to use the resilience metrics described next. Definition of the resilience metrics and the meaning of their numerical values are provided in Table 1. Their relations with each other will be modelled dynamically and explained in Section 3.

(1) **Emotional intensity or fear** (M_{ti}^{E}): Emotion as a core characteristic of human psychological features influences individual behavior and decision-making in different situations[2, 32]. Emotion is envisaged as a psychological bridge between individuals and their environment. When a disaster strikes, the level of fear of the individuals is raised. In turn, it may lead to changes in attitude, interpersonal incompatibility, unpredictable feelings, physical problems due to fear, and so on[14]. The feeling of fear during disasters can affect both the mental and physical health of a person. Although fear has unpleasant consequences, it prompts an individual to try to avoid further danger and therefore, increases his/her chance to survive. The higher the intensity of the emotion, the higher the level of fear and negative emotions. The social well-being of a community is highly dependent on the emotion of its people. Besides, the amount of fear during a disaster is influenced by the accessibility to electricity and emergency services. There are three types of emotion, which are individual disposition, mood, and acute emotional response. The individual disposition—a constant emotional feature of a person—can be positive or negative. This feature is envisaged to be a background to an individual perception and cognition[33]. The mood—different from the disposition—of a person can involve a pleasant feeling (positive appraisal) or an unpleasant feeling (negative appraisal). As for the acute emotional response of an individual, it involves keen feelings like fear, anger, liking, sadness, and joy[33]. We have modeled the emotional intensity of fear as a short term reaction to a particular environmental condition. We have modelled it as a value between 0 and 1, 0 representing no fear and 1 maximum fear. Note that the mood of a person is less intense than

Table 1 Definition of the resilience metrics and the meaning of their numerical values. The social features for community features are assumed to follow a Gaussian distribution with a mean over the interval [0, 1].

No.	Resilience metrics	Definition	Value ([0, 1])
1	Emotional intensity	The fear felt by an individual during a disaster	0 means no fear while 1 means the highest level of fear.
2	Risk perception	The feeling that an agent perceives that he/she is in jeopardy	0 means no risk perceived by an agent while 1 means the highest level of perceived risk.
3	Information-seeking behavior	The information that an agent seeks from his friends, the mass media, and the social networks when placed in a perilous situation	0 means no information sought by an agent while 1 means the highest level of information sought.
4	Flexibility	The ability of changing the view and opinion to adapt to the conditions	0 means no behavioral flexibility of an agent while 1 means the highest flexibility level.
5	Personal experience	Accumulation of knowledge to achieve a broader view of goal	0 means the agent has no hazard-related experience while 1 means the agent has the highest level.
6	Cooperation	Willingness to work unitedly on a particular number of tasks by sharing resources, information, and experience	0 means the agent has no willingness to cooperate while 1 means the agent has the highest level.
7	Empathy	The experience of other people's emotion and thoughts	0 means there is no empathy between two agents while 1 means there is the highest level of empathy.
8	Personal characteristic	The level of being optimistic during a disaster	0 means the agent is pessimistic while 1 means the agent is optimistic.
9	Negative related news	Disaster-related news from the mass media	0 means the related news are extremely negative while 1 means they are extremely positive.
10	Emergency services availability	Treatment assessment, community vulnerability, access to food, sanitation, shelter, water, medication, and health care	0 means the emergency services are not available while 1 means they are completely available.
11	Electric utility services availability	Supplying electricity to customers within their service area	0 indicates that the electric utility cannot meet any demand while 1 indicates that it can meet all demands.
12	On-site generation availability	Small, grid-connected, or distribution system-connected devices typically located near a load that can provide various types of energy	0 means no distributed energy resources is available while 1 means they are completely available.

his/her acute affective response. In addition, the level of 0 for personal characteristic means the agent is pessimistic while 1 means the agent is optimistic.

(2) **Risk perception** (M_{ti}^{R}): When an individual faces a hazard, the level of risk perception of that individual is raised. How an individual evaluates the severity of a disaster influences his/her level of risk perception and his/her behavior. The feeling of being in a dangerous situation prompts people to take action to survive. Risk perception includes three different intuitive biases during a disaster, i.e., the perception of people that they are in danger, the anchoring effect of the people toward the probable occurrence of a given disaster, and the way people communicate between themselves according to their perceived risk[22]. It is also important to note that awareness of the risk is an essential aspect of risk perception, as it can influence epidemics such as COVID-19. Furthermore, the larger the uncertainty that a person has about a disaster, the higher the risk perception that person has. Risk perception is influenced by the culture, his/her previous hazard experience, and the level of industrialization of society, among others. For example, South Asia is exposed to frequent tsunami disasters[15], therefore, the risk perception of the people in that region tends to be biased toward that disaster. We have modelled it as a value between 0 and 1, 0 means the agent does not feel any risk and 1 means the highest level of perceived risk.

(3) **Information-seeking behavior** $\left(M_{ti}^{B}\right)$: People tend to seek information on social network (like Facebook and Twitter), fixed phones, mobile, or face to face when a hazard happen in their community. In addition, young people usually use social media to get information[23]. Information-seeking behavior during a disaster may lead to a decrease in the level of fear and uncertainties related to the situation. We have modelled it as a value between 0 and 1, 0 means the agent does not seek any information, and 1 means the highest level of seeking information.

(4) **Flexibility** $\left(M_{ti}^{F}\right)$: To create a chain of community resilience, flexibility is one of the essential hallmarks of a society facing unforeseen emergencies[2]. Flexibility is the willingness of a person to change his/her view and opinion and adapt himself/herself to a new status. When people do not have previous hazard experience and face an emergency, flexibility can help them and their community to survive[24]. Flexibility contributes to self-awareness and adaptation to new situations in the most effective possible way. We have modelled it as a value between 0 and 1, 0 means that the agents are not flexible in terms of behavior, and 1 means the highest level of flexibility.

(5) **Experience** $\left(M_{ti}^{L}\right)$: Constant learning and experience are listed as key elements of the community resilience chain[2]. Personal experience is an aggregation of knowledge for a broader view of goals and tasks to achieve. Experience may enhance the hazard preparedness of a community by increasing its risk perceptions and skills to prevail in disaster[25]. Experience as a vital factor for hazard preparedness can also be obtained by learning and education[34]. Learning and education are also useful to people who do not have a previous disaster-related experience. We have modelled it as a value between 0 and 1, 0 means the agent does not have any hazard-related experience and 1 means that the agent has the highest level of experience.

(6) **Cooperation** $\left(M_{ti}^{C}\right)$: Cooperation is characterized by the enthusiasm of individuals to work together on a certain number of tasks and share resources, information, and experience to reach a mutual objective. As a result, there are multiple effects resulting from the collaboration. The full effect of collaboration is more than the sum of its part according to a synergistic effect. Cooperation can be considered at different levels of society, including individual, organization, and national levels. Cooperation as a pivotal element for disaster management can lead to enhanced social integration and unity during disaster[26]. More than 400 studies in biology show that our world is based on cooperation rather than competition. Darwin's principle of "survival of the strongest" is therefore invalid since cooperation and solidarity are at the root of the survival of the society as emphasized by Braden[2]. Decisions made by people leading to actions that result in an increase in losses and delay in the rebuilding of the community are some of the unpleasant consequences of the lack of cooperation in society. On the other hand, decisions made by people leading to actions such as sharing electricity, water, shelter, and transportation can help them to overcome adversity[27]. Cooperation at all levels is instrumental in disaster management and preparedness since, without it, resources such as electricity, communications, transpiration, and water

infrastructures may not be available on a large scale. We have modelled it as a value between 0 and 1, 0 means the agent does not have any willingness to cooperate, and 1 means the highest level of cooperation the agent has.

(7) **Empathy** $\left(\gamma_{ij}^{E}\right)$: Empathy is the experience of knowing how other individuals think or feel during an event. Empathy can provoke emotional contagion among people, especially when a disaster occurs[28]. In other words, the positive emotion of some individuals can transfer to those who experience a negative emotion like fear. Although empathy is not only limited to emotion, it may influence the level of collaboration among people: the more empathy, the more emotional resilient the society will be[16]. There are three different types of empathy, which are cognitive, emotional, and compassionate empathy. In the proposed structure, compassionate empathy is considered. During Hurricane Harvey which occurred in 2017, people were empathetic to their neighbors, which resulted in a great deal of help that they have been providing to each other. Furthermore, they have been cooperating with each other during the disaster. Obviously, as the number of people who cooperate with each other increases, their strength increases, too. Besides, vulnerable people such as the children and the elderly, need to be supported when struggling with dangerous situations during a disaster.[§] We have modelled it as a value between 0 and 1, 0 means there is no compassionate empathy between two agents, and 1 means the highest level of empathy exist.

(8) **Level of impact of the news from the mass media** (N_{ti}): News from the mass media (N_t) (like Facebook, Twitter, TV, etc.) has different patterns according to the kind of disaster considered[36, 37]. Natural and sudden disasters (tsunami and explosions) are modeled using damped exponential probability distribution ($N_t = \mathrm{e}^{-t^{\alpha}}$). Gradually events like hurricane and social crisis are modeled using a normal probability distribution ($N_t = \mathrm{e}^{-(\frac{(t-\mu)^2}{\sigma})}$)[3].

(9) **Level of impact of the emergency management services**: The emergency services play a key role in mitigating the impact of abrupt and unexpected extreme events. They can contribute to a decrease in the number of injuries and the amount of damage incurred by a community infrastructure, shield the environment of a community, speed up the resumption of ordinary life, and help the businesses serving a community to resume their activities[29]. While the stress and fear of a community resulting from a hazard can result in immense losses, the duty of the emergency services is to control the situation by many necessary actions taken before, during, and after the occurrence of a disaster[38, 39]. For instance, pre-planning and preparedness to support a community facing a disaster is crucial. The cost of performing resilience planning is much smaller than the losses incurred by a community during disasters.

