Measuring and Enhancing the Resilience of Interdependent Power Systems, Emergency Services, and Social Communities

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(ABSTRACT)

Several calamities occur throughout the world each year, resulting in varying losses. Disasters wreak havoc on infrastructures and impair operation. They result in human deaths and injuries and stress people's mental and emotional states. These negative impacts of natural disasters induce significant economic losses, as demonstrated by the $ 423 billion loss in 2011 in Tohoku, Japan, and the $ 133 billion loss in hurricane Harvey, U.S.A. Every year, hurricanes and tropical storms result in 10,000 human deaths worldwide. To mitigate losses, communities' readiness, flexibility, and resilience must be strengthen. To this end, appropriate techniques for forecasting a community's capacity and functionality in the face of impending crises must be developed and suitable community resilience metrics and their quantification must be established. Collaboration between critical infrastructures such as power systems and emergency services and social networks is critical for building a resilient community. As a result, we require metrics that account for both the social and infrastructure aspects of community. While the literature on critical infrastructures such as power systems discusses the effect of social factors on resilience, they do not model these social factors and metrics due to their complexity. On the other hand, it turns out that the role of critical infrastructures and some critical social characteristics is overlooked in the computational social science literature on community resilience. Thus, this dissertation presents a multi-agent socio-technical model of community resilience, taking into account the interconnection of power systems, emergency services, and social communities. We offer

relevant measures for each section and describe dynamic change and its dependence on other metrics using a variety of theories and expertise from social science, psychology, electrical engineering, and emergency services. To validate the model, we used data on two hurricanes (Irma and Harvey) collected from Twitter, GoogleTrends, FEMA, power utilities, CNN, and Snopes (a fact-checking organization). We also describe methods for quantifying social metrics such as anxiety, risk perception, cooperation using social sensing, natural language processing, and text mining tools.

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(GENERAL AUDIENCE ABSTRACT)

Power systems serve social communities that consist of residential, commercial, and industrial customers. The social behavior and degree of collaboration of all stakeholders, such as consumers, prosumers, and utilities, affect the level of preparedness, mitigation, recovery, adaptability, and, thus, power system resilience. Nonetheless, the literature pays scant attention to stakeholders' social characteristics and collaborative efforts when confronted with a disaster and views the problem solely as a cyber-physical system. However, power system resilience, which is not a standalone discipline, is inherently a cyber-physical-social problem, making it complex to address. To this end, in this dissertation, we develop a socio-technical power system resilience model based on neuroscience, social science, and psychological theories and using the threshold model to simulate the behavior of power system stakeholders during a disaster. We validate our model using on datasets of hurricane Harvey of Category 4 that hit Texas in August 2017 and hurricane Irma of Category 5 that made landfall on Florida in September 2017. We retrieve these datasets from Twitter and GoogleTrend and then apply natural language processing and language psychology analysis tools to deduce the social behavior of the end-users.

Dedication

I dedicate my thesis work to my family. A special feeling of gratitude to my loving parents, whose words of encouragement and push for tenacity ring in my ears.

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Chapter 1

Introduction

Several calamities occur throughout the world each year, resulting in varying losses. Disasters wreak havoc on infrastructures and impair operation [10, 11]. They result in death and have a negative impact on the community. 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 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 health, emergency services and the availability of critical infrastructures services, such as food, agriculture, water, transportation, electric power, communications system. For example, the 2021 winter storm in Texas, which included three severe storms between 10 and 20 February, resulted in widespread power generation failure and blackouts. As a result, over 4.5 million homes and businesses lost power, leaving them without heat, water, or food for several days. Remarkably, during the storms numerous grocery stores have closed and some critical loads, such as hospitals, were short of electricity while experiencing power outages. Thus, the 2021 Texas power crisis had a detrimental effect on people's mental and physical health, resulting in a wave of widespread anger. On the other hand, because the power system managed by the Energy Reliability Council of Texas (ERCOT) is disconnected from the US Eastern and Western interconnections, importing power from these interconnections was impossible during the winter storm. ERCOT issued bills to customers as high as $17,000 for less than a month of service, compared to pre-storm prices of less than $60 per month. The power outages and high electricity prices were exacerbated by a lack of cooperation and empathy and inadequate winterization of the power infrastructure. This example demonstrates the effect of cooperation on the resilience of the power system. A power system is inextricably linked to the social communities it serves. Indeed, making a power system resilient requires that all stakeholders, e.g., utilities, consumers, and prosumers, work together. The ultimate goal of the power system is to balance supply and demand. With the advent of the Internet and the energy of things, consumers can play a critical role in achieving the grid's objectives and assisting the generation side in increasing its operational efficiency, reliability, and resilience. For instance, the consumers may take an active role in demand management by reducing their consumption during disasters. Additionally, prosumers may store their electricity for use during times of peak demand, support critical loads, and share it with their neighbors during power outages. End-users willingness to assist the power utilities during and in the aftermath of a disaster is contingent upon their satisfaction and cooperation. Without collaboration, a power system may struggle to respond to and recover from a disaster as it was the case of the 2021 Texas winter storm.

On the one hand, while there are papers in the literature relating to critical infrastructures such as power systems that discuss the effect of social factors on resilience, they do not model these social factors. The mathematical models focus exclusively on the cyber-physical aspects while ignoring the social aspects of resilience. The primary reasons for this lack of attention is the complexity of modeling the social component of power systems. On the other hand, 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 are not considered. Hence, I present a socio-technical framework for resilience in this dissertation by examining the interdependence of power systems, emergency services, and social networks. To do so, I consider and model the behavior of consumers, prosumers, and utilities through the lens of computational social science. Additionally, I propose a new method for assessing the social behaviors of power system stakeholders and then validate that model by extracting the social behavior characteristics from large-scale data sets, such as Twitter, while using the natural language processing and the text mining techniques.

1.1 Key Contributions

In this dissertation, I address the following questions: (1) How do critical infrastructures and social characteristics influence community resilience and vice versa, and (2) How to measure community resilience accordingly? In summary, I made the following **key contributions** in this work:

- I propose a socio-technical model for power system resilience that leverages social science theories and computational social science to model the social behaviors of consumers, prosumers, and utilities during times of crisis. The proposed multi-agent-based model has the potential to be beneficial for detecting emergent patterns.

- I develop a new method to assess the consumer and presumed social behavior through the use of Natural Language Processing (NLP) and language psychology analysis tools, such as Linguistic Inquiry and Word Count (LIWC), as well as new approaches used in contemporary social science.

- I propose to use the threshold model based on the logistic function to consider the interdependence between socio-technical resilience-related features. This model is based on the theory of morphic resonance and formative causation initiated by Sheldrake [12].

- I investigate the impact of Hurricanes Irma and Harvey on socio-technical power system operation as real-world case studies. We retrieve tweets from Twitter's streaming API by leveraging hashtag search on the terms #electrcity, #power systems, #electric, #power utility, #electric utility, #power grid, from hurricane Harvey's 18,336,283 tweets and hurricane Irma's 17,227,935 tweets. Additionally, Google Trends is used as another social sensing.

- I propose the multi-agent cyber-physical-social model of community resilience. The physical component of disasters consists of two major vital infrastructures: power systems and emergency services. With cyber, we examine the impact of released news, information, and fake news during a disaster on community resilience. We discuss the social characteristics of a community in the social section. Additionally, in this work, we also model the interdependence between all of these different components.

- The following measures are proposed: 1) Cyber: news positivity, amount of fake news; 2) social: fear, physical health, risk perception, information-seeking behavior, cooperation, adaptability, and learning; 3) physical: utility-provided electricity, distributed energy resources (DERs) and microgrids (MGs) electricity, and emergency services availability (functionality).

- I present a method for quantifying each indicator of the cyber, physical, and social components by using natural language processing, text mining, data analytics, and social sensing. Specifically, we suggest a method for quantifying a community's social behaviors through linguistic inquiry and word count (LIWC).

- I validate the model using datasets from hurricanes Irma and Harvey. We collected data from FEMA, Snopes (a fact-checking organization), CNN, and power utilities, as well as Twitter and GoogleTrends, as two social sensing tools. We gathered the following information for each hurricane: 1) hurricane Harvey: 279 news, 24 fake news stories (as recognized by Snopes), and 212000 tweet IDs between 25/08/2017 and 11/09/2017; 2) hurricane Irma: 652 news, 16 fake news stories (as discovered by Snopes), and 275000 tweet IDs between 01/09/2017 and 13/09/2017.

- I developed a method that will motivate end-users to participate in DR by keeping their satisfaction at the highest level while meeting the desired marginal level of load shaving.
- I model the dynamic levels of satisfaction, cooperation and social diffusion of active end-users. We provide an artificial society based on theories from social, cognitive and neuroscience to model the social behaviors of consumers in DR programs.
- I provide a new framework for the DR program to decrease the air and water pollution, and the DALY.
- I take the exergy and the thermo-dynamical cycles of energy into consideration for the DR schedule. We consider the overall chemical exergy of the fuel in the DR program to increase power system sustainability.

1.2 Publications

From this research, we generated the following publications :

- Valinejad J, Mili L, van der Wal CN, Xu Y. Environomic-Based Social Demand Response in Cyber-Physical-Social Power Systems. IEEE Transactions on Circuits and

Systems II: Express Briefs. 2021 Sep 3.

- Mili L, Valinejad J, Xu Y. Alleviating Fractal and Ill-Conditioning Problems of the AC Power Flow Using a Polynomial Form. IEEE Transactions on Network Science and Engineering. 2021 Jul 20;8(3):2495-505.

- Valinejad J, Mili L, Van Der Wal CN, Von Spakovsky M, Xu Y. Multi-Dimensional Output-Oriented Power System Resilience based on Degraded Functionality. In2021 IEEE Power & Energy Society General Meeting (PESGM) 2021 Jul 26 (pp. 1-11). IEEE.

- Valinejad J, Mili L, and Xu Y, ”A Power Flow Method for Power Distribution Systems Based on a Sinusoidal Transformation to a Convex Quadratic Form,” 2021 IEEE Power & Energy Society General Meeting (PESGM), 2021, pp. 1-25.

- Valinejad J, Mili L, van der Wal N. Research Needed in Computational Social Science for Power System Reliability, Resilience, and Restoration. arXiv preprint arXiv:2011.08064. 2020 Oct 22.

- Valinejad J, Mili L, Triantis K, von Spakovsky M, van der Wal CN. Stochastic Multi-Agent-Based Model to Measure Community Resilience. IEEE transactions on affective computing (under review) (arXiv preprint arXiv:2004.05185. 2020 Apr 2)

- Valinejad J, Mili L. Community Resilience Optimization Subject to Power Flow Constraints in Cyber-Physical-Social Systems in Power Engineering. IEEE transactions on power systems (under review) , arXiv preprint arXiv:2004.00772. 2020 Apr 2.

- Valinejad J, Mili L, Van Der Wal CN, Xu Y. Socio-Technical Power System Resilience. IEEE transactions on power systems (under review)

- Valinejad J, Mili L. Cyber-Physical-Social Model of Community Resilience, IEEE Internet of Things Journal (under review).

1.3 Dissertation Outline

This dissertation is organized as follows:

- Chapter 2 provides the literature review on metrics of community resilience, and limitations and gaps of the existing approaches.
- Chapter 3 provides the importance of computational social science for power system and community resilience, the challenges and potential solutions.
- Chapter 4 proposes the 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 system and emergency services, on the social well-being of a society during a disaster is considered. Currently the role of critical infrastructures and social characteristics on community resilience are not considered. Our work intend to address this gap in the research and stimulate others to follow up this research.
- Chapter 5 proposes a community resilience optimization method subject to power flow constraints. The socio-technical power flow model includes the social constraints, i.e., the dynamic change of the level of emotion, risk perception, cooperation, and physical well-being of consumers and prosumers. We also examine the effect of critical loads on the social well-being. The proposed model is implemented in two different case studies, i.e., a two-area 6-bus system and a modified IEEE RTS 24-bus system.

- Chapter 6 leverages an artificial society based on the computational social science approach to model the behavior of active end-users who participate in the demand response (DR). It shows the potential of using computational social science in power system operation. The inherent feature of each end-user consists of the level of satisfaction and cooperation. In the environomic-based social DR, some consumers participate in DR to increase the peak time rebates of the price of electricity. Other consumers participate in DR to decrease air pollution, water pollution, DALY, and exergy.

- Chapter 7 proposes a simple socio-technical model including power systems and social networks. We propose an approach for assessing the behavior of power system stakeholders through the use of social sensing tools such as Twitter and GoogleTrend. We increase the proposed model's reliability by validating it using cross-validation and data sets related to Hurricanes Harvey and Irma. It should be noted that the approach proposed in this chapter for model validation can be applied to a wide variety of socio-technical power system problems.

- Chapter 8 extends the proposed model in chapter 4 and proposes the new approach to validate the multi-agent model including the interdependence between power systems, emergency services and social networks. Fear, risk perception, information-seeking behavior, physical health, cooperation, flexibility, and learning are all social indicators of community resilience. We tracke these indicators using data from Twitter and GoogleTrends. Physical indicators of community resilience include the availability of electricity via DERs, MGs, and utilities, as well as the accessibility of emergency services. We quantified the physical characteristics using data provided by FEMA and the electric utility company. Cyber layer metrics include the news positivity and the propagation level of fake news during events. We evaluated the cyber metrics using data from CNN and fact-checking organizations. The proposed can be used to simulate a variety of circumstances that are either prohibitively expensive or unfeasible in the actual world. We further confirm our socio-technical resilience model using natural language processing and text mining methods.

- The conclusion to the frameworks presented in Chapters 4 to 8 are summarized in Chapter 9. It concludes with a discussion of community resilience.

Chapter 2

Literature Review

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 [13, 14]. 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 [15].

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.* [16], which is the most cited paper in community resilience, propose the following definition: ”resilience is the ability of a social system to respond and recover from disasters and 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 [17] highlights 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 [18, 19, 20]. Among them, power systems and the emergency services play a pivotal role during a disaster, whether being induced by natural, human, or economic stressors [21, 22]. 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 a residential, commercial and industrial sector. Its lack can diminish the 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 the long-term social well-being, especially during a disaster. Similarly to power systems, emergency services are instrumental in mitigating the impact of a disaster on a society [23]. 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 a society during extreme events. Furthermore, emergency services can provide shelter, water, medication, food, sanitation, and treatment assessment to a society during and after a disaster. The availability of these services has a positive impact on the social physical health during a disaster [24]. 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 by re-constructing the damaged or destroyed housing and infrastructures.

This definition is consistent with the one given by Mili *et al.* [24] 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 inter-dependencies and the behavior of the social community they serve are pivotal to disaster planning [25, 26]. For example, if there is an outage of the power lines that serve an emergency service center, the communication infrastructure of that center will go down; consequently, a forthcoming disaster can no longer be communicated to the planning department of the concerned electric utilities and the social communities and planning to face that disaster may not be carried out in a timely manner. Therefore, 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 the 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 [27, 28]. In this chapter, we model an artificial society[1] to evaluate community resilience. The history of agent-based modeling starts 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 micro level) make us able to sociologically analyze the system (at macro level) in the form of computational sociology and vice versa [29, 30]. Currently, there are three distinct types of agent models applied in artificial society: reactive, deliberative, and hybrid agents [31]. Agent characteristics involve both mental and physical aspects [31]. Important mental characteristics for the agents in our artificial society are: include emotion, risk perception, information-seeking behavior, cooperation, empathy, flexibility, personal characteristic such as optimism and experience [5, 17, 32, 33]. Additionally, physical characteristics include the sense of being safe, sheltered, having an hygienic life style to carry out physical activities and perform social responsibilities [34, 35]. The dynamics of the agent behaviors are affected by individual psychological factors in addition to external events, i.e.,

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

power outages and the news from the emergency services and the mass media. A variety of dynamic agent-based models of the human behavior have been proposed in the literature [4, 28].

2.1 Community Resilience Metrics

The 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, the information-seeking behavior, the risk perception, flexibility, cooperation, experience, willingness to share electricity during disaster, and physical health [5, 14, 17, 21, 30, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47]. 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 [24]. It also may raise the level of fear and, in turn, it affects the risk perception of the individuals of that community [5]. 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 [5]. 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 2.1.

1) *Emotional Intensity or Fear* (M^E_{ti}): Emotion as a core characteristic of human psychological feature influences an individual behavior and decision-making in different situations

Table 2.1: 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].

N.	Resilience metrics	Definition	Value (between [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, 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 task 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' 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.

[48, 49]. Emotion is envisaged as a psychological bridge between the 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 [32]. 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 the 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 [50], which are individual disposition, mood, and acute emotional response. The individual disposition - a constant emotional feature of a person - can be positive or negative [50]. This feature is envisaged to be a background to an individual perception and cognition. 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 [50]. 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 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 actions 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 [36]. 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 a society, among others. For example, South Asia is exposed to frequent tsunami disasters [5]; 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. Risk perception can be subjective-based or objective-based. Ping *et al*. [51] model subjective risk perception of a driver by using deep learning while Shin *et al*. [52] propose a human-centered approach to model risk perception. Different people perceive different risks when they face different types of disasters. Factors such as judgment, situational awareness, experience, culture, and cognition influence how people evaluate the danger of a situation [51, 53]. The risk perceived by individuals during disaster form the public risk perception and the social interaction and communication. Allen *et al*. [53] propose the psychological model for public risk perception under extreme heat events, the major weather-related cause of death in the United States, and flooding.

3) *Information-Seeking Behavior* M_{ti}^{B}: People tend to seek information on social network (like Facebook, 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 [37]. 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 (M_{ti}^{F})*: To create a chain of community resilience, flexibility is one of the essential hallmarks of a society facing unforeseen emergencies [17]. Flexibility is the willingness of a person to change his/her view and opinion and to 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 [39]. Flexibility contributes to self-awareness and to 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 is not flexible in terms of behavior and 1 means the highest level of flexibility.

5) *Experience (M_{ti}^{L})*: Constant learning and experience are listed as key elements of the community resilience chain [17]. 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 [40]. Experience as a vital factor for hazard preparedness can also be obtained by learning and education [54] . 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 (M_{ti}^{C})*: 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 [55]. As a result, there are multiple effects resulting from 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 a society, including individual, organization, and national level. Cooperation as a pivotal element for disaster

management can lead to enhanced social integration and unity during disaster[41]. More than 400 studies in biology show that our world is based on cooperation rather than competition. The Darwin's principle of "survival of the most strongest" is therefore invalid since cooperation and solidarity are at the root of the survival of the society as emphasized by Braden [17]. 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 the 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 [42]. Guan *et al.* [56] propose a cooperation model from the multiple social networks. Shao *et al.* [57] discuss the simultaneous impact of cooperation and competition. Besides, different factors influence the level of cooperation among the social group. The main feature for teamwork cooperation is trust between agents [58]. De *et al.* [59] emphasize the importance of mutual trustworthiness between agents to cooperate and to form a social group. In addition, for efficient team cooperation, there is a need for a social connection among agents [60]. Wang *et al.* [60] discuss the effect of the selfish agent in social networks on collective behavior. 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 in 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* (γ_{ij}^{E}): 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 [43]. 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 [33]. Unfortunately, empathy in the United States has declined by 50% during the past 40 years, and the steepest decline happened during the last ten years [61, 62]. This decline in empathy reduces community resilience . To increase empathy among people, benevolent technologies, and Code4Peace program as smartest approaches to social change are recently proposed. Benevolent technologies include peace software[2], media technology, communications technology, compassion, stories, peace games, bicycle power, and green technology. In addition, Code4Peace is a program that encourages programmers and peace workers to collaborate. Code4Peace aims to create peace by making practical and valuable software. 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 that 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 numbers 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.[3] 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) *The level of impact of the News from the Mass Media* N_{ti}: News from the mass media (N_t) (like Facebook, Twitter, TV and ext) has different patterns according to the kind of disaster

[2]Peace software are tools and platforms that aim to make peace in the community and to increase the awareness of global interdependency [61].

[3]Goleman defines cognitive empathy as follows: "Simply knowing how the other person feels and what they might be thinking. Sometimes called perspective-taking"[63]. He also defines 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."

considered [19]. Natural and sudden disasters (tsunami and explosions) are modeled using damped exponential probability distribution ($N_t = e^{-t^{\alpha}}$). Gradually events like hurricane and social crisis are modeled using a normal probability distribution ($N_t = e^{-(\frac{(t-\mu)^2}{\sigma})}$)[20].

9) *The 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 the resumption of ordinary life, and help the businesses serving a community to resume their activities [45]. 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 [64, 65]. 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 a disasters.

The emergency management services deal with risk management, crisis management, and disaster management. They aim to preserving critical properties via a risk reduction by using resources and decreasing the damage that might occur, and by helping the community to rebound to a stable condition [45]. They provide effective emergency management systems and conventional emergency management. Effective emergency management system is more useful than conventional emergency management. As for the effective emergency management systems, they try to mitigate socio-economic threats and disasters.

10) *The level of impact of the Energy on Human Well-Being*: The eradication of poverty is considered as the most critical challenge of the world [66]. According to [67], the worse type of poverty is 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. The interplay between energy and other resources such as health services, food, and education must be propounded to gain the objective of Sustainable Development Goals (SDGs) and Sustainable Energy for All (SE4All) programs [46]. 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 the society. Ortiz *et al.* [21] discuss 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 experience resulting from the lack of energy [68].

As the most crucial energy career, electricity is necessary for streetlight, education, health, modern community, and so forth [18, 69]. For this purpose, Ahmad *et al.* [70] have 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 onsite generation and locally shared electricity is of high importance [68].

Figure 2.1 displays the percentage of the population faced with a lack of energy (blue line) and the extra mortality percentage (red line) in terms of the ratio between the availability and the unavailability of energy in 2012 in the European Union (EU) countries and the United Kingdom. These data are obtained from [1]. Among these nations, Portugal has the largest percentage of over-mortality in 2012, which amounts to 28%. In that year, this country has faced 27% of power shortages. Although the absence of energy directly affects the over-mortality of all nations, some of them are more impacted by energy shortages. For example, Spain, Ireland and the United Kingdom have an over-mortality percentage as high as 21%, 21% and 19% respectively. This does not come as a surprise since these three nations suffered from power shortages of 9 %, 9 % and 8 %, respectively. However, this rule has an exception, Bulgaria. This country is the least impacted EU nation in terms of surplus mortality percentage of 18%, which is much lower than that of Spain, Ireland and the United Kingdom while it has bar far the largest percentage of energy shortage of 47%. These percentages should also be contrasted to those of Slovakia, Finland, the Netherlands and Denmark, which have the highest surplus mortality rate of 8%, 10%, and 12%, respectively, among the least impacted EU nations.

Among these countries, Portugal has the highest rate of excess mortality (28%) in 2012. At the same year, this country face lack of energy as much as (27%). Although, lack of energy directly influence the excess mortality of all countries, Some of them are more affected by lack of energy. For example, Spain, Ireland, United kingdom have the high level of excess mortality rate as much as 21%, 21%, and 19% accordingly. These countries are the most affected countries by lack of energy. The percentage of lack of energy for these countries were 9%, 9%, and 8%. Bulgaria is among the least affected countries by lack of energy. While this country has the highest level of lack of energy (47%), its excess mortality rate is 18% less than that of Spain, Ireland, United kingdom. Also, Lithuania, Italy are among the less affected countries by lack of energy.In addition, Slovakia, Finland, Netherlands, and Denmark have the lowest level of excess mortality rate (8%, 10%, 12%, and 12%).

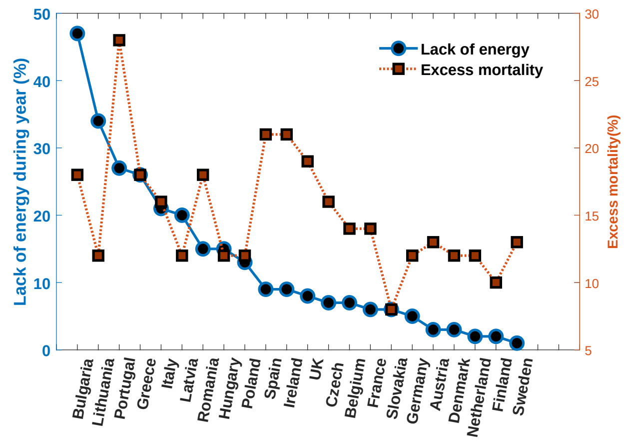

Figure 2.1: The percentage of the population faced with a lack of energy (blue line) and the extra mortality percentage (red line) in the EU countries and the United Kingdom in 2012 [1].

11) *The level of impact of On-Site Generation and 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 [47]. Although damages resulted from the Great East Japan earthquake contribute 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 space 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.

12) *Disaster*: According to the EM-DAT (international disaster database), disasters like drought, earthquake, extreme temperature, flood, landslide, mass movement (dry), storm, volcanic activity, and wildfire have induced more losses than other hazards. Figures 2.2 and 2.3 provide the death toll and the total number of people where affected by the mentioned disasters. It is worth mentioning that there was no mega-disaster in 2018. As part of that case study, the impact of these hazards on the dynamics of the human responses was

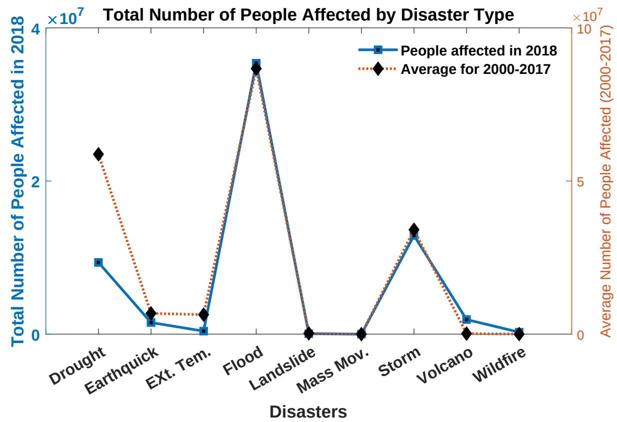

Figure 2.2: Total number of people affected by a disaster type (2018 vs. average 21st century) investigated.

According to Figure 2.2, on average, floods affect 86,696,923 persons every year (average 21st century). This type of disaster affects more people than other types. For instance, in 2018, 35,385,178 persons were impacted by floods. That year, storms and droughts have had an impact on 12,884,845 and 9,368,345 individuals. According to the average database of the 21st century, storms and droughts are among the highest damaging events. On the other side of the spectrum, landslide is the least damaging catastrophe. It has on average only impacted 286 persons each year, while no one was impacted in 2018. In addition, according to Figure 2.3, 46,173 persons die every year as a result of the earthquake. Storms and severe temperatures caused the deaths of 12,722 and 10,414 individuals. In 2018, earthquakes, floods and storms resulted in the death of 4,321, 2,859 and 1,593 persons, respectively.

2.2 Social Computing and Theories

In our community resilience optimization subject to power flow constraints, the novelty of the approach resides in the modeling of the human behavior in CPSS-PE. However, there are a number of chapters dealing with the modeling of the social behavior in cyber-social

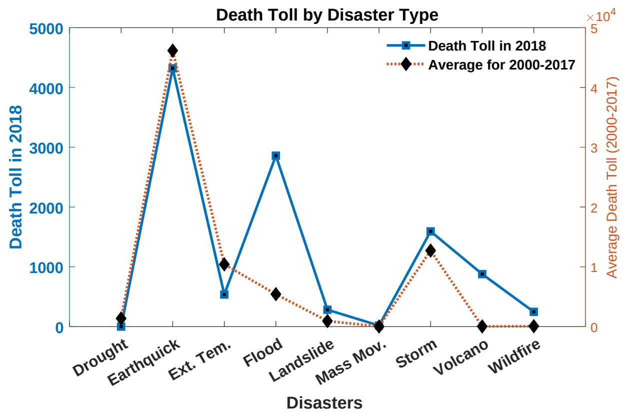

Figure 2.3: Death toll by disaster type (2018 vs. average 21st century)

systems. One approach to model social behavior is multi-agent-based modeling of teamwork cooperation [38, 58, 71]. It is used in various complex system modeling and real-world applications, such as transportation systems, social-economic systems, energy systems, and online friendship network systems (e.g., Facebook and Twitter) [72]. Tan *et al.* [73] model the dynamic of collective behavior by using game theory while considering the effect of the social norms and cultural trends. They also discuss in details a number of collective behavioral patterns, influenced by a variety of conflicts in social networks, such as behavioral flocking, collapse, and oscillation. Ning *et al.* [74] model the collective behavior by using the nearest neighbor rule. Meo *et al.* [59] show that human factors, such as emotion, risk perception, and cooperation, have a profound effect on the dynamics of the collective behavior in social networks. Giraldo and Passino [75] discuss the dependence between the cohesiveness of the group and its performance. They show that a large number of connections between individuals reduces the cohesiveness of the group and its performance. In other words, a decentralized communication network has better performance than a centralized one. Yu *et al.* [76] consider the social norms and conventions to predict collective behavior by applying a multi-agent-based model.

2.2.1 Emotion

In addition to logical intelligence, emotional intelligence is part of human intelligence [77]. Emotions are complex psycho-physiological processes that are controlled by many internal and external factors [77]. Human emotion plays a crucial role in both human-human and human-machine interaction [78]. Emotion in social intelligence is also important. Ficocelli *et al*. [79] provide a model for the human-robot interaction by using robotic emotional behavior. In addition, there are various approaches to reorganize and classify emotional behaviors. Emotion recognition by Electroencephalogram (EEG) is proposed in [77, 78, 80]. Furthermore, Deb *et al*. discuss emotion classification. In our model, to apply emotion, we make use of the Barsade theory, the broaden-and-build theory, the amplification model, and the absorption model. Finally, we explain these concepts in the summary.

2.2.2 Group Emotion: Barsade Theory

Barsade *et al*. [50] propose a top-down and a bottom-up approach to model group emotion. On one hand, in the top-down approach, emotion flows from the group level to the individual level so that the emotion raises at the group level is felt by each person (or agent). On the other hand, in the bottom-up approach, individual emotion can influence the group emotion. It is evident that in the latter approach, the group emotion is formed by the combination of the feeling of each member (or agent).

2.2.3 Upward Emotional Well-Being: Fredrickson Theory

One important question, which is pivotal for the social network emotion, is the following: How do positive and negative emotions influence the agents? Fredrickson *et al*. [81] answer this question by proposing a broaden-and-build theory (or Fredrickson theory). Based on this theory, negative affect (emotion) restricts the individual's thoughts and actions; positive emotion, on the contrary, broadens the set of thoughts and actions of people. According to this theory, joy induces a feeling to play, contributing to physical, socio-emotional, and intellectual resources (skills) so that they lead to brain development. Correspondingly, interest leads to motivation to explore, causing physical, social, intellectual, and psychological skills. As a result, an increase in personal or agent's resources is the consequence of positive emotions. According to the broaden-and-build theory, two new conceptions, i.e., upward spirals and downward spirals, are introduced. In upward spirals theory, it is a belief that positive emotions broaden thought-action proceedings, attention, and cognition, both at present and in the future. Also, based on positive statuses such as well-being, optimism, and success, prognosticate global biases in accordance with widened attention. On the other hand, in downward spirals theory, negative status, such as anxiety, depression, and failure, anticipate local prejudices according to narrowed focus.

2.2.4 Absorption Model - a Multi-Agent-Based Model for Group Emotion

To model the emotion of social networks, computational models are used. According to the social neuroscience, emotion can be considered as a collective feature of the group so that the emotion of an agent can form the feelings, thoughts, and behavior of other agents. In the absorption model, the bottom-up conception based on Barsade theory is used [82]. According to this approach, the team emotion is equal to the sum of its parts in which the group emotion is influenced by homogeneity, heterogeneity, and the mean emotion of agents within the group. This model is appropriate in some situations where the simulation of the emotion dynamics of the agents is important.

2.2.5 Amplification Model

The amplification model to model the emotion of social networks is based on Fredrickson theory, i.e., the broaden-and-build theory, including upward and downward emotional spirals. If there is no outside event or disaster, the absorption model can be appropriate. On the other hand, the amplification model is for cases where there are sudden events and obstacles in the group, emergency, and the factors outside the group that can influence the group emotion. Here, the community resilience planner may use both approaches.

2.3 Power System in Social Science

In addition to environmental and economic issues, the use of energy indicators are relevant to social issues [83, 84]. Consumers of electricity and critical loads are part of the social systems. Arto *et al*. [85] clarify the dependence between human development index, welfare, and electricity. By providing electricity to humans based on their needs and their satisfaction, living standards are improved [86]. Hence, a reliable supply of electricity to a community is essential. By contrast, shortage of electricity and load shedding degrade both the mental and physical quality of life. Physiological changes as a function of electrical energy consumption are not immediately manifested [87]. Alam *et al*. [88] present a model for the physical quality of life as a function of per capita electrical energy consumption. The tool that makes the connection between electricity generation on the physical side and consumer and critical loads on the social side is power flow calculation. Hence, we first discuss the latter. Then, we discuss critical loads and load shedding.

2.3.1 Critical Loads

Critical loads must be supplied with the highest priority, an action that significantly impacts the level of community resilience. They consists of hospitals, operating theaters in hospitals, data centers, information and communication technology centers, ultraviolet lights in water treatment plants, radar equipment for airports, booster systems in pipeline applications, and emergency lighting systems.

2.3.2 Power Flow Equations

Derived from Ohm's law and Kirchhoff's current and voltage law, power flow equations are used for deriving all the functions of an energy management system [89, 90]. These functions include static state estimation, optimal power flow, contingency analysis, power system planning, unit commitment, and reliability assessment [91, 92, 93, 94, 95, 96, 97]. In the power flow model, active and reactive power injections at each bus are expressed as nonlinear equations of the bus voltage magnitudes and voltage phase angles [98]. Various power flow models have been proposed in the literature [90, 91, 98, 99, 100, 101, 102, 103]. These models may be based either on logarithmic transform, or on adaptive polynomial chaos-ANOVA method, or on a general representation of independent variables, or on constructing inner and outer linear approximations, or on Bulirsch–Stoer method. Power flow methods for power distribution systems are reviewed in Yang *et al.* [98].

2.3.3 Load Shedding

Rolling blackout in electric power grid, also known as rotational load shedding, is an emergency control tool initiated by electric utilities aimed at curtailing the excess of load with respect to the power generation due to unplanned failures or an unexpected large increase of the load for blackout prevention [104]. In other words, rolling blackouts are the last resort measure employed by electric utilities to prevent overloading, instability, and system collapse of the power grid [105]. The California electricity crisis of 2000-2001 [106], and Western Victoria and South Australia incidents on 24 and 25 January 2019, respectively, [107], are real examples of rolling blackouts that are due to unplanned system inefficiencies, the lack of maintenance of generating units and power transmission and distribution systems, increased population, and improved living standards [104].

2.3.4 Power System Resilience

Mili [108] elucidates the concept of the resilience of a power system and discusses its robustness, stability, reliability, and homeostasis. Panteli *etal*. [109] define operational metrics for power system resilience from an infrastructure perspective. Watson *etal*. [110] and Panteli *etal*. [111] provide an event-based fragility model for the electric grid's components in order to assess the vulnerability of the critical components to extreme events. To enhance power system resilience, Huang *etal*. [112] propose to integrate in the power system model generation re-dispatch, load shedding, and topology switching; Ma *etal*. [113] develop a model for backup distributed generators and automatic switches; and Mili *etal*. [114] and Panteli *etal*. [115] propose to utilize adaptive islanding.

2.4 Limitations and Gaps of the Existing Approaches

Numerous measures and frameworks have been presented to quantify and predict community resilience. Generally, we can categorize these frameworks as capacity-based or output-oriented [13]. While output-oriented methods quantify a community's degraded functionality over time following a crisis, capacity-based assessments conduct a static examination of community resilience. Early works on community resilience, such as BRIC [116], RAPT [117, 118], and CDRI [119] are capacity-based in nature. COPEWELL [120] and Zobel'model [121] recently proposed output-oriented assessment methods. While these works are excellent starts, they do not: 1)look at the interconnection of a community's cyber, physical, and social components; 2) account for the dynamic changes in resilience-related characteristics that occur during a disaster; 3) account for the flexibility, cooperation, learning, fake news, and availability (functionality) of critical infrastructures such as emergency services and power systems; 4) account for the role of individuals and their connections in community resilience; 5) address the effect of a disaster severity's dynamic change on behavioral change and community resilience while developing their model; 6) look at the network-based feature of community resilience; and 7) provide exhaustive metrics.

As a result, we present an output-oriented cyber-physical-social model of community resilience in this work. We develop the proposed model using a multi-agent framework based on social science and psychological theories. Fig. 8.1 illustrates the physical, cyber, and social layers of community resilience and their interdependence. When a physical, or social characteristic is changed, it may affect the other features, either positively or negatively. For instance, electricity outages can exacerbate people's worry during a disaster. Additionally, negative news can heighten this worry. Although fear is regarded as a negative characteristic of society, it is necessary to increase a community's risk perception during a disaster to take appropriate action. 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. 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.

Chapter 3

Computational Social Science in Smart Power Systems: Reliability, Resilience, and Restoration

Smart grids are modeled as cyber-physical power systems without considering the social aspects. However, end-users are playing a key role in their operation and response to disturbances via demand response and distributed energy resources [30, 69]. Therefore, due to the critical role of active and passive end-users and the intermittency of renewable energy, smart grids must be planned and operated by considering the social aspects in addition to the technical aspects [122]. The level of cooperation, flexibility, and other social features of the various stakeholders, including consumers, prosumers, and microgrids, affect the system efficiency, reliability, and resilience. This article examines the interactions between power systems and the communities using an artificial society approach inspired by social science and neuroscience theories to fulfill the power systems' objectives. In view of the importance of computational social science for power system applications, we provide a list of research topics that need to be achieved to enhance the reliability and resilience of power systems' operation and planning. Having a human-centered approach in the cyber-physical-social system of energy is very important and it is an emerging topic. Attacking such a problem would have significant implications to power systems, energy market and community use, and energy strategies.

3.1 Why We Need Social Computing from Power Systems (Cyber-Physical) Perspective

A power grid can be considered a cyber-physical-social system in its essence. Indeed, humans contribute to all the processes involved in electric generation, transmission, distribution, and consumption, from planning to operation and maintenance. Therefore, considering the social aspects is essential for both the generation side and the end-user side. On the generation side, prosumers' (active end-users) social behavior affects the power system control and operation in real-time via things such as demand responses and batteries of electric vehicles. The cooperation and participation of end-users, whether passive or active, can contribute to their active involvement in the system ancillary services, such as voltage and frequency stability. Putting the consumers (passive end-user) and the prosumers at the center of a power system study is also necessary for assessing its reliability, resilience and associated community resilience. The social aspects account for the involvement, not only of the active end-users, but also of the primary energy industries, e.g., the coal industry and other organizations connected to the power system. Indeed, both the end-users and the primary energy industry shape the smart grid operation's objectives significantly. In addition to these stakeholders, human errors in the power industry influence maintenance, emergency dispatch operation, and rolling blackout. In addition, they may contribute to cascading failures leading to blackouts. Therefore, by considering the social aspects, power systems can be made more efficient, reliable, resilient, and sustainable. To incorporate the social aspects into smart grids, we need to use modern social science and social computing. That makes the cyber-physical-social system in power engineering and energy infrastructure a super wicked

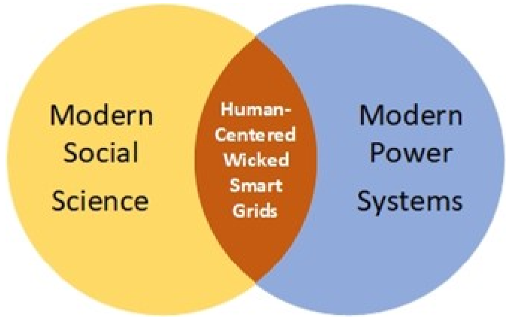

Figure 3.1: Modern Power Systems as Cyber-Physical-Social system: a Super-wicked problem

problem (Figure 3.1).