(10) **Level of impact of the energy on human well-being**: The eradication of poverty is considered the most critical challenge in the world[40]. According to Ref. [41], the worse type of poverty is the scarcity of energy. For example, scarcity of fuel may lead to acute physical and mental problems. By contrast, when people have ample access to energy, they feel less anxious, sleep better, and have enhanced physical and mental well-being. A society without energy, on the other hand, may suffer from cold weather during winter and endure more stress in daily life, contributing to a decrease in social well-being. In fact, without energy, there is no economic wealth, health, opportunity, and mobility in society. Ortiz et al.[4] discussed the nexus among health, comfort, and energy by considering human behavioral features, including habit and controllability, to achieve homeostasis (comfort, less stress). Understandably, individuals eschew inconvenience and unfavorable experiences resulting from the lack of energy[42, 43].

As the most crucial energy career, electricity is necessary for streetlights, education, health, modern community, and so forth[44, 45]. For this purpose, Ahmad et al.[46] studied the effect of the availability of electricity on two human well-being attributes, namely health and education. They showed that the community well-being is highly tied to the accessibility of electricity. As a result, establishing on-site generation and locally shared electricity is of high importance.

(11) **Level of impact of on-site generation and**

§Goleman defined cognitive empathy as follows: "simply knowing how the other person feels and what they might be thinking. Sometimes called perspective-taking"[35]. He also defined emotional empathy as follows: " when you feel physically along with the other person, as though their emotions were contagious", and compassionate empathy as follows: "with this kind of empathy we not only understand a person's predicament and feel with them, but are spontaneously moved to help, if needed".

distributed energy resources: Great East Japan Earthquake affected the power system, the gas supply infrastructure, the customer facilities, the train service, the traffic signals, and so on. The recovery process of the power system took about 1 to 2 years[31]. Although damages resulting from the Great East Japan Earthquake contributed to a number of damages and losses in Japan, there are some positive points resulting from this disaster. For instance, at Roppongi Hills in Tokyo, a set of offices, restaurants, and residential spaces are supplied in energy by an on-site natural gas-fired turbine generator, a steam turbine generator, an absorption chiller, an exhaust hear boiler, and a steam boiler that worked well during that disaster.

3 Modeling the Social Well-Being of a Community During a Disaster

The social well-being of a community is highly contingent on the individual well-being, which is characterized by mental and physical aspects that influence each other[17].

Computational behavior models are based on a variety of theories such as the broad-and-build theory, the upward and downward spirals, the behavioral approach system, Damasio's somatic marker hypothesis, the ripple theory, the behavioral inhibition system, the sensation seeking, the uncertainty reduction theory, and the absorption and amplification theory from social neuroscience and biology[33, 47, 48].

Figure 2 depicts the proposed model for power system, emergency services, and human (agent) response to a disaster as a system dynamic model. To model collective social behavior, especially during a disaster, vital characteristics like cooperation, empathy, experience, flexibility, information-seeking behavior, emotion, perception of risk, openness, channel strength, and extraversion must be considered[2, 4, 14–18, 20, 22–31, 49]. Each of them has a notable role in community resilience. Each of these features influences each other directly or indirectly. As an example, Damasio' somatic marker hypothesis assumes that emotion and information-seeking behavior influence each other[50]. As another example, based on broaden-and-build theory, positive emotion broadens thought-action behavior, as well as cognition and vice versa[48]. In addition, each of these collective behaviors can be investigated through various computational perspectives[51].

To model group emotion, Barsade and Gibson in Ref. [33] developed two different theoretical approaches that complement each other while embracing the top-down as well as the bottom-up approach. Furthermore, in the ripple effect theory initiated by Bosse et al.[47], group emotion empathy, propagation of moods among agents within the group, and group emotion dynamics were investigated by estimating mood, agents' attitudes, behavior, and group-level dynamics. One question that is pivotal to social emotion is the following: How do positive and negative emotions impact agent behavior. The broaden-and-build method based on Fredrickson and Joiner's theory[48] provided an answer to this question. According to this theory, negative emotion restricts an individual's thoughts and actions while

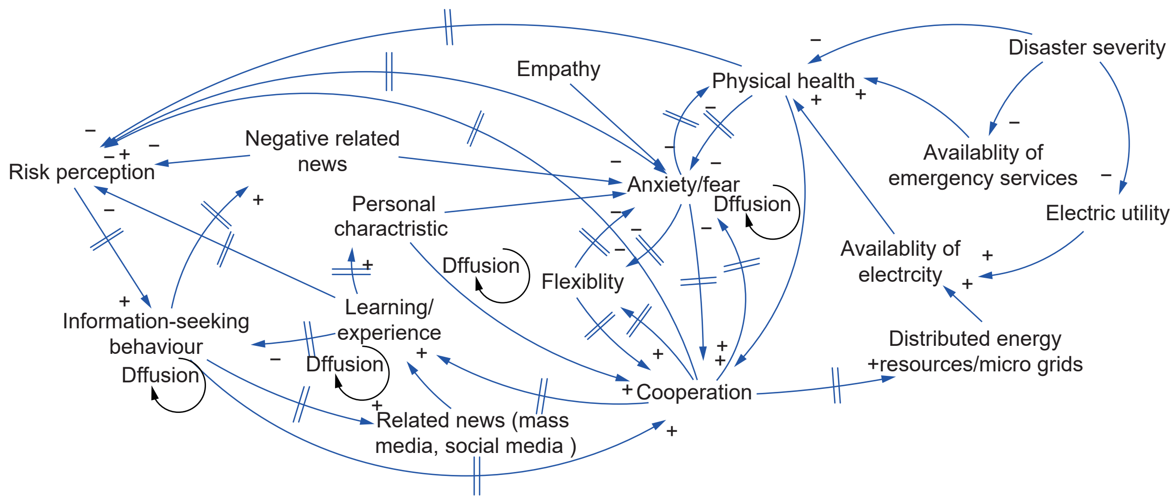

Fig. 2 System dynamical model of power system, emergency services and human (agent) response to a disaster. It is worth noting that social networks contain a large number of agents who influence one another through social behavioral diffusion.

positive emotion broadens the set of thoughts and actions of people. On the other hand, joy prompts a feeling to play, contributing to physical, socio-emotional, and intellectual resources (skills) so that they lead to brain development.

In this model, all mental and physical characteristics are assumed to be Gaussian random variables, as most psychological variables are approximately normally distributed[52]. Similarly, the level of inter- and intra-community behavior diffusion is assumed to be Gaussian variables[15]. Given the mean and the standard deviation of each of these random variables and the population size, samples are generated via Monte Carlo (MC) simulations. Their dynamical models are provided next.

3.1 Human psychological dynamic modeling

A stochastic multi-agent based model of the incremental changes of the mental well-being during the disaster of six human psychological features is developed. These features are emotion, risk perception, information-seeking behavior, flexibility, cooperation, and experience, which are influenced by empathy. They determine the mental well-being, one of the factors that characterize community resilience. In this model, mental well-being and fear are opposite factors in that the more fear, the less mental well-being, and vice versa.

(1) **Emotion dynamic modeling**: The emotion incremental change $\Delta(M^E_{ti})$ is governed by

$$\Delta(M^E_{ti}) = \gamma^E_{ti}(f(\hat{M}^E_{ti}, M^E_{ti}) - M^E_{ti})\Delta t \tag{1}$$

where γ^E denotes the speed of dynamic change related to emotion and $\hat{M}^E$ denotes the amount of emotion of an agent influenced by the emotion of other agents within a group (inter-agents impact) and other features of an agent (intra-agent impact)[20]. Let γ^E_{ij} denote the compassionate empathy between two agents, which takes values between 0 and 1 (0 meaning no empathy, and 1 maximum empathy), and let γ^E_{ti} denote the level of emotional susceptibility of the agent from its network, which is expressed as

$$\gamma^E_{ti} = \frac{\sum_j \gamma^E_{ij} M^E_{tj}}{\sum_j \gamma^E_{ij}} \tag{2}$$

This parameter is dependent on factors like the sender’s emotional expression and openness to receiving emotion and the strength of the channel between the sender and the receiver. The strength of the emotional channel is dependent on the distance, the attachment, the directness of the emotion contagion (direct or indirect), and the relationship between them as indicated in Ref. [53].

Let $f(\hat{M}^E_{ti}, M^E_{ti})$ denote the amount of the impression of the inter- and intra-agent factors through the absorption and amplification model. It is expressed as

$$f(\hat{M}^E_{ti}, M^E_{ti}) = \eta^E[M^R_{ti}(1-(1-M^E_{ti})(1-\hat{M}^E_{ti})) + (1-M^R_{ti})(\hat{M}^E_{ti} M^E_{ti})] + (1-\eta^E)\hat{M}^E_{ti} \tag{3}$$

where η^E is the parameter that accounts for the pace of emotional change. Here, the first term $[M^R_{ti}(1-(1-M^E_{ti})(1-\hat{M}^E_{ti})) + (1-M^R_{ti})(\hat{M}^E_{ti} M^E_{ti})]$ is akin to the amplification model while the second term $\hat{M}^E_{ti}$ is related to the absorption model. According to Fredrickson, also known as the broaden-and-build theory[48, 53], the first term of the amplification model is associated with a positive effect while the second term is associated with a negative effect. In the latter model, the bottom-up concept is used. This implies that the group emotion is equal to the sum of the emotions of the individuals of that group. It is influenced by the homogeneity and the heterogeneity as well as by the mean emotion of the group individuals. The absorption model can be used if there is no external event or catastrophe. On the other hand, the amplification model, which includes upward and downward emotional spirals, can be used as a model when there is a sudden event, i.e., a disaster striking the group. In this situation, factors outside the group affect the emotion of the group. In this case, the community resilience planner may use both models.

The level of fear of an individual $\hat{M}^E_{ti}$ is expressed as

$$\hat{M}^E_{ti} = w^{EE}\left(\frac{\sum_j \gamma^E_{ij} M^E_{tj}}{\sum_j \gamma^E_{ij}}\right) + w^{BE} N_t(1-N^+_t)M^B_{ti} + w^{FE}(1-M^F_{ti}) + W^{CE}(1-M^C_{ti}) + W^{LE}(1-M^O_i)(1-M^L_{ti}) + W^{PE}(1-P_{ti}) + W^{ME}N^t \tag{4}$$

It is influenced by the emotion of the other agents given by $\left(w^{EE}\left(\frac{\sum_j \gamma_{ij}^E M_{tj}^E}{\sum_j \gamma_{ij}^E}\right)\right)$, her/his information-seeking behavior given by $(w^{BE}N_t(1-N_t^+)M_{ti}^B)$[49], her/his flexibility $(w^{FE}(1-M_{ti}^F))$, her/his cooperation given by $(W^{CE}(1-M_{ti}^C))$[54], and her/his experience and learning process given by $(W^{LE}(1-M_i^O)(1-M_{ti}^L))$[55]. The effect of flexibility on the fear of an individual was investigated by Thayer et al.[55] In addition to the inter- and intra-agent psychological factors, the level of fear is contingent on the agent's physical health given by $(W^{PE}(1-P_{ti}))$[17] and outside factors, i.e., social media given by $(W^{ME}N^t)$[15, 56, 57].

(2) **Risk perception dynamic modeling**: The risk perception incremental change $\Delta(M_{ti}^R)$ is governed by

$$\begin{aligned}\Delta(M_{ti}^R) =& (\eta^R+(1-\eta^R)N_t)\frac{1}{1+\mathrm{e}^{-\sigma^E(M_{ti}^E-\phi^E)}}\cdot\\ &(1-P_{ti})(1-M_{ti}^L)(1-M_{ti}^C)(1-M_{ti}^B)\cdot\\ &(1-M_{ti}^F)((1-N_{ti}^+)-M_{ti}^R)\Delta t\end{aligned} \tag{5}$$

It is affected by the flexibility, the learning process, the experience, the cooperation, the information-seeking behavior, the physical health, and the motion of the individual. If the emotion (M_{ti}^E) is lower than the fear or the threshold (ϕ^E), it has no impact on the risk perception[49]. The index N_{ti}^+ indicates the characteristic of the news, which takes values between 0 and 1 (0 meaning negative news and 1 meaning positive news). The lower the value of that index, the lower the perception of risk will be. According to the narrowing hypothesis of Fredrickson's broaden-and-build theory[15], the factor $[(1-N_{ti}^+)-M_{ti}^R]$ measures the tendency of the risk perception to be more or less positive. Regarding the relation between the risk perception and the cooperation among individuals, it was discussed in Ref. [58] while the relation between the risk perception and the experience was investigated in Ref. [59]. As for the relationship between the risk perception and the flexibility, it was analyzed in Ref. [60]. Finally, the relation between the risk perception and the physical health was discussed in Ref. [18].

(3) **Information-seeking behavior dynamic modeling**: The information behavior incremental change $\Delta(M_{ti}^B)$ is governed by

$$\Delta(M_{ti}^B)=\gamma^B(f(\hat{M}_{ti}^B,M_{ti}^B)-M_{ti}^B)\Delta t \tag{6}$$

where γ^B denotes the speed of the incremental change related to the information-seeking behavior and $\hat{M}_{ti}^B$ denotes the amount of the information of an agent influenced by other agents within the group (inter-agents impact) and other features of the agent (intra-agent impact). Let γ_{tij}^B denote the strength of information-seeking behavior contagion, which takes values between 0 and 1 (0 meaning no contagion, 1 meaning maximum contagion), and let γ_{ti}^B denote the level of informational susceptibility of the agent from its network, which is defined as

$$\gamma_{ti}^B=\frac{\sum_j \gamma_{ij}^B M_{tj}^B}{\sum_j \gamma_{ij}^B} \tag{7}$$

Let $f(\hat{M}_{ti}^B,M_{ti}^B)$ denote the amount of the impact of inter- and intra-agent factors through the absorption and amplification model on the information-seeking behavior. It is defined as

$$\begin{aligned}f(\hat{M}_{ti}^B,M_{ti}^B)=&\eta^B[M_{ti}^R(1-(1-M_{ti}^B)(1-\hat{M}_{ti}^B))+\\ &(1-M_{ti}^R)(\hat{M}_{ti}^B M_{ti}^B)]+(1-\eta^B)\hat{M}_{ti}^B\end{aligned} \tag{8}$$

where η^B is the parameter to control the pace of information-seeking behavior change and where $\hat{M}_{ti}^B$ is expressed as

$$\begin{aligned}\hat{M}_{ti}^B =& w^{BB}\left(\frac{\sum_j \gamma_{ij}^B M_{tj}^B}{\sum_j \gamma_{ij}^B}\right)+\\ &w^{LB}(1-M_{ti}^L)+w_{MB}N^t\end{aligned} \tag{9}$$

It is influenced by the information-seeking behavior of other agents given by $\left(w^{BB}\left(\frac{\sum_j \gamma_{tij}^B M_{tj}^B}{\sum_j \gamma_{tij}^B}\right)\right)$, the individual's learning process and experience given by $(w^{LB}M_{ti}^L)$, and the mass media given by $(w_{MB}N^t)$. The relationship between the information-seeking behavior and the learning process and experience was discussed in Refs. [61, 62]. Gao and Liu[15] and Robson and Robinson[63] discussed the relation between the information-seeking behavior and the mass media.

(4) **Flexibility dynamic modeling**: The flexibility incremental change $\Delta(M_{ti}^F)$ is governed by

$$\Delta(M_{ti}^F)=\gamma^{M_{ti}^F}(f(\hat{M}_{ti}^F,M_{ti}^F)-M_{ti}^F)\Delta t \tag{10}$$

where $\gamma^{M_{ti}^F}$ denotes the speed of the incremental change related to the flexibility and $\hat{M}^F_{ti}$ denotes the amount of the flexibility of an agent, which is influenced by that of the other agents within the group (inter-agents impact) and other features of the agent (intra-agent impact). Let γ^F_{ij} denote the strength of flexibility mirroring, which takes values between 0 and 1 (0 meaning no mirroring and 1 meaning maximum mirroring) and let γ^F_{ti} be the level of flexibility susceptibility of the agent from its network, which is defined as

$$\gamma^F_{ti} = \frac{\sum_j \gamma^F_{ij} M^F_{tj}}{\sum_j \gamma^F_{ij}} \tag{11}$$

Let $f(\hat{M}^F_{ti}, M^F_{ti})$ denote the level of the impact of the inter- and intra-agent factors through the absorption and amplification model on the flexibility, which is expressed as

$$f(\hat{M}^F_{ti}, M^F_{ti}) = \eta^F[M^R_{ti}(1-(1-M^F_{ti})(1-\hat{M}^F_{ti}))+ (1-M^R_{ti})(\hat{M}^F_{ti} M^F_{ti})] + (1-\eta^F)\hat{M}^F_{ti} \tag{12}$$

Let $\hat{M}^F_{ti}$ denote the level of flexibility of an individual. It is defined as

$$\hat{M}^F_{ti} = w^{FF}\left(\frac{\sum_j \gamma^F_{ij} M^F_{tj}}{\sum_j \gamma^F_{ij}}\right) + w^{EF} M^O_i (1-M^E_{ti}) + w^{CF}(1-M^c_{ti}) \tag{13}$$

It is influenced by the level of information of the other agents given by $\left(w^{FF}\left(\frac{\sum_j \gamma^F_{ij} M^F_{tj}}{\sum_j \gamma^F_{ij}}\right)\right)$, the individual's level of fear given by $(w^{EF} M^O_i (1-M^E_{ti}))$, and level of cooperation given by $(w^{CF}(1-M^c_{ti}))$. Hollenstein and Lewis[64] and Southward and Cheavens[65] investigated the effect that the emotion has on the flexibility while Allwood[66] analyzed the relation between the flexibility and the cooperation.

(5) **Cooperation characteristic dynamic modeling**: The cooperation characteristic incremental change $\Delta(M^C_{ti})$ is governed by

$$r\Delta(M^C_{ti}) = (\eta^C + (1-\eta^C)N_t)\left(\frac{1}{1+\mathrm{e}^{-\sigma^C(M^E_{ti}-\phi^E)}}\right)\cdot M^F_{ti} P_{ti}[M^O_{ti} M^B_{ti} - M^C_{ti}] \tag{14}$$

It is affected by the emotional intensity, the flexibility, and the physical health of an individual. Here, the factor $[M^O_{ti} M^B_{ti} - M^C_{ti}]$ denotes the tendency of the cooperation characteristic toward positive or negative information according to the narrowing hypothesis of Fredrickson's broaden-and-build theory. The relationship between the emotional intensity and the cooperation among the individuals of a group was discussed in Ref. [54]. The relationship between flexibility and cooperation was discussed in Ref. [66]. The relation between cooperation and physical health was provided in Ref. [67]. According to Ref. [68], social media influences the level of cooperation among the individuals of a group.

(6) **Personal experience dynamic modeling**: The personal experience incremental change $\Delta(M^L_{ti})$ is governed by

$$\Delta(M^L_{ti}) = \gamma^L_{ti}(f(\hat{M}^L_{ti}, M^L_{ti}) - M^L_{ti})\Delta t \tag{15}$$

where γ^L_{ti} denotes the speed of the personal experience incremental change and $\hat{M}^L_{ti}$ denotes the amount of the experience of an individual that is influenced by the experience of the other agents within the group (inter-agents impact) and the other features of an agent (intra-agent impact), and where γ^L_{ti} is the level of learning susceptibility of the agent from its network given by

$$\gamma^L_{ti} = \frac{\sum_j \gamma^L_{ij} M^L_{tj}}{\sum_j \gamma^L_{ij}} \tag{16}$$

where γ^L_{ij} denote the strength of the experience diffusion, which takes values between 0 and 1 (0 meaning no diffusion and 1 meaning maximum diffusion).