3.2 Human-centered approach: Building the Artificial Society to Model the Social Behavior Based on Social Science and Neuroscience Theories

The way that power engineers, scholars, and researchers cope with power system problems is inherently different from how social scientists deal with societal queries. In power systems, researchers seek to find optimal solutions for power system operation and planning while it is so challenging to talk about optimal solutions in social issues. In fact, there is only a subjective definition of an optimal solution unless the optimization problem is casted using social science and psychological theories and social qualifications such as cooperation, flexibility, and experience to name a few. A power system as a cyber-physical system without considering the social aspect is a mostly tame or benign problem. Current approaches proposed in the power systems have developed to deal with tame problems and are ill-equipped and insufficient to understand and deal with social issues and public policies considering multi-disciplinary theories. Social computing and social planning in power systems are ill-defined.

Smart grid objectives cannot be addressed in isolation. Incorporating social science into the power system optimization problems makes them a super-wicked or malignant problem. In other words, a power system as a cyber-physical-social system inherently is intractable, open-ended, unpredictable, and complex problem. Here, there is a need to consider the values and interest (perspective) of various stakeholders, e.g., active end-users, utilities, to name a few, in a planful way.

To incorporate computational social science and collective behavior in power systems operation and planning, we propose to use generative computational social science. There is a need for modern social science and social computing to address the gap between cyber-physical and cyber-physical-social systems. In the literature, social scientists in computational social science advocate the use of an artificial society to model social systems' collective behavior, the interaction between agents and human response. The artificial society can be used for virtual experiments via agent-based modeling and simulations, which is an appropriate and promising method widely accepted by researchers addressing problems in sociology, complex systems, emergence, and evolutionary programming. Artificial society and power system, which are both network-structured, can be incorporated into each other to model the dependence between humans, computers, and the physical environment. This incorporation allows us to model important interactions such as macro-micro social interaction, human-computer interaction, human-physical environment interaction, organization-physical environment interaction, human-organization interaction. In addition, there are various protocols, e.g., the Overview, Design concepts, Details, and Decision (known as ODD+D protocol) to standardize an artificial society. The latter can leverage various social science and neuroscience theories, including broaden-and-build theory, Fredrickson theory, Barsade theory, bottom-up approach, and Damasio's Somatic Marker Hypothesis by using absorption and amplification models. Furthermore, using artificial society we can better analyze and understand end-users' collective behavior in the human-centered power system. That helps us to understand better the cyber-physical-social system in power engineering band to derive new hypotheses that cannot be tested in real-world scenarios. By leveraging an artificial society, the planner can investigate the effect of a wide range of scenarios that can be costly and difficult to conduct with only experiments or surveys.

Emotions are the foundation of psychological and social behaviors of the consumers and prosumers. Indeed, the end-users' social behavior and emotional status affect power system operation in various ways. For example, different types of emotions determine the end-users' satisfaction level. Based on neuroscience, psychology, and social science, the consumers' satisfaction level and social behaviors, influences each other via the use of mass media platforms. Emotions in the group can be expressed, received, or transferred in such a way as to affect the energy level of the group. The dissatisfaction is propagated through the mass media platforms via the Internet if it is available. In summary, people can communicate through the mass media channels and express their emotions, which in turn affects the social dissemination. To account for consumers' and prosumers' levels of emotion, Barsade's and Fredrickson's theories are used by various researchers to model the impact of the human behavior on the emotion spread. The community's collective emotional level depends on the homogeneity and heterogeneity of each agent's emotional state and mood and their minimum, maximum, and mean level. Fredrikson's theory indicates that the interest of a person to something or someone leads to the motivation to explore, enhancing her physical, social, intellectual, and psychological skills. As a result, positive emotions lead to an increase in personal resources. It is a belief that positive emotions broaden thought-action proceedings, attention, and cognition, both at present and in the future. That is the case with negative emotion, i.e., the dissatisfaction level of consumers and prosumers.

3.3 The Outline of the Perceived Cyber-Physical-Social System in a Power System for the Future: Gaps and Obstacles

3.3.1 Gaps

Nowadays, the exchange of information via the Internet between producers and consumers is gradually increasing so that the power industry is turning to an Industrial Internet of Things industry. Because of the close interaction of producers and end-users in various applications of power systems, there is an inevitable demand to incorporate computational social science in power system operation and planning analysis from a reliability, resilience, and restoration perspective (Figure 3.2)). Social aspects should be incorporated into power system analysis, planning, and control with different time scales as seen in the first circular layer of Figure 3. In addition, various operating and planning results are caused by the use of artificial society in the study of resilience, reliability, and restoration of the power system, as shown in the second circular layer. Reliability is enhanced by demand response, electrical vehicle charging, investment planning, communications systems, Internet of energy, electricity markets, to name a few. On the other hand, resilience covers cascading failure, recovery, rolling blackout, and active demand-side management, to name a few. Finally, computational social science should be modeled in the field of both distribution and transmission restoration. The use of social computing and artificial society in power systems in each of these analyses, but not limited to them, are as follows:

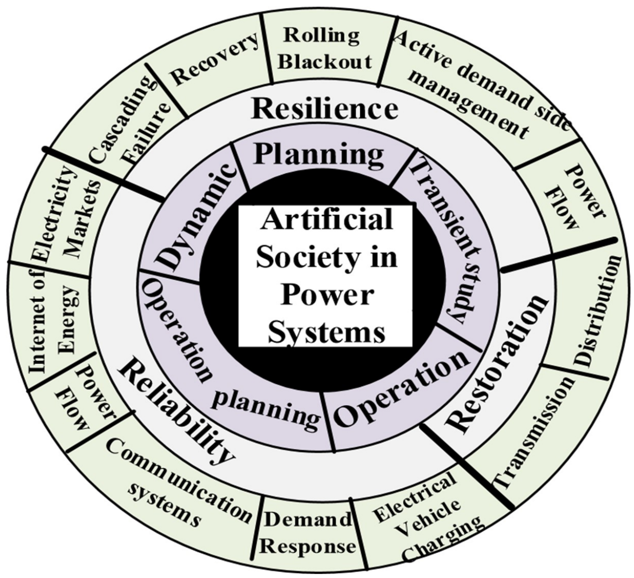

Figure 3.2: An overview of the research topics needed in computational social science for power system reliability, resilience, and restoration modeling using artificial society methodology.

Reliability

The reliability of a system is defined as the probability that this system is able to retain, over a given time period, its intended function under given conditions when it is subject to internal or external failures.

- Socio-Technical Power Flow
- Socially Intelligent Investment in Microgrids and Distributed Energy Resources
- Socially Intelligent Power System Planning
- Socially Intelligent Demand response
- Socially Intelligent Transactive Energy
- Socially Intelligent Electricity Markets
- Electrified Transportation System with Large Penetration of Electric Vehicles
- Renewable Energy
- Socially Intelligent Pandemic Planning

- Socially Intelligent Voltage and Frequency Stability

- Socially Intelligent Economic Dispatch and Unit Commitment

Resilience

The resilience of a system to a class of unexpected extreme disturbances is defined as the ability of this system to (i) gracefully degrade its function by altering its structure in an agile way when it is subject to a set of disturbances of this class and (ii) quickly recover it once the disturbances have ceased with minimum losses.

- Socially Intelligent Preparedness and prediction

- Socio-Technical Power Flow

- Socially Intelligent Investment in Microgrids and Distributed Energy Resources

- Socially Intelligent Power System Planning

- Socially Intelligent Rolling Blackout and Load Shedding

- Electrified Transportation System with Large Penetration of Electric Vehicles

- Pandemic Planning

- Socially Intelligent Voltage and Frequency Stability

- Cascading Failures

- Socially Intelligent Active Demand Side Management

- Socially Intelligent Hierarchical Distributed Adaptive Intelligent Control

- Power System Segmentation/ Islanding into Weakly Connected Subsystems via HVDC

Restoration

Power system Restoration consists of phases, i.e., planning to restart and reintegration of the bulk power system, retaining critical sources of power (degraded level), and restoration after stabilizing at some degraded level.

- Socially Intelligent Distribution-Level Restoration

- Socially Intelligent Transmission-Level Restoration

- Black Start Resources

- Damage Assessment, Repair, and Reenergization

3.3.2 Challenges and Obstacles

Incorporating social computing in power system operation and planning brings new challenges, which are

1) Calibration and validation of social components are a significant challenge for social science modeling in power systems. New methods and techniques for calibrating and validating the model are required. This article will discuss how to calibrate and validate the cyber-physical-social model used in power engineering.

2) Power engineers are unfamiliar with theories from social science, neuroscience, social psychology, and cyberpsychology that can be used to model socially intelligent frameworks in power systems. Hence, they are unable to verify cyber-physical-social models due to a lack of knowledge in computational social science.

3) Social behaviors are inherently uncertain. As a result, incorporating computational social science into the power system increases the model's degree of uncertainty. Hence, appropriate stochastic models are required. Note that this does not imply that we increase the degree of uncertainty associated with the results. Indeed, when we disregard social science, we ignore the social dimension of the power system, producing results that are far from reality.

4) Measuring social and psychological behavior presents a difficult task. Historically, surveys

were a popular method of assessing social behavior. It can be costly and time-consuming. Additionally, because only a small sample of the community is considered, the results may be unreliable. As a result, we require a novel type of social sensing to quantify social behavior in order to model the cyber-physical-social model in power systems.

5) The social component of the cyber-physical-social system lacks an exhaustive list of possible solutions. As a result, it can be described in a variety of ways. Social behaviors are qualitative rather than quantitative. It is necessary to establish an appropriate and quantifiable scale for social behavior in order to incorporate it into the cyber-physical mathematical model.

6) To address cyber-physical-social system problems, a social stopping rule must be defined. Different utilities and power industries may prioritize social objectives at different levels. Additionally, we must define appropriate social constraints and objectives for each application of social science in power systems.

7) Solving a cyber-physical-social system optimization problem that encompasses social, cyber, and physical issues can be complex and time-consuming. Due to the highly nonlinear and uncertain nature of social computing, it exacerbates the challenges inherent in the cyber-physical-social system. We require novel methods and strategies for dealing with socially intelligent models embedded in power systems.

3.4 Active Demand-Side Management as Ancillary Service to Enhance Community Resilience

Meteorology organizations predict the weather. However, in general, weather is so nonlinear and impacts the power system states. There are five power system operation states: normal, alert, emergency, in extremes, and restoration. In an emergency condition, where the system starts to lose its stability, there is a requirement for corrective steps where consumers' roles and level of collaboration are inevitable to retain grid resilience.

In case of an approaching disaster, emergency services are informed and transmit a signal and required information to both utilities and consumers. In conventional power systems, the generation side deals with numerous issues, whereas in modern power systems, by grid modernization, the generation side is not alone anymore. Consumers can participate in active demand-side management and minimize their consumption during disasters in a decentralized power system. Decentralization is one of the main foundations for grid resiliency. In addition, the prosumers can share their electricity with their neighbors and assist critical loads. To have a resilient electricity system, the demand side plays a significant role. The consumer's desire to help power providers overcome a crisis hinges on customer satisfaction and cooperation. Additionally, sharing electricity is inextricably linked to the community's level of cooperation. There are four scenarios to keep grid resilience, voltage, and transient stability:

1- In real-time, it can send a signal through a communication system to consumers to turn off some of their devices, e.g., a computer, refrigerator during the event. One reason that motivates consumers to participate in active demand-side management is to prevent the automatic cutoff of electricity by utilities. In this circumstance, the level of collaboration and flexibility of consumers can affect grid resilience. Plus, numerous policies might be enacted to attract customers to engage. In this scenario, the consumers a day ahead (although it can be real-time) select they want to participate in active demand-side management and which devices they only use to aid the utility to address grid resilience.
2- In the planning mode, the utility has a contract with consumers to turn off their devices during an event. Every device has a sensor and can be controlled by utilities. Here, the level of collaboration of consumers can help the utility to manage the incident.

3- In real-time, utilities can evaluate the risk of occurrences and turn off the electricity of consumer devices automatically without letting them know. In this instance, the consumer's satisfaction diminishes. In addition, some consumers like hospitals, while they are in desperate need of electricity, may be disconnected.

4- In addition, in the planning mode, prosumers and consumers can share their electricity with their neighborhoods and critical loads. We suppose that demand is 20 MW. In this scenario, if each home shares its electricity with only one neighborhood, the electricity demand reduces dramatically to 10 Mw. In this scenario, the customers can respond to the utility signal that they share their electricity with n number/ KW of neighborhoods/consumers.

In all scenarios, a utility may set the level of disconnection based on different desired frequency thresholds. Utilities may view the 59-61 as a normal range of frequency fluctuations. In the case of three thresholds, we have the following scenarios:

a) If the frequency is lower than 59 HZ, the utility decrease the 10 percent load to keep grid resilience.

b) If the frequency is lower than 55 HZ, the utility drops the 30 percent load to keep grid resilience

c) If the frequency is lower than 50 HZ, the utility drops the 50 percent load to keep grid resilience.

3.5 Human-Centered Features in the Cyber-Physical-Social Systems of Power Systems

The Internet of Things, big data and cloud computing, complex networks, blockchain, instant data and edge computing, artificial intelligence, and power system SCADA are typical

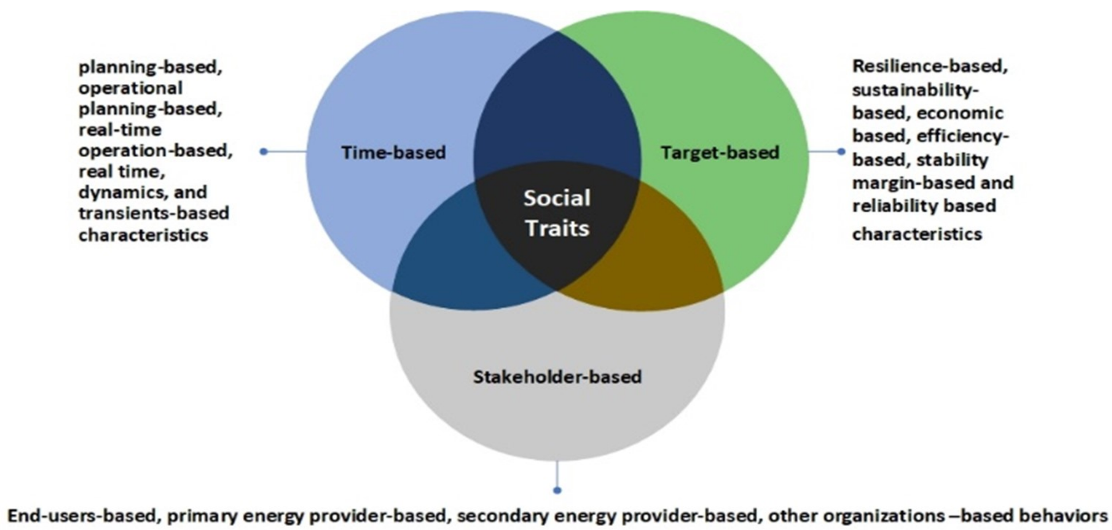

Figure 3.3: Classification of Social Features in Super-Wicked Cyber-Physical-Social System in Power engineering

cyber-physical systems and technologies. However, a power system today is a cyber-physical-social system where the social system refers to stakeholders' social behaviors, which affect the way the power system operates. Obviously, these stakeholders' social behavior has a significant impact on the efficiency, reliability, and resilience of a power system. We extend these features to power systems stakeholders. We classify the social elements in different manners. Figure 3.3 show the classification of social features in super-wicked cyber-physical-social system in power engineering. The classification of social traits can be target-based, time-based, or stakeholder-based. In the target-based classification, social features are categorized into resiliency-based, sustainability-based, economic based, efficiency-based, stability margin-based, and reliability based characteristics. In the time-based classification, social components are categorized into planning-based, operational planning-based, real-time operation-based, and real time, dynamics, and transients-based characteristics. In the stakeholder-based classification, social features are categorized into end-users-based, primary energy provider-based, secondary energy provider-based, other organizations –based behaviors.

The social behavior of the end-users is individual-based. When they are highly satisfied, the end-users, such as prosumers and electric vehicle owners, increase their level of flexibility, cooperation, and trust to secondary energy providers such as electric utilities or retailers. Consequently, they are more willing to participate in demand response, active demand side management, and vehicle to grid programs, to name a few. Furthermore, if the consumers and the prosumers exhibit a high level of empathy and collaboration, they may be willing to enhance the power system efficiency, reliability, and resiliency. On the other hand, how the end-users think affects their decision-making related to the power system operation. Their decision-making is also affected by their experience and their learning behavior. In addition, the secondary energy providers can increase the motivation of the end-users to contribute to better efficiency of the demand response.

During a disaster, when the end-users experience fear and a shortage of electricity, they perceive risk. This risk, in turn, increases their level of cooperation. Hence, they are more prone to participate in an active demand side management program and share electricity with their neighbors who have experienced an outage. In addition to the quality of service, social diffusion through the mass media platforms affects their satisfaction level. Social diffusion means that an end-user's emotion affects the feeling of others about power system services. The social behavior of secondary energy providers, primary energy companies, and other entities are organizational-based. The social behaviors of each stakeholder can affect its service quality and decisions that are very important to the performance, reliability, and resilience of power systems.

3.6 Calibration and validation of the cyber-physical-social model in power engineering

The previous sections highlighted the necessity to consider social factors when studying and analyzing power systems. To this end, mathematical cyber-physical models should be developed for each application that has been discussed, namely reliability, resilience, and restoration, by leveraging social computing. While the cyber and physical components of the power system are well modeled, the social component, as previously discussed, presents modeling challenges. Regarding the cyber and physical components, they are provided with a large number of sensors that can be used to calibrate and validate the associated models. As for the social component, traditional social science has relied on surveys to measure social behavior. However, today new tools can be utilized, including natural language processing, machine learning algorithms, computer-text analysis tools, and social media, to name a few. For instance, prosumers', consumers', and organizations' social behavior can be quantified by utilizing social media platforms such as Twitter and Facebook and social sensing tools and performing sentiment analysis. Social scientists, or psychologists in the modern era can unveil social patterns through an analysis of the text's language. The language that people utilize reveals their psychological state. For instance, when individuals use the first plural pronouns more frequently in their speech, this demonstrates a high level of cooperation and cohesion among them. Additionally, GoogleTrend can be utilized to detect social and psychological patterns. Obviously, these novel social sensing technologies generate a wealth of data for social model calibration and validation. Figure 12 indicates the process of validation of Cyber-Physical-Social System in Power engineering. When social computing is employed, the social model is calibrated using social datasets, which are gathered via appropriate social sensing techniques, such as social media. In particular, when studying resilience, social-related datasets can be collected for a specific event by analyzing social data gathered from Tweeter. Then, the parameters of the social model are estimated. Finally, the model is validated by comparing the predicted data against the social data collected from another event. Model validation is an integral part of the social computing model since it allows us to discover new social features not accounted for in the model if the predictions are far off.

3.7 Conclusion

In this article, we have highlighted the need to account for the cyber-physical-social dependence in power engineering in order to model and optimize the efficiency, resilience, sustainability, reliability, stability, and economic aspect of the power infrastructure and the associated social community. To meet that need, we leverage social computing to model the social behavior of prosumers, consumers, utilities, and other related entities. We have provided a comprehensive list of research topics needed in computational social science for various power system operation and planning activities. We believe that our approach represents a paradigm shift in that it integrates power systems and social computing. Each of the applications stated needs a significant research effort to mature. Integrating social computing into the power system planning and operation process allows us to derive new hypotheses and test different scenarios that will be validated using real data gathered from various social media tools, like Twitter and Facebook. By leveraging natural language processing, machine learning algorithms, and text mining tools, these social sensing tools enable us to identify linguistic and psychological patterns. Validating the model, which is a necessary component of social computing models, enables us to learn from real-world data.

Chapter 4

Multi-Agent-Based Stochastic Dynamical Model to Measure Community Resilience

In this chapter, we propose an agent-based model of community resilience, which consists of the social physical and mental well-being. The dependence amongst the social physical and mental well-being and outside determinants in our artificial society are displayed in Figure 4.1. Interestingly, neuro-scientists have discovered the existence of 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.

In this chapter, 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. In particular, because of the importance of the emergency services, we model them together with the electric utility, on-site generation, and distributed energy resources in the artificial society exposed to disasters. Note that in computational social science

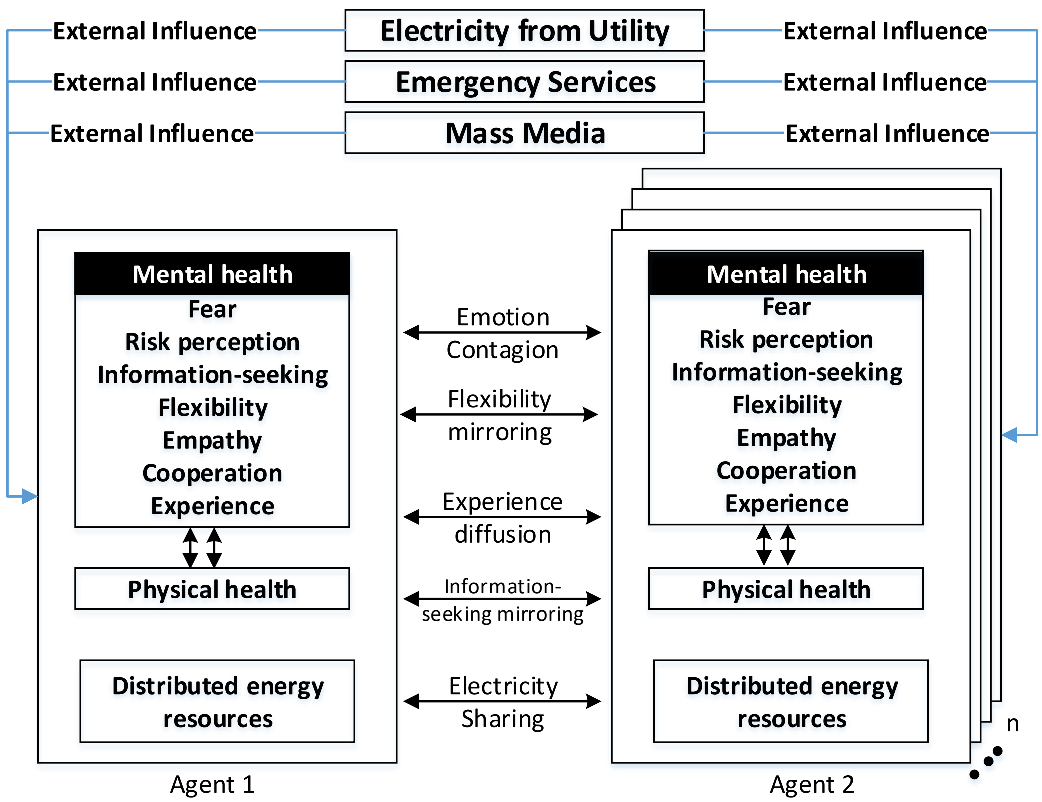

Figure 4.1: Artificial society including agents and external factors, i.e., critical infrastructures, power systems , emergency services, and mass media. Critical infrastructures influence both the mental and physical well-being while mass media only affects the mental well-being.

literature, the emergency services are not considered. We also model and analyze important features of social community, such as compassionate empathy, flexibility, experience, and cooperation for sharing electricity during disasters, which are currently not considered in the computational social science literature. Our multi-agent-based stochastic dynamical cyber-physical-social model is derived from social neuroscience [123] to measure community resilience in terms of mental and physical well-being. This model is standardized by the ODD+D protocol, which stands for Overview, Design concepts, Details and Decision. In the appendix, an online link provides a standardized form of the ODD+D protocol [124] for 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 situation. 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.

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 [29]. We created our conceptual model for our multi-agent-based stochastic dynamical model based on studying the literature from neuroscience, psychological, social science and via discussions with our colleagues in these fields.

We will have a detailed look in 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 from the individual rules of the agents. These aggregated effects will help us to understand the community resilience better. By creating a model from the bottom up, we allow ourselves to create more understanding of these aggregated impacts.

4.1 Nomenclature

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, 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

4.2 Inputs and Outputs of the Proposed Stochastic Multi-Agent-Based Model

There are four different types of inputs to our stochastic multi-agent-based model, namely community-based, diffusion-based, disaster-based, and initial-based inputs.Specifically, the inputs are the number of communities, the size of the population of each community, the level of personal characteristics such as optimism or pessimism (M_i^O). Regarding the diffusion features, the inputs include the emotional diffusion factor (γ_{ij}^E), the information-seeking behavior mirroring factor (γ_{ij}^B), the flexibility contagion factor (γ_{ij}^F), the willingness to share an experience or the experience diffusion factor (γ_{ij}^L), and the willingness to share electricity (γ_{ij}^{DER}). The disaster-based inputs include the fraction of the electricity supplied by the DERs to each agent W_i^{DER}, the fraction of electricity available to each agent (Q_{ti}^e), the fraction of emergency services available to each agent (Q_t^s), the fraction of the event-related information of the public news provided by the mass media (N_t), the fraction of the positive news provided by the mass media N_t^+, and the injury factor of the disaster Z_{ti}. Other inputs are the assumed initial value of fear ($M^E_{(t=1)i}$), the risk perception ($M^R_{(t=1)i}$), the information seeking behavior ($M^B_{(t=1)i}$), the flexibility ($M^F_{(t=1)i}$), the experience ($M^L_{(t=1)i}$), the cooperation ($M^C_{(t=1)i}$), the physical health ($P_{(t=1)i}$), the social well-being ($S_{(t=1)}$), and the initial electricity supply by DERs to each agent ($Q^{DER}_{(t=1)i}$).

As for the outputs of the purposed model, they comprise the incremental changes of fear ($M^E_{(t\neq1)i}$), the risk perception ($M^R_{(t\neq1)i}$), the information seeking behavior ($M^B_{(t\neq1)i}$), the flexibility ($M^F_{(t\neq1)i}$), the experience ($M^L_{(t\neq1)i}$), the cooperation ($M^C_{(t\neq1)i}$), the physical health ($P_{(t=1)i}$), the social well-being ($S_{(t\neq1)}$), the availability of electricity supplied by the DERS to each agent ($Q^{DER}_{(t\neq1)i}$), and the social mental and physical well-being.

4.3 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 a mental and a physical aspect that influence each other [34].

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 [2, 50, 81].

Figure 4.2 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, experi-

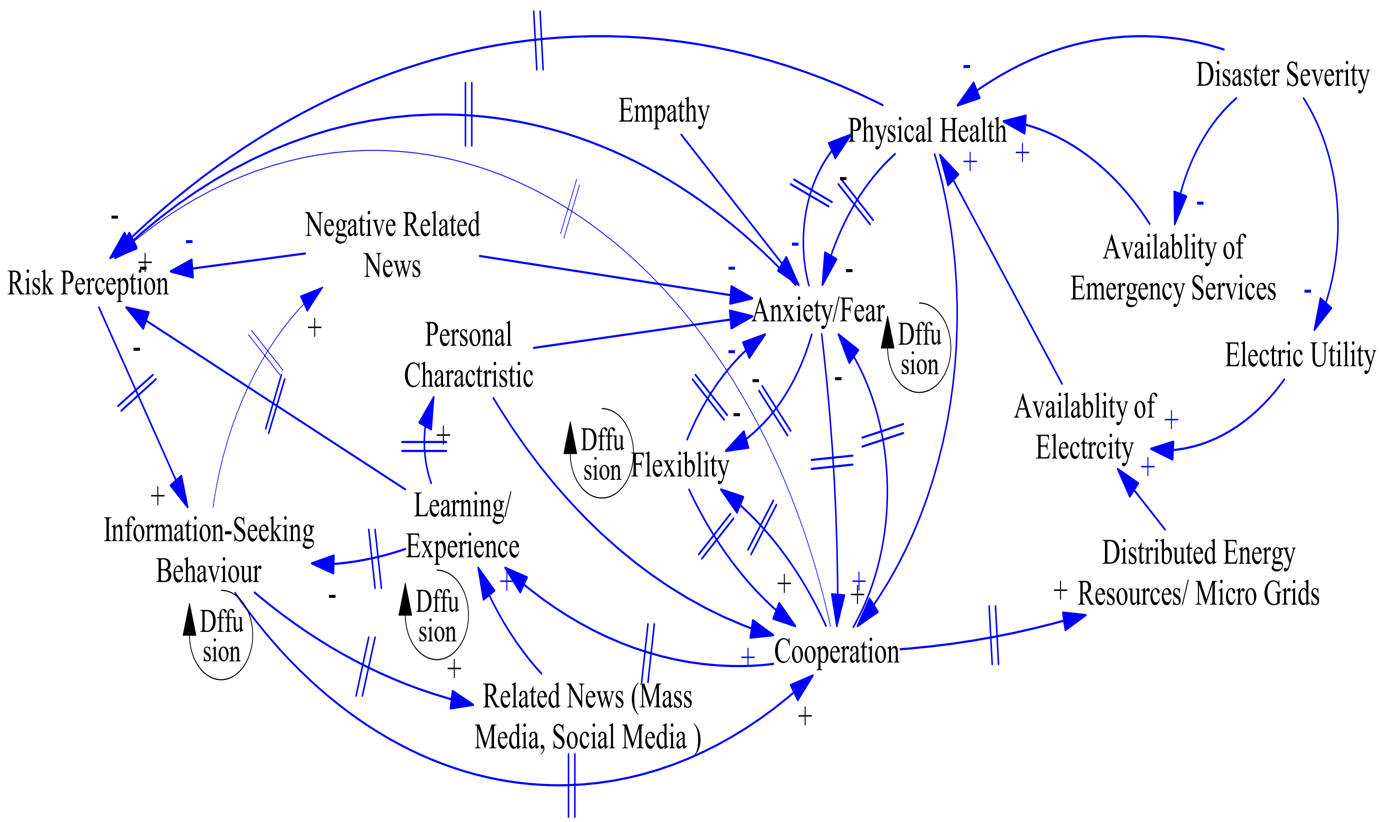

Figure 4.2: System dynamical model of power system, emergency services and human (agent) response to a disaster. It is worth noting that social networks contain a large number of agents who influence one another through social behavioral diffusion.

ence, flexibility, information-seeking behavior, emotion, perception of risk, openness, channel strength, and extraversion must be considered [4, 5, 17, 21, 32, 33, 34, 35, 36, 37, 39, 40, 41, 42, 43, 45, 46, 47, 125]. Each of them has a notable role in community resilience. Each of these features influences each others directly or indirectly. As an example, Damasio' somatic marker hypothesis assumes that emotion and information-seeking behavior influence each other [126]. As another example, based on broaden-and-build theory, positive emotion broadens thought-action behavior as well as cognition and vice versa [81]. In addition, each of these collective behaviors can be investigated through various computational perspective [127, 128].

To model group emotion, Barsade and Gibson in [50] develop 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.* [2], group emotion empathy, propagation of moods among agents within the group, and group emotion dynamics are 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 [81] provides an answer to this question. According to this theory, negative emotion restricts individual's thoughts and actions while 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 [129]. Similarly, the level of inter- and intra-community behavior diffusion are assumed to be Gaussian variables. Given the mean and the standard deviation of each of these random variable and the population size. Samples are generated via Monte Carlo (MC) simulations. Their dynamical models are provided next.

4.3.1 Human Psychological Dynamic Modeling

A stochastic multi-agent-based model of the incremental changes of the mental well-being during 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 characterizes the 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.

Emotion Dynamic Modeling

The emotion incremental change, $\Delta(M_{ti}^E)$, is governed by

$$\Delta(M_{ti}^E) = \gamma_{ti}^E(f(\hat{M}_{ti}^E, M_{ti}^E) - M_{ti}^E)\Delta t, \tag{4.1}$$

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)[4]. Let γ_{ij}^E denotes the compassionate empathy between two agents, which takes values between 0 and 1 - 0 meaning no empathy and 1 maximum empathy. It is defined as

$$\gamma_{ti}^E = \frac{\sum_j \gamma_{ij}^E M_{tj}^E}{\sum_j \gamma_{ij}^E}, \tag{4.2}$$

This parameter is dependent on factors like the sender's emotion expression and openness for 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 [130].

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

$$\begin{aligned} f(\hat{M}^E_{ti}, M^E_{ti}) = \eta^E[M^R_{ti}(1-(1-M^E_{ti})(1-\hat{M}^E_{ti})) \\ +(1-M^R_{ti})(\hat{M}^E_{ti}M^E_{ti})] + (1-\eta^E)\hat{M}^E_{ti}, \end{aligned} \tag{4.3}$$

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 also known as the broaden-and-build theory [81, 130], the first term of the amplification model is associated with a positive affect 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

$$\begin{aligned} &\hat{M}^E_{ti} = w^{EE}\left(\frac{\sum_j \gamma^E_{tij} M^E_{tj}}{\sum_j \gamma^E_{tij}}\right) + w^{BE}N_t(1-N^+_t)M^B_{ti} \\ &+w^{FE}(1-M^F_{ti}) + W^{CE}(1-M^C_{ti}) \\ &+W^{LE}(1-M^O_i)(1-M^L_{ti}) + W^{PE}(1-P_{ti}) + W^{ME}N^t. \end{aligned} \tag{4.4}$$

It is influenced by the emotion of the other agents ($w^{EE}(\frac{\sum_j \gamma^E_{tijc} M^E_{tj}}{\sum_j \gamma^E_{tijc}})$), its information-seeking behavior $(w^{BE}N_t(1-N_t^+)M_{ti}^B)$ [125], its flexibility $(w^{FE}((1-M_{ti}^F)(1-M_{ti}^L))])$, its cooperation $(W^{CE}(1-M_{ti}^C))$ [6], and its experience and learning process $(W^{LE}(1-M_i^O)(1-M_{ti}^L))$ [131]. The effect of flexibility on the fear of an individual is investigated Thayer *et al.* [131]. In addition to the inter- and intra-agent psychological factors, the level of fear is contingent on the agent's physical health $(W^{PE}(1-P_{ti}))$ [34] and outside factors, i.e., mass media $(W^{ME}N^t)$ [5].

Risk Perception Dynamic Modeling

The risk perception incremental change, $\Delta(M_{ti}^R)$, is governed by

$$\begin{aligned}\Delta(M_{ti}^R) = (\eta^R + (1-\eta^R)N_t)\frac{1}{1+e^{-\sigma^E(M_{ti}^E-\phi^E)}}\\(1-P_{ti})(1-M_{ti}^L)(1-M_{ti}^C)(1-M_{ti}^B)(1-M_{ti}^F)\\((1-N_{ti}^+)-M_{ti}^R)\Delta t.\end{aligned} \tag{4.5}$$

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 [125]. 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 will be the perception of risk. According to the narrowing hypothesis of Fredrickson's broaden-and-build theory [5], 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 is discussed in [132] while the relation between the risk perception and the experience is investigated in [133]. As for the relationship between the risk perception and the flexibility, it is analyzed in [134]. Finally, the relation between the risk perception and the physical health is discussed in [35].

Information-Seeking Behavior Dynamic Modeling

The information behavior incremental change, $\Delta(M_{ti}^B)$, is governed by

$$\Delta(M_{ti}^B) = \gamma^B(f(\hat{M}_{ti}^B, M_{ti}^B) - M_{ti}^B)\Delta t, \tag{4.6}$$

where γ^B denotes the speed of the incremental change related to the information-seeking behavior and where $\hat{M}_{ti}^B$ 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 menaing maximum contagion. It is defined as

$$\gamma_{ti}^B = \frac{\sum_j \gamma_{ij}^B M_{tj}^B}{\sum_j \gamma_{ij}^B}, \tag{4.7}$$

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 the amplification model on the information-seeking behavior. It is defined as

$$\begin{aligned} f(\hat{M}_{ti}^B, M_{ti}^B) = \eta^B[M_{ti}^R(1 - (1 - M_{ti}^B)(1 - \hat{M}_{ti}^B)) \\ +(1 - M_{ti}^R)(\hat{M}_{ti}^B M_{ti}^B)] + (1 - \eta^B)\hat{M}_{ti}^B, \end{aligned} \tag{4.8}$$

$$\hat{M}_{ti}^B = w^{BB}(\frac{\sum_j \gamma_{tij}^B M_{tj}^B}{\sum_j \gamma_{tij}^B}) + w^{LB}(1 - M_{ti}^L) + w_{MB}N^t. \tag{4.9}$$

It is influenced by the information-seeking behavior of other agents $(w^{BB}(\frac{\sum_j \gamma_{tijc}^B M_{tj}^B}{\sum_j \gamma_{tijc}^B}))$, its learning process and experience $(w^{BL}M_{ti}^L)$, and the mass media $(w_{MB}N^t)$. The relationship between the information-seeking behavior and the learning process and the experience is discussed in [135, 136]. Gao and Liu [5] and Robson and Robinson [137] discuss the relation between the information-seeking behavior and the mass media.

Flexibility Dynamic Modeling

The flexibility incremental change, $\Delta(M^F_{ti})$, is governed by

$$\Delta(M^F_{ti}) = \gamma^{M^F_{ti}}(f(\hat{M}^F_{ti}, M^F_{ti}) - M^F_{ti})\Delta t, \tag{4.10}$$

where $\gamma^{M^F_{ti}}$ denotes the speed of the incremental change related to the flexibility and where $\hat{M}^F_{ti}$ 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_{tij} denotes the strength of flexibility mirroring, which takes values between 0 and 1: 0 meaining no mirroring and 1 meaning maximum mirroring. It is defined as

$$\gamma^F_{ti} = \frac{\sum_j \gamma^F_{ij} M^F_{tj}}{\sum_j \gamma^F_{ij}}, \tag{4.11}$$

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 the amplification model on the flexibility. It is expressed as

$$\begin{aligned} f(\hat{M}^F_{ti}, M^F_{ti}) = \eta^F[&M^R_{ti}(1-(1-M^F_{ti})(1-\hat{M}^F_{ti})) \\ &+(1-M^R_{ti})(\hat{M}^F_{ti} M^F_{ti})] + (1-\eta^F)\hat{M}^F_{ti}, \end{aligned} \tag{4.12}$$

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

$$\begin{aligned} \hat{M}^F_{ti} &= w^{FF}(\frac{\sum_j \gamma^F_{tij} M^F_{tj}}{\sum_j \gamma^F_{tij}}) \\ &+w^{EF} M^O_i (1-M^E_{ti}) + w^{CF}(1-M^c_{ti}). \end{aligned} \tag{4.13}$$

It is influenced by the information of the other agents $(w^{FF}(\frac{\sum_j \gamma^F_{tij} M^F_{tj}}{\sum_j \gamma^F_{tijc}})$, its level of fear $(w^{EF} M^O_i (1 - M^E_{ti}))$, and its level of cooperation $(w^{CF}(1 - M^c_{ti}))$. Hollenstein and Lewis [138] and Southward and Cheavens [139] investigate the effect that the emotion has on the flexibility while Allwood [140] analyzes the relation between the flexibility and the cooperation.

Cooperation Characteristic Dynamic Modeling

The cooperation characteristic incremental change, $\Delta(M^C_{ti})$, is governed by

$$\begin{aligned}\Delta(M^C_{ti}) &= (\eta^C + (1 - \eta^C) N_t) \\ &(\frac{1}{1 + e^{-\sigma^C (M^E_{ti} - \phi^E)}}) M^F_{ti} P_{ti} [M^O_{ti} M^B_{ti} - M^C_{ti}].\end{aligned} \tag{4.14}$$

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 a positive or a 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 is discussed in [6]. The relationship between flexibility and cooperation is discussed in [140]. The relation between cooperation and physical health is provided in [141]. According to [142], the social media influence the level of cooperation among the individuals of a group.