Let $f(\hat{M}^L_{ti}, M^L_{ti})$ denote the amount of the impact of the inter- and intra-agent factors through the absorption and amplification model on the learning process. It is expressed as

$$f(\hat{M}^L_{ti}, M^L_{ti}) = \eta^L[M^R_{ti}(1-(1-M^L_{ti})(1-\hat{M}^L_{ti}))+ (1-M^R_{ti})(\hat{M}^L_{ti} M^L_{ti})] + (1-\eta^L)\hat{M}^L_{ti} \tag{17}$$

where $\hat{M}^L_{ti}$ denotes the level of flexibility of an individual, which is defined as

$$\hat{M}^L_{ti} = w^{LL}\left(\frac{\sum_j \gamma^L_{ij} M^L_{tj}}{\sum_j \gamma^L_{tij}}\right) + w^{BL} M^B_{ti} N_t + w^{CL} M^C_{ti} + w^{ML} N_t \tag{18}$$

It is influenced by the experience of other agents given by $\left(w^{LL}\left(\frac{\sum_j \gamma^L_{ij} M^L_{tj}}{\sum_j \gamma^L_{ij}}\right)\right)$, the individual's level of information-seeking behavior given by ($w^{BL}M_{ti}^{B}N_t$), level of cooperation given by ($w^{CL}M_{ti}^{C}$), and the mass media given by ($w^{ML}N_t$). The relationship between the experience and the information-seeking behavior was discussed in Ref. [69]. The relationship between the experience and the cooperation behavior was discussed in Ref. [70]. The relationship between the experience and the mass media was analyzed in Ref. [71].

3.2 Human physical health dynamic modeling

Two resources for electricity are considered in the suggested multi-agent based model. The electric utilities as primary resources supply electricity to the communities. Nonetheless, some communities may lose their availability of electricity from utilities during extreme hazards. Therefore, it is assumed that some agents own distributed energy resources, which are useful resources that will enhance the community resilience during a disaster. In addition, these agents may be willing to share their electricity with people who do not have electricity. The latter is highly contingent on the level of cooperation of these agents. As declared in the previous parts, the level of cooperation is affected by psychological features like mental well-being, flexibility, and so on. The availability of electricity influences the physical health of the agents and society through various kinds of disasters. Furthermore, the availability of emergency services affects the physical well-being of a community.

(1) **Sharing distributed energy resources**: The distributed energy resources sharing incremental change is governed by

$$\Delta(Q_{ti}^{DER}) = \gamma_{ti}^{DER}(\gamma_{ti}^{DER} - Q_{ti}^{DER})\Delta t \tag{19}$$

where γ_{ti}^{DER} denotes the speed of the incremental change of the distributed energy resources sharing, which is given by

$$\gamma_{ti}^{DER} = \frac{\sum_j \gamma_{tij}^{DER} M_{tj}^{C} Q_{ti}^{DER}}{\sum_j \gamma_{tij}^{L} M_{tj}^{C}} \tag{20}$$

where γ_{tij}^{DER} denotes the level of empathy between two agents willing to share electricity.

This electricity sharing also depends on the level of cooperation of agents.

(2) **Available electricity during a disaster**: Let Q_{ti}^{e} denote the amount of electricity supplied by the power grid and that shared by the DERs during a disaster. It is given by

$$Q_{ti}^{e} = W_i^{DER} Q_{ti}^{DER} + (1 - W_i^{DER}) Q_{ti}^{U} \tag{21}$$

(3) **Human physical health dynamical modeling**: The incremental change of the physical health $\Delta(P_{ti})$ is given by

$$\Delta(P_{ti}) = \eta^{P}\left(\frac{1}{1 + \mathrm{e}^{-\sigma^{C}(M_{ti}^{E} - \phi^{E})}}\right)\cdot (((1 - M_{ti}^{E})(1 - (1 - Q_{ti}^{e})(1 - Q_{ti}^{s}))Z_{ti}) - P_{ti})\Delta t \tag{22}$$

It is a function of the availability of emergency services, the availability of electricity, and the injury factor of a disaster. Different hazards have different injury factors, which express the following fact: the more extreme the hazard is, the more injury factor will be.

3.3 Social well-being modeling

Social well-being for a society encompasses both social mental well-being and social physical well-being. Understandably, social well-being is formed by a set of individual well-being. It is given by

$$S_t = \frac{\sum_i \eta^{M}(1 - M_{ti}^{C})}{\sum_i 1} + \frac{\sum_i (1 - \eta^{M}) P_{ti}}{\sum_i 1} \tag{23}$$

The first term is related to the social mental well-being while the second term is associated with the social physical well-being. As for η^{M}, it is a mental well-being coefficient.

Remark: Equations (1)–(3) and (6)–(8) are derived from Refs. [15, 20]. Equations (4), (5), and (9) are modified on the basis of the equations stated in Refs. [15, 20]. Equations (10)–(15) are proposed in this paper and used in the new stochastic multi-agent-based model.

4 Simulation Results for Case Study 1: Community of Nine Agents Facing a Hurricane

This section provides an analysis of the proposed dynamical model of a community of agents experiencing a hurricane. Specifically, the dynamic changes in the mental and physical characteristics of the agents are assessed.

4.1 Soft validation of the proposed stochastic multi-agent based modelling

At this step, a soft validation is done. We investigate if the intended patterns/social phenomena from the real world can be simulated with the proposed model. After verification, we pinpoint and analyze the emergent effects that result from the social interactions using multi-agent based modeling. These emergent effects cannot be predicted from the individual agent rules and will give us valuable data to learn from. Our computational model is verified by case study 1 which is taken from Ref. [20]. Specifically, we will verify if information-seeking behavior, the emotion of fear, and bias show expected patterns, similar to Ref. [20]. When soft validation is successful, the model is extended with: mental resilient-related characteristics, the physical well-being of agents, and critical infrastructures, including emergency services and the power grid. The aim is to analyze the effects of all these characteristics and influences on collective behavior and community resilience.

This community consists of three areas. Each area involves three individuals empathetic to each other. The individuals of each area do not have any communication with those of another area.

The parameter setting of the models of the mental and physical characteristics of consumers and prosumers† , mass media, emergency services, and electric grid is assumed to take a value in the interval [0, 1][20]. The initial values of M_{ti}^{E}, M_{ti}^{R}, M_{ti}^{B}, M_{ti}^{C}, M_{ti}^{O}, M_{ti}^{L}, and Q_{ti}^{e} are assumed to be 0.5 (It means the medium level of each of these features). N_t^{+} is assumed to be 0 (it means there is no positive news). Other parameters are assumed to be equal to 1. The electricity consumption of each individual is assumed to be 1 kW·h of which 0.8 kW·h is supplied by utilities through distribution power lines and 0.2 kW·h is supplied by distributed energy resources (DERs), photovoltaics (PVs), and wind turbines to name a few. Furthermore, the fraction of electricity W^{DER} that the DERs supply for each individual is set to 0.2.

4.2 Validation process with real datasets

We explore and suggest the following social indicators for assessing community resilience: mental health, physical health, risk perception, information-seeking behavior, flexibility, cooperation, and learning. Measuring these characteristics during a disaster can be difficult. Psychologists and researchers in conventional social science typically use surveys to assess social behavior. However, surveys have several disadvantages, such as high cost, limited sample size, and the possibility of response bias. To overcome these obstacles, we can use various social sensing tools, such as Twitter, Facebook, and GoogleTrends, to quantify and assess social behaviors and responses[72]. In contemporary social science, we can evaluate and analyze text, such as tweets, from a social and phycological perspective using the phycological meaning of the words and natural language processing[73]. For social sensing tools, we use Twitter and GoogleTrends. To ascertain the community's social behavior during a disaster, we collected two samples of tweets from hurricanes Irma and Harvey (275 000 and 212 000 IDs). Additionally, we used GoogleTrends to identify information-seeking behavior associated with these occurrences. We measure each feature of social resilience using the Linguistic Inquiry and Word Count (LIWC) as a text-mining tool. In addition, the process of social behavior validation was explained in Ref. [11] in summary.

4.3 Effects of flexibility on human responses

First, we will examine the effects of flexibility on community resilience. Figure 3 displays dynamic changes in fear, information-seeking behavior, and risk perception as a result of the changes in individuals' flexibility. These patterns are consistent with the discussions given in Refs. [15, 55, 60, 64–66]. Flexibility has a direct effect on emotion and risk perception, while it has an indirect impact on information-seeking behavior. It is obvious that when the flexibility increases (from ($M^F = 0$) to ($M^F = 0.5$) to ($M^F = 1$)), individuals demonstrate a lower level of fear. More flexible people are able to more thoroughly evaluate their emotions so that, consequently, the level of fear and depression is decreased. Negative affects‡, like the feeling of fear, make a person less flexible in interpersonal cognition and expressive behavior. Conflict is caused in discussions among startled people. In other words, flexibility is diminished among these individuals. In contrast, a high level of flexibility and a low level of fear decrease the perceived risk of agents during a disaster. As a result, information-seeking behavior which is profoundly entwined with risk

† Consumers are agents who do not have distributed energy resources, while prosumers are agents who own distributed energy resources.

‡ In social science, emotion and affect are considered to be similar words to each agent's response to feelings[33].