Personal Experience Dynamic Modeling

The personal experience incremental change, $\Delta(M^L_{ti})$, is governed by

$$\Delta(M^L_{ti}) = \gamma^L_{ti} * (f(\hat{M}^L_{ti}, M^L_{ti}) - M^L_{ti}) \Delta t, \tag{4.15}$$

where γ_{ti}^L denotes the speed of the personal experience incremental change and $\hat{M}_{ti}^L$ 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). Let γ_{tijc}^L denotes the strength of the experience diffusion, which takes values between 0 and 1: 0 meaninig no diffusion and 1 meaning maximum diffusion. It is given by

$$\gamma_{ti}^L = \frac{\sum_j \gamma_{ij}^L M_{tj}^L}{\sum_j \gamma_{ij}^L}, \tag{4.16}$$

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

$$\begin{aligned} f(\hat{M}_{ti}^L, M_{ti}^L) = \eta^L[M_{ti}^R(1-(1-M_{ti}^L)(1-\hat{M}_{ti}^L)) + \\ (1-M_{ti}^R)(\hat{M}_{ti}^L M_{ti}^L)] + (1-\eta^L)\hat{M}_{ti}^L, \end{aligned} \tag{4.17}$$

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

$$\hat{M}_{ti}^L = w^{LL}\left(\frac{\sum_j \gamma_{ij}^L M_{tj}^L}{\sum_j \gamma_{tij}^L}\right) + w^{BL} M_{ti}^B N_t + w^{CL} M_{ti}^C + w^{ML} N_t. \tag{4.18}$$

It is influenced by the experience of other agents ($w^{LL}(\frac{\sum_j \gamma_{ijc}^L M_{tj}^L}{\sum_j \gamma_{tijc}^L})$), its level of information-seeking behavior ($w^{BL} M_{ti}^B N_t$),its level of cooperation ($w^{CL} M_{ti}^C$), and the mass media ($w^{ML} N_t$). The relationship between the experience and the information-seeking behavior is discussed in [143]. The relationship between the experience and the cooperation behavior is discussed in [144]. The relationship between the experience and the mass media is analyzed in [145].

4.3.2 Human Physical Health Dynamic Modeling

Two resources for electricity is 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 the society through various kinds of disasters. Furthermore, the availability of the emergency services affects the physical well-being of a community.

Sharing Distributed Energy Resources

The distributed energy resources sharing incremental change is governed by

$$\Delta(Q_{ti}^{DER}) = \gamma_{ti}^{DER}(\gamma_{ti}^{DER} - Q_{ti}^{DER})\Delta t, \tag{4.19}$$

where γ_{ti}^{DER} denotes the speed of the incremental change of the distributed energy resources sharing and γ_{ti}^{DER} denotes the amount of the electricity of an agent shared by other agents within the group. Let γ_{tij}^{DER} denote the level of empathy between two agents willing to share electricity. It is given by

$$\gamma_{ti}^{DER} = \frac{\sum_j \gamma_{tij}^{DER} M_{tj}^{C} Q_{tj}^{DER}}{\sum_j \gamma_{tij}^{L} M_{tj}^{C}}. \tag{4.20}$$

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

Available Electricity During a Disaster

Let Q^e_{ti} denote the amount of electricity supplied by the power grid and that shared by the DERs during a disaster. It is given by

$$Q^e_{ti} = W^{DER}_i Q^{DER}_{ti} + (1 - W^{DER}_i) Q^U_{ti}. \tag{4.21}$$

Human Physical Health Dynamical Modeling

The incremental change of the physical health, $\Delta(P_{ti})$, is given by

$$\begin{aligned}\Delta(P_{ti}) = \eta^P (\frac{1}{1 + e^{-\sigma^C (M^E_{ti} - \phi^E)}}) \\ ((1 - M^E_{ti})(1 - (1 - Q^e_{ti})(1 - Q^s_{ti}))Z_{ti}) - P_{ti})\Delta t.\end{aligned} \tag{4.22}$$

It is function of the availability of the emergency services, the availability of the 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.

4.3.3 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

$$S_t = \frac{\sum_i \eta^M (1 - M^C_{ti})}{\sum_i 1} + \frac{\sum_i (1 - \eta^M) P_{ti}}{\sum_i 1}. \tag{4.23}$$

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 (8.1)–(8.4) and Equations (8.6)–(8.9) are derived from [4, 5]. Equations (8.5)–(8.5) and Equation (8.10) are modified on the basis of the equations stated in [4, 5]. Equations (8.10)–(5.4) are proposed in this chapter and used in the new stochastic multi-agent-based model.

4.4 Simulation

Modeling human-related characteristics, the availability of critical infrastructures during a disaster, electricity sharing, and social behavior diffusion is entwined with uncertainties. The uncertainties related to human-community features assumed to follow a Gaussian distribution. In this chapter, the following effects are simulated:

- The effect of flexibility on human responses to disaster;
- The effect of the human experience on the collective behavior and the mental well-being of a society during and after a disaster;
- The effect of cooperation, coordination, and experience on community resilience to disasters;
- The effect of the availability of electric energy and the willingness to share among the individuals of a community on physical well-being and community resilience to disasters;
- The effect of the actions taken by the emergency services, the injury factor of a disaster, and the news polarity [1] on the physical and mental well-being of a society;
- The effect of varying mass media trends on community resilience to disasters;

[1] News polarity measures the degree to which the news are positive or negative.

- The effect of the level of compassionate empathy among people on their social well-being;
- The effect of the occurrence of one disaster in a community on its collective behavior;
- The effect of the occurrence of two concurrent disasters in two different communities on the human response;
- The effect of emergencies that arise at different times on community resilience to disasters;
- The effect of a diversified community population on its social well-being during and after a disaster;
- An analysis of the effect of the international Emergency Events Database (EM-DAT) on mental and physical well-being as well as community resilience;
- A discussion about the effect of the time-banking as an alternative currency on community resilience to disasters;

The proposed stochastic multi-agent-based model is implemented in two different case studies. This model is verified by The soft validation and sensitivity analyses. The social effect of human characteristics, mass media, and critical infrastructures on community resilience are analyzed in the first case study, i.e., a community of nine persons facing a hurricane. The aim of the second case study, i.e., a society of six separate communities, is to clarify the social effect of different community characteristics and various scenarios of disasters (in terms of time, place, and a specific type of disaster) on mental well-being, physical well-being, and community resilience.

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

This section analyzes the performance of the proposed dynamical model of a community of nine agents experiencing a hurricane. Specifically, the dynamic changes of the mental and physical characteristics of the agents is assessed.

The first case study aims to clarify the effect of each human feature, including emotion, risk perception, information-seeking behavior, empathy, cooperation, flexibility, and experience on the collective behavior and the mental well-being of society during and after a disaster. In addition, the social effect of mass media, availability of electricity, and the availability of emergency services on community resilience is analyzed.

This community, which consists of three areas, is represented in Figure 4.3. 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, mass media, emergency services, and electric grid are provided in Table 4.1. These features are assumed to taking a value in the interval [0 1] [4, 5]. The meaning of each value is comprehensively discussed in [146]. The electricity consumption of each individual is assumed to be 1 kWh of which 0.8 kWh is supplied by utilities through distribution power lines and 0.2 kWh is supplied by distributed energy resources (DERs), photo-voltaics (PVs), and wind turbines to name a few. Furthermore, the fraction of electricity that the DERs supply for each individual W^{DER} is set to 0.2.

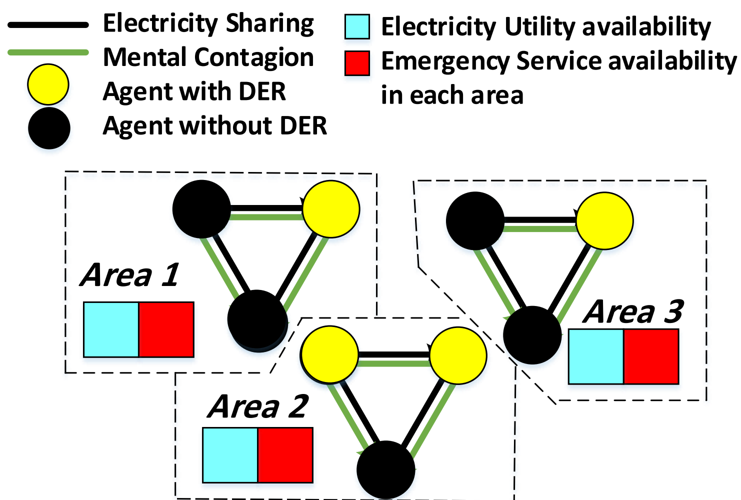

Figure 4.3: Case study 1: nine agents (prosumers or consumers) during the disaster. Prosumers have accessibility to distributed energy resources. It is assumed that the agents in each area have similar initial behaviors and conditions. There is empathy among individuals in each area, while individuals are not empathetic to individuals in other areas.

Table 4.1: Parameter settings for the mental and physical characteristic, mass media, emergency services, and electric grid

Parameter	Definition	Value
M^E_{ti}	the level of fear of an individual	0.5
M^R_{ti}	The level of risk perception	0.5
M^B_{ti}	The level of information-seeking behavior	0.5
M^C_{ti}	The level of cooperation	0.5
M^O_{ti}	The level of personal characteristics	0.5
M^L_{ti}	The level of experience	0.5
γ^E_{ij}	The level of compassionate empathy between two individuals	1
M^F_{ti}	The level of flexibility	1
P_{ti}	The level of physical health	1
N_t	The fraction of the event-related information of the public news provided by the mass media (e.g., television, newspapers, social networks)	1
N^+_t	The fraction of the information conveyed by the mass media that are positive	0
Z_{ti}	The level of injury factor of disaster	1
Q^{DER}_{ti}	The fraction of electricity that is available from DERs to an individual	1
Q^e_{ti}	The fraction of electricity that is available from utilities to a costumer	0.5
Q^s_t	The degree of help that an individual gets from emergency services during, and after a disaster	1

4.5.1 Soft Validation of the proposed stochastic multi-agent-based modelling

At this step, a soft validation is done. Our computational model is verified by Case Study 1 that is taken from [4]. For this step, information-seeking behavior, the emotion of fear, and bias are considered in the model. After soft validation, the model is extended to consider the mental resilient-related characteristics, the physical well-being of agents, and critical infrastructures, including emergency services and the power grid. We investigate if the patterns/social phenomena 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.

4.5.2 Effects of Flexibility on Human Responses

One of the most pivotal human characteristics for enhanced community resilience is flexibility. Figure 4.4 displays dynamic changes of fear, information-seeking behavior, and risk perception as a result of the changes in individuals′ flexibility. 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 [131]. Negative affects[2], 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 [138]. In contrast, a high level of flexibility and a low level of fear decrease the perceived risk of agents

[2]In social science, emotion and affect are considered to be similar words to each agent's response to feelings [50].

during a disaster. As a result, information-seeking behavior which is profoundly entwined with risk 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 of 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.

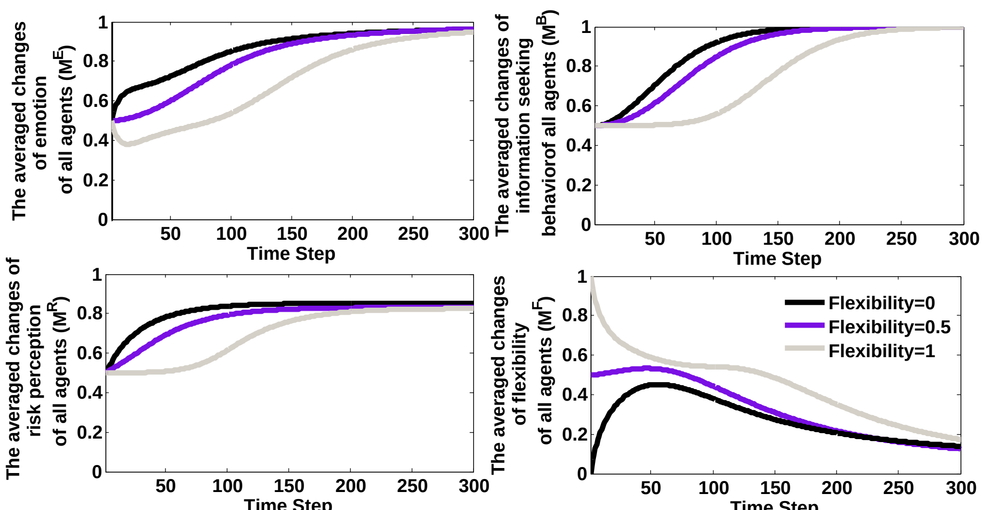

Figure 4.4: Effects of flexibility on collective behavior and mental characteristics. The dynamic change of emotion, information-seeking behavior, risk perception, and flexibility of all agents are shown. Results are provided for three different initial values of flexibility (0, 0.5, and 1). The time duration of the dynamic evolution is 300 time steps.

4.5.3 Effects of Cooperation on Human Responses

Another human aspect that is vital during a disaster is cooperation. Cooperation is somewhat similar to flexibility in that they both have a direct influence on fear as well as risk perception. Furthermore, cooperation affects flexibility and vice versa. Figure 4.5 shows changes in fear, information-seeking behavior, risk perception, and flexibility induced by changes in the cooperation of individuals. When the level of cooperation increases from $M^C = 0$ to $M^C = 0.5$ to $M^C = 1$, the agents experience a lower level of fear, risk perception, and information-seeking behavior. Flexibility, in contrast, increases. High levels of cooperation can make positive changes in individual behavior [147].

Since the level of fear is less than the fear threshold when $M^C = 1$ and the level of cooperation is high in the ideal case, risk perception shows no noticeable increase during a crisis. The level of information-seeking behavior roughly follows the same trend as the risk perception. When $M^C = 0$, the perceived risk, the level of fear, and the information-seeking behavior of agents increases.

On the other hand, the feeling of fear during disasters makes humans cooperate and be more flexible. Hence, when the individual cooperation and flexibility of individuals are augmented, the level of fear deceases. However, a decrease in the level of fear results in a lower level of cooperation. Of note, the loop of fear, cooperation, and flexibility formed here is directly or indirectly impacted by the mass media, the accessibility of electricity and emergency services and other mental peculiarities during dynamic change. According to Figure 4.5(b), an increase in cooperation among individuals in the community is associated with an increment in mental resilience or well-being. Thus, the society with more mental well-being has more community resilience.

4.5.4 Effects of Experience on Human Responses

People with previous experience in disasters can cope with the fear from a disaster easier than the ones without experience. Additionally, people who have experienced special disasters

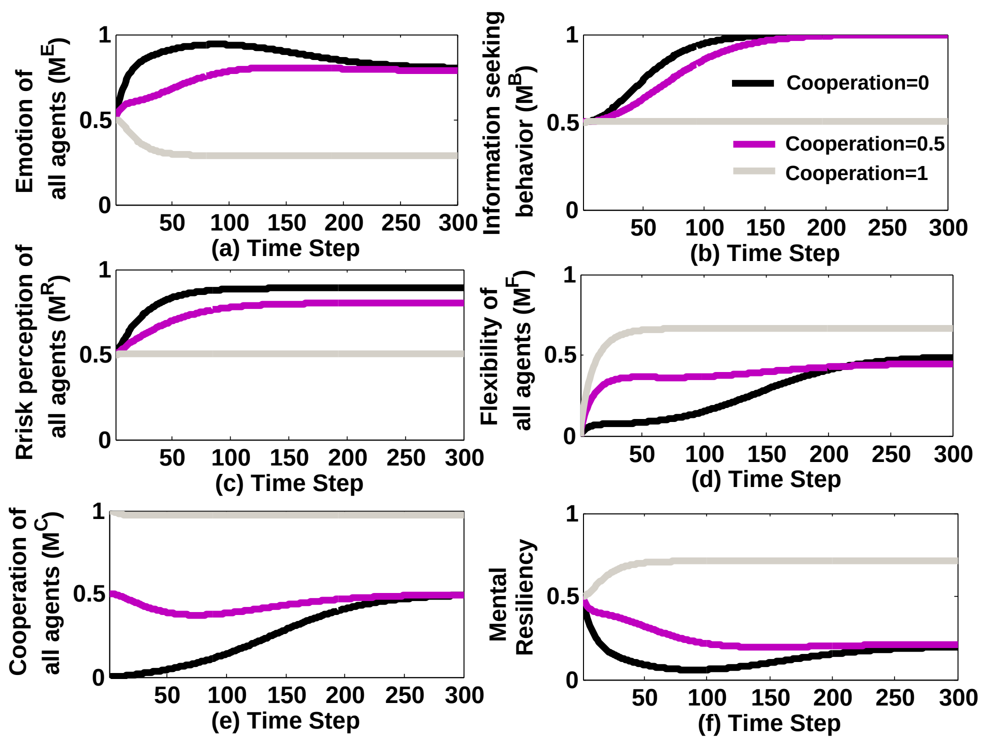

Figure 4.5: Effects of the different initial values of cooperation on the dynamic change of emotion (panic in this study), information-seeking behavior, risk perception, flexibility, and mental resilience (mental well-being). The initial value of cooperation is assumed to be 0, 0.5, and 1. These figures are related to the collective behavior of all agents.

have a higher level of risk perception with respect to this event happening. Figure 4.6 shows the changes in fear, information-seeking behavior, risk perception, and flexibility in tandem with changes in the experience levels of individuals. Experience has an inverse effect on fear, information-seeking behavior, and risk perception. It positively affects flexibility if agents are optimistic.

Because all people of this community are optimistic, the feeling of fear of agents tends to reach the same level when the initial level of experience is different. When the agents do not have previous experience, they seek new information during a disaster. Therefore, their experience increases. If the initial experience is low, fear and risk perception increase in the first time interval, while flexibility reduces compared to when the initial experience is higher. [133] discusses the correlation between experience and risk perception. The society that has previous experience with one particular hazard perceives a higher level of risk than the society without previous disasters. There is a stable feedback mechanism between experience and risk perception [148] in the cognitive mechanism. Furthermore, flexibility and experience can lead to distinguished achievements [149]. If people have more experience at the beginning of the disaster, they have more mental resilience and social well-being. Because people gain experience during disasters, society becomes more resilient compared to when the disaster first occurred. Of note, experience of agents with the uncertainty based-opinion is increased faster than informed agents [150].

4.5.5 Effects of Cooperation and Experience on Human Responses

Figure 4.7 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,

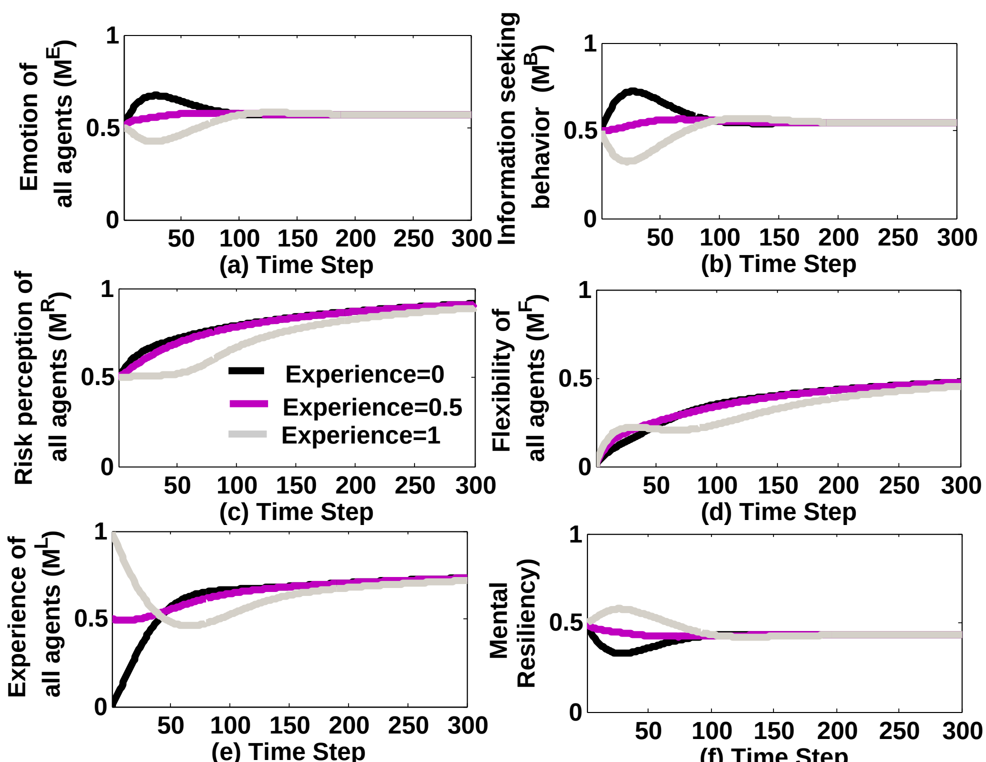

Figure 4.6: Effects of experience on other human characteristics in a community with similar behavior. To carry out the sensitivity analysis, the initial value of experience is assumed to be equal to 0, 0.5, and 1. In this figure, the dynamic change of emotion, risk perception, information-seeking behavior, flexibility, experience, and mental resilience of all agents involved in the community is presented for the time interval [0 300].

they do not have previous experience regarding 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.

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 panic 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 [132]. In perilous circumstances, agencies raise public risk perception to levels that exceed what individuals experience privately. According to [132], the obstacles to private-private cooperation are more than those that individuals experience with private-public cooperation.

4.5.6 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 are assumed to be 0, 0.5, and 1, respectively. The results are provided for two different levels of cooperation in Figures 4.8 and 4.9. 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 panic. As a result, the level of perceived risk and information-seeking behavior among agents is decreased

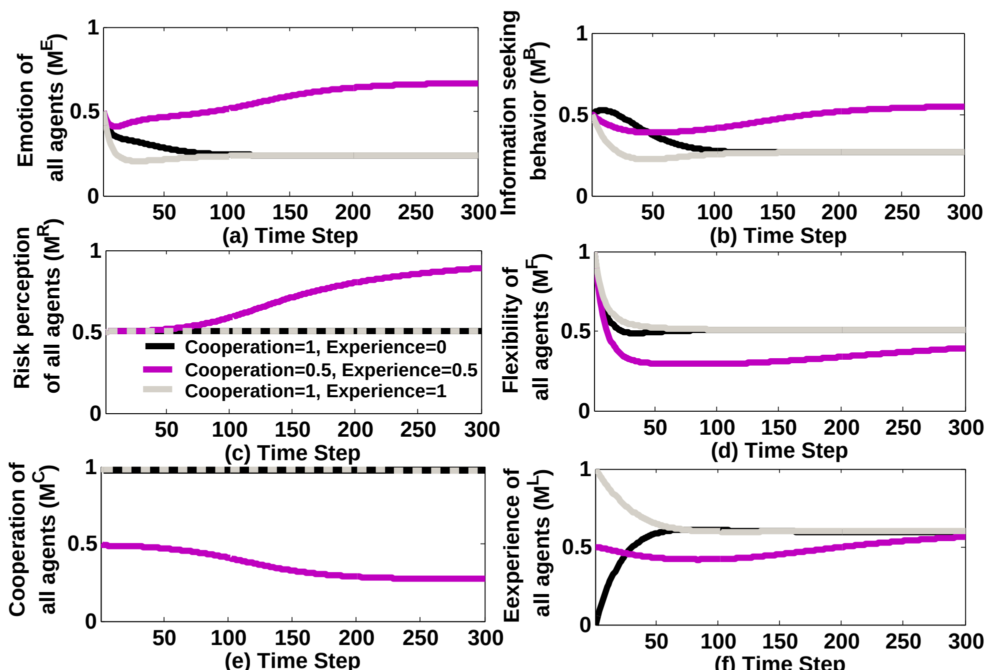

Figure 4.7: Effects of the different initial values of cooperation and experience on the dynamic change of the collective mental behavior in the homogeneous community. The black lines denote when people are well-experienced and enthusiastic to cooperate. On the other hand, grey denotes agents that are not interested in cooperating at all. The purple lines represent individuals, who are only partially experienced and for whom the level of enthusiasm to cooperate is not high.

compared to when $M^C = 0.2$. However, the level of panic 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. Furthermore, according to [151], cooperation is of high importance for a successful society in both fixed (static) social networks and fluid (dynamic) social network. The social diffusion of cooperation exists in both kinds of networks.

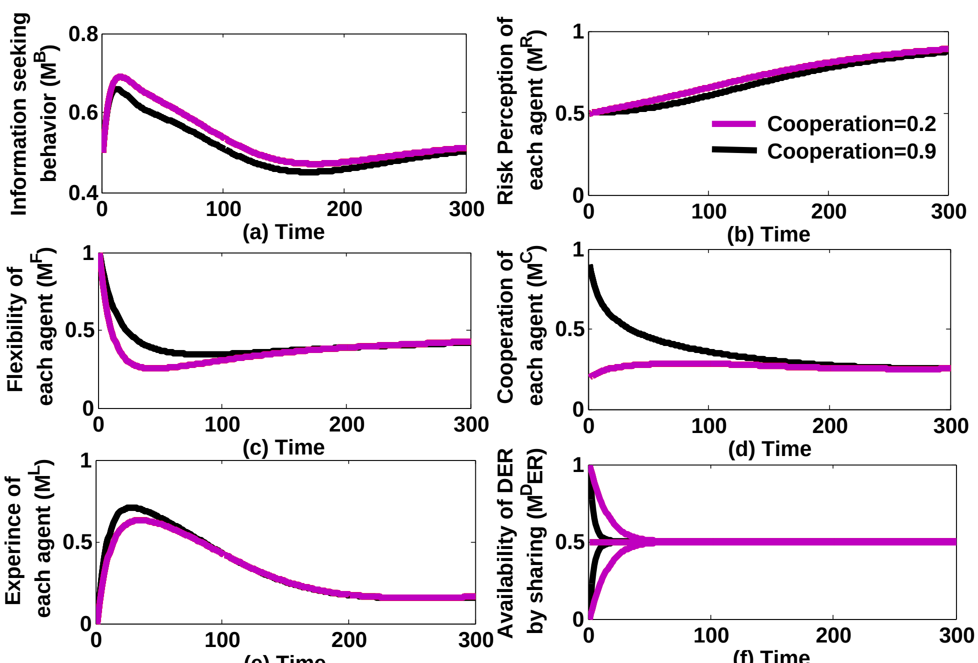

Figure 4.8: Effects of cooperation on electricity sharing and the impact of the availability of electricity (and also cooperation) on information-seeking behavior, risk perception, flexibility, and experience. It is assumed that agents have a varying value of accessibility to distributed energy resources, i.e., 0, 0.5, and 1. The results are provided for initial values of cooperation of 0.2 (low cooperation) and 0.9 (high cooperation).

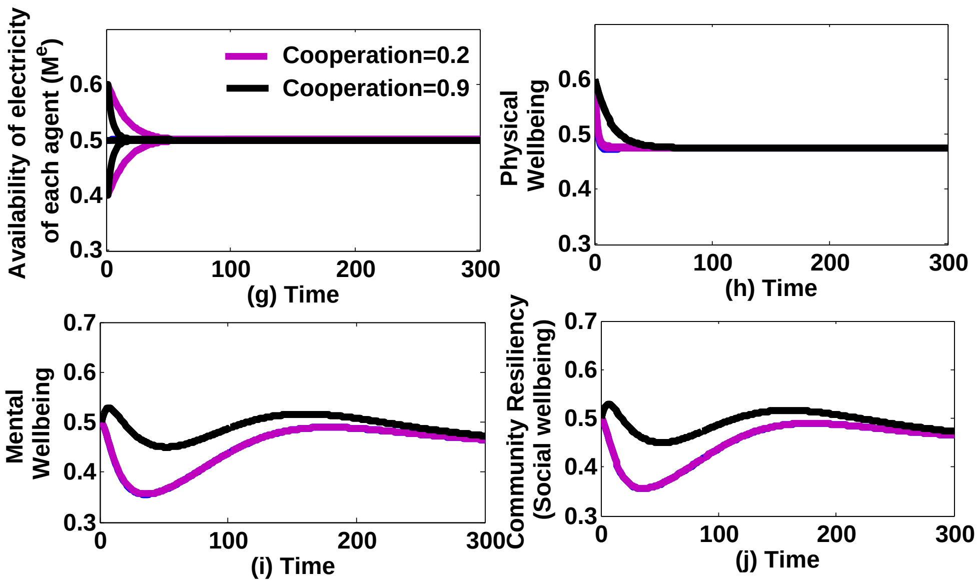

Figure 4.9: Effects of different initial values of cooperation on the availability of electricity, physical well-being, mental well-being, and community resilience. Results are provided for different levels of cooperation (0.2 and 0.9). In this homogeneous community, the accessibility of agents to DERs varies. The dynamic change of all kinds of well-being is provided for the time interval [0 300].

4.5.7 Importance of Emergency Services, the Injury Factor of a Disaster, and News Polarity on Physical and Emotional Well-Being

In this section, the effect of emergency services, the injury factor of a disaster, and news polarity on collective mental features, physical and emotional well-being, and community resilience is investigated. Results are shown in Figures 4.10 and 4.11. In Example 1, $M^S = 1$, Z=0.1 and $N^+ = 0$. M^S is assumed to be 0.1 from time stamp 100 to 300 in Example 2. To show the effect of the injury factor of disaster, Z is 0.9 in Example 3. To present the effect of news polarity, N^+ is 0.9 in Example 4.

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 stamp 100, emergency services cannot effectively perform their function. When emergency services decrease, 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 increases. 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 the similar. Note that the human response in case 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 level of fear, perceived risk, and information-seeking drops. For this example, the community obtains less experience as compared to Examples 1, 2, and 3. In addition, individuals tend to be less flexible compared to when they feel endangered.

4.5.8 Effects of Different Mass Media Trends on Community Resilience

Figures 4.12 and 4.13 show the dynamic changes in the mental characteristics and physical health for different media values. In Example 5, all news is assumed to be related. Examples 6 and 7 are related to sudden events (tsunamis, earthquakes) and gradually unfolding events (like a hurricane and social crisis), respectively. The fitting function for the mass media are $N_t = 2.5 * e^{(-3*t)} + 0.04$, $N_t = 1 * e^{-(\frac{(t-50)^2}{50})} + 0.06$, respectively. For events which happen suddenly, the feeling of panic is stimulated at the beginning of the disaster. As a

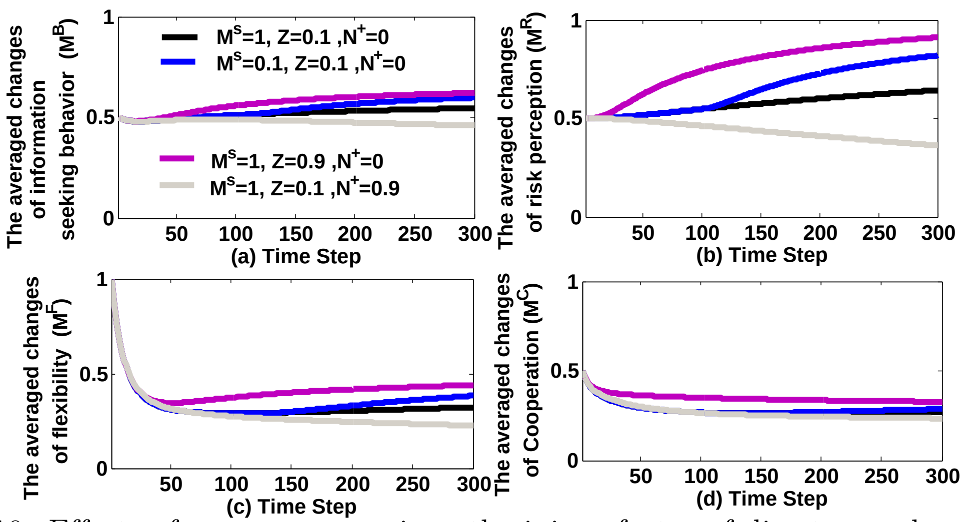

Figure 4.10: Effects of emergency services, the injury factor of disaster, and news polarity on collective information-seeking behavior, risk perception, flexibility, and cooperation. The black lines represent the effects when emergency services are entirely available, and the disaster is benign. However, there are a lot of rumors and negative news among individuals. In contrast, the blue lines represent the effects when emergency services are not available to the community. In the case of the purple lines, emergency services are wholly available but the disaster is severe, and there is positive news at the level of the society. The grey lines also represent a case when emergency services are available. However, in this case, there is lots of positive news and the disaster is not severe

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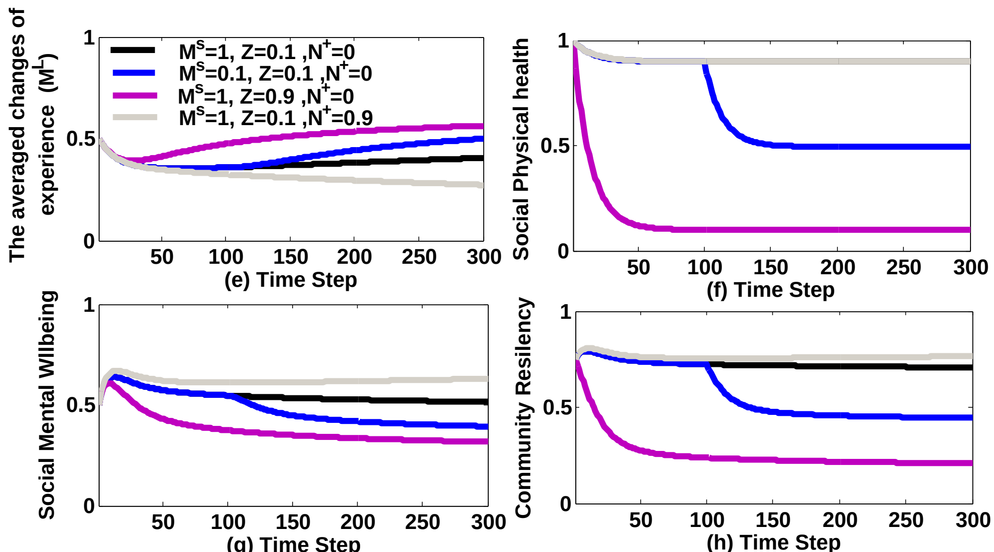


Figure 4.11: Effects of emergency services, the injury factor of disaster, and news polarity upon experience, physical and mental well-being, and community resilience. The grey lines represent the effects when all outside factors, i.e., emergency services, the disaster, and the mass media, do not have a negative effect on the community. Understandably, there is more community resilience in this case compared to that of other scenarios for time interval [0 300].

consequence, individuals seek more information during this time. Understandably, they also obtain more experience. On the other hand, when the event occurs gradually, the level of fear, information-seeking behavior, and risk perception of the community is raised during the midterm.

4.5.9 Effects of Compassionate Empathy on Collective Behavior During and After a Disaster

Figures 4.16 and 4.15 show the dynamic changes in human response and community resilience for a different levels of compassionate empathy among individuals. To clarify the importance of empathy on community resilience, the human mental and physical characteristic of 3 agents inside each area are assumed to be 0%, 0.5%, and 1%, respectively. The

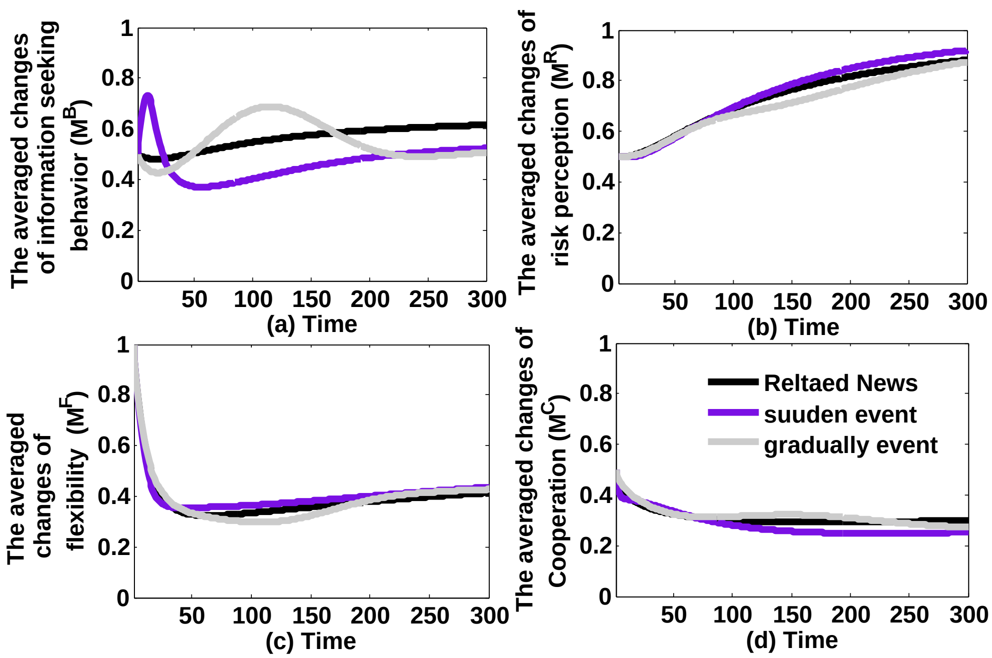


Figure 4.12: Effects of different mass media trends on collective information-seeking behavior, risk perception, flexibility, and cooperation. The black lines are associated with all the news being sensational during the entire interval [0 300]. For the purple lines, the mass media trends follow a damped exponential model (sudden events), while for the grey lines the mass media trends follow an exponential model (gradual events).

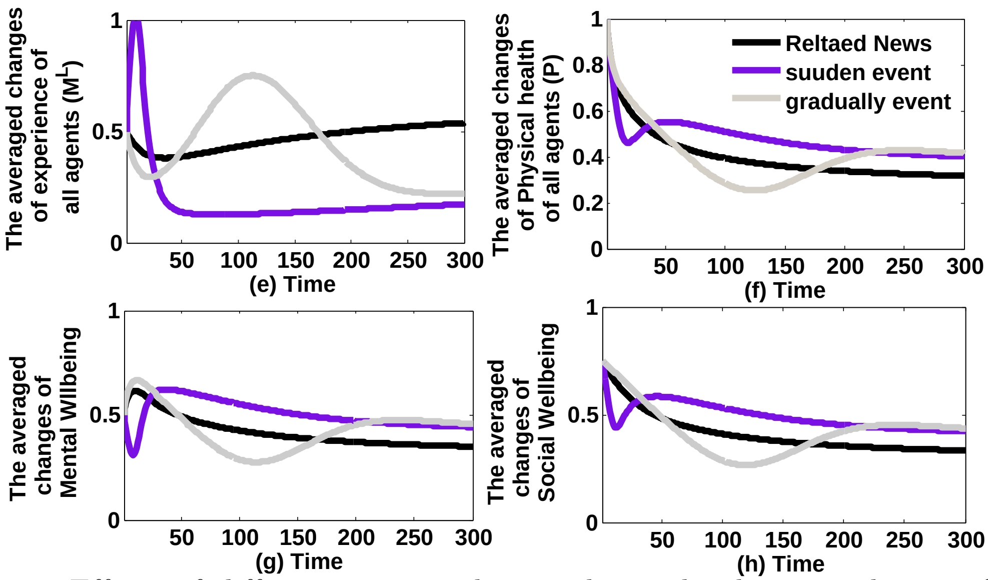


Figure 4.13: Effects of different mass media trends on the dynamic change of collective experience, physical health, mental well-being, and social well-being (community resilience) for the time interval [0 300]. Various mass media trends influence community resilience differently. As a result, the importance of the mass media on community resilience can be easily grasped.

results are presented for two different levels of empathy, 0.1 and 1. Less empathy among individuals plus other characteristics, including fear, information-seeking behavior, flexibility, and cooperation, all tend to converge at the same level. Also, agents share their electricity later than when compassionate empathy is 1. As a result, when the empathy is high, the average level of physical well-being, mental well-being, and community resilience for the whole time interval [0 300] is more than that when individuals are not empathetic.

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

This case study aims to clarify the effect of the different scenarios of disasters (in terms of time, place, and kind of emergency) on the mental well-being, physical well-being, and

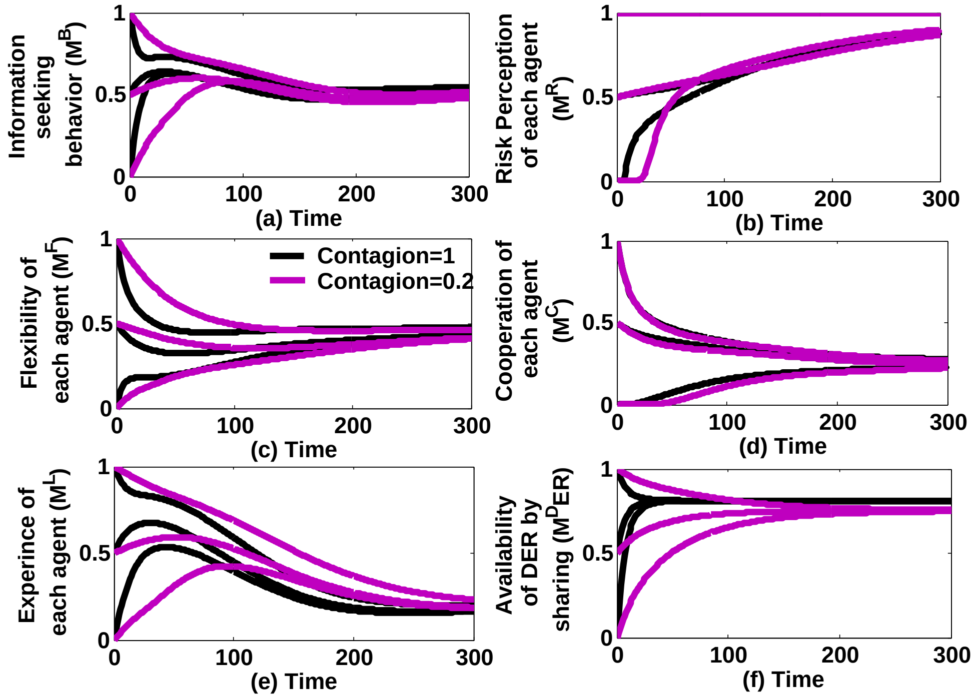


Figure 4.14: Effects of different values of compassionate empathy on collective information-seeking behavior, risk perception, flexibility, cooperation, experience, and availability of electricity supplied by DERs. Two different values of compassionate empathy are 0.2 (low level of empathy among individuals) and 1 (high level of empathy among individuals).

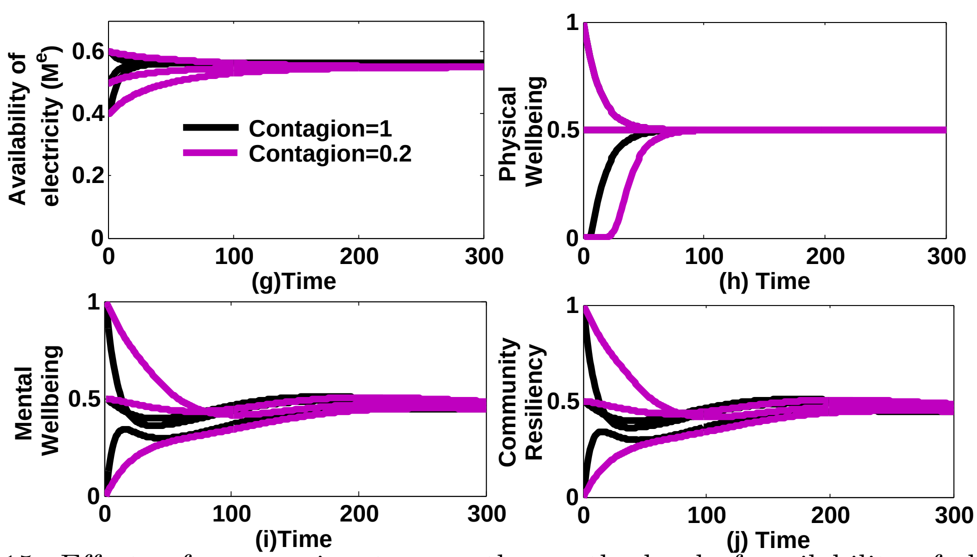


Figure 4.15: Effects of compassionate empathy on the level of availability of electricity in the community, physical well-being, mental well-being, and community resilience (social well-being). The difference between outputs of the two examples is related to the time they begin to assist each other.

community resilience. Three different scenarios in this case study are analyzed. These scenarios are presented in Table 4.2. In addition, the social effect of the diversified community population on its social well-being during and after a disaster is analyzed.

Figure 4.16 depicts a society, consisting of six communities with different characteristics. The parameter setting for the mental and physical characteristics, population, and electric grid related to each Community are provided in Table 4.3. The level of intra- and inter-community empathy is shown in Table 4.4. It is found that Communities 1 and 2 are extremely close-knit. As a result, empathy among these communities are assumed to follow the Gaussian distribution $N(0.9, 0.1^2)$. Regarding the other communities, its is assumed that there is no empathy among them.

Table 4.2: Three scenarios of disasters in terms of time, place, and type of emergency.

Scenario	Emergency feature
1	The occurrence of one disaster in a community
2	The occurrence of two concurrent disasters in two different communities
3	Emergencies that arise at different times

Table 4.3: 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 4.4: 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	$N(0.9, 0.1^2)$	$N(0.9, 0.1^2)$	-
$C_{i(i \in 3,4,5,6)}$	-	-	$N(0.9, 0.1^2)$

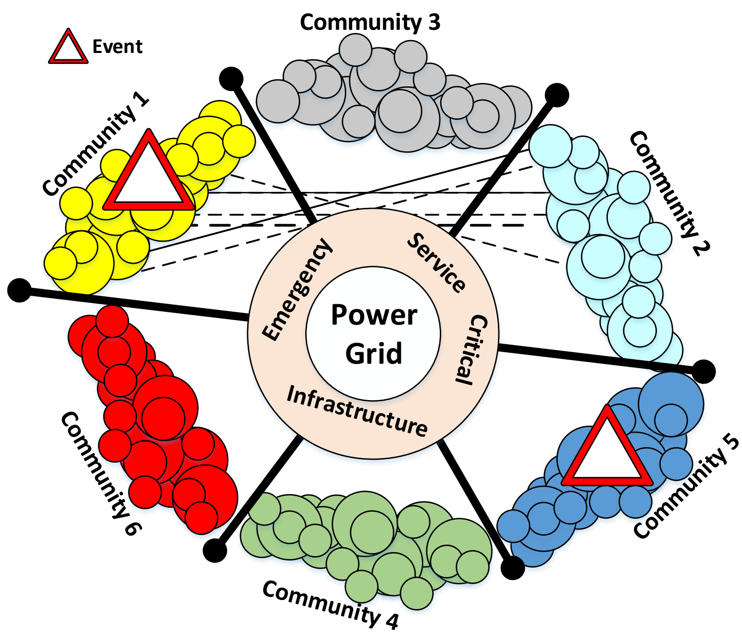


Figure 4.16: A society consisting of six separate communities. It is assumed that individuals in Communities 1 and 2 are empathetic to each other. Two critical infrastructures, i.e., power system and emergency services, are considered to support communities during disasters. The availability of each of these two critical infrastructures in each community highly depends on the kind of disaster that occurred in the community. Additionally, there are two potential places the where the disaster occurs directly (i.e., in Communities 1 and 5).

4.6.1 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 disaster is assumed to be $N(0.9, 0.1^2)$. Because of severe hazards, 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 4.17 and 4.18 show the average dynamic change of collective behavior and community resilience for the six communities during a disaster. 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 occurs. The level of fear of 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 of panic 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 response in Communities 3 to 6 follows the same trends, resulting in the same status.

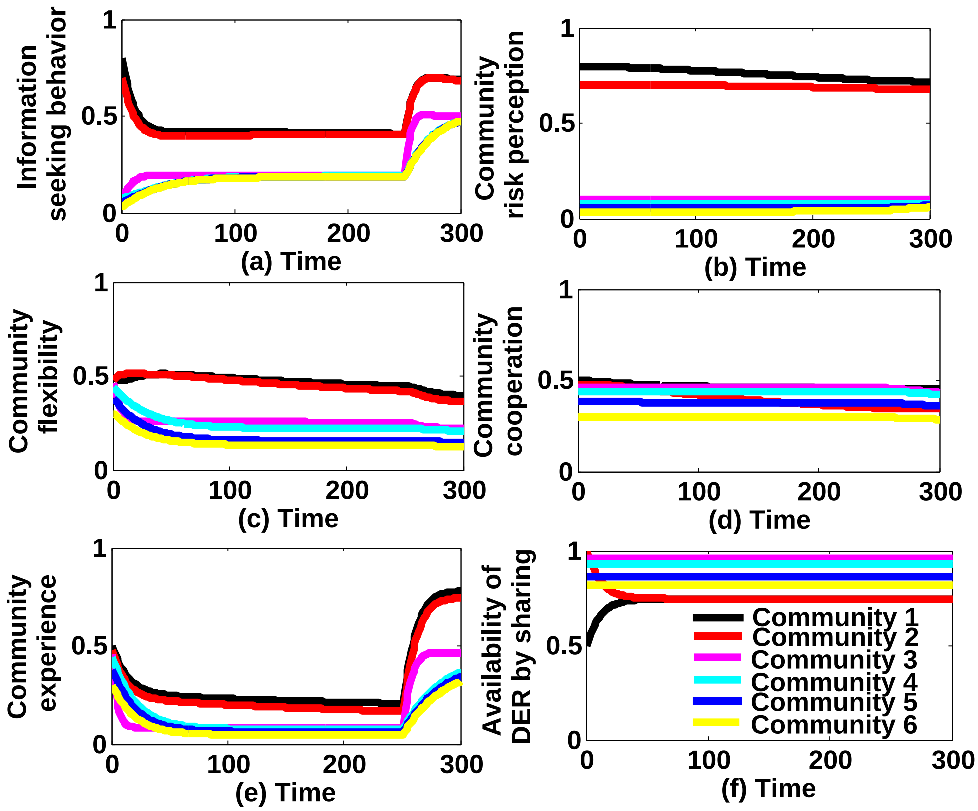


Figure 4.17: Dynamic change of information-seeking behavior, risk perception, flexibility, cooperation, experience, and the availability of the electricity supplied by DERs for six communities. The disaster occurs in Community 1. Because Community 2 and 1 are empathetic to each other, the disaster influences the mental characteristics of individuals in Community 2. In addition, other communities are not empathetic at all.

4.6.2 Effects of Two Concurrent Disasters on Human Response

In Example 2, one disaster strikes Community 1, while a second 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 is assumed to follow the Gaus-

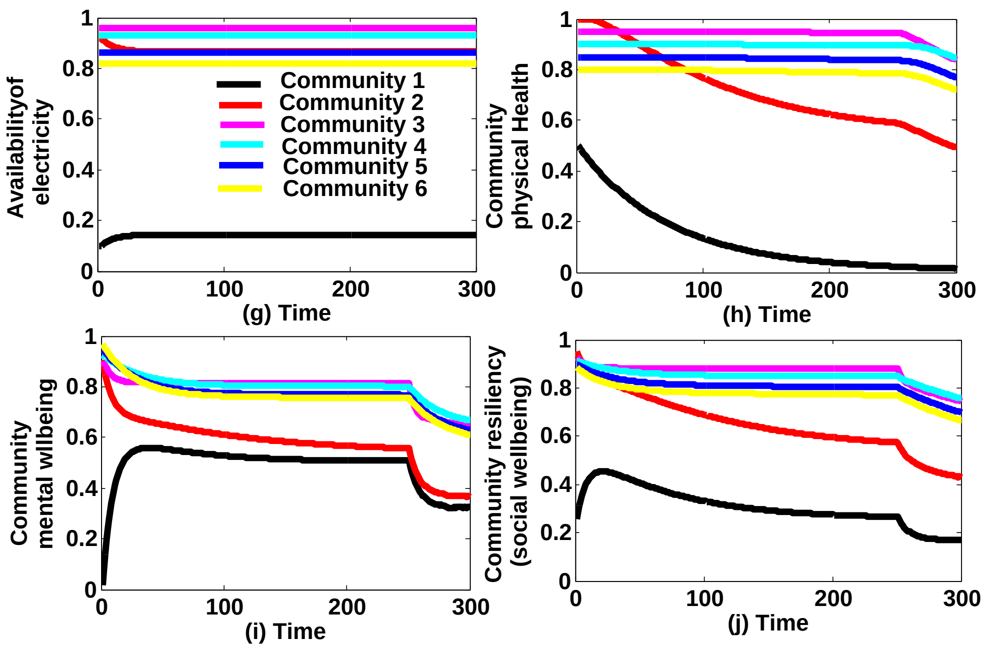


Figure 4.18: Trends of the availability of electricity, physical health, mental well-being, and community resilience for six communities. Because the disaster happens in Community 1, its people have the lowest level of physical health, mental well-being, and community resilience. The mental well-being of people in Community 2 is affected by this disaster; consequently, community resilience is diminished.

sian distribution $N(0.1, 0.1^2)$. Electric energy supplied by utilities and emergency services are 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.

Figures 4.19 and 4.20 show the average dynamic change of collective behavior and community resilience for the six communities during the disasters. The physical health of the individuals in Community 5 increases because of the availability of power, emergency services, and the low level of the injury factor of the disaster. There is emotion diffusion and empathy among people of Communities 1 and 2. Community 2 does not have any initial panic. People in community 2 are empathetic to Community 1. This is why the level of fear of Community 1 is lower than that of Community 5. Since physical health in Community 5 increases until time step 200, the average level of fear of this community falls.

4.6.3 Effects of the Occurrence of Disasters at Different Times in Separate Communities on Human Response

In Example 3, one disaster occurs in Community 1 at time step 0, while another occurs in Community 5 at time step 100. The characteristics of Community 1 and its disaster are the same as those of Example 1. The disaster in community 5 causes a power outage at time step 100. All news from the mass media is relevant. The other characteristics of the communities are similar to those of Example 1.

Figures 4.21 and 4.22 show the average dynamic change of collective behavior and community resilience for the six communities during the disasters. As expected, the physical health of Community 5 is sharply lower beginning at time step 100. Understandably, because of the occurrence of the event during this time interval, the level of fear of Community 5 is

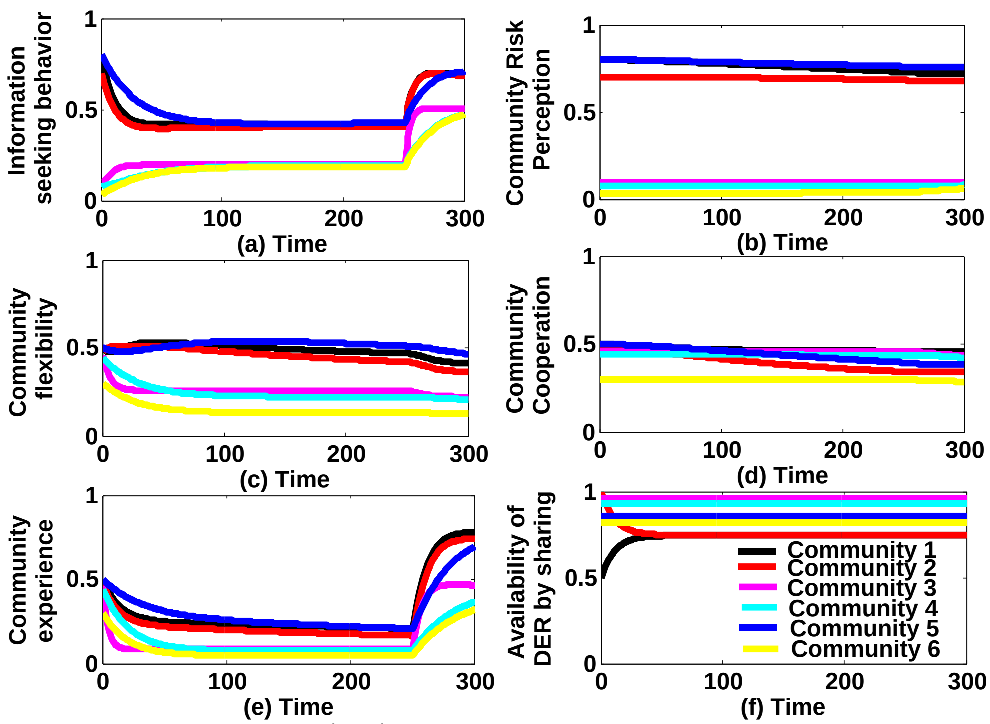


Figure 4.19: Dynamic change of information-seeking behavior, risk perception, flexibility, cooperation, experience, and the availability of the electricity supplied by DERs for the six communities. Two disasters occur simultaneously in society. One severe disaster occurs in Community 1. The disaster, which befalls Community 5 is not too dangerous (the injury factor is equal to 0.1).

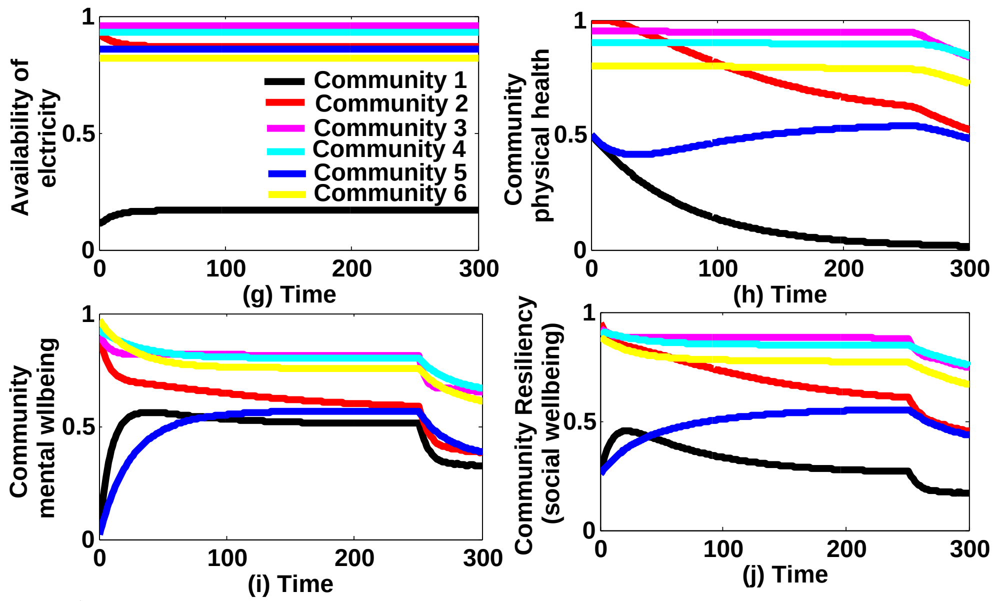


Figure 4.20: Average dynamic change of availability of electricity, physical health, mental well-being, and community resilience for the six communities. Although the resilience of Community 1 is similar to that of 5 at the beginning of the disasters, these communities do not have the same trends. Because of the availability of emergency service and electricity during the disaster, the resilience of Community 5 increases over time.

high.Individuals in this community perceive a high level of risk and seek information. As a result, they obtain experience.

4.6.4 Effects of Different Population Features on Community Resilience

Figure 4.23 shows the changes that occur in the experience, mental well-being, and physical well-being of different population groups who live in a community. This community is similar to Community 1 in that all features, excluding the population size, are the same. An increase in the population size with the same level of empathy is associated with an increase in the level of experience and mental well-being. Moreover, a society with more experience induces a higher physical well-being. If the level of cooperation and experience during and after a

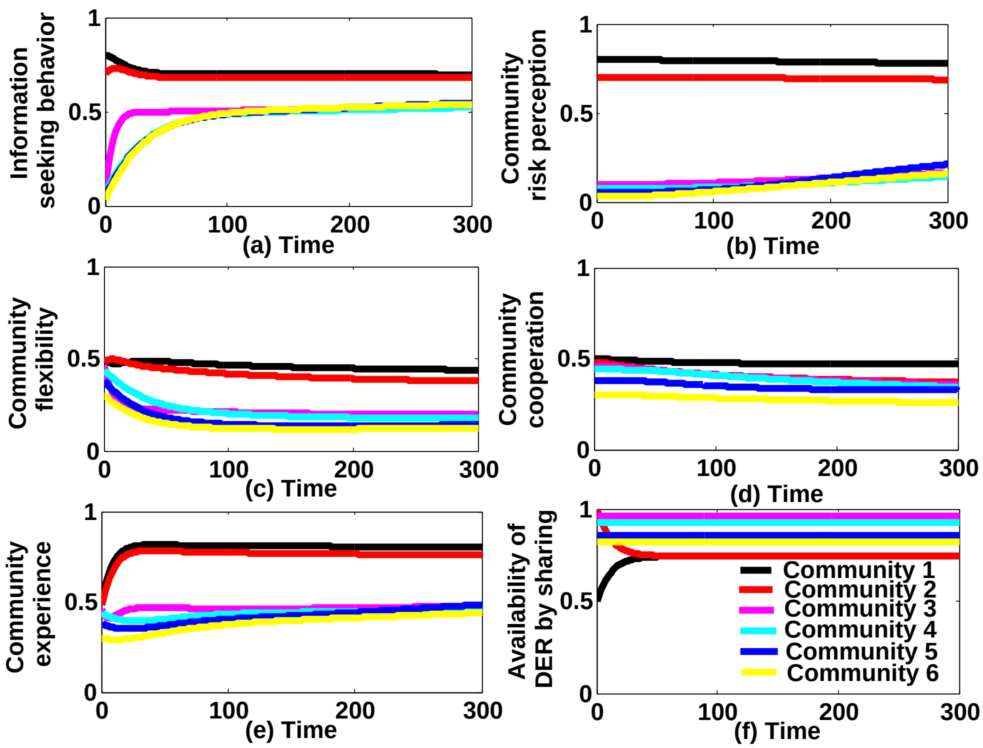


Figure 4.21: Dynamic change of information-seeking behavior, risk perception, flexibility, cooperation, experience, and the availability of the electricity supplied by DERs for the six communities. Two disasters occur in society at different times. One severe disaster happens in Community 1 at time 0. The other transpires in Community 5 at time step 100. Because of the disaster, the power utilities can not supply electricity to individuals in Community 5.

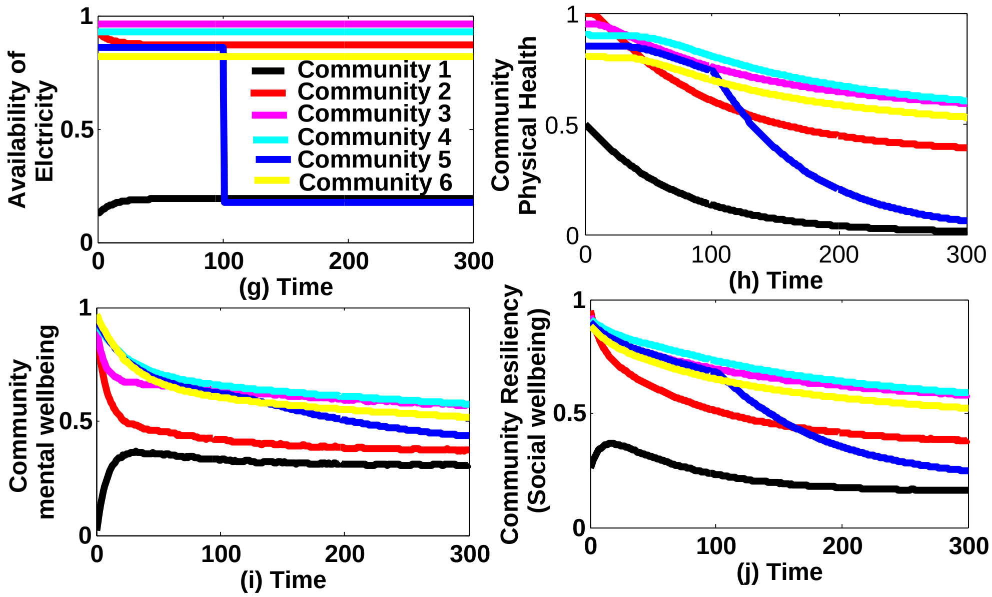


Figure 4.22: Dynamic change of the availability of electricity, physical health, mental well-being, and community resilience for the six communities. The disaster in Community 5 is very severe. After the disaster occurs in Community 5, the social well-being and community resilience of their people sharply decreases.

disaster is raised, then the level of panic among people is lowered, while the mental well-being is increased. The larger the number of individuals with empathy in a community, the more resilient that community will be. When the population is the same (50), a community with more empathetic individuals (empathy = 0.9) is more resilient than a community with less empathetic individuals (empathy = 0.2). The relationship among the individuals of a community is an essential characteristic of community resilience. A community with a smaller population (20) and more empathy (0.9) is more resilient than a community with a larger population (60) and less empathy (0.2). In Figure 4.23, the dynamic changes of other human characteristics are not shown. The fluctuation in mental well-being and community resilience curve is a consequence of the existence of feedback, from other characteristics, i.e., fear, risk perception, information-seeking behavior, cooperation, and flexibility.

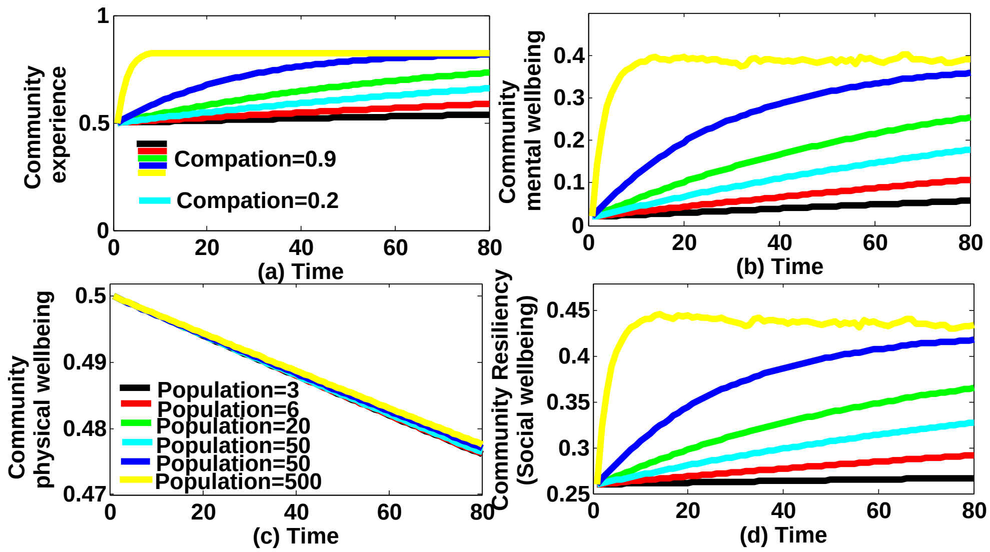


Figure 4.23: Effects of varying community population on community experience, mental well-being, physical well-being, and social well-being. To signify the importance of compassionate empathy (compassion or empathy), two different values of the empathy with the same community population is assumed. The population of the community is assumed to be 3, 6, 20, 50, and 500. A high population combined with a high level of empathy in the community, can induce a high level of community resilience.

4.6.5 Study of the Impact of Disasters on a Community using the EM-DAT International Disaster Database

Each community has unique attributes, including the injury factor, fear, availability of electric energy, and availability of emergency services. Table 4.5 lists the deadliest disasters in the last decade based on an international disaster database. In this table, the features of each disaster are provided. According to the EM-DAT international disaster database, the injury factor is determined from 0.5+(Death Toll by Disaster Type/ (2* Maximum death)), while the fear from a disaster is determined from 0.5+(Total Number of People Affected by Disaster Type/ (2* Maximum People Affected)). To calculate these factors, average EM-DAT data during 2000-2017 is used. We use real world data[3] as input of the proposed stochastic

[3]The data related to the death toll by disaster, maximum death, total number of people affected by disaster type, and maximum people affected are available online at the EM-DAT international disaster database.

Table 4.5: Data regarding the injury factor, level of initial fear, and availability of emergency services (AES) and electricity (AE) for different types of disasters based on the EM-DAT international disaster database.

Disaster	Injury factor	Fear	AE	AES
Drought	0.51473	0.83873	1	0.8
Earthquake	1.00000	0.53912	0	0.4
Extreme temperature	0.61277	0.53672	0	0.5
Flood	0.55873	1.00000	0	0.4
Landslide	0.51005	0.50152	1	1
Mass movement (dry)	0.50021	0.50000	1	1
Storm	0.63776	0.69656	0	0.6
Volcanic activity	0.50033	0.50097	1	1
Wildfire	0.50076	0.50011	1	1
Severe terrorist attack	1	1	0	0

multi-agent-based model to evaluate the effect of different types of disaster on communities. In addition, we propose how to measure injury factors and induced fear for different types of emergency.

We consider here a community similar to Community 1 for which Figure 4.24 shows dynamic changes of physical and mental well-being for different kinds of disasters using the EM-DAT database. As seen, the community suffering a drought, storm, flood, or terrorist attack shows a low level of community resilience at the beginning of the disaster (between 0 and 0.4). The flood and terrorist attack result in the lowest levels of social well-being (0), while community resilience for all four disasters rises during a given disaster due to the positive human characteristics of community such as cooperation and flexibility.

When the disaster is an earthquake or terrorist attack, the physical well-being of the community sharply drops. In contrast,the physical well-being of the community during storms, extreme temperatures, and flooding only gradually decreases. At the beginning of the disaster, flooding and terrorist attacks induce a high level of fear in the community so that the community's mental well-being is low. This level of panic decreases during a disaster because of an increase in the risk perception, cooperation, and experience of the people. Droughts and storms scare individuals. The other disasters do not induce much fear, and yet the mental well-being of a community during these disasters decreases over time. If the community is more resilient to a specific failure class, it may be more brittle to another failure type [114]. As can be seen from Figure 4.24, the community is more resilient to some disasters rather than to others.

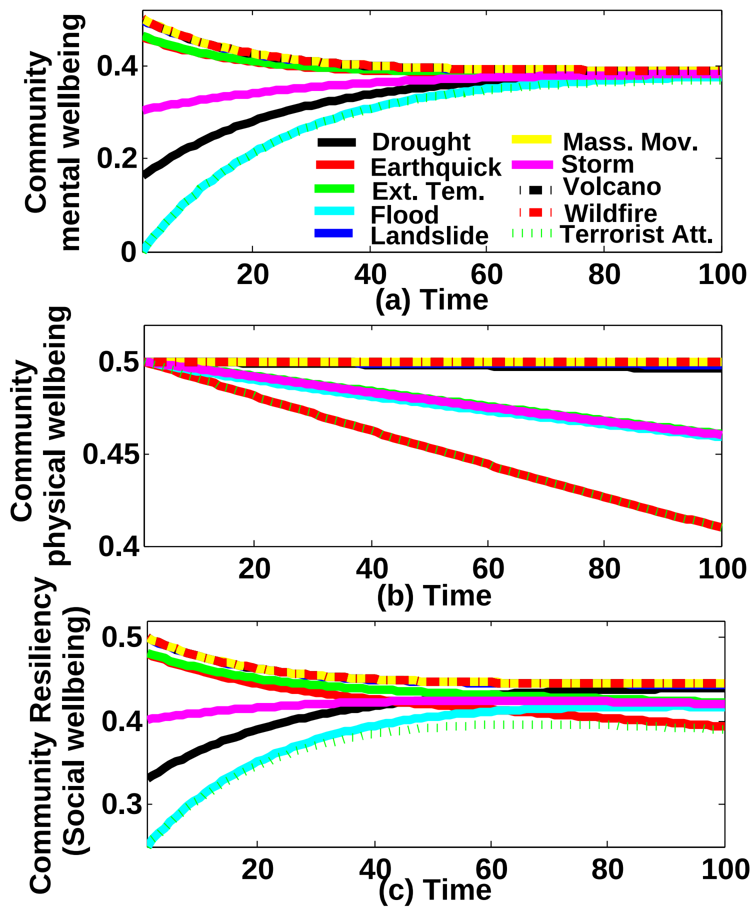


Figure 4.24: Effects of the most destructive disasters from the EM-DAT database on community mental well-being, physical well-being, and community resilience. These disasters include droughts, earthquakes, extreme temperatures, floods, landslides, mass movements, storms, volcanoes, wildfires, and terrorist attacks (Not from EM-DAT). Each of these disasters is modeled by features like the injury factor, level of initial fear, availability of emergency services, and availability of electricity based on data from the EM-DAT international disaster database.

4.7 General Idea to Enhance Community Resilience

This chapter has examined the most vital factors of community resilience based on simulations with a proposed agent-based model [146]. However, there are some invaluable strategies to enhance community resilience that are not covered in the proposed model:

- *Increase the social well-being of the community during a disaster by time banking:* One course of action to overcome different challenges in the society is alternative currencies, which can lead to community resilience. BERKSHARE in Massachusetts advocates buying local, resulting in greater social well-being for the community [152, 153]. Other alternative currencies which have been used in past decades include FUREAI KIPPU in Japan in response to elder care [154, 155]; BUS TOKEN in Curitiba, Brazil in response to a garbage problem[156, 157]; TOREKES in Ghent, Belgium in response to high unemployment and urban decay [158]; and TIME BANKING in Blaengarw, Wales in response to events, disasters, and unemployment [159] along with BONUS for emergency situations to help the local economy [153, 160]. Time banking, which is beneficial for community resilience and social well-being, is an adequate alternative currency. Time banking has a local market place so that time instead of money is used as a trading currency. Trade controlled by a dealer is non-reciprocal [153, 161]. All individuals are in control of their community position during the danger. People must not expect the state to rebuild their communities. In this scenario, the presence of human sympathy and cooperation, as mentioned in the article, leads to effective time banking. In addition, although time banking is not against economic banking, it has more impact on improving community resilience during a disaster. Peoples' lives, needless to say, are more essential than cash. Time banking contributes to strong ties among individuals, social support to vulnerable communities, and economic benefit.

Economic capacities, communication, social capacities, and community competency are all necessary adaptive facets of time banking. As a result, modeling time banking in the proposed model should be considered to satisfy social well-being during a disaster.

- *Other useful concepts for community resilience:* In addition to features like cooperation, experience, flexibility, and empathy, other features including coordination and collaboration can significantly enhance community resilience. Furthermore, there is a difference between cooperation and collaboration. When people cooperate, each individual does one part of the shared aim separately. On the other hand, when people collaborate, there is a direct interaction among people to reach the shared aim [162].

4.8 Conclusions

This chapter provided a general discussion and set of results for two different case studies on the importance of different mental and physical characteristics to the resiliency of individuals and communities during and after disasters. The effect of empathy, experience, flexibility, and cooperation on emotions, risk perception, and information-seeking behavior is investigated. Furthermore, the importance of emergency services, power systems, and DERs is demonstrated. The proposed stochastic multi-agent-based model in this chapter is useful for emergent processes and for finding new hypotheses that can be tested in real-world scenarios.The model provides the option of modeling many different effects, which would be costly and difficult to do with only experiments or surveys.

Chapter 5

Community Resilience Optimization Subject to Power Flow Constraints in Cyber-Physical-Social Systems in Power Engineering

This chapter develops a community resilience optimization method subject to power flow constraints in the Cyber-Physical-Social Systems in Power Engineering, which is solved using a multi-agent-based algorithm. The tool that makes the nexus between electricity generation on the physical side and the consumers and the critical loads on the social side is the power flow algorithm [30]. Specifically, the levels of emotion, empathy, cooperation, and the physical health of the consumers, prosumers are modeled in the proposed community resilience optimization approach while accounting for the electric power system constraints and their impact on the critical loads, which include hospitals, shelters, and gas stations, to name a few. The optimization accounts for the fact that the level of satisfaction of the society, the living standards, and the social well-being are depended on the supply of energy, including electricity. Evidently, the lack of electric energy resulting from load shedding has an impact on both the mental and the psychical quality of life, which in turn affects the community resilience. The developed constrained community resilience optimization method is applied to two case studies, including a two-area 6-buses system and a modified IEEE RTS 24-bus system. Simulation results reveal that a decrease in the initial values of the emotion, the risk perception, and the social media platform effect factor entails an increase in load shedding, which in turn results in a decrease in community resilience. In contrast, an increase in the initial values of cooperation, empathy, physical health, the capacity of microgrids and distributed energy resources results in a decrease in the load shedding, which in turn induces an enhancement of the community resilience.

Nomenclature

t	Index for time
n/m	Index for bus (N is the total number of buses)
M^e_{tn}	The level of emotion (fear) in each bus
M^r_{tn}	The level of risk perception in each bus
M^c_{tn}	The level of cooperation in each bus
M^a_{n}	The level of empathy in each bus
M^p_{tn}	The level of physical health in each bus
S_t	The level of social well-being of a community
$\alpha_{nt}/\ \beta_{nt}$	The Load shedding of consumers, prosumers/critical loads
P_{nmt}	The electricity transferred between two buses
θ_{nt}	The voltage angle
P^{der}_{nt}	The electricity produced by Distributed energy resources
P^{u}_{nt}	The electricity produced by utilities
P^{mg}_{nt}	The electricity produced Micro Grids
P^{cl}_{nt}	The electricity consumed by critical Loads

P_{nt}^{d}	The electricity consumed by consumers and prosumers
$\overline{P}_{nm}^{l}$	The capacity of transmission line
$\overline{P}_{n}^{der}$	The capacity of distributed energy resources
$\overline{P}_{n}^{mg}$	The capacity of micro grids
$\overline{P}_{n}^{u}$	The capacity of generation unit
N_{t}^{m}	The level of the related and negative news of mass media

5.1 Introduction

When a social community is exposed to natural and human-induced disasters, it faces a variety of emotional and physical stresses and strains, which may result in physical and financial losses and loss of life [14, 38]. The question is hence the following: What should that community do to better face a given disaster and decrease the losses that it may experience? To address this question, the resilience of a community must first be defined and characterized by relevant metrics, whose levels must be assessed and enhanced. The features of a social system include emotion, empathy, risk perception, cooperation, social well-being, and community resilience. In this chapter, community resilience is defined as the ability of a community to bounce back and recover from a given class of severe disturbances [16, 114]. One social system feature that has an important impact on community resilience is social well-being, whose modeling and assessment require an interdisciplinary approach, integrating knowledge and ideas from a variety of disciplines such as neuroscience, social and cognitive psychology, artificial intelligence, cognition, multimedia development, engineering, and healthcare [163]. Social well-being consists of mental well-being and physical well-being. In this chapter, we measure the level of mental well-being by the level of fear, which is of course affected by psychological and mental characteristics such as cooperation, empathy, and risk perception. In contrast, we measure the level of physical well-being by the level of physical health. Using these metrics, we investigate how the availability of electricity impacts the community resilience.

While the availability of electricity, as the main type of energy sources, directly affects the physical quality of life, the life expectancy, the human development and health, just to name a few [164], the risks associated with its shortage are not always promptly visible. Evidently, its shortage or unavailability threatens human lives and makes people mentally unsatisfied with the power suppliers, e.g., utilities, retailers, and the government. Hence, it is essential to consider the community's social well-being in Cyber-Physical-Social Systems in Power Engineering (CPSS-PE), before, during, and after the striking of a disaster. Evidently, in case of shortage of electricity, the critical loads must be supplied with the highest priority. Furthermore, experience has shown that the level of the social well-being is higher if there is some supply of electricity as compared to the case where there is no supply of electricity, especially during a disaster [165]. Figure 5.1 displays in a graphical manner a simple example of a four-bus system, where only consumers are connected to Bus 1, consumers and prosumers are connected to Bus 2, a microgrid is connected to Bus 3, and critical loads are connected to Bus 4. When an emergency occurs, the microgrid of Bus 3 supplies first the critical loads of Bus 4 with a priority level 1 by switching on its circuit breaker while the circuit breakers of the other loads are turned off. If the microgrid has enough electric energy, it supplies then the consumers of Bus 1 with a priority level 2. Finally, it supplied the consumers and prosumers of Bus 2 with a priority level 3.