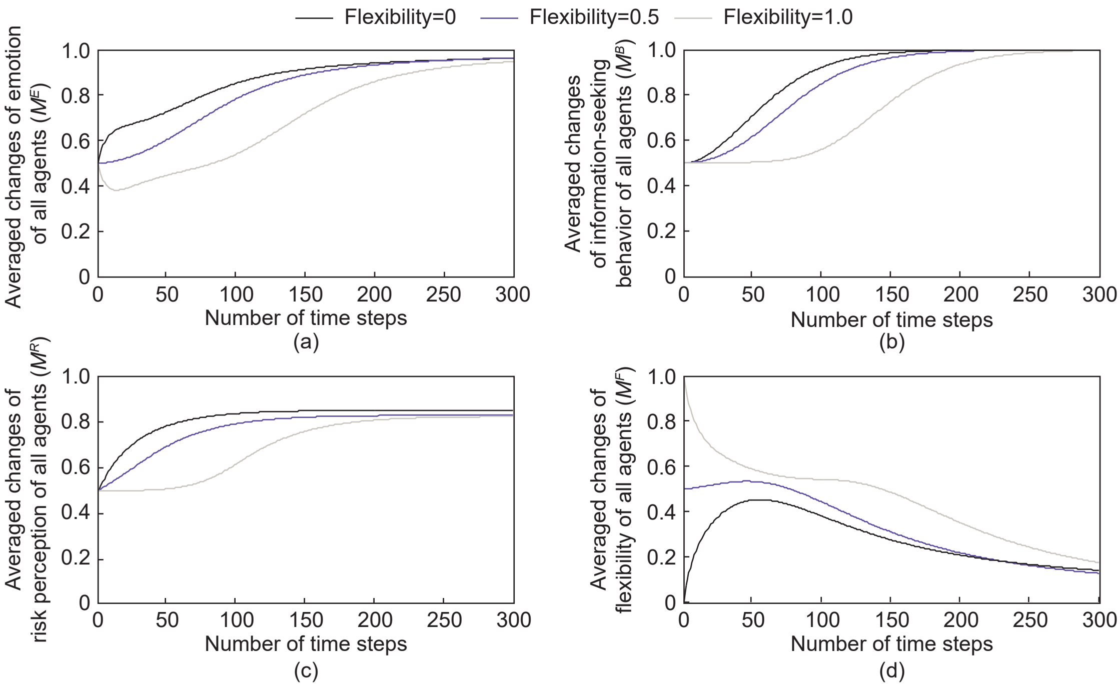

Fig. 3 Effects of flexibility on collective behavior and mental characteristics. The dynamic change of emotion, information-seeking behavior, risk perception, and flexibility of all agents are shown. Results are provided for three different initial values of flexibility (0, 0.5, and 1). The time duration of the dynamic evolution is 300 time steps.

perception is reduced.

Conversely, the feeling of fear causes people to be flexible if they are optimistic. That is why flexibility is increased at the beginning of the event when $M^F = 0$. Because all of the individuals in the community mentioned above are optimistic, they tend to be more flexible during the first time interval. In general, positive features can disguise a person's behavioral drawbacks. Since the news from the mass media is often related and stressful, the average emotional changes increase over time, no matter how much flexibility there is. Correspondingly, the level of risk perception and information-seeking behavior of agents will increase.

4.4 Effects of cooperation and experience on human responses

Figure 4 presents changes in fear, information-seeking behavior, risk perception, and flexibility with respect to changes in the cooperation and experience of individuals. Three different examples are provided. In Example 1, although people are willing to cooperate, they do not have previous experience with the disaster. In Example 2, both M^L and M^C are equal to 0.5 while they are equal to 1 in Example 3. These patterns are consistent with the discussions given in Refs. [54, 58, 66–68, 70].

In Examples 1 and 3, when $M^L = 1$, a high level of cooperation and optimism lead to a low level of fear such that the fear is lower than the fear threshold. In Example 3, since the agents have a high level of cooperation and experience, they do not feel a need to seek new information. Additionally, individuals are more flexible than the individuals in Examples 1 and 2. In Examples 1 and 3, because of the low level of fear, the level of risk perception and cooperation among agents do not show substantial variations. The level of experience of the agents in Example 1 is higher than that in Example 2, resulting from higher levels of cooperation among individuals. Risk perception and individuals' information-seeking behavior hinge upon cooperation. In perilous circumstances, agencies raise public risk perception to levels that exceed what individuals experience privately. According to Ref. [58], the obstacles to private-private cooperation are more than those that individuals experience with private-public cooperation.

4.5 Effects of cooperation on electric energy sharing

To investigate the effect of the level of cooperation on electricity sharing, the availability of electricity from distributed energy resources for three agents within each area is assumed to be 0, 0.5, and 1, respectively.

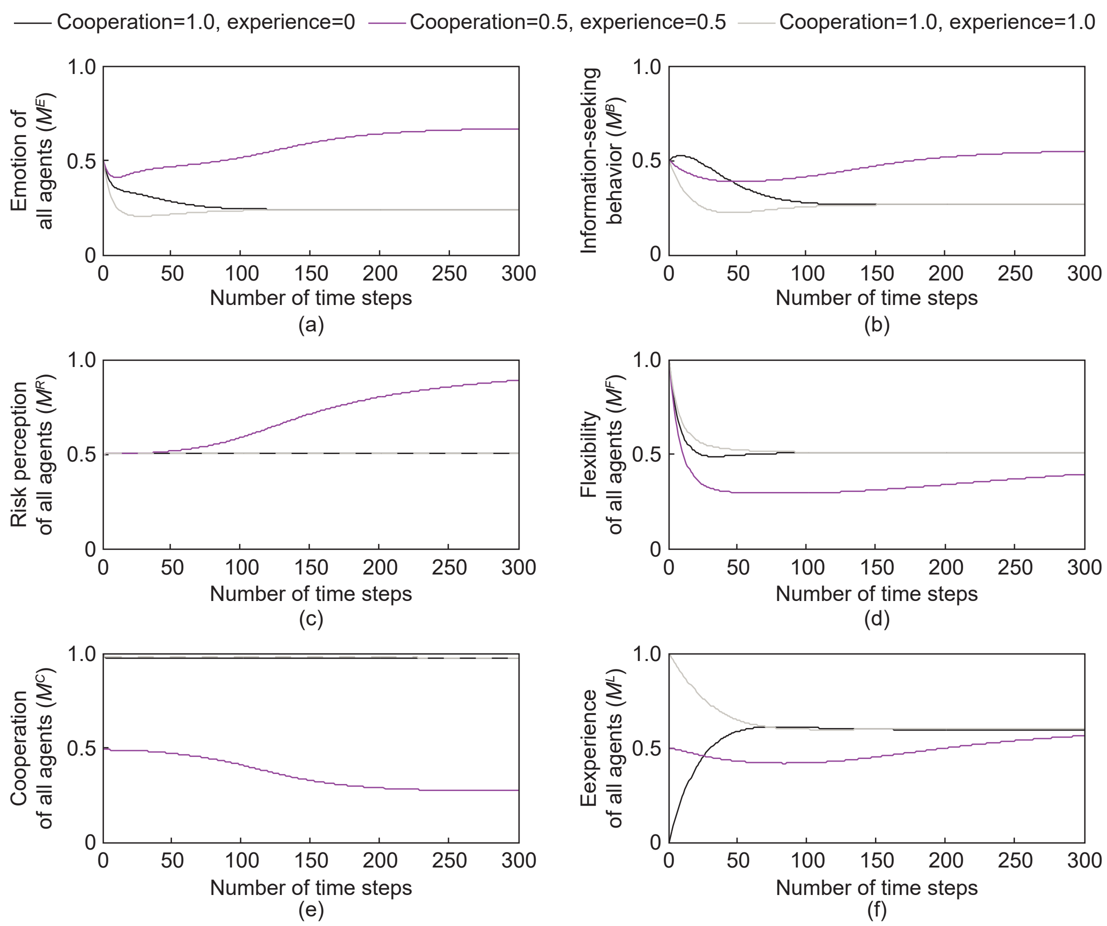

Fig. 4 Effects of different initial values of cooperation and experience on the dynamic change of the collective mental behavior in the homogeneous community. Black lines are related to individuals who are well-experienced and enthusiastic to cooperate. Grey lines are related to individuals who are not interested in cooperating at all. Purple lines are related to individuals who are only partially experienced with average or low levels of enthusiasm to cooperate.

The results are provided for two different levels of cooperation in Figs. 5 and 6 . These patterns are emergent effects, which can not be predicted from the individual rules, that give in sight into the behavior of the people. According to these results, when people have a high level of cooperation, they share their electricity sooner than when they have a low level of cooperation. Consequently, they have a higher level of physical health when $M^C = 0.9$. Furthermore, with a high level of cooperation and physical health, people experience less fear. As a result, the level of perceived risk and information-seeking behavior among agents is decreased compared to when $M^C = 0.2$. However, the level of fear climbs with time as a result of relevant negative news from the mass media. Thus, when $M^C = 0.9$, the level of flexibility drops after its initial growth. These factors make the average cooperation lower over time. In addition, a society with more cooperation has a higher level of physical and mental well-being and community resilience (social well-being) when there are both prosumers and consumers in the community. Note that both cooperative and selfish behavior among individuals is assumed to be epidemic. Furthermore, cooperation is of high importance for a successful society in both fixed (static) social networks and fluid (dynamic) social networks. The social diffusion of cooperation exists in both kinds of networks.

4.6 Importance of emergency services, the injury factor of a disaster, and news polarity on physical and emotional well-being

In this section, we simulate 4 examples whose results are depicted in Figs. 7 and 8. In Example 1, $M^S = 1$, Z=0.1, and $N^+ = 0$. In Example 2, M^S is assumed to be 0.1 for time stamps from 100 to 300. In Example 3, to show the effect of the injury factor of disaster, Z is 0.9. In Example 4, to present the effect of news polarity, N^+ is