The tool that makes the nexus between the electricity generation on the physical side and the consumer and the critical loads on the social side is the power flow algorithm. The latter is the essential tool for the long-term and operational planning of a power system [166, 167]. Owing to its importance, the power flow method in cyber-physical systems has already been

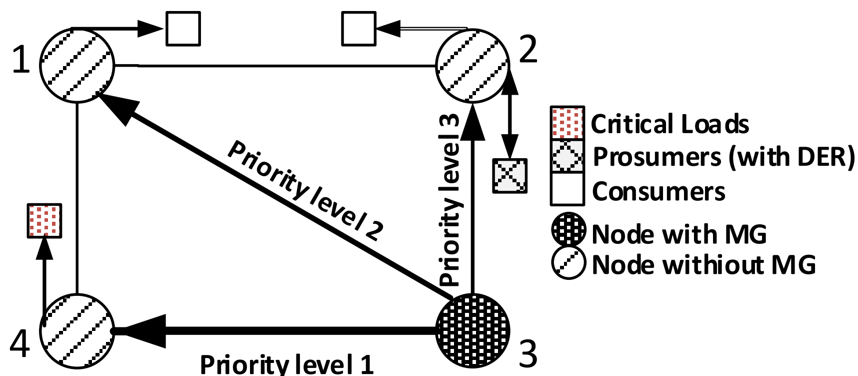


Figure 5.1: Community resilience maximization subject to power flow constraints in the CPSS-PE. Node 1 includes consumers. Node 2 includes both consumers and prosumers. Node 3 includes a Microgrid (MG). Node 4 includes critical loads.

studied for various applications, but without considering the social science aspects [102, 168]. Hence, we are motivated to propose the socio-technical power flow [1] in the CPSS-PE. The socio-technical power flow algorithm is the main tool for the analysis of a power system in the CPSS-PE. In this algorithm, the loads that impact the most the community resilience and that provides the highest community satisfaction need to be given the highest priority of supply. These loads must be supplied according to the capacities of the microgrids, the distributed energy resources (DERs), and the transmission lines [170]. In reality, we face a more sophisticated power system than the example presented in Figure 5.1. Consequently, the socio-technical power flow becomes a challenging problem to solve due to the numerous technical and social constraints.

In this chapter, we will address here the following question: How to maximize community resilience subject to power flow constraints in CPSS-PE? To this end, our CPSS-PE model considers the social perspectives of engineering systems, where the human and social dynamics are considered as an integral part of any effective cyber-physical system design and operation [171]. It accounts for the tight conjoining and coordination between the physical world, the cyber world, and the social world, as first proposed by Karl Popper [172]. Fig-

[1]Socio-technical system is a joint system referring to the interaction between human behavior and community's complex infrastructure such as power systems.[169].

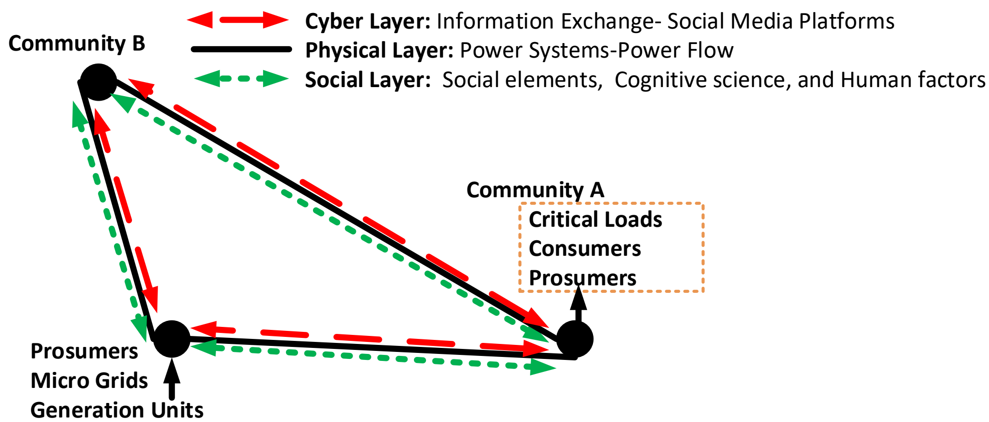


Figure 5.2: Diagram displaying a cyber layer, a physical payer, and a social layer of our CPSS-PE model. The cyber layer comprises the social media platform that performs the exchange of information. The physical layer comprises the power system. The social layer comprises social elements and human factors.

ure 5.2 displays a diagram of the CPSS-PE that we developed, which consists of a cyber layer, a physical payer, and a social layer. The cyber layer comprises the social media platform that performs the exchange of information. The physical layer comprises the power system. As for the social layer, it comprises social elements and human factors described by the social and cognitive science and psychology. In summary, our CPSS-PE models the cyber-physical-social dependence among prosumers, consumers, micrograms, power utilities, and mass media platforms.

This chapter addresses the following sub-questions:

- How can we model the social well-being of a society subject to power flow constraints?
- How can we demonstrate the effect of the level of cooperation of DERs and prosumers on the sharing of electricity?
- How can we model the impact of load shedding and mass media platforms on the level of fear, cooperation, risk perception of consumers and prosumers, and social well-being?
- What is the effect of load shedding on the emotion, risk perception, physical health,

empathy, and cooperation, and hence on community resilience in CPSS-PE?

- What are the effects of the capacity of microgrids and DERs on the social characteristics?
- What are the effects of the mass media platforms on the load shedding?
- What are the effects of the availability of electricity on the physical and mental well-being?
- How do the emotions, risk perception, physical health, and cooperation dynamically change during a day?
- How does the amount of load shedding that consumers, prosumers, and critical loads may experience change during a day?
- How to maximize the community resilience under a limited amount of electric energy by minimizing the load shedding that consumers, prosumers, and critical loads may experience while satisfying the power flow constraints?

We answer the three first sub-questions in Section III. The other sub-questions are answered in Section IV. The community resilience optimization method subject to power flow constraints is implemented in two different case studies. This model is verified by the soft validation and sensitivity analyses. The aim of the first case study, i.e., two-area 6-buses system, is to investigate the effect of the level of empathy, the amount of mass media effect factor, the DERs capacity, the microgrid capacity, the initial value of fear, the social cooperation, the risk perception, and the physical health on consumer load shedding, prosumers, and critical loads, the reporting of negative news by the mass media platform, the mental well being, the physical well being, the social well-being, and the community resilience. To reach our aims, we provide the results for 24 distinct scenarios. The sub-questions 4-7 are elucidated in this case study. The second case study is carried out on the modified IEEE RTS 24-bus system. It intends to provide a dynamic change of load shedding of consumers, prosumers, critical loads, levels of fear, cooperation, risk perception, and community resilience for 24 hours. The three last sub-questions are clarified in this case study.

The remainder of this chapter is structured as follows. Section II introduces the social computing and social characteristics considered in our model. It also discusses the social behavior and emotion, the Barsade theory, the Fredrickson theory, the amplification model, and the absorption model. In addition, it provides the definition and stresses the importance of cooperation, empathy, risk perception, social well-being, critical loads, power flow, and load shedding. Section III deals with the community resilience optimization problem subject to power flow constraints in CPSS-PE. It also explains the inputs and the outputs of the proposed model as well as cyber-physical-social dependence in the proposed multi-agent-based model. Section IV discusses the results of the proposed method for the first case study carried out on the two-area 6-bus system. Section V discusses the results of the proposed method for the second case study carried out on the modified IEEE RTS 24-bus system. The conclusions are provided in Section VI.

5.2 Community Resilience Optimization Subject to Power Flow Constraints

There are three different types of inputs to our multi-agent-based model, namely cyber-based, physical-based, and social-based inputs. The cyber-based inputs consist of the social media effect factor (ζ^m). Physical inputs include the capacity of the transmission line ($\overline{P}^l_{nm}$), the capacity of distributed energy resources ($\overline{P}^{der}_n$), the capacity of microgrids ($\overline{P}^{mg}_n$), and the generation unit capacity ($\overline{P}^u_n$). There are two different types of social-based inputs, including diffusion-based and social-initial-based inputs. Regarding the inputs of the diffusion features, they consists of the emotion contagion as a diffusion factor (γ^e_{ij}), the assumed initial value of fear ($M^e_{(t=1)i}$), the risk perception ($M^r_{(t=1)i}$), the cooperation ($M^c_{(t=1)i}$), the empathy (M^a_i), the physical health ($M^p_{(t=1)i}$), and the social well-being ($S_{(t=1)}$).

As for the outputs of our multi-agent-based model, they consist of cyber-based, physical-based and social-based outputs. Cyber-based output include the related and negative news propagated in the mass media platforms because of load shedding (N^m_t). Physical-based Variables and outputs include the Load shedding of consumers/critical loads (α_{nt}/β_{nt}), the electricity transferred between two buses (P_{nmt}), the voltage angle (θ_{nt}), the electricity produced by DERs (P^{der}_{nt}), the electricity produced by utilities (P^u_{nt}), the electricity produced by microgrids (P^{mg}_{nt}), the electricity consumed by critical Loads (P^{cl}_{nt}), and the electricity consumed by the consumers and the prosumers (P^d_{nt}). As for the social-based outputs, they comprise the incremental changes of fear ($M^e_{(t\neq1)i}$), the risk perception ($M^r_{(t\neq1)i}$), the cooperation ($M^c_{(t\neq1)i}$), the physical health ($M^p_{(t=1)i}$), the social well-being ($S_{(t\neq1)}$), and the social mental and physical well-being.

5.2.1 Description of the Constrained Optimization Model

The social well-being of a CPSS-PE is formed of the social mental well-being and the social physical well-being of a set of consumers, prosumers, and critical loads. In this section, we plan to maximize the social well-being, S_t, that is, the community resilience, subject to a set of cyber-physical-social constraints. Formally, we have

$$\mathbf{Max} \sum_t S_t \tag{5.1}$$

subject to

$$S_t = \frac{1}{N}(\sum_n \eta(\zeta^e(1 - M^e_{tn}) + \zeta^{ecl}(1 - M^{ecl}_{tn})) \\ + \sum_n (1-\eta)(\zeta^p M^p_{tn} + \zeta^{pcl} P^{cl}_{tn})). \tag{5.2}$$

and eleven other equality or inequality constraints that are defined next.

In (2), the first term of the summation is the social mental well-being while the second term is the social physical well-being. The well-being coefficients are contained in the set L_{WC}=$\{\eta, \zeta^e, \zeta^{ecl}, \zeta^p, \zeta^{pcl}\}$. The reader is referred to the nomenclature for the definitions of the variables and their indices shown in (2). The critical loads respectively influence the mental and the physical well-being via

$$M^{ecl}_{tn} = \varpi^e(1 - \beta_{tn}) \tag{5.3}$$

$$P^{cl}_{tn} = \varpi^p \beta_{tn} \tag{5.4}$$

where ϖ^e and ϖ^p are respectively the mental and the physical coefficients. The load shedding variable, β_{tn}, is constrained to takes values between 0 and 1, $0 \leq \beta_{tn} \leq 1$.

The optimization given by (1) is subject to a second set of equality constraints, which are given by the human psychological dynamics. These are the dynamical changes of the level of emotion (fear) of consumers and prosumers in CPSS-PE. they are expressed as

$$M^e_{(t+1)n} = \gamma^e_{tn}(f(\hat{M}^e_{tn}, M^e_{tn}) - M^e_{tn})\kappa^t + M^e_{tn}, \tag{5.5}$$

where κ^t denotes the time coefficient such that $\kappa^t \leq \frac{1}{n-1}$ as indicated in [82] and where

$$\gamma^e_{tn} = \frac{\sum_m \gamma^e_{nm} M^e_{tm}}{\sum_m \gamma^e_{nm}}, \tag{5.6}$$

$$f(\hat{M}^e_{tn}, M^e_{tn}) = \eta^e[M^r_{tn}(1-(1-M^e_{tn})(1-\hat{M}^e_{tn})) \\ +(1-M^r_{tn})(\hat{M}^e_{tn}M^e_{tn})] + (1-\eta^e)\hat{M}^e_{tn}, \tag{5.7}$$

$$\hat{M}^e_{tn} = w^{ee}(\frac{\sum_m \gamma^e_{tnm} M^e_{tm}}{\sum_m \gamma^e_{tnm}}) + W^{ce}(1-M^c_{tn}) \\ +W^{pe}(1-M^p_{tn}) + W^{\alpha e}(1-\alpha_{tn}) + W^{me}N^m_t, \tag{5.8}$$

where α_{tn} denotes the load shedding variable, which is constrained to takes values between 0 and 1, $0 \leq \alpha_{tn} \leq 1$. Here, γ^e_{tn} denotes the weighted emotion contagion of each agent based on the bottom-up approach, which is also considered as the speed of the dynamic change of the total emotion strength of a consumer or a prosumer of a group receiving the emotion of the other consumers and prosumers within that group. As for $f(\hat{M}^e_{tn}, M^e_{tn})$, it denotes the amount of the impression of the inter- and the intra-agent factors through the absorption and the amplification model. Akin to the absorption model based on the Barsade theory, $\hat{M}^e_{tn}$ denotes the amount of emotion of an agent influenced by the emotion of the other consumers and prosumers, which account for the inter-agent impacts [4]. Here, the term, $[M^r_{tn}(1-(1-M^e_{tn})(1-\hat{m}^e_{tn})) + (1-M^r_{tn})(\hat{M}^e_{tn}M^e_{tn})]$, is associated with the amplification model based on the Fredrickson theory. This model consists of two different terms that are related to an upward and a downward emotional spiral, respectively. In (8), the weighting factors are contained in the set L_W=$\{w^{ee}, W^{ce}, W^{pe}, W^{\alpha e}\}$.

Note that $\hat{M}^e_{tn}$ is influenced by the social-social dependence including the emotion of the other agents $(w^{ee}(\frac{\sum_m \gamma^e_{tnm} M^e_{tm}}{\sum_m \gamma^e_{tnm}}))$, its cooperation $(W^{ce}(1-M^C_{tn}))$ [6, 7, 8, 9], and agent's physical health $(W^{pe}(1-M^p_{tn}))$ [34]. In addition to the social-social dependence, the level of panic is contingent on the physical-social dependence,i.e., the load shedding of consumers and prosumers $(W^{\alpha e}(1-\alpha_{tn}))$ and the cyber-social dependence, i.e., the mass media $(W^{me}N^m_t)$

[5]. It is prevalent for users to follow news or events conveyed by the social media platforms, such as Twitter, Facebook, Sina Weibo, WeChat, and energy media [173]. They use these social media services to share their emotions and thoughts [174]. The dynamic change of the level of the related and negative news of mass media is given by

$$N_t^m = \zeta^m[\zeta^{'e}(1-\alpha_{tn}) + \zeta^{'ecl}(1-\beta_{tn})] \tag{5.9}$$

Here, the mass media news are directly related to the load shedding of consumers, prosumers, and critical loads. ζ_m is the effect Coefficient. Note that in (9), we have disregarded the effect of the fake, exaggerated, or tendentious news. If the level of satisfaction of a consumer at a bus is desired to be high, we can set the level of emotion in (5) accordingly. The optimization given by (1) is subject to a third equality constraint, which is the dynamic change of the level of risk perception of consumers and prosumers in CPSS-PE given by

$$\begin{aligned} M^r_{(t+1)n} = (\eta^r + (1-\eta^r)N_t^m)\frac{1}{1+e^{-\sigma^e(M^e_{tn}-\phi^e)}}(1-M^p_{tn})(1-M^c_{tn}) \\ ((1-\alpha_{tn}) - M^r_{tn})\kappa^T + M^r_{tn} \end{aligned} \tag{5.10}$$

It is affected by the load shedding, mass media, the cooperation, the physical health, and the emotion of the consumers and prosumers. If the emotion (M^e_{tn}) is lower than the fear or the threshold (ϕ^e), it has no impact on the risk perception [125]. According to the narrowing hypothesis of Fredrickson's broaden-and-build theory [5], the factor, $[(1-\alpha_{tn}) - M^r_{ti}]$, measures the tendency of the risk perception to be more or less positive. The relation between the risk perception and the cooperation is provided in [132, 175]. The connection between risk perception and physical health is provided in [35, 176].

The optimization given by (1) is subject to a fourth equality constraint, which is the dynamic change of the level of cooperation of consumers and prosumers in CPSS-PE given by

$$M^{c}_{(t+1)n} = (\eta^{c} + (1-\eta^{c})N^{m}_{t})(\frac{1}{1+e^{-\sigma^{c}(M^{e}_{tn}-\phi^{e})}})$$
$$M^{p}_{tn}M^{a}_{n}[(1-\alpha_{tn}(1-M^{e}_{tn})) - M^{c}_{tn}]\kappa^{t} + M^{c}_{tn}. \quad (5.11)$$

It is affected by the emotion, load shedding, and the physical health of consumers and prosumers. Here, the factor $[(1-\alpha_{tn}(1-M^{e}_{tn})) - M^{c}_{tn}]$ is based on the narrowing hypothesis of Fredrickson's broaden-and-build theory. The relationship between the fear and the cooperation is provided in [6, 7, 8, 9]. The relation between cooperation and physical health is discussed in [141, 177]. According to [142, 147, 178], social media influence the level of cooperation among the individuals of a group.

The optimization given by (1) is subject to a fifth equality constraint, which is the dynamic change of the physical health of consumers and prosumers in CPSS-PE given by

$$M^{p}_{(t+1)n} = \eta^{p}(\frac{1}{1+e^{-\sigma^{c}(M^{e}_{tn}-\phi^{e})}})((1-M^{e}_{tn})\alpha_{tn} - P_{tn})\kappa^{t} + M^{p}_{tn} \quad (5.12)$$

It is affected by the fear and load shedding of consumers and prosumers. The set of L_{MP}=$\{\eta^{r}, \eta^{c}, \eta^{p}\}$ includes the mental and physical coefficients. All of the above-mentioned features are assumed to take values in the interval [0 1].

The optimization given by (1) is subject to a sixth set of equality constraints, which are the power flow equations using a DC model. They are given by

$$P_{nmt} = \frac{\theta_{nt} - \theta_{mt}}{X_{nm}} \quad (5.13)$$

Using these power flow equations, we model a set of DERs connected to a bus of the power system that are willing to share their electricity with customers, retailers, private and public organizations connected to other buses of that system [179]. Their behavior may be viewed as one single group behavior by using a bottom-up approach [50] and the equality constraints given by (5)-(11).

The optimization given by (1) is subject to a seventh equality constraint [71, 180], which is the power balance between generation and load in the power system expressed as

$$\sum_{m} P_{nmt} + P^{mg}_{nt} + P^{der}_{nt} + P^{u}_{nt} = \alpha_{nt} P^{d}_{nt} + \beta_{nt} P^{cl}_{nt} \tag{5.14}$$

Note that $(1-\alpha_{nt})$ denotes the fraction of consumers and prosumers that are shed while $(1-\beta_{nt})$ denotes the fraction of the critical loads that are shed. While the effect of the load on the social well-being changes with the seasons or the weather, this effect has not been considered here.

The optimization given by (1) is subject to an eighth set of inequality constraints, which represent the power flow limitations of the transmission lines given by

$$-\overline{P}^{l}_{nm} \leq P_{nmt} \leq \overline{P}^{l}_{nm} \tag{5.15}$$

The optimization given by (1) is subject to a ninth set of inequality constraints, which represent the limitations of the DERs to generate electricity. They are given by

$$0 \leq P^{der}_{tn} \leq M^{c}_{tn} \overline{P}^{der}_{n} \tag{5.16}$$

The maximum level of sharing of electricity depends on the level of cooperation of the prosumers. The latter may be willing to share their electricity with the customers who do not have electricity during and after a disaster strikes.

The optimization given by (1) is subject to a tenth set of inequality constraints, which represent the capacities of the microgrids to generate electricity. They are given by

$$0 \leq P_{nt}^{mg} \leq \overline{P}_{n}^{mg} \tag{5.17}$$

Here, the microgrids and the DERs connected to a bus are assumed to share their electricity with the critical loads such as hospitals, firefighter, police stations, to name a few. Regarding the sharing of electricity with other customers, we may model more complex behaviors of subsets of DERs and microgrids attached to a bus. As for the data centers, they are assumed to have enough backup generation due to the critical role that they play for smart businesses and government organizations in the modern computing age.

The optimization given by (1) is subject to a eleventh set of inequality constraints, which are the power plant capacities to generate electricity. They are given by

$$0 \leq P_{nt}^{u} \leq \overline{P}_{n}^{u} \tag{5.18}$$

The optimization given by (1) is subject to a twelfth set of inequality constraints, which are the voltage angle bounds given by

$$-\pi \leq \theta_{nt} \leq \pi \tag{5.19}$$

In the proposed model, the severity level of influence of all of the cyber-physical-social factors on each other can be easily modified by adjusting the values given to the mental and physical coefficients in L_{MP}, the weighting factors in L_W, and the well-being coefficients in L_{WC}.

5.2.2 Cyber-Physical-Social Dependence in the Multi-Agent-Based Model

Figure 5.3 displays the CPSS-PE dependence among the characteristics considered in the multi-agent-based model. The social well-being is influenced by the load shedding factor of critical loads, mental well-being, physical well-being of consumers, and prosumers. In this work, we consider the inverse level of fear of consumers and prosumers as their mental well-being. The less fear, the more mental well-being consumers and prosumers have. To model group emotion, we inspire Barsade theory and Fredrickson theory [50, 81]. We also consider emotion contagion. The level of empathy among consumers and prosumers influences emotion contagion among them. In addition to the fear propagation, the emotion is affected by the news and information exchanged by mass media platforms, the level of risk perception, cooperation, physical health, load shedding of consumers and prosumers. The news exchanged in mass media platforms is directly associated with the load shedding related to consumers, prosumers, and critical loads. Here, we disregard the fake news propagated in mass media platforms. The level of risk perception is affected by the level of emotion, physical health, cooperation, load shedding factor of consumers and prosumers. It is also affected by news and information exchanged by mass media platforms. Load shedding and the level of mental well-being influence the level of physical well-being. The availability of electricity by prosumers, microgrids, and utility affect the load shedding of consumer, prosumers, and critical loads. The availability of power by prosumers is affected by their level of cooperation. The news exchanged thorough mass media platforms , level of fear, physical well-being, and load shedding influence how the prosumers are willing to share electricity.

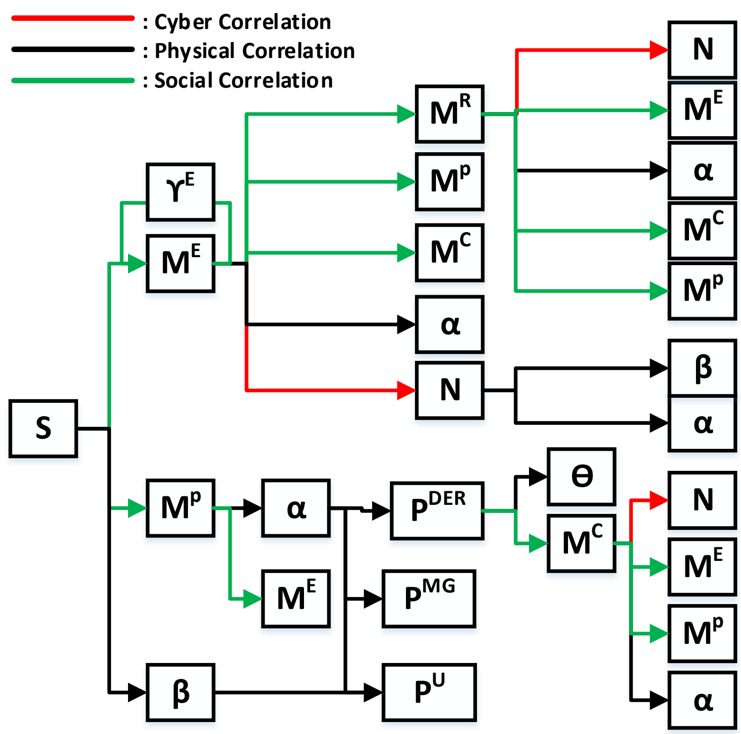


Figure 5.3: Cyber-Physical-Social dependence. Social well-being or community resilience encompasses mental well-being and physical well-being. Load shedding related to both consumers and critical loads influence community resilience. In addition to cyber-physical-social factors, the level of emotion of other connected consumers and prosumers influences that of a particular consumer or prosumer.

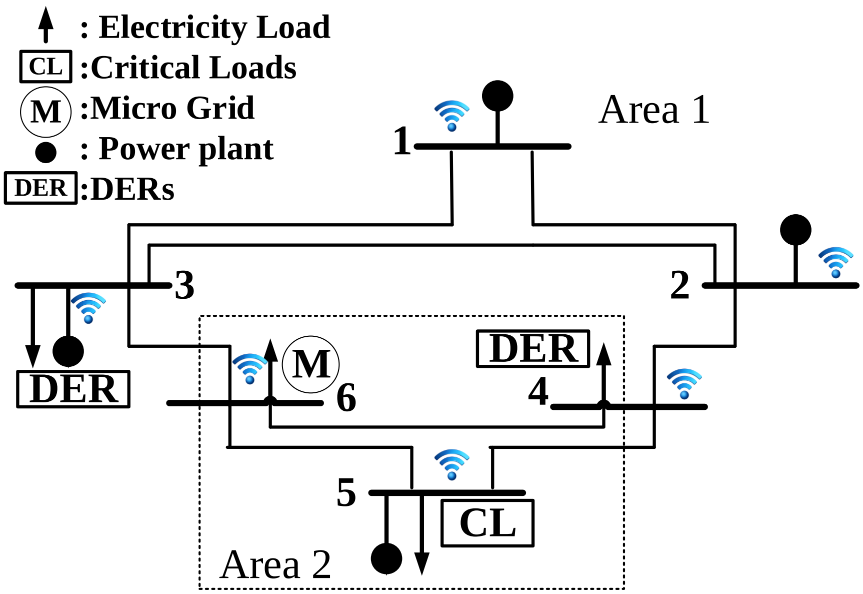


Figure 5.4: Two-area 6-buses system. There is no congestion between intra-area transmission lines. The inter-area transmission lines have a limited capacity as much as 450 MW (lines 3-6 and 2-4).

5.3 Case Study: Two-Area 6-Bus System

The first case study is a two-area 6-buses system, as shown in Figure 6.2. This case study aims to provide the results related to the sensitive analysis of different cyber, physical, and social factors shaping community resilience. The data associated with this network are provided in Table 5.1. This table includes the data related to the capacity of power plants, microgrid, and DERs in MW. It also provides the MW demand of consumers and critical loads. The susceptance of transmission lines is assumed to 10 P.U. (100 MW base). It is assumed that all buses have access to the internet and mass media platforms.

Table 5.2 provide the hourly load coefficient for daily consumption. The demand in each hour is obtained by multiplying these coefficients by demand of each bus provided in Table 5.1. It is assumed that all consumers and prosumers follow the same hourly load coefficient trend.

Table 5.1: The data associated with a Two-area 6-buses system (MW).

Bus	Power Plant	Microgrid	DER	Demand	Critical load
1	650	-	-	-	-
2	297	-	-	-	-
3	231	-	30	750	-
4	-	-	30	675	-
5	100	-	-	537.5	100
6	-	50	-	600	-

Table 5.2: Hourly Load coefficient for a day. H means hour while LC stands for load coefficient. The data is for 24 hours.

H	LC	H	LC	H	LC	H	LC	H	LC	H	LC
1	0.23	2	0.32	3	0.45	4	0.40	5	0.31	6	0.42
7	0.55	8	0.21	9	0.40	10	0.49	11	0.54	12	0.55
13	0.06	14	0.18	15	0.26	16	0.30	17	0.37	18	0.45
19	0.51	20	0.57	21	0.61	22	0.84	23	1.00	24	0.89

5.3.1 Soft Validation of the Proposed CPSS-PE model

We make a soft validation by verifying the result of the socio-technical power flow model with Case Study 1 provided by [4]. In the soft validation, only information-seeking behavior, the emotion of fear, and bias are considered in the model. After soft validation, we extend our model to the socio-technical power flow dscribed in the CPSS-PE. To do so, we consider the cooperation, the empathy, the mass media, the physical well-being of the agents along with the power flow constraints.

5.3.2 Sensitivity Analysis of Various CPSS-PE Factors in 24 Scenarios

Table 5.3 displays the sensitivities of different social, cyber, and physical factors influencing the community resilience. The social factors consist of the level of emotion (fear), cooperation, risk perception, empathy, and physical health. The cyber factor includes the mass media effect factor (ζ^m). The physical factors consist of the capacities of the microgrid and of the DERs. Note that in the columns of Table 5.3 are M_{tn}^E, M_{tn}^C, M_{tn}^R, M_n^A, and M_{tn}^P, which provide the initial values used for the emotion (fear), cooperation, risk perception, empathy, and physical health, respectively. Here, it is assumed that all the buses have similar initial values. All the outputs of the CPSS-PE in the power system are at an average levels. In total, the results for 24 different scenarios are provided.

Scenarios 1-3 (Changes in the Initial Value of Emotion): In these scenarios, the initial value of emotion (fear) is increased from 0.1 to 0.5 to 0.9 while the initial values of the other factors are fixed. This increase results in an increase in the average level of fear. Consequently, the level of risk perception and cooperation is increased while the average level of the physical well-being and community resilience is decreased. An increase in the cooperation reduces the average level of the load shedding. Therefore, less negative news are reported in the mass media platforms.

Scenarios 4-6 (Changes in the Initial Value of Cooperation): In these scenarios, the initial value of cooperation is increased from 0.1 to 0.5 to 0.9 while the values of the other factors are fixed. This increase results in an increase in the average level of cooperation. Consequently, the amount of load shedding of the consumers, the prosumers, and the critical loads is decreased. Hence, there is less negative news reported in the mass media platforms. In addition, the average level of fear and the risk perception of the consumers and the prosumers are also decreased. Finally, both the physical well-being and the community resilience are increased.

Scenarios 7-9 (Change in the Initial Value of Risk Perception): In these scenarios, the initial value of the risk perception is increased from 0.2 to 0.5 to 0.9 while the values of the other factors are fixed. This increase results in an increase in the average level of risk perception, fear, and cooperation while the average level of the physical well-being is decreased due to a greater level of fear, stress, and anxiety. Because of an increase in the level of cooperation, the amount of load shedding decreases, resulting in a smaller amount of reported negative news by the mass media platforms. However, the social well-being and the community resilience are reduced.

Scenarios 10-12 (Change in the Level of Empathy): In these scenarios, the initial value of empathy is increased from 0.1 to 0.5 to 0.9 while the values of the other factors are fixed. This increase results in an increase in the average level of empathy. Consequently, the amount of load shedding and related negative news in the mass media platforms is decreased. Also, the average level of fear along with the risk perception of the consumers and the prosumers decline. Finally, both the physical well-being and the community resilience increase.

Scenarios 13-15 (Change in the Initial value of the Physical Health): In these scenarios, the initial value of the physical health of people is increased from 0.1 to 0.5 to 0.9 while the values of the other factors are fixed. This increase results in an increase of the average level of the physical well-being, mental well-being, and cooperation. The amount of load shedding and negative news reported by the mass media platforms declines. Therefore, the community resilience improves.

Scenarios 16-18 (Change in the Mass Media Effect Factor): In these scenarios, the level of the social media effect factor is increased from 0.1 to 0.5 to 1 while the values of the other factors are fixed. This increase results in an increase in the negative news and the average level of fear. Hence, the average level of cooperation and risk perception increases. On the other hand, the amount of load shedding and physical well-being decreases. In addition, because of the high effect of the mass media on the propagation of negative news, the average level of community resilience decline.

Scenarios 19-21 (Change in the Total DER Capacity): In these scenarios, the total DER capacity is increased from 0 to 60 to 200 MW while the values of the other factors are fixed. This increase results in a decrease of the load shedding, especially of the critical loads. The negative news reported by the mass media is decreased. In addition, the average level of fear, cooperation, risk perception is decreased while that of the physical health is increased. As a result, the community resilience is enhanced.

Scenarios 21-24 (Change in the Total Microgrid Capacity): In these scenarios, the total microgrid capacity is increased from 0 to 50 to 300 MW while the values of the other factors are fixed. This increase results in a decrease in the load shedding, resulting in an increase of the community resilience. The levels of the social well-being factors and negative news have the same trends as those of Scenarios 19-21.

5.4 Case Study 2: the Modified IEEE RTS 24-Bus System

A modified IEEE RTS 24-bus system is used to implement the proposed socio-technical power flow in the CPSS-PE, as it is displayed in Figure 5.5. Bus 16 has a microgrid with a capacity of 310 MW. Additionally, the total capacities of the DERs connected to Buses 1, 7, 13, 15, and 18 are 50, 50, 100, 50, and 100 MW, respectively. It is assumed that there are two critical loads connected to Buses 8, and 19 of 426 MW and 451 MW, respectively. An initial level of 0.5 is assumed for the cooperation, emotion (fear), risk perception, and physical health of all buses, including consumers, prosumers, microgrid owners, critical loads, and utilities. In addition, to prevent making the problem complex, we assume that there is an empathy level of 1 between two buses if there is a transmission line between them.

Table 5.3: The results of our community resilience optimization method subject to power flow constraints in CPSS-PE. All the results are at an average level for 24 hours. CR, L^α & L^β stand for community resilience, load shedding of consumers and prosumers, and load shedding of critical loads, respectively. DER and microgrid capacities are in MW.

CPSS in power engineering		Inputs of community resilience optimization in CPSS-PE								Outputs of community resilience optimization in CPSS-PE							
System	Change Factor	M^E_{tn}	M^C_{tn}	M^R_{tn}	M^A_n	M^P_{tn}	ζ^m	$\overline{P}^{DER}$	$\overline{P}^{MG}$	CR(S)	L^α	L^β	M^E	M^C	M^R	M^P	N^M
Social	Emotion	0.1	0.5	0.5	1	0.5	1	60	50	0.655	0.632	0.153	0.616	0.669	0.593	0.384	0.651
	Emotion	0.5	0.5	0.5	1	0.5	1	60	50	0.634	0.632	0.149	0.686	0.713	0.62	0.347	0.649
	Emotion	0.9	0.5	0.5	1	0.5	1	60	50	0.614	0.631	0.148	0.75	0.727	0.625	0.334	0.649
	Cooperation	0.5	0.1	0.5	1	0.5	1	60	50	0.604	0.635	0.171	0.751	0.502	0.691	0.341	0.657
	Cooperation	0.5	0.5	0.5	1	0.5	1	60	50	0.634	0.632	0.149	0.686	0.713	0.62	0.347	0.649
	Cooperation	0.5	0.9	0.5	1	0.5	1	60	50	0.665	0.627	0.131	0.606	0.933	0.526	0.363	0.642
	Risk Perception	0.5	0.5	0.2	1	0.2	1	60	50	0.656	0.632	0.149	0.609	0.692	0.38	0.365	0.65
	Risk Perception	0.5	0.5	0.5	1	0.5	1	60	50	0.634	0.632	0.149	0.686	0.713	0.62	0.347	0.649
	Risk Perception	0.5	0.5	0.9	1	0.9	1	60	50	0.609	0.631	0.148	0.767	0.719	0.912	0.341	0.649
	Empathy	0.5	0.5	0.5	0.1	0.5	1	60	50	0.616	0.634	0.17	0.726	0.53	0.661	0.345	0.655
	Empathy	0.5	0.5	0.5	0.5	0.5	1	60	50	0.625	0.633	0.158	0.705	0.628	0.641	0.346	0.652
	Empathy	0.5	0.5	0.5	1	0.5	1	60	50	0.634	0.632	0.149	0.686	0.713	0.62	0.347	0.649
	Physical Health	0.5	0.5	0.5	1	0.1	1	60	50	0.524	0.635	0.167	0.785	0.561	0.711	0.074	0.655
	Physical Health	0.5	0.5	0.5	1	0.5	1	60	50	0.634	0.632	0.149	0.686	0.713	0.62	0.347	0.649
	Physical Health	0.5	0.5	0.5	1	0.9	1	60	50	0.744	0.63	0.14	0.587	0.772	0.537	0.647	0.647
Cyber	Mass Media	0.5	0.5	0.5	1	0.5	0.1	60	50	0.666	0.633	0.16	0.517	0.597	0.566	0.396	0.065
	Mass Media	0.5	0.5	0.5	1	0.5	0.5	60	50	0.649	0.632	0.153	0.597	0.663	0.601	0.359	0.325
	Mass Media	0.5	0.5	0.5	1	0.5	1	60	50	0.634	0.632	0.149	0.686	0.713	0.62	0.347	0.649
Physical	DER Capacity	0.5	0.5	0.5	1	0.5	1	0	50	0.59	0.642	0.231	0.697	0.719	0.624	0.343	0.674
	DER Capacity	0.5	0.5	0.5	1	0.5	1	60	50	0.634	0.632	0.149	0.686	0.713	0.62	0.347	0.649
	DER Capacity	0.5	0.5	0.5	1	0.5	1	200	50	0.694	0.601	0.042	0.66	0.695	0.606	0.36	0.601
	MG Capacity	0.5	0.5	0.5	1	0.5	1	60	0	0.571	0.646	0.266	0.701	0.722	0.627	0.341	0.683
	MG Capacity	0.5	0.5	0.5	1	0.5	1	60	50	0.634	0.632	0.149	0.686	0.713	0.62	0.347	0.649
	MG Capacity	0.5	0.5	0.5	1	0.5	1	60	300	0.717	0.574	0.006	0.638	0.685	0.592	0.366	0.568

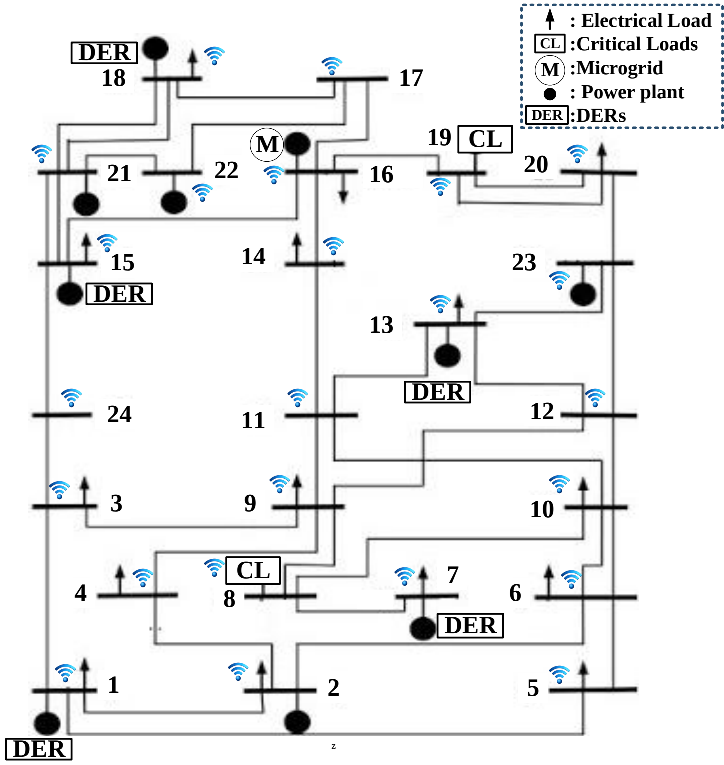


Figure 5.5: The one-line diagram of the modified IEEE RTS 24-bus system. It is assumed that all the buses have access to the internet and to the mass media platforms.

The socio-technical power flow algorithm is executed for 24 hours. It is assumed that the generation units located at Buses 21 and 23 are turned off since hour 5. Moreover, the generation units located at Buses 1, 2, 7, 13, 15, and 16 are turned off since hour 14. All the DERs and microgrids are connected to the power system for the whole time.