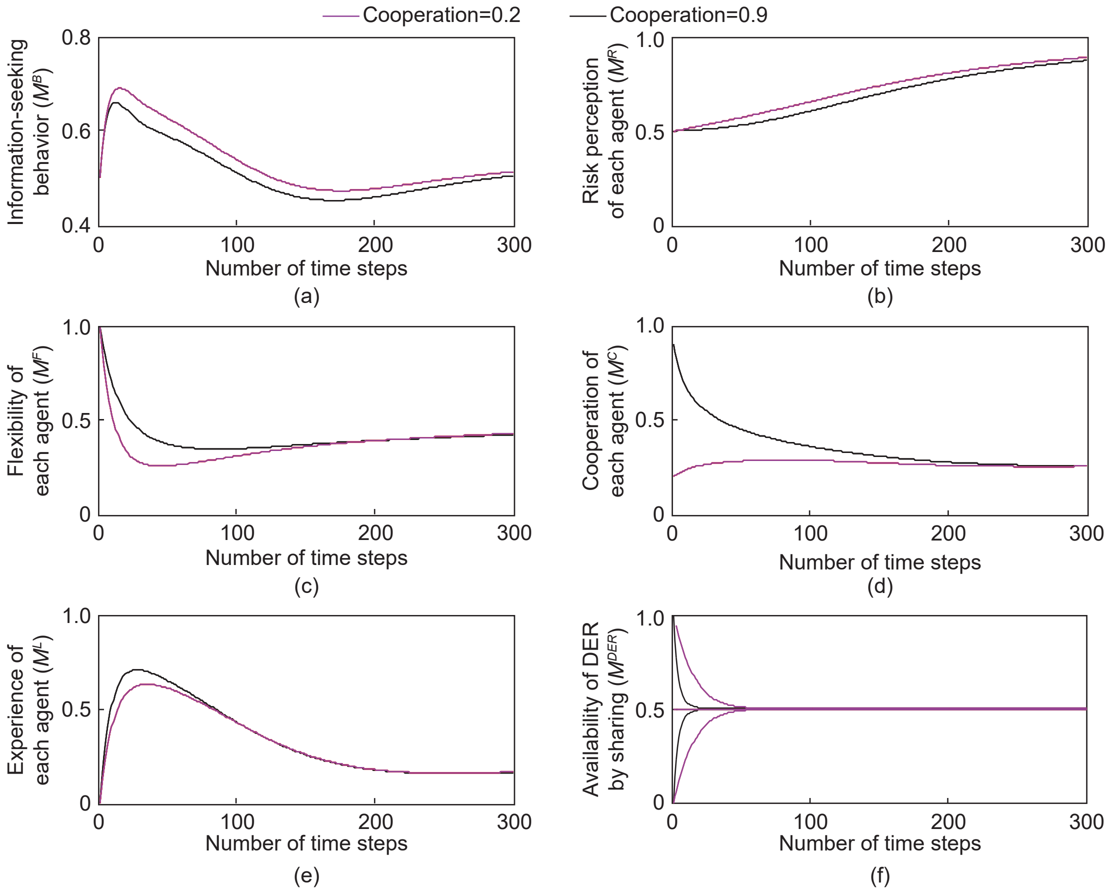

Fig. 5 Effects of cooperation on electricity sharing and the impact of the availability of electricity (and also cooperation) on information-seeking behavior, risk perception, flexibility, and experience. It is assumed that agents have a varying value of accessibility to distributed energy resources, i.e., 0, 0.5, and 1, meaning no, medium, or maximum levels, respectively. The results are provided for initial values of cooperation of 0.2 (low cooperation) and 0.9 (high cooperation).

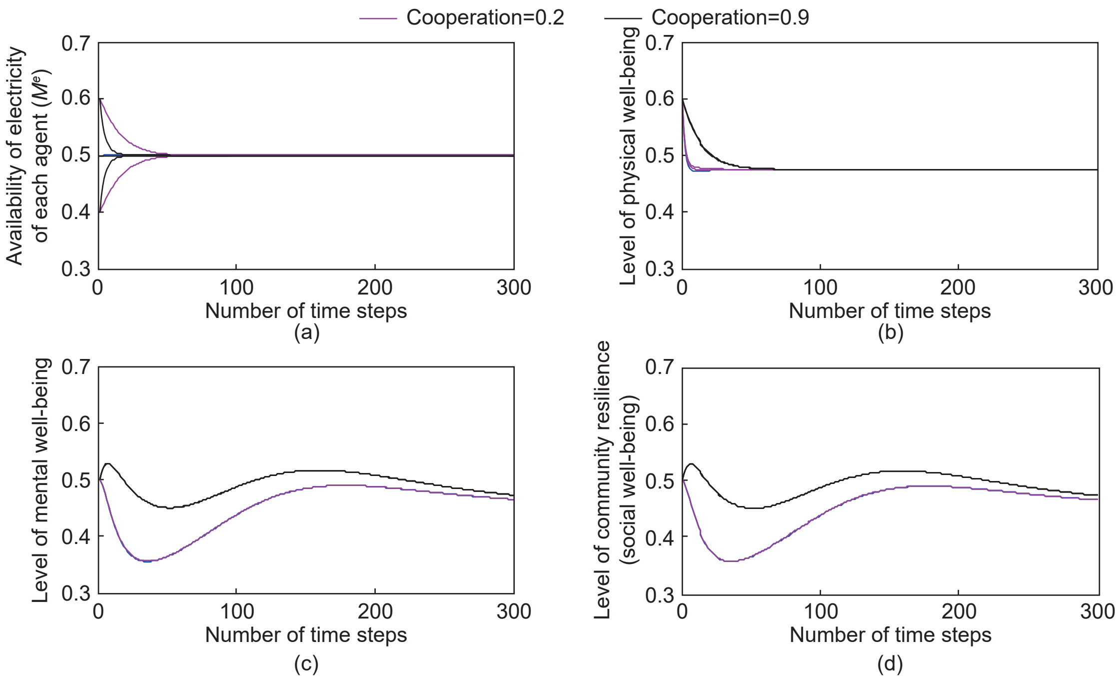

Fig. 6 Effects of different initial values of cooperation on the availability of electricity, physical well-being, mental well-being, and community resilience. Results are provided for different levels of cooperation (0.2 and 0.9). In this homogeneous community, the accessibility of agents to DERs varies. The dynamic change of all kinds of well-being is provided for the time interval [0, 300].

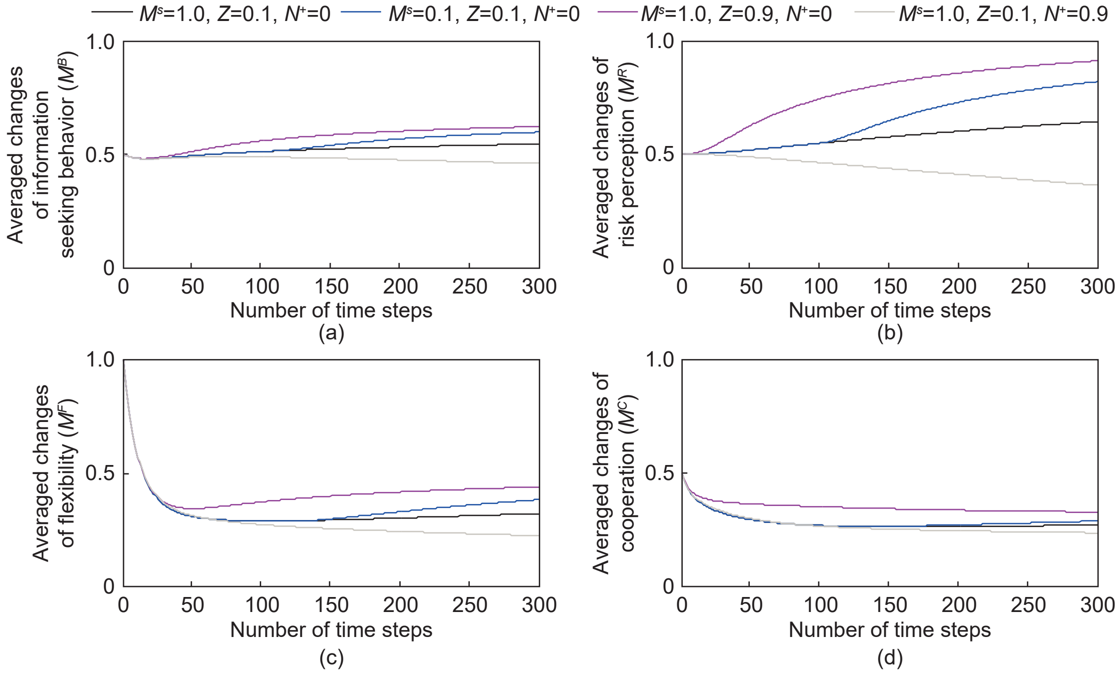

Fig. 7 Effects of the emergency services, the injury factor of disaster, and news polarity on the collective information-seeking behavior, risk perception, flexibility, and cooperation. The black lines represent the effects when the emergency services are entirely available, and the disaster is benign. However, there are a lot of rumors and negative news among individuals. In contrast, the blue lines represent the effects when the emergency services are not available to the community. In the case of the purple lines, the emergency services are wholly available but the disaster is severe, and there are positive news in the society. The grey lines also represent a case when emergency services are available. However, in this case, there are lots of positive news and the disaster is not severe.

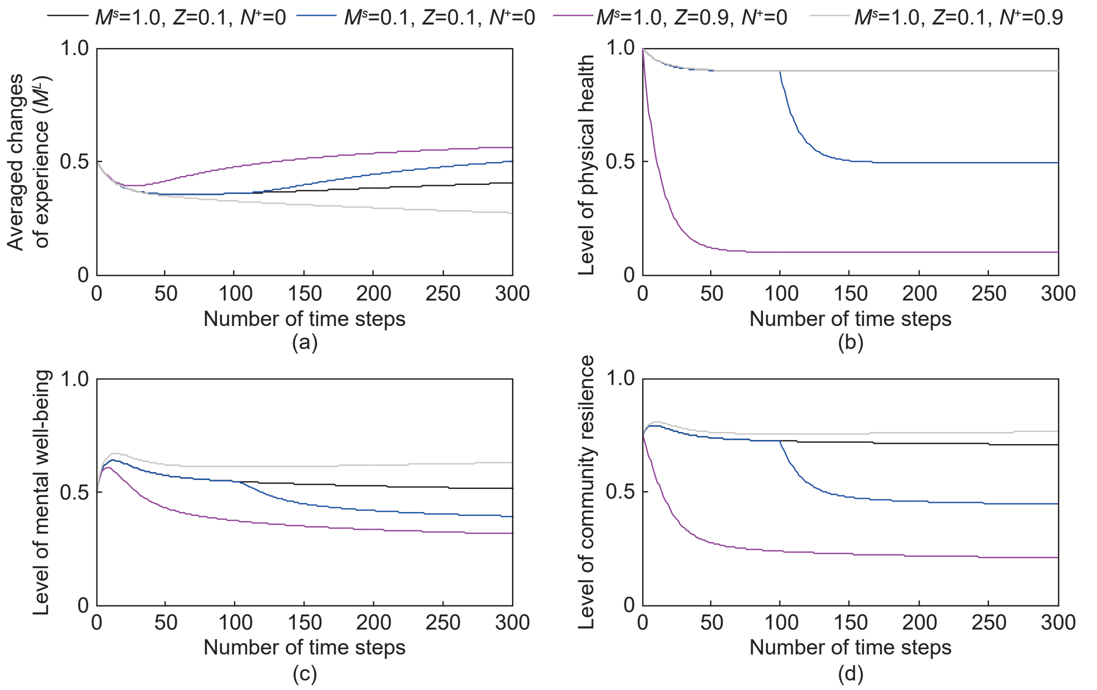

Fig. 8 Effects of the emergency services, the injury factor of disaster, and news polarity upon experience, physical and mental well-being, and community resilience. The grey lines represent the effects when all outside factors, i.e., the emergency services, the disaster, and the mass media, do not have a negative effect on the community. Understandably, there is more community resilience in this case compared to that of other scenarios for the time interval [0, 300].

0.9. These patterns are emergent effects provided by the model outcomes, which cannot be predicted from the individual rules, but that provide information about the behavior of the people.

In Example 2, because of the disaster, a lack of appropriate emergency infrastructure, the destruction of part of the emergency facilities during an event, and a shortage of emergency staff since time step 100, emergency services cannot effectively perform their function. When the information provided by the emergency services decreases, the average physical health of individuals sharply declines. Therefore, the agents' level of fear increases from time step 100 on, and, in turn, risk perception and information-seeking behavior increase. As a consequence, individuals obtain more experience and become more flexible compared to when emergency services are sufficiently available. In Example 3, when the injury factor of disaster is very high with a value of 0.9, the physical health of individuals is dramatically lower. This case is similar to Example 2 in that the trends of fear, information-seeking behavior, and risk perception are similar. Note that the human response in Example 3 changes more quickly than in Example 2. In addition, due to the high level of community fear, the level of cooperation among individuals grows. In Example 4, the news from the mass media is positive with a value of 0.9, and the levels of fear, perceived risk, and information-seeking drop. For this example, the community obtains less experience as compared to Examples 1−3. Furthermore, when people are threatened, they tend to be more flexible.

5 Simulation Results for Case Study 2: Society of Six Separate Communities

This case study aims to clarify social effect of the diversified community on its social well-being and community resilience during and after a disaster. The parameter setting for the mental and physical characteristics, population, and electric grid related to each community are provided in Table 2. The level of intra- and inter-community empathy is shown in Table 3. It is found that Communities 1 and 2 are extremely close-knit. As a result, empathy among these communities is assumed to follow the Gaussian distribution $N(0.9, 0.1^2)$. Regarding the other communities, it is assumed that there is no empathy among them. There is related negative news released in all communities within the time interval [250, 300].

(1) Effects of the occurrence of a disaster on human response

Each disaster can be modeled with the distinct characteristics of Z, Q^s, Q^e, and M^e. In Example 1, the disaster only occurs in Community 1. The injury factor of the disaster is assumed to follow the Gaussian distribution $N(0.9, 0.1^2)$. Because of severe hazards, the emergency services and the power utility are inaccessible in Community 1, but the individuals in this community can still utilize on-site generation. Q_{ti}^{DER} follows the Gaussian distribution $N(0.5, 0.1^2)$. In other communities, Q_{ti}^s, Q_{ti}^e, and Q_{ti}^{DER} follow the Gaussian distribution $N(0.9, 0.1^2)$, while Z is assumed to follow the Gaussian distribution $N(0.01, 0.01^2)$. In addition, N_t^+ in all communities follows the Gaussian distribution $N(0.5, 0.1^2)$. Figures 9 and 10 show the average dynamic change of collective behavior and community resilience for the six communities during a disaster. These collective behaviors are emergent effects, which cannot be predicted from the individual agent rules because they result from the interactions between people and communities. What can be learned from

Table 2 Parameter settings for the community characteristic of the second case study, i.e., the society of six separate communities, where C_i means community i ($i \in 1, 2, 3, 4, 5, 6$).

Parameter	C_1	C_2	C_3, C_4, C_5, and C_6
M_{ti}^R	$N(0.8, 0.1^2)$	$N(0.7, 0.1^2)$	$N(0.1, 0.1^2)$
M_{ti}^B	$N(0.8, 0.1^2)$	$N(0.7, 0.1^2)$	$N(0.1, 0.1^2)$
M_{ti}^E	$N(0.98, 0.02^2)$	$N(0.1, 0.1^2)$	$N(0.1, 0.1^2)$
M_{ti}^F	$N(0.5, 0.1^2)$	$N(0.5, 0.1^2)$	$N(0.5, 0.1^2)$
M_{ti}^L	$N(0.5, 0.1^2)$	$N(0.5, 0.1^2)$	$N(0.5, 0.1^2)$
M_{ti}^C	$N(0.5, 0.1^2)$	$N(0.5, 0.1^2)$	$N(0.5, 0.1^2)$
P_{ti}	$N(0.5, 0.1^2)$	$N(0.98, 0.02^2)$	$N(0.98, 0.02^2)$
Population	150	250	135, 450, 500, and 120

Table 3 Levels of intra- and inter-communities empathy.

Community	C_1	C_2	$C_{i\,(i\in 3,4,5,6)}$
C_1	$N(0.9, 0.1^2)$	$N(0.9, 0.1^2)$	–
C_2	$N(0.9, 0.1^2)$	$N(0.9, 0.1^2)$	–
$C_{i\,(i\in 3,4,5,6)}$	–	–	$N(0.9, 0.1^2)$

these emergent effects is that when a disaster strikes one community and there is another community that is empathetic to the former, the changes in the mental characteristics in these two communities are roughly the same.

In Community 1, because of a high level of the injury factor, the lack of emergency services, and electric energy availability from the power grid, a high level of fear and low level of physical health occur. The level of fear in this community is higher than that of other communities. Because Community 2 has a close relationship with Community 1, their levels of fear are intertwined. As a result, these two communities have a close level of risk perception and information-seeking behavior. Other mental characteristics in these two communities are approximately the same. Community 2 shares its electric energy with Community 1. Hence, the availability of electric energy in the latter is increased. Owing to the fact that the disaster happened in Community 1 and not in Community 2 and due to the higher level of availability of electric energy and emergency services, the physical health of Community 2 is not as endangered as in Community 1. Therefore, people in Community 2 are safe. Furthermore, because of the positive emotion of Community 2 and the high level of empathy between both communities, fear in Community 1 is lowered until time step 2. The feeling

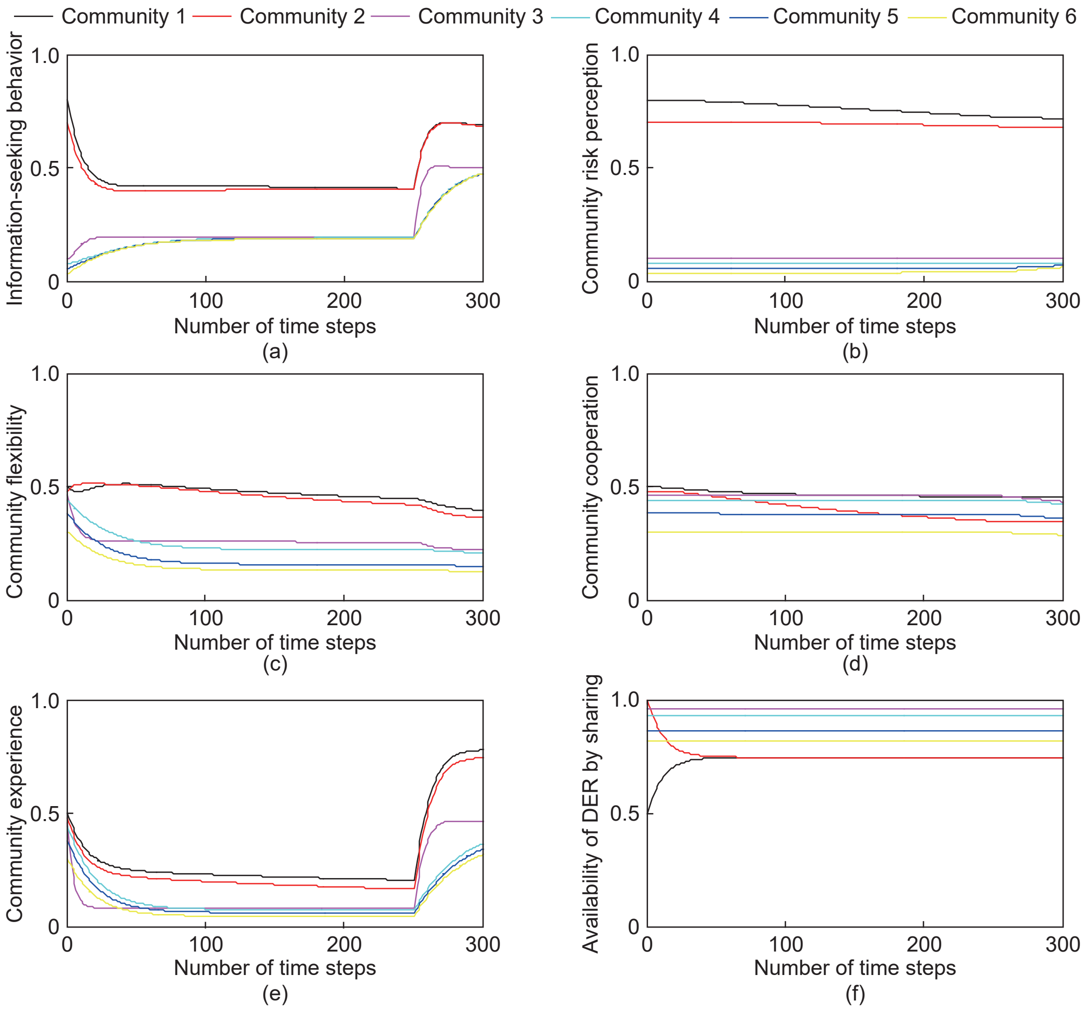

Fig. 9 Dynamic change of information-seeking behavior, risk perception, flexibility, cooperation, experience, and the availability of the electricity supplied by DERs for six communities. The disaster occurs in Community 1. Because Communities 2 and 1 are empathetic to each other, the disaster influences the mental characteristics of individuals in Community 2. In addition, other communities are not empathetic at all.