Figures 5.6 and 5.7 provide the result of the socio-technical power flow in CPSS-PE. Figure 5.6 displays the dynamic change in the level of emotion, risk perception, cooperation of costumers, and prosumers, in addition to the dynamic change in the level of community resilience of the entire society connected to the IEEE RTS 24-bus system. The level of emotion (fear) of consumers and prosumers depends on the emotion contagion, cooperation, load shedding, and physical health, to name a few. The level of emotion fluctuates from hour 1 to hour 14. Afterward, the levels of fear of the consumers and the prosumers increase

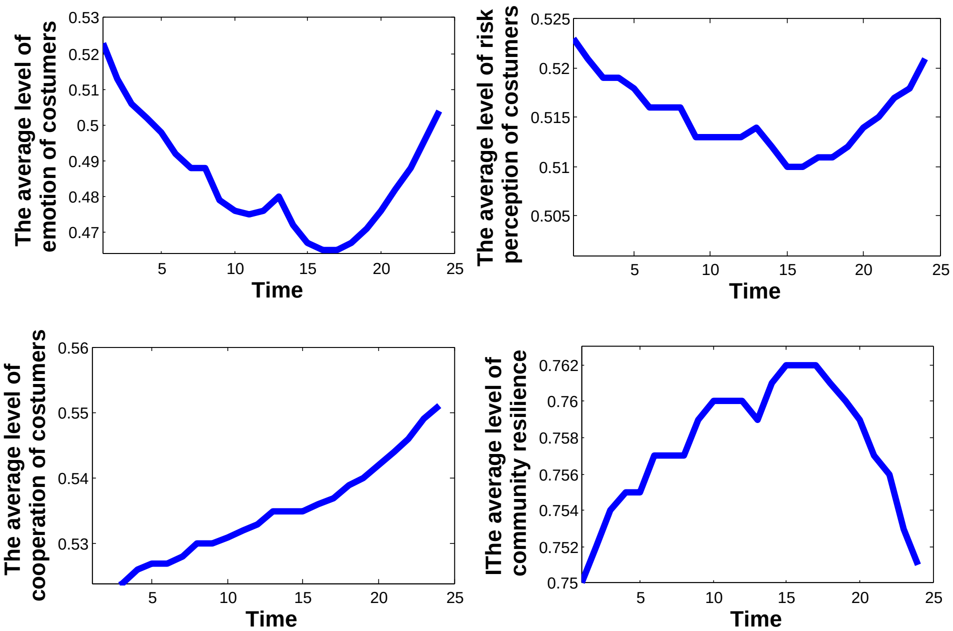


Figure 5.6: Dynamic change of social behavior of the consumers, prosumers, and the whole community of the modified IEEE RTS 24-bus system; (a) The average level of emotion per hour; (b) The average level of risk perception per hour; (c) The average level of cooperation per hour; (d) The average level of community resilience per hour.

significantly due to the high level of load shedding. Furthermore, because some generating units are turned off since hour 14, the consumers and prosumers experience a high level of risk of not being supplied with electricity. This situation prompts them to cooperate by sharing electricity in case of a shortage. Because the community resilience is highly intertwined with the critical loads in the CPSS-PE, it decreases noticeably since hour 14 due to power generation shortage. The average level of community resilience of the entire society connected to the IEEE RTS 24-bus system attains 0.682. The highest level of community resilience occurs at hour 13 since the load shedding is at its lowest level.

Figure 5.7 presents the results of the load shedding experienced by the consumers at Buses 2 to 6 and at Buses 9, 10, 14, 20 and the prosumers at Buses 1, 7, 13, 15, and 18, and the critical loads at Buses 8 and 19 in CPSS-PE. Understandably, there is no load shedding in the buses without a demand. The average levels of load shedding experienced by the critical

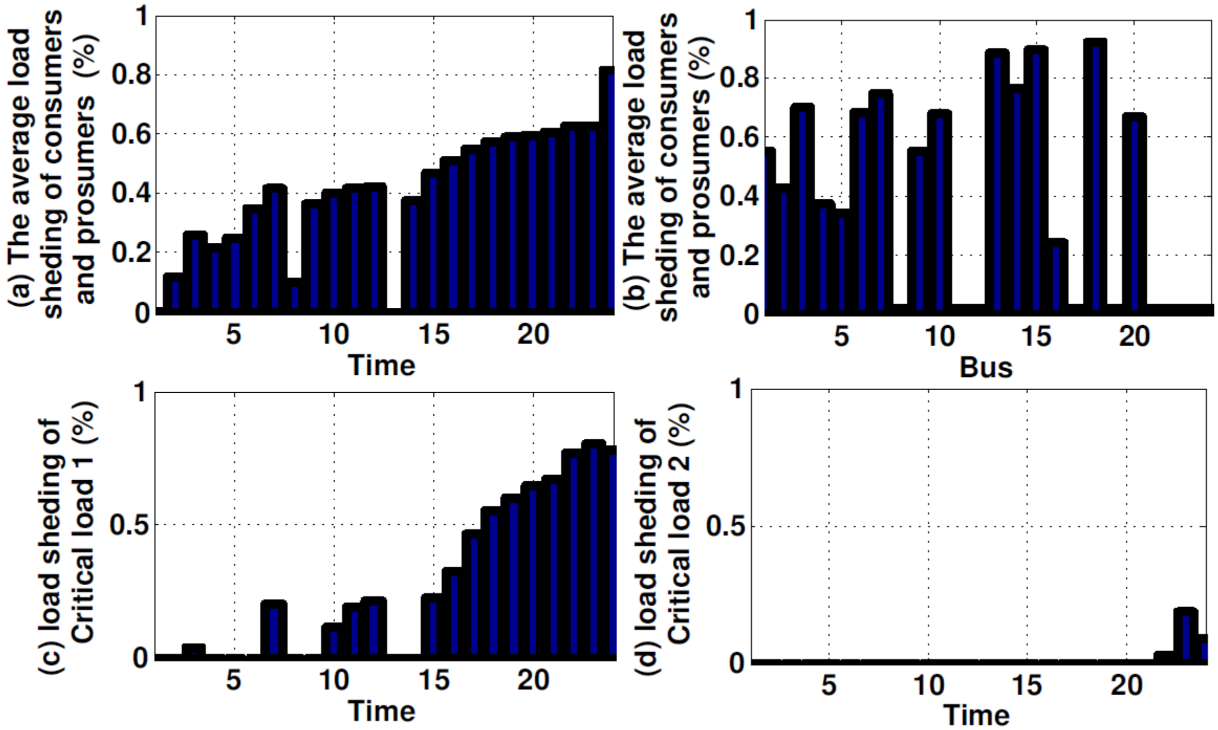


Figure 5.7: Load shedding experienced by the consumers, the prosumers, and the critical loads obtained by running a socio-technical power flow algorithm on the modified IEEE RTS 24-bus system; (a) the average load shedding experienced by consumers and prosumers per hour; (b) the average load shedding experienced by consumers and prosumers per bus; (c) the load shedding experienced by the critical load at Bus 8 per hour; (d) the load shedding experienced by the critical load at Bus 19 per hour.

loads at Bus 8 and 19 amount to 0.275 and 0.013, respectively, yielding a total average of 0.144. The average levels of load shedding experienced by the consumers and the prosumers amount to 0.401.

5.5 Conclusions

In this chapter, we developed a community resilience optimization method subject to power flow constraints in CPSS-PE. The socio-technical power flow model includes the social constraints, i.e., the dynamic change of the level of emotion, risk perception, cooperation, and physical well-being of consumers and prosumers. We also examine the effect of critical loads on the social well-being. In addition to the social constraints, we include in the model the cyber constraints and the physical constraints. The proposed model is implemented in two different case studies, i.e., a two-area 6-bus system and a modified IEEE RTS 24-bus system. The result of a sensitive analysis carried out on the cyber-physical-social factors that characterize the community resilience can be summarized as follows:

- In the social aspect, an increase in the initial value of the emotion, risk perception of the society under study because of the culture and the previous experience, to name a few, results in the decrease of the level of both the load shedding and the community resilience. On the other hand, an increase in the initial value of cooperation, empathy, and physical health results in the decrease of the level of the load shedding and an increase in the level of the community resilience.
- In the cyber aspect, an increase in the social media platform effect factor leads to a decrease in the level of both the load shedding and the community resilience.
- In the physical aspect, the larger the installed capacity of the microgrids and DERs, the smaller the level of load shedding and the larger the level of community resilience.

We also provided the dynamic effect of the load shedding experienced by the consumers, prosumers, and the critical loads on the social behavior. The results show that the prosumers cooperate to share electricity since they face a power shortage.

Chapter 6

Environomic-Based Social Demand Response

According to the Department of Energy, demand response provides an opportunity for end-users to play a significant role in the efficiency, reliability, resilience, and sustainability of a power grid. This is made possible owing to the existence of storage devices and diversity of energy sources at the customer level and the advent of the Internet of Things [122]. Social influences and psychological traits of consumers affect their behavior and decision-making. Consequently, there is a necessity to bring the influences of humans, organizations, and societies on the power system together through computational social science into a cyber-physical-social system. Hence, in this chapter, we introduce our development of an artificial society of the social demand response of a power system, a well-known approach in computational sociology based on a bottom-up approach, starting from theory instead of data. We assume that consumers can engage in demand response to fulfill two aims: save their cost or enhance the sustainability of a power system. Here, sustainability is defined as the ability of a power system to operate in an efficient manner while subjecting the earth's ecosystem to a minimum damage in terms of resource usage and waste disposal during the system's entire life cycle. The literature concerning sustainability-based demand response is limited to only considering CO_2, NO_X, and SO_2. In addition to NO_X, and SO_2, we examine the impact of power systems on water pollution, disability-adjusted loss of life year, and exergy in demand response, and provide an environomic-based social demand response. We show that when the level of satisfaction and cooperation of end-user is low, the marginal level of load shaving and improvement in sustainability cannot be fulfilled.

The balance between electricity supply and demand at every instant of time is the core problem of power system operation and planning [166, 181, 182]. When the supply of the electricity is insufficient, the demand of end-users is expected to reduce to satisfy the power balance. In addition, the intermittency of renewable energy raises hurdles for power system operation [183, 184, 185]. Hence, there is a need of Demand Response (DR) to mitigate this problem. The demand response is a change in the consumption of the electric utility end-user in order to better balance the electricity load with the supply. DR has many benefits for consumers, the utility, and the community as a whole. On the one hand, consumers engage in the DR program to decrease their electricity bills and environmental emissions. Although a few studies consider air pollution as an incentive for power system DR programs, there is no discussion of water pollution and Disability-Adjusted Loss of Life Year (DALY)[1]. Hence, in this chapter, we address this problem. The electric utility, on the other hand, aims to overcome the intermittency of renewable energy, shift system peak loads, decrease generation backup, flatten out the daily loads, and decrease the exergy. In the thermodynamic cycle of power plants, the exergy, the energy accessible to be used, is decreased. Hence, the power plants with a higher value of exergetic efficiency have priority in the DR program. That is important from a sustainability point of view while it is ignored in the literature. Hence, in this chapter, we address this second problem.

In DR programs, aggregators recruit flexible commercial, residential, and industrial customers who are willing to shift their load Advanced metering facilities and bidirectional communication infrastructure make customers able to engage actively in DR schemes [186].

[1]The DALY measures life loss from premature death and years of living with a lousy quality of life due to health problems related to the pollution produced by power plants.

Besides, according to the U.S. Energy information, 38% of the total electricity consumption is devoted to residential customers, who form the largest sector [187]. Hence, the decision-making of costumers and their behavior is critical. The decision-making of consumers is tight with their level of satisfaction and cooperation. A high level of satisfaction and cooperation of customers make them compliant to participate in a DR program. The involvement of the active end-users implies that a power system is a cyber-physical-social system, not the conventional cyber-physical system. That is due to the diversity of the energy sources, and the engagement of social entities, the Internet of Things, and the Internet of energy into the traditional centralized operation mode. Since the customers are an integral part of a power system, there is a need for computational social science to model their behavior, by including insights from psychology, social and cognitive sciences [188]. DR programs influence the human habits, activities, and mental states of customers and vice versa. On the other hand, the level of satisfaction, cooperation, flexibility, and other social features of consumers affect the sustainability, stability, reliability, and resiliency of a power system. Without considering the social behavior of customers, DR programs may never fulfill their intended purpose and face failure in practice.

6.1 Model Property

We propose an environomic-based (thermodynamic, environmental, and economic) model of social DR. Figure 1 provides the framework of our proposed model. We developed an artificial society to model the social behavior of consumers as active end-users. The incentive of these consumers to participate in a DR program is environomic-based.

To reach various aims of DR,i.e, peak load shaving, frequency stability, and sustainability , the role of consumers as active end-user is inevitable [92, 189]. The participation of the

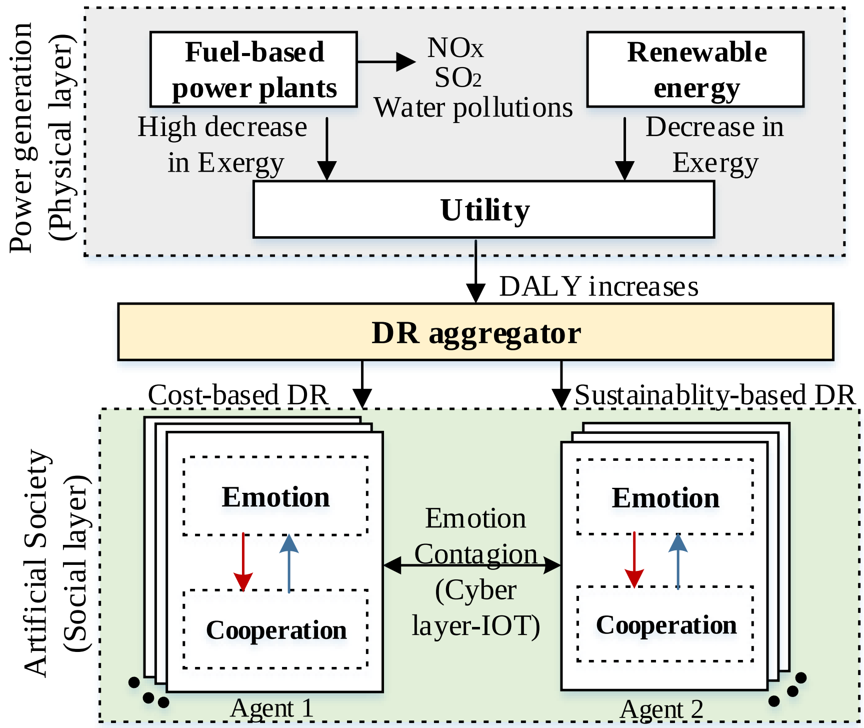


Figure 6.1: The proposed framework of an environomic-based social DR.

consumers in a DR schedule depends directly on the level of their social cohesion. Social cohesion consists of the level of cooperation, the community's empathy, which influences to what extent the people of a community are willing to participate in a DR program [3, 7, 8, 190]. In addition to the social cohesion, the emotion of the people, i.e, the level of their satisfaction is significantly important and can influence their willingness to participate in a DR program [2, 4, 5, 191]. Hence, there is a need to consider the level of satisfaction (emotion), and cooperation of the people in the DR study. However, in the literature, the main optimization considered is minimizing the cost of power generation or the emissions while ignoring the social science aspect of DR. We introduce a new objective function of social well-being. As we discuss in the next section, a decrease in cost and emissions can lead to an increase in social well-being. A social DR program aims to achieving the maximum level of community well-being.

To model the satisfaction, emotion and cooperation of the community and their effect on a DR program, we propose to use an artificial society, which has generally been recognized as a promising method in sociology. Specifically, we build an artificial society based on theories from psychology, social and neuroscience. We use the bottom-up approach in modelling, where we build our model from the theory, not top-down, from the data. We have based our model on Barsade's theory [50] of emotional contagion and use the absorption model of emotional spread to model the collective behavior and community emotion as proposed in [2]. We adopt the term of emotional spread ,or influence, from here on, as the word contagion can be misleading in explaining the spread [192]. According to Barsade, group emotion is viewed as a combination of personal feelings [50]. The essential features that are discussed are associated with group homogeneity and heterogeneity, minimum, maximum, and mean level of each agent's emotional state and moods. A high level of satisfaction and cooperation of the consumers is associated with a high level of their participation in DR programs. In addition to model the emotion (here, satisfaction) and cooperation, we consider the social diffusion inside a community based on diffusion neurons in neuroscience [193, 194]. The people in a community are connected to each other through mass media platforms and other communication devices. Social diffusion means that the high level of satisfaction of one consumer has a positive effect on that of other consumers and vice versa [3]. During a disaster, we should consider community resilience instead of social well-being as an objective function. It means that the consumers participate in the DR program to decrease the various type of losses during a specific class of disturbance. As a result, in a DR program, there is a trade-off between social well-being, community resilience, sustainability, economic, reliability, and frequency stability.

The literature considers three different motivations, i.e., cost, frequency, and emissions, for the initiation or involvement in DR programs. For instance, [71, 170, 195] consider decreasing electricity cost as an incentive to motivate consumers to participate in a DR program. Frequency stability as ancillary service is another motivation to initiate a DR program [196]. A few papers have suggested DR based on emission [189, 197]. It targets wealthy people who are concerned about environment degradation. In this chapter, the incentives of consumers to participate in a DR program are a decrease in the electricity cost or an increase in sustainability. Most papers dealing with the sustainability aspect of a DR program aim to decrease the emission of CO_2. Here, we consider three indexes of sustainability, i.e., pollution, DALY, and exergy, which have a high effect on social life. One of the primary aims of sustainability is to decrease air and water pollution. Nowadays, coal accounts for about one-quarter of the world's total primary energy supply, and it is estimated that its share will not change substantially until 2030 [198]. Coal-fired power plants release fly ash, bottom ash, boiler slag, and flue gas emission control wastes. They release zinc and copper, arsenic, boron, mercury, selenium, and lead, resulting in severe water pollution, which induce toxicity to fish and brain damage in mammals [199], neurological disorders, and piccka-piccka disease [200]. In addition to water pollution, we consider air pollution by NO_x and SO_2. The second index of sustainability, i.e., DALY, investigates the effect of power plants on the physical health [201]. The third index of sustainability, exergy, which is ignored in the literature, is considered. From an exergetic point of view, it is electricity rather than steam that should be used when calculating the performance of a power plant. Although energy only converts from one form to another, the exergy can decrease. As a result, various types of outputs have different values. The outputs with higher quality or exergy per unit energy are desirable. Using exergy-based indicators in DR-program increase the effectiveness of energy resource use in power systems.

6.2 Environomic-Based Social DR

In this section, we develop an optimization model for environomic-based social DR. For the electric utilities, the motivation to initiate DR programs is to achieve a specified marginal level of load shaving, Ξ, and to enhance sustainability. For the end-users, the motivation to engage in a DR program is peak time rebates of the price of electricity or environmental preservation. Hence, the objective function of the problem is to minimize the level of dissatisfaction of the end-users with DR, that is,

$$\mathbf{Min} \sum_t R_{tn} \tag{6.1}$$

where R_{tn} is the dynamic change of the level of dissatisfaction of the consumers and prosumers (consumers who own distributed energy resources) over time t and for load n. It is expressed as

$$R_{(t+1)n} = \frac{h(R_{tn})}{\varpi^{rr}}(\hat{R}_{tn} - R_{tn})\kappa^t + R_{tn}, \tag{6.2}$$

where $h(R_{tn})$ denotes the social influence of dissatisfaction, ϖ^{rr} denotes weighting factor of social contagion, t denotes the time, n denotes the load, κ^t denotes the time coefficient such that $\kappa^t \leq \frac{1}{n-1}$ as indicated in [82], and $\hat{R}_{tn}$ denotes the amount of the effect of dissatisfaction diffusion on the active consumers and prosumers, which in turn is a function of cooperation, peak time rebates of the price of electricity, and sustainability . It is given by

$$\begin{aligned} \hat{R}_{tn} = & \underbrace{\varpi^{rr}\left(\frac{\sum_m \gamma^R_{tnm} R_{tm}}{\sum_m \gamma^R_{tnm}}\right)}_{Social\ contagion} + \underbrace{\varpi^{cr}(1 - C_{tn})}_{Cooperation} \\ & + \underbrace{\varpi^{pr}\left(1 - \left(\frac{\sum_i 0.5\alpha_{\Delta t_i} \hat{d}_{\Delta t_i n}}{\bar{C}}\right)\right)}_{Rebate} + \underbrace{\varpi^{sr}(1 - S_t)}_{Sustainability}, \end{aligned} \tag{6.3}$$

where ϖ^{rr}, ϖ^{cr}, ϖ^{pr}, and ϖ^{sr} are weighting factors. Here, γ^{R} denotes the emotional spread, which is the weighted dissatisfaction of each agent based on [191]. The social diffusion is discussed in detail in [4, 5]. The dependence between the emotion and cooperation is discussed in [6, 7, 8, 9]. Besides, we explain the terms of rebate and sustainability as follows:

Rebate (peak time rebates of the price of electricity), $\alpha_{\Delta t_i}$: it motivates the shift of the load from time t_{i-1} to time t_i, denoted as Δt_i. Here, $\hat{d}_{\Delta t_i n}$ and $\bar{C}$ are the load shifting. Because the number of end-users participating in DR to achieve enhanced sustainability may not be sufficient, there is another type of motivation, i.e., rebates of the price of electricity. In this case, when the end-users save cost, their level of satisfaction is increased and, in turn, they are willing to engage in DR. The price of electricity depends on their initial level of satisfaction (to electric utilities) and cooperation. In the case study, we will further investigate this topic.

Sustainability: S_t, in Eq. (8.4) consists of four terms defined as follows:

$$\begin{aligned} S_t = & \underbrace{\frac{\varpi^1}{\overline{S}^1}\sum_k(\kappa^{NO_x}P_{tk} + \kappa^{SO2}P_{tk})}_{NO_x\, and\, SO_2\, emissions} + \underbrace{\frac{\varpi^2}{\overline{S}^2}\sum_k \kappa^w P_{tk}}_{Water\, pollution} \\ & + \underbrace{\frac{\varpi^3}{\overline{S}^3}\sum_k \kappa^{NO_x}\varrho^{NO_x}P_{tk}}_{DALY} + \underbrace{\frac{\varpi^4}{\overline{S}^4}\sum_k \frac{P_{tk}}{\eta_k}}_{Exergy} \end{aligned} \tag{6.4}$$

where κ^{NO_x} (Kg/MW), and κ^{SO_2} (Kg/MW) are linear coefficients associated with the amount of NO_x, and SO_2 emissions particular to each power plants. κ^w (Kt/MW), and η_k are coefficients of water pollution and exergetic efficiency, respectively. Note that, κ^w is the release of effluents from the fuel combustion residue per MW [198]. P_t^u denote the power produced by various types of power plants. ϖ^1, ϖ^2, ϖ^3, and ϖ^4 are weighting factors getting value between 0 and 1. $\overline{S}^1$, $\overline{S}^2$, $\overline{S}^3$, and $\overline{S}^4$ are maximum value of air pollution, water pulsations, DALY, and the exergy generated by the power plants, respectively. Let us express the related terms in per units. The first term of Eq. (8.5) is associated with the air pollution and SO_2, and NO_x emissions [201]. The second term is related to water pollution [198, 199, 200]. The third term is related to DALY. These terms consider the effect of the power plants on the physical health of the community. The last term is associated with exergy. Renewable energy has a higher level of efficiency. i.e, η_k [201]. In this plan, some end-users are willing to shift their demand to the hours that enhance the sustainability indexes. Hence, because these end-users have contributed to the enhancement of sustainability by shifting their demand, their satisfaction level is increased and their aim is fulfilled.

The level of cooperation of the end-users to participate in a DR program is obtained by

$$C_{(t+1)n} = -\eta(R_{(t+1)n} - R_{tn})\kappa^t + C_{tn}, \tag{6.5}$$

where κ, $\in$ [0,1], is the dynamic speed factor of the cooperation. The final demand after shifting d_{tn} can obtained by

$$d_{tn} = \tilde{d}_{tn} + \sum_i \hat{d}_{tin}, \tag{6.6}$$

where $\tilde{d}_{tn}$ denote the predicted load of end-users. It is noted that if $\alpha_{ti} \geq 0$, $\hat{d}_{tin} \geq 0$ and vice versa. The maximum amount of load shifting from t to other time of day is obtained by

$$\sum_i \hat{d}_{tin} \leq (1 - (1 - C_{tn})R_{tn})\tilde{d}_{tn} \tag{6.7}$$

The constraint related to satisfying the marginal level of load shaving, i.e., Ξ_n, is expressed as

$$\frac{24 d_{tn}}{\sum_t \tilde{d}_{tn}}) - 1 \leq \xi_n, \tag{6.8}$$

The power balance is provided by

$$\sum_k P_{tk} - \sum_n d_{tn} = 0, \tag{6.9}$$

The constraint related to the real power maximum value of the kth type of power plants,

$\bar{P}_k$, is expressed as

$$0 \leq P_{tk} \leq \bar{P}_k, \tag{6.10}$$

Noted that $h(R_{tn})$, ϖ^{rr}, $\hat{R}_{tn}$, $R_{tn})$, κ^t, γ^R, ϖ^{rr}, ϖ^{cr}, ϖ^{pr}, ϖ^{sr}, C_{tn}, S_t, ϖ^1, ϖ^2, ϖ^3, ϖ^4, η_k, and Ξ_n take values within the interval

01

. Besides, 0 means the lowest level of variables (e.g., dissatisfaction, cooperation) while 1 is their highest level. We start the validation process of our artificial society, with verifying our computational model outcomes in Case Study 1 below with those from [4]. In addition, we verify our model against the model proposed by *Chao* and *Liu* [5]. In the next section, the purpose of the case study is to show the patterns of emotional spread and cooperation of end-users by participating in DR and their effect on the load shaving, utility cost, and sustainability.

6.3 Case Study

There are three active consumers participating in DR. Consumers 1 and 3 are interested in DR based on price, while consumer 2 is interested in DR based on emission reduction, that is, sustainability. The level of dissatisfaction and cooperation of Consumers 2 and 3 is assumed to be 0.5 (medium level), while those of Consumer 1 is equal to 0.45. The marginal level of load shaving is considered to be 0.2. The sustainability-based factors of various power plants, i.e., Ultra Super-critical Coal (USC), Natural Gas Combined Cycle (NGCC), Wind turbine (WT), and Solar thermal panel (STP) [198, 199, 200, 201]. are provided in Table 2.

The result of the DR schedule for the three types of consumers is shown in Figure 6.2. This figure displays the dynamic change of the level of dissatisfaction and cooperation, the

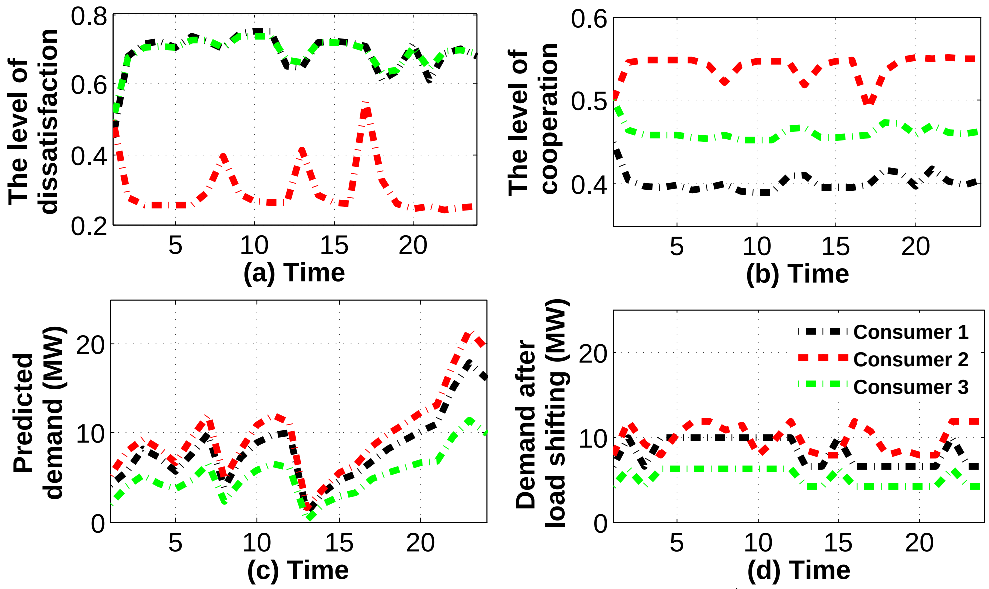


Figure 6.2: The results of the environomic-based social DR: a) the level of dissatisfaction. These patterns are consistent with the discussions given in [2, 3, 4, 5]; b) the level cooperation. These patterns are consistent with the discussions given in [6, 7, 8, 9]; C) the predicted demand; and D)the demand after load shifting. These patterns are emergent effects provided by the model outcomes showing the effect of behavior of the costumers.

predicted demand, and the demand after shift for 3 active end-users. According to this figure, because the DR for Consumers 1 and 3 are price-paced with approximately the same initial values, the dynamic change of their level of dissatisfaction and cooperation have the same trends. We can observe they shave the predicted load, especially for an hour after 20, and the flat load curve is obtained by shifting the demand based on price. For the hour the electricity price is high, the price–based DR increases the level of satisfaction of customers who participate in this program. The final demand of the Consumer 2 is shifted to an hour that electricity is produced by renewable energy to fulfill sustainability goals.

The consumers, by shifting their load to hours that renewable energy generates electricity, induce the maximum sustainability index as much as 0.754. The NO_x and SO_2 emissions are equal to 23.569, and 39.282 Kg, respectively. The effluents for water pollution is equal to 62.411 kt. The amount of Disability-Adjusted Loss of Life Year (DALY) and exergy is equal to 3.299 $\times 10^{-5}$ DALY, and 1254.93 MW, respectively. DR cost for utility as much as 993

Table 6.1: The average level of dissatisfaction, and cooperation, sustainability indexes, and utility cost for various scenarios. In case 1, Ξ_2 is equal to 0.9 while that of other cases is equal to 0.5.

Case	Inputs				Outputs							
	R_0	C_0	Υ (Cost increase rate)	$\Xi_{1,3}$	R	S	Utility cost ($\times 10^3$ \$)	NO_x (Kg)	SO_2 (Kg)	Water pollution (Kt)	DALY ($\times 10^{-3}$ DALY)	Exergy (MW)
1	0.1	0.9	1	0.5	0.398	0.824	1.605	21.448	35.747	56.794	0.030027	1207.397
2	0.1	0.9	1	0.5	0.399	0.803	1.564	22.206	37.01	58.801	0.031088	1223.485
3	0.1	0.9	1	0.2	0.439	0.782	0.855	22.983	38.306	60.86	0.032176	1240.208
4	0.5	0.1	1	0.2	-	-	-	-	-	-	-	-
5	0.5	0.1	1	0.3	0.68	0.775	0.98	23.246	38.743	61.554	0.032543	1243.248
6	0.5	0.1	2	0.2	0.664	0.777	1.53	23.161	38.602	61.33	0.032425	1242.942
7	0.9	0.1	2,3	0.2	-	-	-	-	-	-	-	-
8	0.9	0.1	4	0.2	0.613	0.765	2.938	23.639	39.398	62.596	0.033094	1252.563

\$. Each of the end-users 1, 2, and 3 participate in DR as much as 3.365, 3.617, 2.254 MWh. The average level of dissatisfaction of consumers increases to 0.559 to reach the marginal level of load shaving that is 0.2. When the marginal level of load shaving forced by the utility is increased to 0.5, the average level of dissatisfaction of consumers decreases to 0.518.

Table 6.1 provide various outputs of environomic-based social DR for different initial values for the dissatisfaction, R_0 , and cooperation, C_0 , of active end-users, and motivation price factor (Υ) (to encourage the end-users to participate in cost-based DR), and the marginal level of load shaving Ξ_n. Note that we use $\Upsilon\alpha_{ti}$ instead of α_{ti} in Eq. (8.4). Here, S is a sustainability index showing the capacity of used renewable energy. Utility cost is the cost that utility should spend to motivate costumers to participate in the DR program.

Because the marginal level of load shaving for emission-based DR, i.e., Ξ_2, is decreased from 0.9 in Case 1 to 0.5 in Case 2, the index of sustainability, S, is reduced by 2.54%. As expected, all of sustainability metrics, i.e., NO_x, SO_2, water pollution, DALY, exergy, are increased. When $\Xi_{1,3}$ decreases from 0.5 to 0.2 in Case 3, the level of dissatisfaction of the end-users increases. Furthermore, because of the high level of limitation, they cannot participate freely in DR to save more cost. As a result, they participate less in DR. Utility cost decreases in this case. Different communities and societies have different cultures and characteristics, influencing the level of dissatisfaction and cooperation. When the level of dissatisfaction and cooperation of end-user is as low as 0.5 and 0.1 in case 4, the marginal level of load shaving of 20%, cannot be fulfilled by the proposed motivation price. In this situation, the utilities should increase the marginal level of load shaving to 30%, i.e., Case 5, or they must increase the motivation price by 20%, i.e., Case 6, to reach their aim. Case 6 costs more for utilities. As we can see, the social behavior of end-users also affects the cost of utilities and, therefore, the economic aspects of power systems. When the level of dissatisfaction of people is high, the situation even worse. The utility must increase the motivation price by at least 40% to fulfill its aims (appropriate load shaving).

We modeled the social features of the community participating in DR based on social science, psychological, and neuroscience theories. We verified our model first by checking that the expected patterns from the literature were outputted by our model then by soft validation. These are the first two steps in the validation process. The trends in our model output matched with the expected trends discussed in the literature. After that, we conducted a sensitivity analysis to observe the relative predictive strength of the variables in our model.

6.4 Conclusions

In this chapter, we leveraged an artificial society based on the computational social science approach to model the behavior of active end-users who participate in the DR. It shows the potential of using computational social science in power system operation. The inherent feature of each end-user consists of the level of satisfaction and cooperation. These features can bring both economic and sustainability benefits for the utility and the society as a whole. In addition, these features make the community more resilient. In the environomic-based social DR, some consumers participate in DR to increase the peak time rebates of the price of electricity. Other consumers participate in DR to decrease air pollution, water pollution, DALY, and exergy. By transparently basing our model on theories from psychology, social and neuroscience, soft validation, and sensitivity analysis, we increase confidence in our model by our peers. The engagement of end-users in DR depends not only on incentives, such as increased rebate and sustainability but also on the degree of satisfaction, customer cooperation, and social diffusion.

Chapter 7

Validation of Socio-Technical Power System Resilience

Power systems serve social communities that consist of residential, commercial, and industrial customers. The social behavior and degree of collaboration of all stakeholders, such as consumers, prosumers, and utilities, affect the level of preparedness, mitigation, recovery, adaptability, and, thus, power system resilience. Nonetheless, the literature pays scant attention to stakeholders' social characteristics and collaborative efforts when confronted with a disaster and views the problem solely as a cyber-physical system. However, power system resilience, which is not a standalone discipline, is inherently a cyber-physical-social problem, making it complex to address [122]. To this end, in this chapter we develop a socio-technical power system resilience model based on neuroscience, social science, and psychological theories and using the threshold model to simulate the behavior of power system stakeholders during a disaster. We calibrate and validate our model using Tenfold cross-validation on datasets of hurricane Harvey of Category 4 that hit Texas in August 2017 and hurricane Irma of Category 5 that made landfall on Florida in September 2017. We retrieve these datasets from Twitter and GoogleTrend and then apply natural language processing and language psychology analysis tools to deduce the social behavior of the end-users.

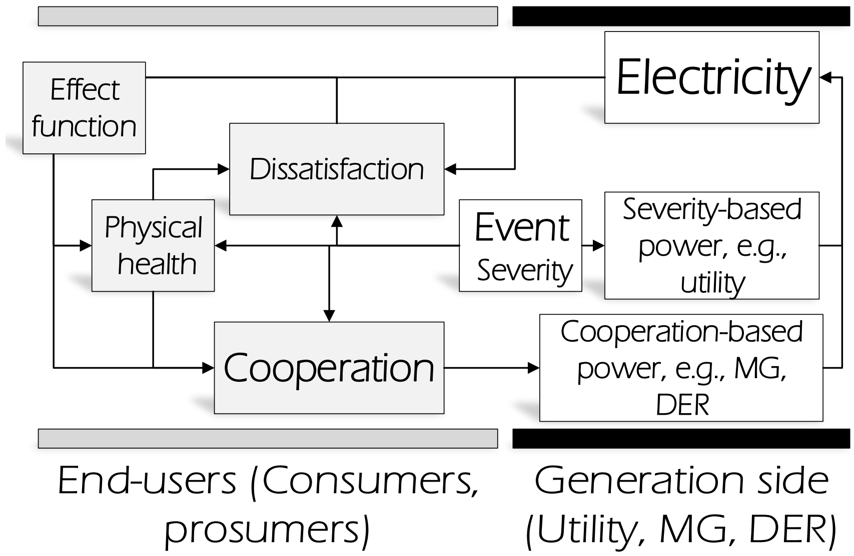


Figure 7.1: Interdependence between disasters, generational factors, and end-user behavior.

7.1 Socio-Technical Power System Resilience

To capture the dynamical change in consumer, prosumer, and utility behaviors in response to a disaster, we develop a multi-agent-based dynamical model. This socio-technical model is beneficial for capturing emergent processes and for analyzing the multi-dimensional aspects of power system resilience. Figure 8.1 illustrates the interdependence between disasters, generational factors, and end-user behavior. We consider dissatisfaction, cooperation, and physical health to be end-user social behaviors. Additionally, we consider two distinct types of electricity generation, namely, (1) severity-dependent type as exemplified by electricity generated by utilities and cooperation-dependent type as exemplified by electricity generated by Microgrids (MGs) and Distributed Energy Resources (DERs). Indeed, the performance of the utility power system to serve the load decreases with the severity of the disaster since the latter typically damages part of the electric infrastructure. As for the MGs and DERs, they are less affected by the disaster and therefore, can cooperate with electric stakeholders and share electricity during time of shortages.

Prior to discussing the socio-technical power system resilience model, we will introduce next the threshold model using logistic function to consider the socio-technical effect, which is widely used in sociology, medicine, biology, ecology and neural networks [202, 203].

7.1.1 Threshold Model Using Logistic Function

The threshold model using logistic function allows us to set up thresholds beyond which the socio-technical behavior changes [4, 204]. For instance, a power outage can result in consumer and prosumer dissatisfaction if the level of outages exceeds a given threshold, $\phi(X)$. The logistic value, $\psi(X)$, of each factor on the resilience-related feature, X, is expressed as

$$\psi(X) = \frac{1}{1 + e^{-\sigma^X (X_{ti} - \phi^X)}} \tag{7.1}$$

Additionally, we define $\psi^{'}(X) = 1 - \psi(X)$.

7.1.2 The Socio-Technical Power System Model

Eqs.8.4-8.11 describe the dynamical changes in socio-technical behaviors. Note that all variables, parameters, and functions defined thus far take values between 0 and 1.

$$\Delta(X^E_{ti}) = \alpha^{'E}_{ti}(f(\hat{X}^E_{ti}, X^E_{ti}) - X^E_{ti})\Delta t, \tag{7.2}$$

$$\alpha^{'E}_{ti} = \frac{\sum_j \alpha^E_{ij} X^E_{tj}}{\sum_j \alpha^E_{ij}}, \tag{7.3}$$

$$f(\hat{X}^E_{ti}, X^E_{ti}) = \eta^E[X^O_{ti}(1-(1-X^E_{ti})(1-\hat{X}^E_{ti})) \\ +(1-X^O_{ti})(\hat{X}^E_{ti}X^E_{ti})] + (1-\eta^E)\hat{X}^E_{ti}, \tag{7.4}$$

$$\hat{X}^E_{ti} = w^{EE}(\frac{\sum_j \alpha^E_{tij} X^E_{tj}}{\sum_j \alpha^E_{tij}}) + W^E(1 - X^C_{ti}\psi(X^C_{ti})) \\ (1 - X^P_{ti}\psi(X^P_{ti}))\ (1 - Q^e_{ti}\psi(Q^e_{ti}))(X^S_{ti}\psi(X^S_{ti})). \tag{7.5}$$

$$\Delta(X^P_{ti}) = \eta^P \psi^{'}(X^E_{ti})[Q^e_{ti}(1-X^S_{ti}) - P_{ti}]\Delta t. \tag{7.6}$$

$$\Delta(X^C_{ti}) = \eta^C \psi(X^E_{ti})\psi(X^P_{ti})\psi(X^S_{ti})[X^O_{ti}(1-Q^e_{ti}) - X^C_{ti}]\Delta t. \tag{7.7}$$

$$\Delta(Q^{DER}_{ti}) = \alpha^{DER}_{ti}(\alpha^{DER}_{ti} - Q^{DER}_{ti})\Delta t, \tag{7.8}$$

$$\alpha^{DER}_{ti} = \frac{\sum_j \alpha^E_{ij} X^C_{tj} Q^{DER}_{tj}}{\sum_j \alpha^E_{ij} X^C_{tj}}. \tag{7.9}$$

$$Q^e_{ti} = \varpi Q^{DER}_{ti} + (1-\varpi)X^S_{ti}\psi(X^S_{ti})Q^U_{ti}. \tag{7.10}$$

Eqs. 8.4- 8.5 are related to the dynamical changes in end-user dissatisfaction levels, where X^E_{ti} is associated with the i-th consumer/prosumer dissatisfaction at time t with an incremental change, $\Delta(X^E_{ti})$. Note that a value of 0 or 1 for X^E_{ti} indicates a low or a high level of dissatisfaction, respectively. Here, $f(\hat{X}^E_{ti}, X^E_{ti})$ denotes the magnitude of the absorption and amplification's effect on the end-user emotion [130]; $\hat{X}^E_{ti}$ denotes the magnitude of the effect of dissatisfaction diffusion among consumers, prosumers, and external features on the end-user dissatisfaction. Additionally, α'^E_{ti} denotes the strength of the link between two consumers/prosumers i and j. A value of 1 for α^E_{ij} indicates a strong connection. In Eq. 8.5, X^O_{ti} denotes an agent's optimism. A X^O_{ti} value of 1 indicates that the consumer/prosumer is optimistic. The first term (with coefficient of η^E) represents the amplification effect while the final term (with coefficient of $(1 - \eta^E)$) represents the absorption effect. The former effect is based on Fredrickson's broaden-and-build theory, and includes upwards and downwards spirals [130, 205]. If there is no external disaster within the group, the bottom-up absorption effect may be used. On the other hand, when an unexpected event occurs, the amplification effect should be considered as well. Combining the two effects makes sense for disaster resilience and planning. Eq. 8.5 consists of two components, namely the social diffusion and the impact of external factors. Social contagion or diffusion implies that end-users' dissatisfaction is contingent on the dissatisfaction of other consumers and prosumers. Additionally, the dissatisfaction is influenced by external factors, i.e., cooperation, X^C_{ti}, [6], physical health,X^P_{ti}, [34], and accessibility to electricity, Q^e_{ti}, [206] and severity of a disaster, X^S_{ti}.