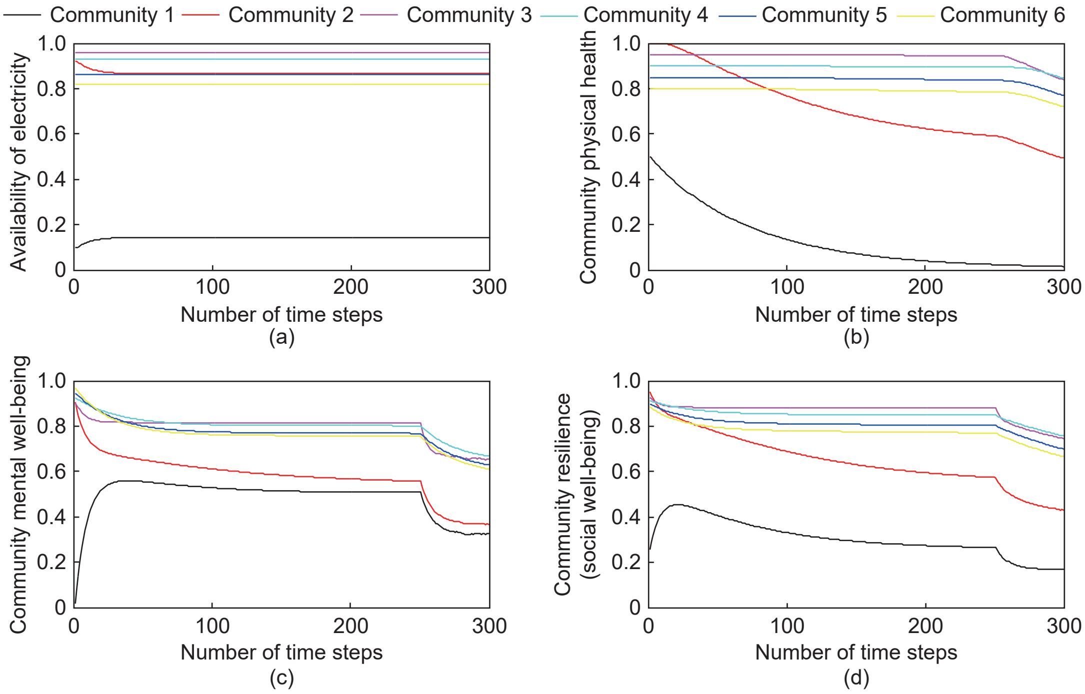

Fig. 10 Trends of the availability of electricity, physical health, mental well-being, and community resilience for six communities. Because the disaster only strikes Community 1, its people have the lowest level of physical health, mental well-being, and community resilience. Because Community 2 has a close relationship with Community 1, the mental well-being of its people is affected by this disaster; consequently, its resilience is diminished.

of fear among all communities is increased after time step 2 as a result of the mass media, which provides relevant negative news. As a result, the risk perception, the information-seeking behavior, and the experience of the individuals in all communities rise after time step 2. In general, human responses in Communities 3 to 6 follow the same trends, resulting in the same status. When a disaster strikes Community 1, both Communities 1 and 2 suffer losses. Because of empathy between these two communities, the losses associated with Community 1 are decreased compared to when there is no empathy between them. With the help of Community 2, Community 1 recovers faster than in the absence of any help. Community 2, understandably, recovers faster than Community 1.

(2) Effects of two concurrent disasters on human response

In this example, a disaster strikes Community 1, while another one simultaneously strikes Community 5. The characteristics of Community 1 and its disaster are the same as those of Example 1. The injury factor of disaster in Community 5 follows the Gaussian distribution $N(0.1, 0.1^2)$. Electric energy supplied by utilities and emergency services is available. The M^E, M^R, and M^B of the people in Community 5 follow the Gaussian distribution $N(0.9, 0.1^2)$. Other characteristics of the communities are similar to those of Example 1. Figure 11 shows the average dynamic change in collective behavior and community resilience for the six communities during the disasters. It is observed that the physical health of the individuals in Community 5 increases because of the availability of electricity, emergency services, and the low level of the injury factor of the disaster. Regarding Communities 1 and 2, there is emotion diffusion and empathy among their people. Furthermore, Community 2 does not have any initial panic. Because its people are empathetic to Community 1, the level of fear in the latter is lower than that of Community 5. Since physical health in Community 5 increases until time stamp 200, the average level of fear in this community falls.

6 Conclusion

In this paper, we proposed a stochastic multi-agent based model using Monte Carlo simulation to analyze the dynamics of the social well-being of communities during a disaster. In the proposed model, the effect of two vital critical infrastructures, namely power systems and emergency services, on the social well-being of a society during a disaster is considered. Currently, the

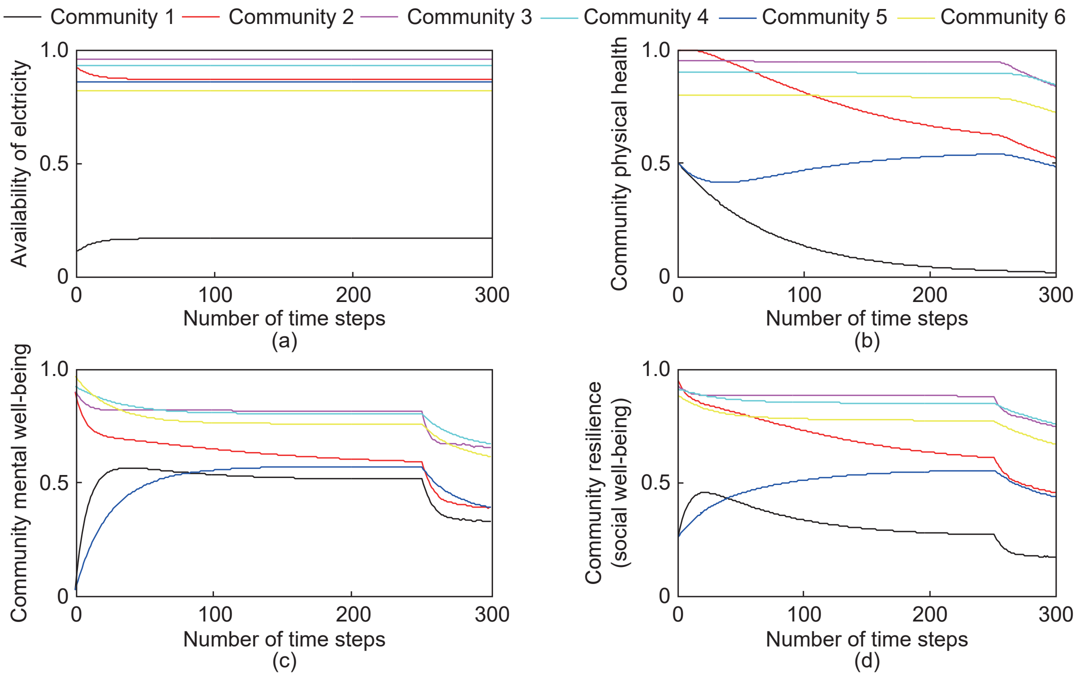

Fig. 11 Average dynamic change of availability of electricity, physical health, mental well-being, and community resilience for the six communities. Although the resilience of Community 1 is similar to that of Community 5 at the beginning of the disasters, these two communities do not exhibit the same trends. Because of the availability of emergency services and electricity during the disaster, the resilience of Community 5 increases over time.

role of critical infrastructures and social characteristics on community resilience is not considered. Our work intends to address this gap in the research and stimulate others to follow up on this research. Specifically, in our simulations, we assumed that some of the agents have distributed energy resources because of the importance of on-site generation on community resilience. This model accounts for the fact that the social well-being of a community is influenced by both the mental and the physical well-being of its individuals. we also considered critical psychological features such as fear, risk perception, information-seeking behavior, compassionate empathy, flexibility, cooperation, and experience during a disaster. Each of these features for a given community was assumed to be based on normal distribution. The most important results inferred from the two case studies are as follows. Experience and flexibility have a negative impact on the level of fear, information-seeking behavior, and risk perception of agents. Experience positively influences the flexibility of the agents if the latter optimistic. When the level of cooperation is increased, the agents show a lower level of fear, risk perception, and information-seeking behavior. Furthermore, they share their electricity sooner than when they have a low level of cooperation. In addition, the positive features of the agents may rectify their behavioral drawbacks. Consequently, we may say that society has a different amount of community resilience under different disasters.

The strength of our work comes from the computational social science approach, where we create artificial societies from the bottom up, to gain more understanding of collective behavior, through structured simulations. Specifically, our research has initiated a set of individual agent rules while entrenching the modeling process in the scientific evidence found in the literature and representing the relations among social community agents. Through the agent interactions in the model, our simulation results show emergent patterns —collective behaviors —that cannot be predicted from the individual agent rules. These emergent effects give us an understanding of which communities are more or less vulnerable during disasters, based on which combinations of factors. They help us understand community resilience better and help us to derive new hypotheses that can be tested in real-world scenarios. Another strength is that the model provides the option of modeling many different effects, which would be costly and difficult to carry out with only experiments or surveys. Each research has limitations, as has ours. In this paper, we have made no distinction between people's expressed opinions and their private opinions, despite the fact that there is a distinction between these two features in reality. This must be taken into account in future research. Because a complete validation of our model is a lengthy and costly process, each relation between the model variables will be tesed separately, for example, through direct observation during disasters or via surveys and other methods. The parameter settings of our model will then be calibrated with these real-world data. Specifically, we plan to structurally validate our model, step by step, to increase confidence in the modelling choices. While the current model has given us more understanding of community resilience, it is essential to predict the resilience of various communities with different features to various types of disasters, and compare them to real data, and adjust the models accordingly. Once our models are validated, they can be used to assess the resilience of a community to an upcoming disaster.

Appendix

The standardised form of the ODD+D protocol of the proposed artificial society to measure community resilience is available at https://github.com/Jab-V/ODD-D/.

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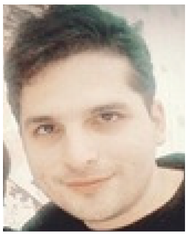

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