Eq. 8.6 is related to the dynamical changes in physical health, $\Delta(X^P_{ti})$, where η^P denotes the dynamical coefficient of physical health. The latter is influenced by the level of dissatisfaction, the severity of a disaster, X^S_{ti}, and the access level to electricity, Q^e_{ti}, [1]. Eq. 8.9 is related to the dynamical changes in the level of consumer and producer cooperation, $\Delta(X^C_{ti})$. The level of cooperation is a function of the positive or negative emotion level based on the narrowing hypothesis of Fredrickson's broaden-and-build theory [81]. Indeed, cooperation is conditional on dissatisfaction [6], physical health [141], and the level of optimism among end-users [207], and access level to electricity by the end-users, Q^{e}_{ti}.

Eqs. 8.10-8.11 model the dynamical changes of accessibility to electricity by the end-users. The primary energy sources that supply electricity to consumers include utilities, MG, and DERs. Utilities are the primary suppliers of the demand of electricity. However, during disasters, some communities may lose access to utility-provided electricity. In this case, depending on their level of cooperation, end-users who own DERs, namely prosumers, may wish to share their electricity with consumers and critical loads that are not connected to the grid, but they are connected to them. Here, $\Delta(Q^{DER}_{ti})$ denotes the dynamical changes in accessibility to DER-generated electricity. A value of 1 for Q^{DER}_{ti} indicates that the consumer/prosumer makes full use of the DERs' capacity to meet its demand. Additionally, available electricity, Q^{e}_{ti}, is the total amount of electricity supplied by utilities and consumers, whereas Q^{U}_{ti} is the amount of electricity generated by utilities, which varies according to the severity of a disaster. A value of 1 for Q^{U}_{ti} indicates that utilities are fully utilizing their capacity to meet consumer/prosumer demand. Additionally, ϖ is the fraction of an end-user's total electricity consumption that is supplied by DERs.

In this section, we have presented a mathematical model of the socio-technical power system resilience. In the following section, we discuss how to calibrate and validate that model using Tenfold cross-validation.

7.2 Calibrating and Validating the Socio-Technical Power System Resilience Model

The process for calibrating and validating the socio-technical power system resilience model proposed in Section II is depicted in Figure 7.2. Prior to validating the model, we measure the social behavior of the end-users. Social scientists and cognitive, personality, clinical, and social psychologists use surveys and direct qualitative questions to measure social behavior in conventional social science. While the surveys provide us with an appropriate dataset, they exhibit several significant drawbacks. In practice, they are costly and time-consuming to execute. Typically, they are only composed of subsets of the society. Last but not least, individuals have varying interpretations of the level of social behavior. On the other hand, in the new era of language psychology, utilizing community communication via social media platforms such as Twitter and Facebook can circumvent survey limitations and provide a rich dataset. This social media platform is being used to deduce linguistic and psychological patterns associated with social behavior. Due to the strong correlation between linguistic patterns and personality and psychological state in contemporary social science, social behavior is estimated using linguistic patterns. The words and language we use on a daily basis reflect our internal thoughts, our quality of life, our personality, our cognitive styles, our emotions, and our psychological and social behavior. Now, let us utilize the Tweeter and GoogleTrend datasets in order to analyze the resiliency during Hurricanes Irma and Harvey. We retrieve tweets about the power system by filtering them and utilizing the hashtag search for #electricity, #power system, #electric, #DER, #power plant, #distributed generation, #micro grid, #power utility, #electric utility, #renewable energy, #blackout, #power grid, #power network.

Following the collection of the raw dataset, we employ psychology-based natural language processing, specifically the Linguistic Inquiry and Word Count (LIWC), to extract end-users social behavior, including dissatisfaction, cooperation, and physical health.

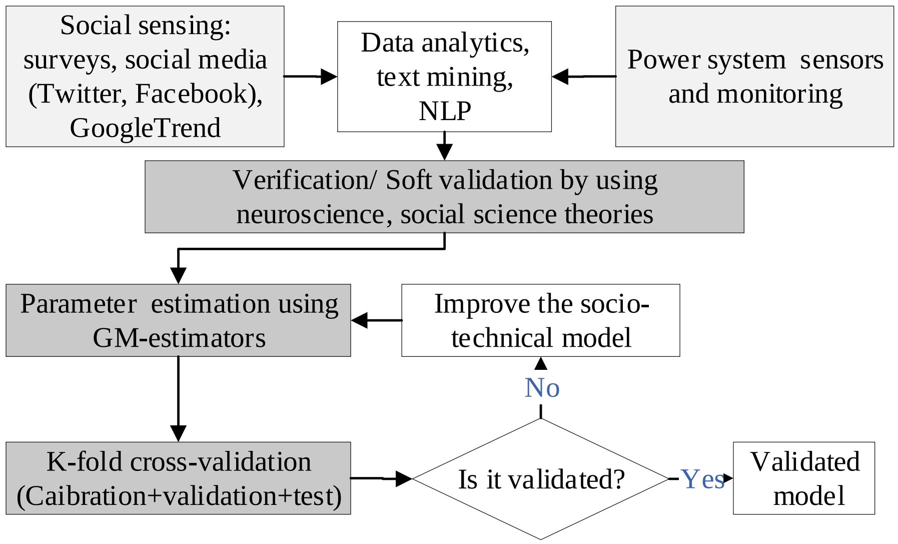


Figure 7.2: Validation of the cyber-physical-social power system

7.2.1 Dissatisfaction

Disasters such as the 2021 Texas winter storm, Hurricane Irma, and Hurricane Harvey result in end-user dissatisfaction. The latter is caused by negative emotional traits, such as anxiety, sadness, and anger [208, 209, 210]. Using the Tweeter dataset, we quantify spatial-temporal dissatisfaction by quantifying these features. The measure of dissatisfaction is calculated by averaging the normalized values of anxiety, sadness, and anger. By using the categories of the LIWC, the level of fear is obtained by

$S^E = LIWC['anx']/LIWC[`WC'],$

where $LIWC['anx']$ means the category of ”anx” from outputs of LIWC.

7.2.2 Cooperation

According to psychological research on language, the more words used in communication, the greater the level of agreement and cooperation. The increased use of complex words and words with more than six letters implies a decrease in communication efficiency, cooperation, and social interaction [211]. Additionally, the plural form of the first person indicates group interaction and cohesion [212]. Increasing the use of social process languages, such as family and friend-related terms, implies an increase in social interaction, engagement, and cooperation[213, 214]. Finally, assent-related language promotes group consensus, interaction, and cooperation [215]. Hence, the level of cooperation is obtained by

$X_C = (LIWC['WC'] - LIWC['Sixltr'] + LIWC['we'] + LIWC['social'] + LIWC['family'] + LIWC['friend'] + LIWC['assent'])/(LIWC['WC'])$.

7.2.3 Physical Health

According to psychological research on language, increased use of the first-person singular can imply physical pain [216]. Individuals who are physically ill frequently draw attention to themselves. The increased use of motion, leisure, and work-related terms reflect an increase in physical activity and health. Additionally, the more health-related words a person uses, the better their physical health. The increased use of positive body-related terms implies physical health [217, 218, 219, 220]. By using the categories of the LIWC, the level of physical health is obtained by

$S^P = (-LIWC['i'] + LIWC['health'] + LIWC['leisure'] + LIWC['work'] + LIWC['body'] + LIWC['motion'])/LIWC[`WC']$.

The calibration and validation process can be summarized as follows:

Step1) Amassing disaster-related data on power systems: First, we collect all tweets about the considered disaster. Then, we retrieve tweets about the power system via a hashtag or

related word search. Additionally, we utilize GoogleTrend as a second social sensing tool.
Step 2) Resilience-related text cleaning: To improve the effectiveness of the result for linguistic and behavioral patterns, we use natural language processing to remove URLs, email addresses, dates, punctuation, and stop words from retrieved tweets about power system response and recovery. After that, we tokenize all tweets for the purpose of word stemming.
Step3) Measuring social behavior: We leverage language psychology analysis tools, such as LIWC, to assess social behavior from the cleaned text. We look for social patterns associated with resilience using the following categories: anxiety, sadness, anger, First-person singular, health, leisure, work, body, motion, word count, words >6 letters, first-person plural, social process, family, friends, exclusive, and assent.

By using the categories of the LIWC, the level of fear is obtained by
$S^E = LIWC['anx']/LIWC[`WC'],$
where $LIWC['anx']$ means the category of "anx" from outputs of LIWC.

Hence, the level of cooperation is obtained by
$X_C = (LIWC['WC'] - LIWC['Sixltr'] + LIWC['we'] + LIWC['social'] + LIWC['family'] + LIWC['friend'] + LIWC['assent'])/(LIWC['WC']).$

By using the categories of the LIWC, the level of physical health is obtained by
$S^P = (-LIWC['i'] + LIWC['health'] + LIWC['leisure'] + LIWC['work'] + LIWC['body'] + LIWC['motion'])/LIWC[`WC'].$

Step 4) Concluding social behavior: We begin this step by dealing with missing values via an interpolation approach. Specifically, we use the foo

In order to fairly consider each category to estimate community resilience, we normalize the measure of each category using min-max scaling [221]. Given a feature $x(t)$, an arbitrary interval of values, i.e., $[\alpha, \beta]$ based on min-max scaling, a normalized measure is obtained by:

$$x'(t) = \alpha + \frac{(x(t) - x_{\min}(t)))(\beta - \alpha)}{x_{\max} - x_{\min}}, \tag{7.11}$$

where we set $\alpha = 0$ and $\beta = 1$, and $x_{\max}$ and $x_{\min}$ are the maximum and minimum measure collected during the period considered, and $x'(t)$ is a normalized measure as a real number in $[0, 1]$. After that, we deduce spatial-temporal trends in end-user social behavior during a disaster.

Step 5) Soft validation: We verify the model using soft validation.
Step 6) Parameter estimation: We calibrate the model using a Huber M-estimator.
The Huber loss are as follows:

$\theta = argmin(\sum log(f(x))) = argmin(\sum \rho(x_i, \theta))$

and

$$\rho(x_i, \theta) = \begin{cases} \frac{1}{2}x_i^2 & |x_i| \leq \sigma \\ \sigma(|x_i| - \frac{1}{2}\sigma) & \text{otherwise} \end{cases} \tag{7.12}$$

Step 7) Validation by cross-validation: We validate the model using tenfold cross-validation. We classify 60% of data as calibration data, 20% as validation data, and 20% as test data.
Step 8) Updating the model: If the proposed socio-technical power system resilience model

does not perform well after cross-validation, we modify the model accordingly.

7.3 Multi-Agent-Based Modelling to Evaluate the Community Resilience

Algorithm 1 implements the social well-being, which characterizes the community resilience, by using multi-agent-based modeling. The society is made of a set of communities, each of them has a distinct population, geographic exposure to a specific disaster, inter- and intra-community behavior diffusion, and social well-being characteristics. The latter include the level of fear, the information-seeking behavior, the risk perception, flexibility, cooperation, experience, willingness to share electricity during disaster, and physical health. In this model, these characteristics are assumed to be Gaussian random variables. Similarly, the level of inter- and intra-community behavior diffusion are assumed to be Gaussian variables. Given the mean and the standard deviation of each of these random variable and the population size, samples are generated via Monte Carlo (MC) simulations. 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. It also may raise the level of fear and, in turn, it affects the risk perception of the individuals of that community. 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. 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.

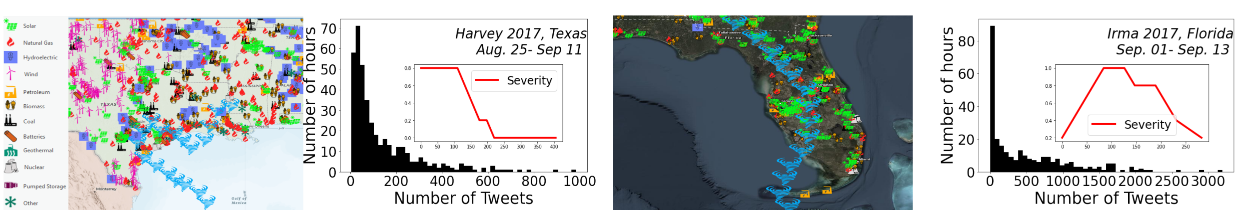
7.4 Calibrating and Validation the Model by using Datasets from Hurricanes Harvey and Irma

We collect a variety of data samples for Hurricanes Harvey and Irma. We retrieve power-system-related tweets from Twitter's streaming Application Programming Interface (API) by leveraging hashtag search on the hashtag search on #electricity,#power system, #electric,#DER,#power plant,#distributed generation,#micro grid,# power utility, #electric utility,#renewable energy, #blackout,#power grid,#power network, from 18,336,283 tweets of Hurricane Harvey and 17,227,935 tweets of Hurricane Irma for validation purpose. We use the same words as hashtags for word-related searches. We also use Google Trend as another social sensing. Table 7.1 provides a summary of 5 samples for each hurricane.

Table 7.1: The summary of samples for Hurricanes Harvey and Irma

Sample	Social sensing	Type of search	Harvey Tweets IDs	Irma Tweets IDs
1	Tweeter	Hashtag	217	271
2	Tweeter	Word related	11500	54100
3	Tweeter	Event related	20000	30000
4	Tweeter	Word related	82000	245000
5	GoogleTrend	Word related	-	-

Hurricane Harvey and Irma's tracks, in-hurricane power plants, Tweets, and severity are depicted in Figure 8.2.



(a) Harvey track. (b) Harvey Tweets. (c) Irma track. (d) Irma Tweets.

Figure 7.3: Hurricane Harvey and Irma's tracks, in-hurricane power plants, Tweets frequency, and hurricane severity.

The following is a summary of the impact of these hurricanes:

Hurricane Harvey in Texas: Between 08/25/2017 and 09/11/2017, Hurricane Harvey struck Texas and the ERCOT territory. On 08/25/2017, it strengthened to Category 4. Like Hurricane Katrina, this hurricane is the most expensive tropical cyclone in the US history. In Texas, 1168 MW of wind energy capacity and 5679 MW of solar energy capacity in ERCOT became unavailable and energy production fell by 21%. As a result, power systems throughout ERCOT's territory experienced outages between 08/25/2017 and 08/29/2017, leaving many people without power or water. The maximum number of outages reached 309204, which affected two of ERCOT's major utilities, namely AEP Texas North Company (#20404) and AEP Texas Central Company (#3278). For these power utilities, the total number of meters, including smart and non-smart meters, is 1028900. It took about two weeks, namely from 08/29/2017 to 09/12/2017, for the power system to be restored. We extract various samples of tweets about Hurricane Harvey from the Table 7.1. Between 2:00 p.m. and 11:00 p.m. on 08/30/2017, the customer outage dataset contains missing values due to the loss of an entity website.

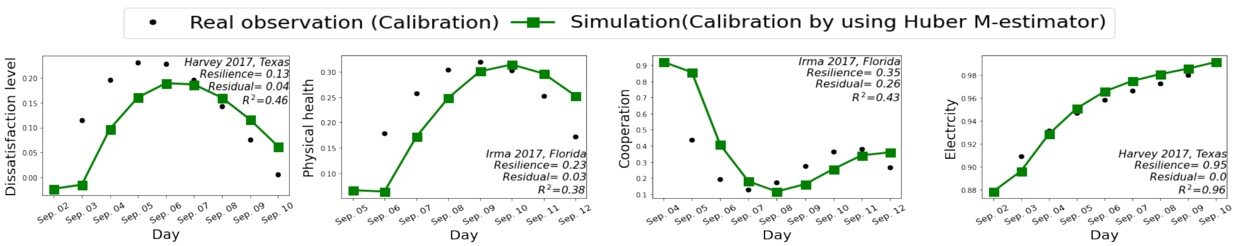
Hurricane Irma in Florida: Between 09/01/2017 and 09/13/2017, Hurricane Irma made landfall primarily in Florida and to a lesser extent in Georgia and South Carolina. Between 09/06/2017 and 09/08/2017, this storm was a Category 5 hurricane. Hurricane Irma was downgraded to a Category 3 storm before making landfall in Florida on 09/09/2017. However, on 09/10/2017, it was upgraded to a Category 4 hurricane. Hurricane Irma was then downgraded to Category 1 status on 09/11/2017. Between 09/09/2017 and 09/11/2017, power systems faced outages. It damaged several utilities, including the City of Tallahassee (TAL#18445), the Jacksonville Electric Authority (JEA#9617), Gainesville Regional Utilities (GVL#6909), the City of New Smyrna Beach (NSB#13485), Florida Power Corp. (FPC#6457), Tampa Electric Co. (TEC#18454), Seminole Electric Cooperative (SEC), Florida Municipal Power (FMPP#19804), and Florida Power & (SOCO). The recovery of the power system began on 09/11/2017 and lasted 12 days.

7.4.1 Results for the First Sample

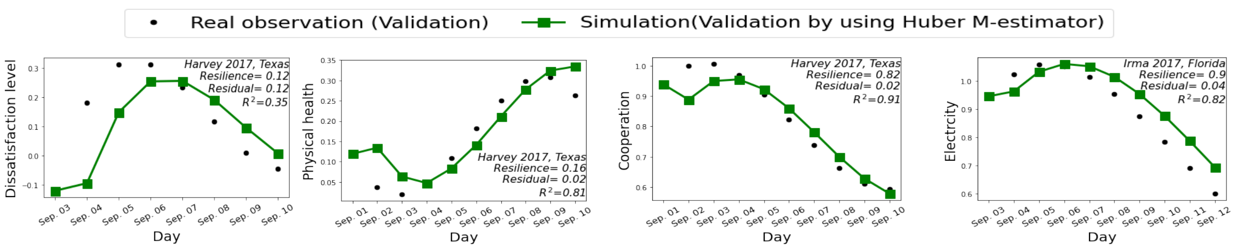
The results of a 10-fold cross-validation of the socio-technical power system resilience model using the Huber M-estimator for the first sample are displayed in Fig. 7.4. This graph depicts consumer/prosumer dissatisfaction, physical health, cooperation, and the cooperation/severity-dependent electricity using real datasets. The figure also show simulation results related to various scenarios used for calibration, validation, and testing of multi-agent-based model. Each subfigure contains information about the type of event, its resilience level, value of R^2= $1 - (RSS/TSS)$, where $RSS = \sum(y - \tilde{y})^2$, and $TSS = \sum(y - \bar{y})^2)$. We calibrate and validate the model using data obtained from both Hurricanes Irma and Harvey. Additionally, we calibrate and validate the model for Hurricanes Irma and Harvey separately. The estimated threshold level at which cooperation among end-users has an effect on dissatisfaction is equal to 0.5. Similarly, the estimated threshold levels are 0.500002, 0.500017, and 0.500071 for the effects of physical health, electricity, and disaster severity on consumer/prosumer dissatisfaction, respectively. The estimated threshold levels of electricity and severity on dissatisfaction among Florida end-users are equal to 0.499355 and 0.501454, respectively. These estimated threshold levels for ERCOT areas are equal to 0.500039 and 0.499944, respectively. Additionally, the amplification and absorption effects on the level of dissatisfaction are 0.501797 and 0.498203, respectively. The end users in the ERCOT area and Florida have an optimistic attitude of up to 0.502206. Florida end-users and utilities are less optimistic than their counterparts in Texas with an optimistic level estimated to 0.478854 versus 0.498893 for Texas. For both areas, the estimated threshold level for the effect of dissatisfaction on physical health is equal to 0.415647. Additionally, this threshold is equal to 0.494225, 0.493983, and 0.495111 for the effect of dissatisfaction, physical health, and severity on cooperation, respectively. The estimated threshold level for the effect of severity on electric utility services is equal to 0.458197. This means that if the hurricane is a category three or higher, it has a detrimental effect on the utility's performance. Additionally, approximately 100% of electricity services are cooperatively provided. The estimated threshold level for the effect of severity on ERCOT is 0.457566, while that of Florida is 0.479339. Additionally, 76% of electricity services in ERCOT is of a cooperative-type while 24% are severity-type. Indeed, ERCOT is more vulnerable to hurricane damage than Florida utilities.

Fig. 7.5 illustrates the QQ-plot for the test dataset's various socio-technical resilience-related features. It demonstrates that the simulation and the real datasets have a similar distribution. The distributions of dissatisfaction and cooperation/severity dependent electricity for the simulation case are more similar to the real case than the physical health and cooperation of the end-users.

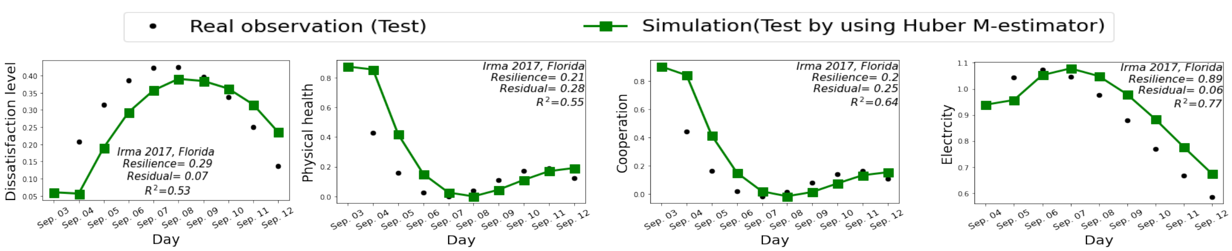
Table 7.2 shows the results of the statistical analysis using real-world and simulation datasets for calibration, validation, and test scenarios. The Shapiro-Wilk normality test demonstrates that the majority of cases follow the normal distribution except for cooperation during calibration and testing, as well as the physical health of end-users in the test scenario. Indeed, 0.75 of features exhibit normal distribution behavior. Additionally, the Pearson and Kendall tau correlations demonstrate the high degree of correlation between the simulation and the real datasets. Additionally, Student's t-test p-values (as parametric statistical hypothesis test) and Mann-Whitney U test p-values (as non-parametric statistical hypothesis test) indicate that the distribution of the socio-technical resilience-related features obtained from the real data set and simulation outputs are similar in all cases.



(a) Dissatisfaction. (b) Physical health. (c) Cooperation. (d) Electricity.

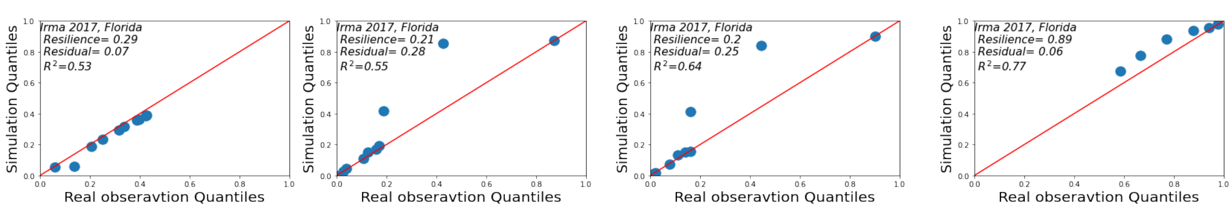


(e) Dissatisfaction. (f) Physical health. (g) Cooperation. (h) Electricity.



(i) Dissatisfaction. (j) Physical health. (k) Cooperation. (l) Electricity.

Figure 7.4: Consumers' and prosumers' level of dissatisfaction, physical health, cooperation, and the cooperation/severity-dependent level of electricity. These are determined using 10-fold cross-validation, which included calibration, validation, and test. The socio-technical power system resilience model is calibrated using a Huber M-estimator and data obtained from Hurricanes Irma and Harvey.



(a) Dissatisfaction. (b) Physical health. (c) Cooperation. (d) Electricity.

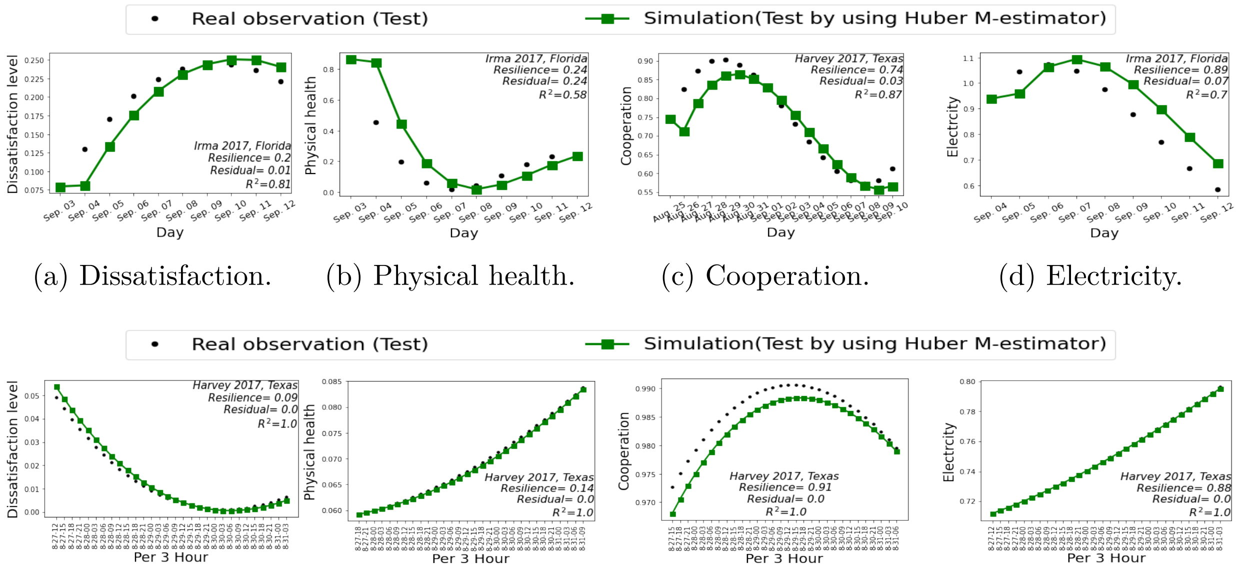
Figure 7.5: The QQ-plot depicts the level of dissatisfaction, physical health, and cooperation of consumers, prosumers, and the level of cooperation/severity-dependent electricity of socio-technical power systems resilience for the test data set.

Table 7.2: Results of the statistical analysis of socio-technical power systems resilience including Shapiro-Wilk normality test, Pearson correlation, Kendall tau correlation, parametric statistical hypothesis tests (Student's t-test), and non-parametric statistical hypothesis tests (Mann-Whitney U Test). Note that in the table, the Gaussian probability distribution is denoted as "Gauss." and the dependence between the simulation and real datasets is denoted as "Dep.".

10-fold Cross-validation	Calibration				Validation				Test			
Statistic test	X_{ti}^E	X_{ti}^P	X_{ti}^C	Q_{ti}^e	X_{ti}^E	X_{ti}^P	X_{ti}^C	Q_{ti}^e	X_{ti}^E	X_{ti}^P	X_{ti}^C	Q_{ti}^e
Real data set p-value	0.3 (Gauss.)	0.24 (Gauss.)	0.012 (not Gauss.)	0.45 (Gauss.)	0.52 (Gauss.)	0.22 (Gauss.)	0.16 (Gauss.)	0.15 (Gauss.)	0.27 (Gauss.)	0.002 (not Gauss.)	0.002 (not Gauss.)	0.28 (Gauss.)
Simulation P-value	0.17 (Gauss.)	0.07 (Gauss.)	0.036 (not Gauss.)	0.16 (Gauss.)	0.34 (Gauss.)	0.21 (Gauss.)	0.09 (Gauss.)	0.16 (Gauss.)	0.07 (Gauss.)	0.007 (not Gauss.)	0.006 (not Gauss.)	0.32 (Gauss.)
Pearson corr	0.74 (Dep.)	0.77 (Dep.)	0.81 (Dep.)	0.99 (Dep.)	0.67 (Dep.)	0.91 (Dep.)	0.96 (Dep.)	0.96 (Dep.)	0.8 (Dep.)	0.88 (Dep.)	0.89 (Dep.)	0.93 (Dep.)
kendalltau corr	0.61	0.43	0.5	1	0.57	0.73	0.82	0.78	0.64	0.64	0.68	0.77
Student's t-test p value	0.54 (same)	0.72 (same)	0.69 (same)	0.9 (same)	0.68 (same)	0.84 (same)	0.95 (same)	0.55 (same)	0.61 (same)	0.59 (same)	0.63 (same)	0.57 (same)
Mann-Whitney U Test p value	0.2 (same)	0.26 (same)	0.48 (same)	0.38 (same)	0.34 (same)	0.33 (same)	0.38 (same)	0.27 (same)	0.22 (same)	0.41 (same)	0.5 (same)	0.22 (same)

7.4.2 Summary Results for All Samples

Fig. 7.6 provides the graphs of the tenfold cross-validation of the socio-technical power system resilience model using the median estimated values of five samples and a three-hourly-based dataset for the real and simulated datasets. The results indicate that the socio-technical resilience-related features in the three-hourly-based dataset have a higher R^2 value. In other words, the 10-fold cross-validation produces more precise results than the daily datasets. This is because we calibrate the model with more data for the former case. Using the median estimated values of five samples, we found that the level of optimism is equal to 0.537192. The estimated threshold levels for the effect of electricity and disaster severity on the level of dissatisfaction among power system stakeholders are respectively 0.499162 and 0.498763. Additionally, the estimated threshold level of the effect of severity on electricity is equal to 0.45721. On the other hand, using 10-fold cross-validation on a three-hourly basis, the estimated level of optimism among the end-users is equal to 0.594039. The estimated threshold levels for the effect of electricity and disaster severity on dissatisfaction among stakeholders in the power system is 0.475009 and 0.538839, respectively. The amplification



(a) Dissatisfaction. (b) Physical health. (c) Cooperation. (d) Electricity.

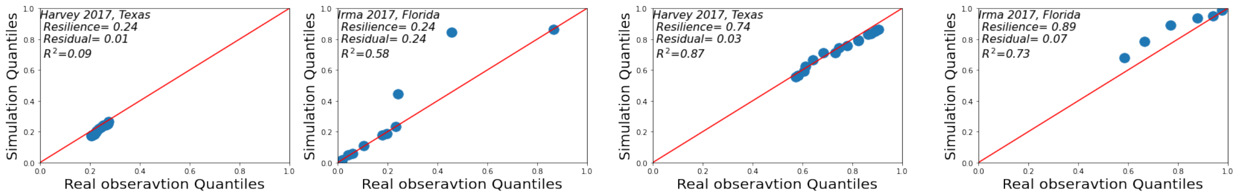
(e) Dissatisfaction. (f) Physical health. (g) Cooperation. (h) Electricity.

Figure 7.6: Graphs of the level of dissatisfaction, physical health, and cooperation of consumers and prosumers, and the level of cooperation/severity-dependent electricity in the socio-technical power systems resilience model for two scenarios: 1) median of all samples and 2) three-hourly-based data set.

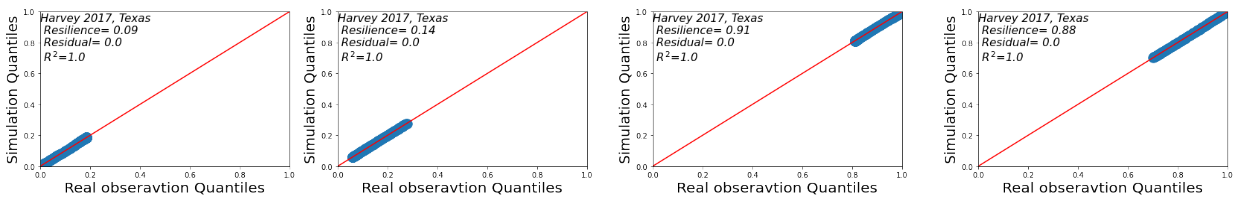
effect, as defined by the broaden-and-build theory, accounts for 67% of the dissatisfaction level, while the absorption effect, as defined by the bottom-up emotion theory, accounts for 33%. When we use a daily-based dataset, these values are 50% and 50%. The estimated threshold values for the effect of severity on electricity is equal to 0.458702 in three-hourly-based analyses. Additionally, 76% of electricity services are cooperation-based while 24% are severity-based. As illustrated in Fig. 7.7, there is a greater similarity in the distributions of three-hourly-based datasets than in the daily-based dataset.

7.5 Conclusions

In this chapter, we used neuroscience and social science theories to model the complex collective behavior of consumers and prosumers during a disaster. The proposed socio-technical power system resilience model is beneficial for observing emergent processes and



(a) Dissatisfaction. (b) Physical health. (c) Cooperation. (d) Electricity.



(e) Dissatisfaction. (f) Physical health. (g) Cooperation. (h) Electricity.

Figure 7.7: The QQ-plot of consumers' and prosumers' level of dissatisfaction, physical health, and cooperation, as well as cooperation/severity-dependent level of electricity, using the median of all samples (Figures a-d) and three-hourly-based data (Figures e-h).

developing new hypotheses that can be tested in real-world scenarios. We proposed an approach for assessing the behavior of power system stakeholders through the use of social sensing tools such as Twitter and GoogleTrend. We increased the proposed model's reliability by validating it using cross-validation and data sets related to Hurricanes Harvey and Irma. It should be noted that the approach proposed in this chapter for model validation can be applied to a wide variety of socio-technical power system problems.

Chapter 8

Validation of Multi Agent-Based Model of Community Resilience by Considering the Interdependence Between Power Systems, Emergency Services, and Social Networks

Each year, several disasters occur, resulting in enormous human, infrastructural, and economic losses. To minimize losses and ensure an adequate emergency response, it is vital to prepare the community for greater shock absorption and recovery after an occurrence. This raises the concept of community resilience and also demands appropriate metrics and prediction models for improved preparedness and adaptability. While a community is impacted in three main ways during a disaster- namely social, physical, and cyber- there are currently no tools to model their interrelationship. Thus, this chapter presents a multi-agent cyber-physical-social model of community resilience, taking into account the interconnection of power systems, emergency services, social communities, and cyberspace. We offer relevant measures for each section and describe dynamic change and its dependence on other metrics using a variety of theories and expertise from social science, psychology, electrical

Figure 8.1: Physical, cyber, and social layers of a community resilience.

engineering, emergency services, and cybersecurity. To validate the model, we used data on two hurricanes (Irma and Harvey) collected from Twitter, GoogleTrends, FEMA, power utilities, CNN, and Snopes (a fact-checking organization). We also describe methods for quantifying social metrics such as using social sensing, natural language processing, and text mining tools. We examine the suggested paradigm through three different case studies: 1) hurricanes Irma and Harvey; 2) a group of nine agents; and 3) a society comprised of six distinct communities.

8.1 Cyber-Physical-Social Model of Community Resilience

We develop a multi-agent-based dynamic model to capture the dynamic change in community behaviors in response to a disaster. This cyber-physical-social paradigm is advantageous for capturing emerging processes and studying the multifaceted characteristics of output-oriented community resilience. Before describing the suggested model, we will explain the threshold model with a logistic function that is frequently used in sociology, medicine, biology, ecology, and neural networks to consider the cyber-physical-social effect [202, 203].

8.1.1 Threshold Model Using Logistic Function

The logistic function-based threshold model enables us to define thresholds for behavior change [4, 204]. For example, if the power outages surpass a certain threshold, $\phi(X)$, consumer panic can ensue during a crisis. Each factor's logistic value, $\psi(X)$, on the resilience-related characteristic, X, is given as

$$\psi(X) = \frac{1}{1 + e^{-\sigma^X (X_{ti} - \phi^X)}}. \tag{8.1}$$

Additionally, we define $\psi^{'}(X) = 1 - \psi(X)$.

8.1.2 Multi-Agent Cyber-physical-social model

Eqs.8.2-8.12 describe the dynamic changes in resilience-related behaviors. Note that all variables and functions defined take values between 0 and 1. There are two kinds of features: diffusional and non-diffusional. It is worth noting that C, P, and S represent the cyber, physical, and social characteristics, respectively. For instance, S^E_{ti} denotes the intensity of fear, as a social feature (S), experienced by agent i at time t.

1) Diffusion-based features:

Social diffusion-based features, i.e, θ_{ti} consist of fear ,(S^E_{ti}), information-seeking behaviour, ,(S^I_{ti}), and flexibility ,(S^F_{ti}). The level of each of these features can be affected by another agent if they are connected. Hence, we should consider panic diffusion, information mirroring, and flexibility contagion in the related equations. According to θ_{ti} =$\{S^E_{ti},\ S^I_{ti},\ S^F_{ti}\}$, the dynamic change of θ_{ti} is determined via Eqs.8.2-3.

$$\Delta(\theta_{ti}) = \alpha^{'\theta}_{ti}(f(\hat{\theta}_{ti}, \theta_{ti}) - \theta_{ti})\Delta t, \quad \alpha^{'\theta}_{ti} = \frac{\sum_j \alpha^{\theta}_{ij}\theta_{tj}}{\sum_j \alpha^{\theta}_{ij}}. \tag{8.2}$$

$$f(\hat{\theta}_{ti}, \theta_{ti}) = \eta^{\theta}[S^{R}_{ti}(1-(1-\theta_{ti})(1-\hat{\theta}_{ti})) \\ +(1-S^{R}_{ti})\hat{\theta}_{ti}\theta_{ti}] + (1-\eta^{\theta})\hat{\theta}_{ti}. \tag{8.3}$$

Eq.8.2 yield the incremental change, $\Delta(\theta_{ti})$. We regard the peace of dynamic change to be equivalent to the social diffusion of related characteristics, i.e., α'^{θ}_{ti}. Additionally, α^{θ}_{ij} is proportional to the intensity of the connection between agents i and j. Eq.3 illustrates the amplification and absorption effects of the event [130] on the feature, where S^{R}_{ti} denotes the level of risk perception. The amplification effect (the term with the coefficient of η^{θ}), which is based on Fredrickson's broaden-and-build theory, is composed of two components, namely upward spirals (the term with the parameter of S^{R}_{ti}) and downward spirals (the term with the parameter of $(1-S^{R}_{ti})$) [81]. According to the Fredrickson theory, positive emotion can offer resources and expand the mind's capacity, a process referred to as spirals upward. On the other side, negative emotions can narrow the mind's ability resources, a phenomenon known as downward spirals. On the other hand, the absorption effect (the phrase with the coefficient of $(1-\eta^{\theta})$) is related to the level of collective behavior which is based on Barsade theory' bottom-up approach [50]. Note that $\hat{\theta}ti$={$\hat{S}^{E}_{ti}$, $\hat{S}^{I}_{ti}$, $\hat{S}^{F}_{ti}$}. The level of $\hat{\theta}ti$ for each of the diffusion-based features is derived using the following:

$$\hat{S}^{E}_{ti} = \iota^{\theta_1}(\frac{\sum_j \alpha^{E}_{ij}S^{E}_{tj}}{\sum_j \alpha^{E}_{ij}}) + \iota^{1}\psi^{'}(S^{C}_{ti}) + \iota^{2}\psi^{'}(S^{P}_{ti}) + \\ \iota^{3}\psi^{'}(P^{E}_{ti}) + \iota^{4}\psi(P^{S}_{ti}) + \iota^{4}\psi^{'}(S^{F}_{ti}) + \iota^{5}\psi^{'}(S^{L}_{ti}) + \iota^{6}\psi^{'}(C^{+}_{t}). \tag{8.4}$$

$$\hat{S}^{I}_{ti} = \iota^{\theta_2}(\frac{\sum_j \alpha^{I}_{ij}S^{I}_{tj}}{\sum_j \alpha^{I}_{ij}}) + \iota^{7}\psi^{'}(S^{L}_{ti}) + \iota^{8}\psi(S^{R}_{ti}) \tag{8.5}$$

$$\hat{S}^F_{ti} = \iota^{\theta_3}(\frac{\sum_j \alpha^F_{ij} S^F_{tj}}{\sum_j \alpha^F_{ij}}) + \iota^9 \psi^{'}(S^C_{ti}) + \iota^{10} \psi^{'}(S^E_{ti}), \tag{8.6}$$

where $\hat{\theta}_{ti}$ is composed of two components: social diffusion (the term with parameters $\iota^{\theta_{1,2,3}}$) and the impact of external factors, i.e., influential features of Agent i. The external factors of fear, S^E_{ti}, as defined in (4), consists of cooperation, S^C_{ti}, [6], physical health, S^P_{ti}, [34], and accessibility to electricity, P^E_{ti}, [206], severity of a disaster, P^S_{ti}, flexibility, S^F_{ti}, [131], learning, S^L_{ti}, [131], and news positiveness , C^+_t, [5]. Additionally, the information-seeking behaviour, S^I_{ti}, as defined in (8.5) is influenced by external factors, i.e., learning, S^L_{ti}, [135, 136], and risk perception, S^R_{ti}, [5]. Furthermore, the external factors of flexibility, S^F_{ti}, as defined in (8.6) consists of cooperation, S^C_{ti}, [140], and fear, S^E_{ti}, [138]. Note that $\iota^{1,..,10}$ are parameters.

2) Non-diffusional features:

Eqs.7-8.10 provide the dynamic change of physical health, risk perception, cooperation, and learning, respectively.

$$\begin{aligned} \Delta(S^P_{ti}) = \eta^P \psi^{'}(S^E_{ti}) \\ [\frac{\iota^{11}\psi(P^M_{ti}) + \iota^{12}\psi(P^E_{ti}) + \iota^{13}\psi^{'}(P^S_{ti})}{3} - S^P_{ti}]\Delta t. \end{aligned} \tag{8.7}$$

$$\begin{aligned} \Delta S^R_{ti} = \eta^R \psi(S^E_{ti})\psi^{'}(S^C_{ti})\psi^{'}(S^I_{ti}) \\ [\frac{\iota^{14}\psi^{'}(P^E_{ti}) + \iota^{15}\psi^{'}(P^M_{ti}) + \iota^{16}\psi(P^S_{ti}) + \iota^{17}\psi(S^E_{ti}) + \iota^{18}\psi^{'}(C^+_t)}{5} \\ - S^R_{ti}]\Delta t. \end{aligned} \tag{8.8}$$

$$\begin{aligned} \Delta(S^C_{ti}) = \eta^C \psi(S^E_{ti})\psi(S^F_{ti}) \\ [\frac{\iota^{19}\psi^{'}(P^E_{ti}) + \iota^{20}\psi(P^S_{ti}) + \iota^{21}\psi(S^E_{ti}) + \iota^{22}\psi(S^I_{ti})}{4} - S^C_{ti}]\Delta t. \end{aligned} \tag{8.9}$$

$$\Delta S^L_{ti} = \eta^L \psi(S^F_{ti})[\frac{\iota^{23}\psi(S^C_{ti}) + \iota^{24}\psi(S^I_{ti}) + \iota^{25}\psi^{'}(C^F_t)}{3} - S^L_{ti}]\Delta t. \tag{8.10}$$

The dynamical changes in physical health, $\Delta(S^P_{ti})$, as defined by (7) is affected by the level of panic [34], the availability of emergency services, P^M_{ti}, the access level to electricity, P^E_{ti}, [1], and the severity of a disaster, X^S_{ti}. The dynamic changes in risk perception, $\Delta(S^R_{ti})$, as defined by Eq.8 is affected by level of panic [5, 125], cooperation, [132], information-seeking behaviour, [133], the availability of emergency services, the access level to electricity, the severity of a disaster, and news positivity. The dynamical changes in cooperation, $\Delta(S^C_{ti})$, as defined by (9) is affected by the level of panic [6], flexibility [140], information-seeking behaviour [142], the severity of a disaster, and the access level to electricity. The dynamical changes in learning, $\Delta(S^L_{ti})$, as defined by (8.10) is affected by the level of flexibility [222], cooperation [144], information-seeking behaviour [143], and the amount of fake news, C^F_{ti}, [145]. Note that $\Xi = \{\eta^P, \eta^R, \eta^C, \eta^L\}$ denotes the coefficient of related features. In addition, the relationship between the level of experience, S^X_{ti}, and the level of learning is given by $S^L_{ti} = \frac{\Delta S^X_{ti}}{\Delta t}$. The dynamic change of electricity provided by DERs, and MGs, $\Delta(P^D_{ti})$, as well as the total accessibility to electricity, P^E_{ti}, are obtained by

$$\Delta(P^D_{ti}) = \alpha^D_{ti}(\alpha^D_{ti} - P^D_{ti})\Delta t, \quad \alpha^D_{ti} = \frac{\sum_j \alpha^D_{ij} S^C_{tj} P^D_{tj}}{\sum_j \alpha^D_{ij} S^C_{tj}}. \tag{8.11}$$

$$P^E_{ti} = \varpi P^D_{ti} + (1 - \varpi)\psi(P^S_{ti})P^U_{ti}. \tag{8.12}$$

Electricity demand can be met primarily by DERs and MGs, P^D_{ti}, as well as by power utilities, P^U_{ti}. Depending on the intensity of a disaster, the utility's functionality may be compromised. End-users who own DERs, known as prosumers, may desire to share their power with consumers and critical loads that are not linked to the grid but are connected to them in this situation, α^D_{ij}, depending on their level of cooperation, S^C_{tj}. In (8.12), ϖ denotes the fraction of end-users' total electricity consumption that DERs supply.

8.2 Metrics of Community Resilience and Their Measurements

This section addresses the cyber-physical-social metrics that characterize community resilience and how they can be quantified using real-world data on hurricanes Harvey and Irma.

8.2.1 Cyber Layer Metrics and Their Measurement

We consider the positivity of news and the spread of fake news as cyber layer indicators that affect community resilience. To gather news on the event, we relied on CNN. Additionally, several fact-checking organizations, such as Snopes, examine and disseminate false information throughout various events. As a result, we used a web scraper and manually verified news and fake news from CNN and Snopes. From 25/08/2017 to 11/09/2017, we gathered 279 news and 24 fake news about Hurricane Harvey. Additionally, from 01/09/2017 to 13/09/2017, we gathered 652 news and 16 fake news about Hurricane Irma.

1- News Positiveness: We scraped the headline and text of CNN news regarding hurricanes Irma and Harvey using the Google Chrome Extension "Web Scraper - Free Web-Scraping." Then, we used LIWC to assess the news's positivity over time.

2- Fake News: Several fact-checking organizations, such as Snopes, Politifact, and Factcheck, conduct investigations into the news validity. Snopes provides a variety of news types, including real, mostly true, half true, mostly false, and false news. We classified all of the following categories as fake news: half true, mostly false, and false news.

8.2.2 Physical Layer Metrics and Their Assessment

As Physical layer measures of community resilience, we evaluate the availability of power provided by DERs, MGs, and utilities, as well as the availability of emergency services. Specifically, for Hurricane Harvey and Hurricane Irma, we acquired data on emergency services and power systems from FEMA and power utilities. Emergency services indicators include response staff, meals, water, blankets, hygiene kits, rescue teams, and medical deployment teams. In the United States, numerous organizations, including the American Red Cross (ARC), the Corporation for National and Community Service (CNCS), the U.S. Department of Defense (DOD), the U.S. Army Corps of Engineers (USACE), the U.S. National Guard Bureau (NGB), the U.S. Department of Homeland Security (DHS), the U.S. Immigration and Customs Enforcement (ICE), and the U.S. Department of the Interior (DOI), collaborate to address a disaster. We quantified the availability of emergency services by analyzing open-access data given by FEMA. For Hurricane Harvey, we utilized HQ-17-59 to HQ-17-79 reports, and for Hurricane Irma, we used HQ-17-85 to HQ-17-120 reports.

8.2.3 Social Layer Metrics and Their Assessment

We explore and suggest the following social indicators for assessing community resilience: mental health, physical health, risk perception, information-seeking behavior, adaptability, 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. 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 [223]. 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 (275000 and 212000 IDs). Additionally, we used GoogleTrends to identify information-seeking behavior associated with these occurrences. We explore how each feature of social resilience can be quantified using the psychological meaning of the words and computerized text analysis as follows:

1-Fear: We measure the fear of the social community based on the level of anxiety of the community during a disaster. By using the categories of the LIWC, the level of fear is obtained by

$S^E = LIWC['anx']/LIWC[`WC'],$

where $LIWC['anx']$ means the category of "anx" from outputs of LIWC.

2- Physical Health: According to a psychological study of language, higher usage of first-person singular pronouns can signify physical discomfort and more attention to oneself [216]. Also, positively using phrases associated with physical activities such as 'motion,' 'work,' 'leisure,' 'health,' and 'body' can indicate physical health [217, 218, 219, 220]. By using the categories of the LIWC, the level of physical health is obtained by

$S^P = (-LIWC['i'] + LIWC['health'] + LIWC['leisure'] + LIWC['work'] + LIWC['body'] +$

$LIWC['motion'])/LIWC[`WC'].$

3- Cooperation: Increased use of complicated words and terms with more than six letters is known to be inefficient for communication, cooperation, and social interaction from a psychological standpoint [211]. Conversely, the frequent use of the first person pronoun implies group engagement and cohesion [212]. According to language behavior research, assent-related languages (e.g., 'agree,' 'OK,' 'yes') are known in psychological linguistics to convey group consensus, interaction, and collaboration [215]. Finally, increased use of social process terms such as 'social,' 'friend,' and 'family' imply increased social interaction, involvement, and collaboration [213, 214]. Hence, the level of cooperation is obtained by $X_C = (LIWC['WC'] - LIWC['Sixltr'] + LIWC['we'] + LIWC['social'] + LIWC['family'] + LIWC['friend'] + LIWC['assent'])/(LIWC['WC'])$.

4- Risk Perception: Increased ambiguity is associated with an increase in risk perception. According to the psychological analysis of the words, the more the present tense is used, the more undisclosed an event is. In contrast, the more that past tense is used, the lower the level of ambiguity [223]. Also, increased use of certain related language can bolster assurance. The use of tentative language (e.g., maybe, perhaps, guess) and additional filler words (blah, I mean, you know) indicates that the speaker is unsure about the subject [223]. Additionally, phrases denoting discrepancies (e.g., should, would, could) should incorporate the degree of uncertainty [223].

$XR = (LIWC['risk'] + LIWC['tentat'] - LIWC['certain'] + LIWC['filler'] + LIWC['focuspresent'] + LIWC['discrep'] - LIWC['focuspast'])/(LIWC['WC'])$.

5- Adaptability: Respect, empathy, trust, and optimism are the main characteristics of adaptation and flexibility. Languages associated with assent (e.g., 'agree,' 'OK,' and 'yeah') indicate agreement and flexibility, [223]. Pronouns are critical in language psychology study. The use of second-person pronouns denotes a lower quality relationship and flexibility. When people are lying, they employ a greater degree of negative emotion and motion language (arrive, car, go), reducing trust and adaptability. Increased use of negation-related phrases (e.g., no, not, never) indicates that the individual is less adaptable.

$X_f = (LIWC['posemo'] - LIWC['negate'] + LIWC['assent'] - LIWC['you'] - LIWC['motion'])/(LIWC['WC'])$.

6- learning: The level to which people pay attention demonstrates their desire to learn. Cognitive mechanisms (e.g., cause, know, ought) and prepositions imply that the subject is informed. The abstracts and introductions of published journal articles contain more complicated language and prepositions. The use of casual language ("because, effect, hence") and insight terminology (e.g., think, know, consider) demonstrates the learning process.

$X_L = (LIWC['insight'] + LIWC['cause'] + LIWC['prep'] + LIWC['cogproc'])/(LIWC['WC'])$.

7- Information-Seeking Behavior: The volume of tweets sent by individuals over time and throughout the disaster demonstrates their information-seeking behavior. Along with Twitter, GoogleTrends can be used to detect social trends. For instance, the amount of searches for the terms “Hurricane Irma” and “Hurricane Harvey” demonstrates the extent of information-seeking behavior. We combine the two datasets obtained by Twitter and GoogleTrends to derive a more precise measure of information-seeking behavior.

8.2.4 Normalization and Dealing with Missing Values:

We have two types of the datasets, i.e., non-polarity and polarity-based datasets, which are normalized as follows:

1- Non-Polarity Values: We normalize all values between the interval [0, 1] using a min-max normalization.

2- Polarity-Based Values: L^+ and $L-$ denote the length of the range of positive and negative values, respectively. The following two cases are considered:

1) If $L^- < L^+$: The positive values are normalized between the interval [0.5, 1]. By using $X^{min} = 0.5 - \frac{L^- * 0.5}{L^+}$, we determine the intervals for the negative values, i.e, [X^{min},0.5]. Then, we use a min-max normalization to standardize the values inside the intervals $[X^{min}, 1]$.

2) If $L^- > L^+$: Here, we normalize the negative values between intervals [0, 0.5]. By using $X^{max} = 0.5 + \frac{L^+ * 0.5}{L^-}$, we can determine the intervals for positive values, i.e, [0.5,X^{max},]. Then, we normalize values within intervals $[0, X^{max}]$ using min-max normalization.

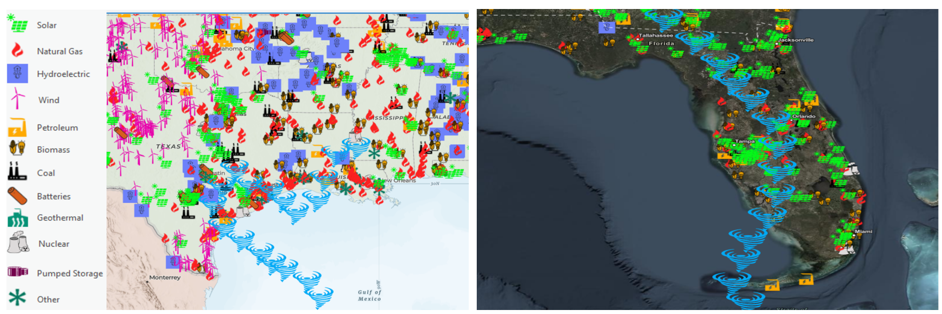
After normalization, we deal with missing values via an interpolation approach.

8.3 Case study 1: Hurricanes Harvey and Irma

We validate the suggested model by examining datasets related to hurricanes Harvey and Irma. For validation purposes, We retrieved tweets from Hurricane Harvey's 18,336,283 and Hurricane Irma's 17,227,935 tweets via Twitter's streaming Application Programming Interface (API). We also leveraged GoogleTrends for social sensing. Hurricane Harvey and Irma's paths, in-storm power plants, hurricane severity, electricity and emergency services availability, the spread of fake news, and news positivity are represented in Figure 8.2. Hurricane Harvey struck Texas and the ERCOT territory between 08/25/2017 and 09/11/2017. It was upgraded to Category 4 on 08/25/2017. As was the case with Hurricane Katrina, this hurricane is the most expensive tropical cyclone to strike the United States. Hurricane Irma made landfall largely in Florida and to a lesser extent in Georgia and South Carolina between 09/01/2017 and 09/13/2017. This storm was a Category 5 hurricane from 09/06/2017 and 09/08/2017. The electricity system's restoration began on 09/11/2017 and lasted 12 days.

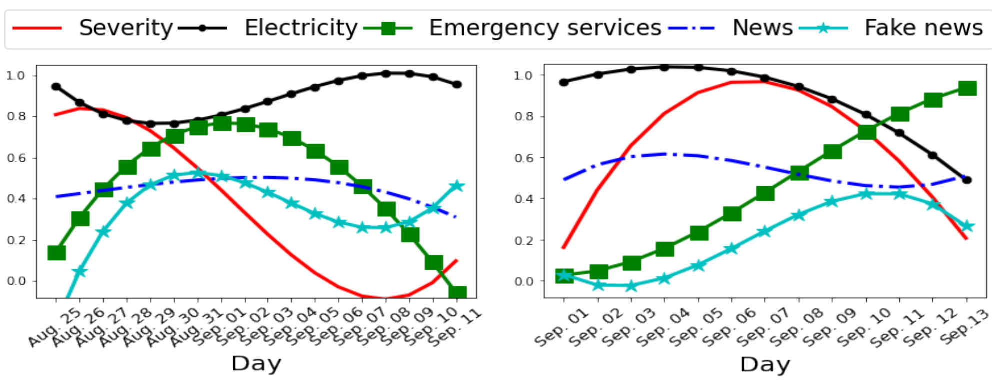
8.3.1 Analysis of Cyber-Social Layer:

Table 8.1 displays the top five 1- and 2-grams for news, fake news, and tweets on hurricanes Harvey and Irma. For both events, the most often used term in people's Tweets is "power." This demonstrates that they are concerned about the state of the electricity at that time period. Similarly, among the 2-grams, one of the most frequently repeated terms is "power outage." Interestingly, during hurricane Irma, the term "climate change" was constantly used. On the other hand, the phrase "category 6" is repeated for both incidents in fake news. Fig. 8.3 illustrates the positivity and negativity (affect aspect) of hurricanes Harvey and Irma over time associated with news, fake news, and tweets (representative of community behavior). Generally, news for both events is more negative than positive. Similarly, fake news is negative. Additionally, while those affected by Hurricane Harvey had a higher level



(a) Harvey track.

(b) Irma track.



(c) Harvey features.

(d) Irma features.

Figure 8.2: Hurricane tracks, in-hurricane power plants, hurricane severity, availability of electricity and emergency services, propagation of fake news, and and news positivity.

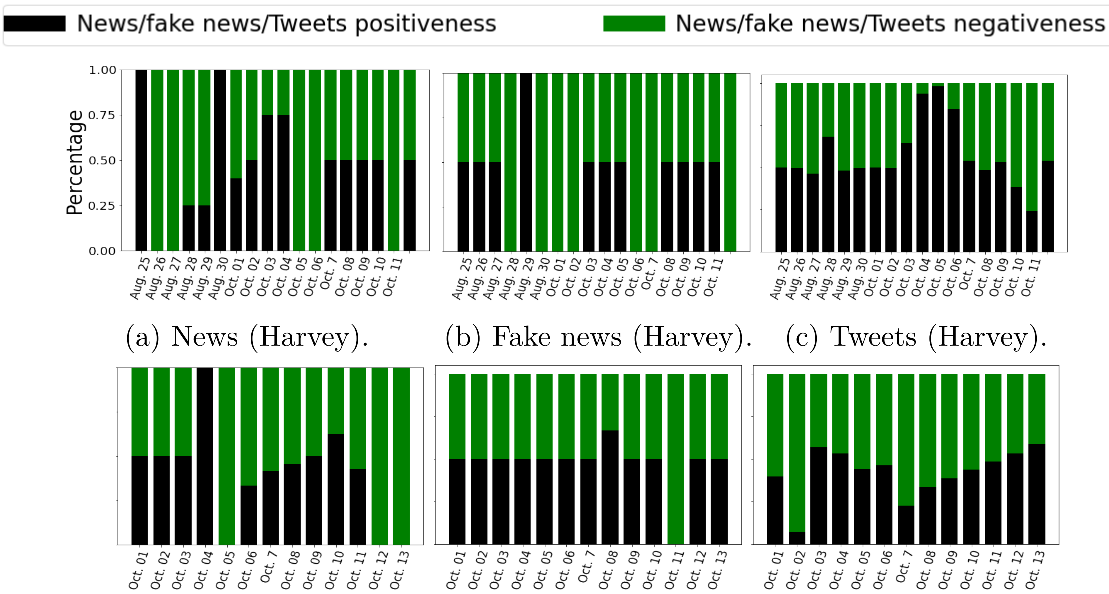
Table 8.1: Top 5 1-gram and 2-grams for news, fake news, and tweets about Hurricanes Harvey and Irma.

Analysis		1-gram	2-grams
Tweets	Harvey	power, harvey, hurrican, weather, annisepark	power weather, annisepark darn, darn thought, weather annisepark, without power
	Irma	power, irma, hurrican, florida, puerto	hurrican irma , power outag, categori 4, power florida, climat chang
News	Harvey	harvey, texa, irma, rescu, katrina	thing august, thing septemb, hurrican irma,hurrican harvey, lost everyth
	Irma	irma, florida, septemb, caribbean, trump	hurrican irma, thing septemb, catch day, irma path, irma relief (3)
Fake	Harvey	harvey, houston, presid, rescu, trump	hurrican harvey, church houston, harvey flood, victim hurrican (2), categori 6
	Irma	hurrican, irma, florida , pet, shark	hurrican irma, categori 6, show hurrican,irma project, becom categori

of positive emotions, those in Florida had a higher level of negative emotions.

8.3.2 Daily-Based Validation and Analysis

Fig. 8.4 illustrates real-world observations, related fitting curves, and simulation results for Hurricane Irma using a cyber-physical-social model of community resilience over time. The provided characteristics include the level of mental and physical health, risk perception, information-seeking behavior, cooperation, adaptability (flexibility), learning, and the level of electricity that is cooperative/severity-dependent. For each subfigure, we show the information related to type of event, capacity-based level of resilience (area under curve), residuals and value of statistical $R^2 = 1 - (RSS/TSS)$, where $RSS = \sum(y - \tilde{y})^2$, and $TSS = \sum(y - \bar{y})^2$). Although Irma arrived in Florida later than Puerto Rico, it affected Floridians immediately, e.g., 01 September. At first, there was a high level of risk perception. The level of fear fell till 08 September. Following that, by intensifying power interruptions, the level of fear increased. Then, with a high level of risk perception and an increase in the severity of Irma, people's information-seeking behavior increased until 07 September, at which point it declined. Fear, social diffusion, and risk perception all contributed to a



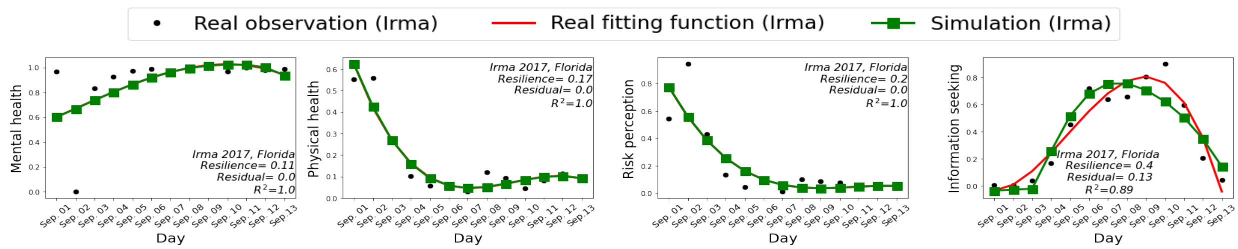
(a) News (Harvey). (b) Fake news (Harvey). (c) Tweets (Harvey).

(d) News (Irma). (e) Fake news (Irma). (f) Tweets (Irma).

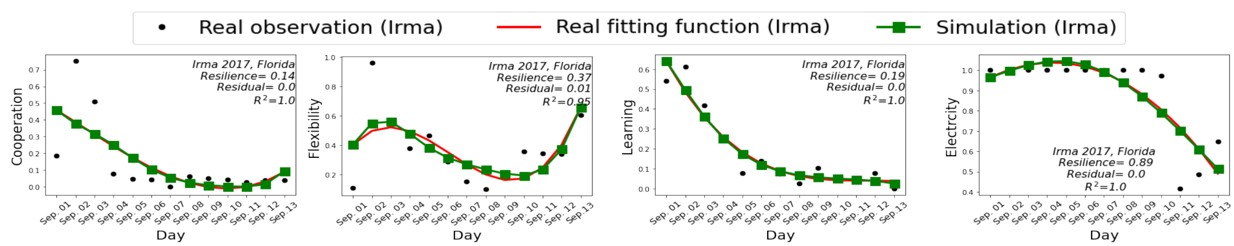
Figure 8.3: The positiveness and negativeness of the news, fake news, and tweets for hurricanes Harvey and Irma over time.

high level of cooperation at the start. It first stimulates a high level of learning. By gradually reducing fear and risk perception, the level of cooperation decreased. As a result of the decline in cooperation and the proliferation of fake news over time, the level of learning declined. After the first surge, the level of flexibility decreased until 08 September. After 08 September, due to the power outage and increased panic, the level of cooperation and flexibility increased.

Fig. 8.5 illustrates real-world observations, fitting curves, and simulation results for hurricane Harvey using the proposed cyber-physical-social model of community resilience. At first, as the intensity of Harvey and the power loss increased, the level of worry increased, and physical health declined. Additionally, the initial level of risk perception and information-seeking behavior was high. By reducing fear and increasing access to emergency services, both risk perception and information-seeking behavior gradually declined. Cooperation increased until 30 August and then diminished. Similarly, people's level of adaptability increased initially.



(a) Mental health. (b) Physical health. (c) Risk perception. (d) Info-Seeking.



(e) Cooperation. (f) Flexibility. (g) Learning. (h) Electricity.

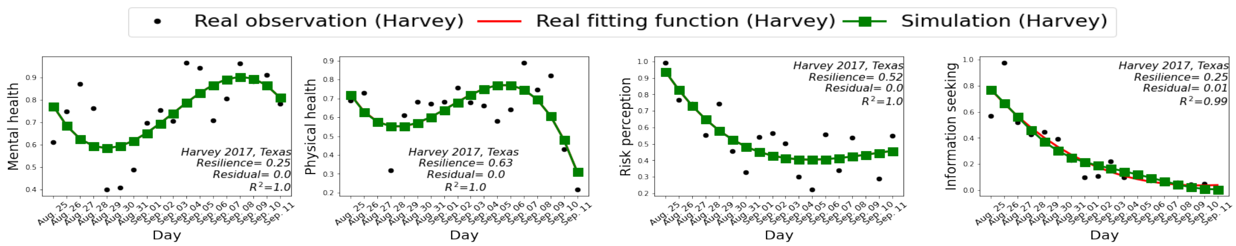
Figure 8.4: Results for hurricane Irma by using the cyber-physical-social model of community resilience over time.

At first, due to the prevalence of fake news and the decrease of information-seeking behavior, the level of learning reduced and then increased as the prevalence of fake news declined. Take note that while this study focuses on a single event occurring at a single moment, these traits can also be impacted by events other than Hurricane Harvey. The multi-hazard assessment of community resilience can be researched in the future.

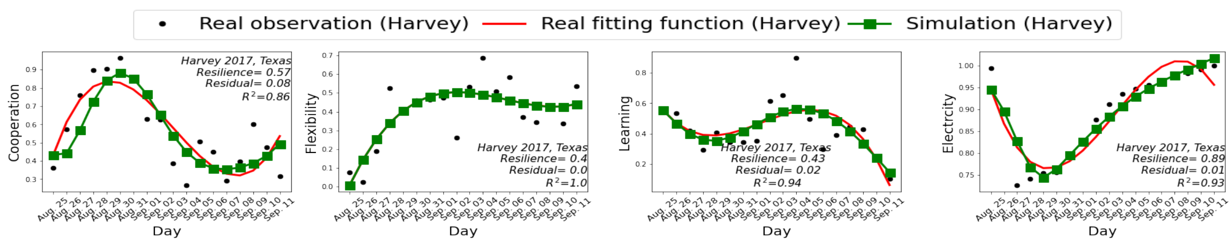
Fig. 8.6 depicts the QQ-plot for Hurricane Harvey and Irma's level of cooperation. It illustrates that the distributions of the simulated and real datasets are similar.

8.3.3 3 Hourly- and Hourly-Based Analysis

Depending on the requirement and type of study, the time step can be every hour or every three hours rather than every day. Table 8.2 provides the goodness results, i.e., residual and $R2$, for 3 hourly-, and hourly-based assessments of all community-resilience-related features for both hurricanes Irma and Harvey. The residuals are insignificant, and statistical R^2 is

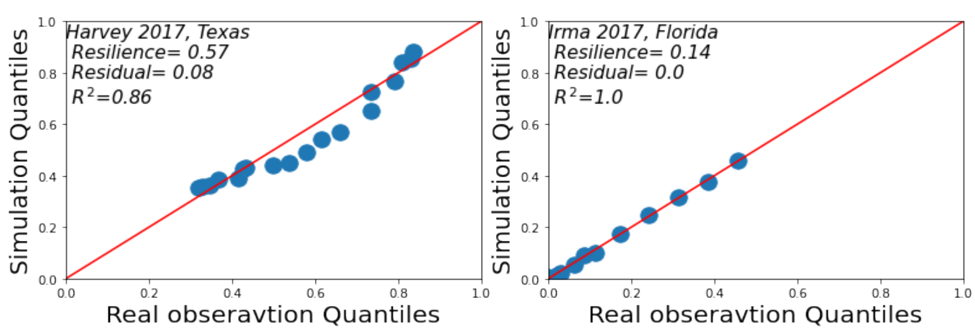


(a) Mental health. (b) Physical health. (c) Risk perception. (d) Info-Seeking.



(e) Cooperation. (f) Flexibility. (g) Learning. (h) Electricity.

Figure 8.5: Results for hurricane Harvey by using the cyber-physical-social model of community resilience over time.



(a) Cooperation (Harvey). (b) Cooperation (Irma).

Figure 8.6: The QQ-plot for Hurricane Harvey and Irma's level of cooperation.

Table 8.2: The goodness results, i.e., residual and R^2 for daily-based, 3 hourly, and hourly-based analysis for Hurricanes Irma and Harvey.

Residual and R^2			S^E	S^P	S^R	S^I	P^E	S^C	S^F	S^L
3 Hourly	Irma	R	0	0	0	0	0.05	0	0	0.01
		R^2	1	1	1	1	0.98	1	0.99	0.94
	Harvey	R	0	0	0	0.14	0.07	0	0.03	0.06
		R^2	1	1	1	0.97	0.94	1	0.95	0.9
Hourly	Irma	R	0	0	0	1.15	0.18	0	0	0.02
		R^2	1	1	1	0.9	0.98	1	0.94	0.94
	Harvey	R	0	0	0	1.07	0.19	0	0	0.02
		R^2	1	1	1	0.9	0.95	1	1	0.92

close to 1. Table 8.3 contains the findings of a statistical analysis conducted on real-world and simulated datasets for 3 hourly and hourly studies of all community-resilience-related features following hurricanes Irma and Harvey. The Shapiro-Wilk normality test indicates that not all cases conform to the normal distribution. Additionally, Pearson and Kendall tau correlations reveal a strong correlation between the simulation and the real datasets for all 3 hourly and hourly-based studies. Additionally, Student's t-test and Mann-Whitney U test p-values (as parametric and non-parametric statistical hypothesis tests, respectively) indicate that the distribution of community resilience-related features obtained from the real data set and simulation outputs are similar in all cases except for information-seeking behavior during hurricane Harvey for the hourly-based case. Note that we can enhance this outcome by improving the precision of the parameter estimation.

8.4 Conclusions

We proposed a multi-agent cyber-physical-social model of community resilience. Fear, risk perception, information-seeking behavior, physical health, cooperation, flexibility, and learning are all social indicators of community resilience. We tracked these indicators using data

Table 8.3: Results of the statistical analysis of resilience metrics including Shapiro-Wilk normality test, Pearson correlation, Kendall tau correlation, Student's t-test, and Mann-Whitney U Test (Note that after P-value results of each test, we bring the related descriptions in the next row).

	Event	Hurricane Irma								Hurricane Harvey							
	Features	S^E	S^P	S^R	S^I	P^E	S^C	S^F	S^L	S^E	S^P	S^R	S^I	P^E	S^C	S^F	S^L
3 hourly-based outputs	P-value for real dataset	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Gausian distribution	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	P-value for simulation dataset	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Gausian distribution	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Pearson correlation	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.97	1.00	1.00	1.00	0.99	0.97	1.00	0.98	0.95
	Dependent	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	kendalltau correlation	0.94	1.00	1.00	0.98	0.99	0.96	0.84	0.79	0.99	1.00	1.00	0.46	0.84	0.96	0.85	0.75
	Student's t-test p value	0.98	1.00	1.00	0.99	0.96	0.98	1.00	0.91	0.99	1.00	1.00	0.87	0.94	0.99	0.72	0.96
	same distribution	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Mann-Whitney U Test p value	0.49	0.50	0.50	0.49	0.23	0.49	0.46	0.22	0.43	0.50	0.50	0.29	0.38	0.46	0.22	0.24
	same distribution	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Hourly-based outputs	P-value for real dataset	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Gausian distribution	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	P-value for simulation dataset	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Gausian distribution	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗
	Pearson correlation	1.00	1.00	1.00	0.95	0.99	1.00	0.97	0.97	1.00	1.00	1.00	0.96	0.97	1.00	1.00	0.96
	Dependent	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	kendalltau correlation	0.95	1.00	0.99	0.90	0.98	0.97	0.85	0.81	0.99	1.00	1.00	0.63	0.86	0.99	0.96	0.77
	Student's t-test p value	0.98	1.00	0.99	0.97	0.95	0.98	0.98	0.83	1.00	1.00	1.00	0.95	0.88	0.99	0.93	0.87
	same distribution	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
	Mann-Whitney U Test p value	0.41	0.50	0.48	0.45	0.09	0.46	0.13	0.08	0.46	0.50	0.50	0.02	0.32	0.48	0.49	0.08
	same distribution	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓	✓	✓	✓

from Twitter and GoogleTrends. Physical indicators of community resilience include the availability of electricity via DERs, MGs, and utilities, as well as the accessibility of emergency services. We quantified the physical characteristics using data provided by FEMA and the electric utility company. Cyber layer metrics include the news positivity and the propagation level of fake news during events. We evaluated the cyber metrics using data from CNN and fact-checking organizations. The proposed model provides various advantages that compensate for the literature's shortcomings. It considers the cyber-physical-social interdependence of metrics in order to model their dynamic behavior. It can be used to simulate a variety of circumstances that are either prohibitively expensive or unfeasible in the actual world. We further confirmed our cyber-physical-social model using natural language processing and text mining methods.

Chapter 9

Conclusions

Several calamities occur throughout the world each year, resulting in varying losses. Disasters wreak havoc on infrastructures and impair operation. They result in death and affect people's mental and physical health. Additionally,the negative impacts of a disaster can result in significant economic losses, as demonstrated by the $ 423 billion loss in 2011 in Tohoku, Japan, and the $ 133 billion loss in hurricane Harvey, U.S.A. To mitigate losses, we must strengthen communities' readiness, flexibility, and resilience. Before strengthening community resilience, we need to have appropriate techniques for forecasting a community's capacity and functionality in the face of impending crises. Before enhancing and predicting resilience, we should establish suitable community resilience metrics and identify how to quantify the proposed metrics.

Following an introductory chapter, I conducted a literature review on resilience and discussed appropriate metrics in the following chapter. I discussed the importance of computational social science for power system and community resilience in the third chapter.

In the fourth chapter, 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 system and emergency services, on the social well-being of a society during a disaster is considered. Currently the role of critical infrastructures and social characteristics on community resilience are not considered. Our work intended to address this gap in the research and stimulate others to follow up 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 were assumed to be based on normal distribution.

In the fifth chapter, we developed a community resilience optimization method subject to power flow constraints. The socio-technical power flow model includes the social constraints, i.e., the dynamic change of the level of emotion, risk perception, cooperation, and physical well-being of consumers and prosumers. We also examine the effect of critical loads on the social well-being. In addition to the social constraints, we include in the model the cyber constraints and the physical constraints. The proposed model is implemented in two different case studies, i.e., a two-area 6-bus system and a modified IEEE RTS 24-bus system. We also provide the dynamic effect of the load shedding experienced by the consumers, prosumers, and the critical loads on the social behavior. The results show that the prosumers cooperate to share electricity since they face a power shortage.

In the sixth chapter, we leveraged an artificial society based on the computational social science approach to model the behavior of active end-users who participate in the demand response (DR). It shows the potential of using computational social science in power system operation. The inherent feature of each end-user consists of the level of satisfaction and cooperation. These features can bring both economic and sustainability benefits for the utility and the society as a whole. In addition, these features make the community more resilient. In the environomic-based social DR, some consumers participate in DR to increase the peak time rebates of the price of electricity. Other consumers participate in DR to decrease air pollution, water pollution, DALY, and exergy.

In the seventh chapter, we used neuroscience and social science theories to model the complex collective behavior of consumers and prosumers during a disaster. The proposed socio-technical power system resilience model is beneficial for observing emergent processes and developing new hypotheses that can be tested in real-world scenarios. We propose an approach for assessing the behavior of power system stakeholders through the use of social sensing tools such as Twitter and GoogleTrend. We increase the proposed model's reliability by validating it using cross-validation and data sets related to Hurricanes Harvey and Irma. It should be noted that the approach proposed in this chapter for model validation can be applied to a wide variety of socio-technical power system problems.

In the eighth chapter, we proposed a multi-agent cyber-physical-social model of community resilience. Fear, risk perception, information-seeking behavior, physical health, cooperation, flexibility, and learning are all social indicators of community resilience. We tracked these indicators using data from Twitter and GoogleTrends. Physical indicators of community resilience include the availability of electricity via DERs, MGs, and utilities, as well as the accessibility of emergency services. We quantified the physical characteristics using data provided by FEMA and the electric utility company. Cyber layer metrics include the news positivity and the propagation level of fake news during events. We evaluated the cyber metrics using data from CNN and fact-checking organizations. The proposed model provides various advantages that compensate for the literature's shortcomings. It considers the cyber-physical-social interdependence of metrics in order to model their dynamic behavior. It can be used to simulate a variety of circumstances that are either prohibitively expensive or unfeasible in the actual world. We further confirmed our cyber-physical-social model using natural language processing and text mining methods.

The following conclusions can be extracted from the results of the proposed models:

9.0.1 Agent-Based Conclusions

The main agent-based results of the proposed stochastic multi-agent-based model are as follow:

- When flexibility is high, individuals experience a lower level of panic. Furthermore, the perceived risk of agents is lowered because of the high level of flexibility and low level of fear. As a result, information-seeking behavior which is very much linked with risk perception is diminished. In general, the positive features of individuals may rectify their behavioral drawbacks.

- Experience has a negative impact upon the level of fear, information-seeking behavior, and risk perception of agents. It positively influences flexibility if agents are optimistic. When agents do not have previous experience, they seek new information during a perilous situation. Therefore, their experience is increased. There is stable feedback between experience and risk perception in the cognitive process.

- When emergency services are reduced, the average physical health of individuals falls precipitously. As a result, the level of fear of the agents rises suddenly. Following that, risk perception and information-seeking behavior are also increased.

- When the severity of a disaster (i.e., the injury factor) is noticeable, the average physical health of agents dramatically fades.

- If all relevant news from the mass media is not very promising, panic increases on average.

- When the level of cooperation is increased, the agents show a lower level of fear, risk perception, and information-seeking behavior. On the other hand, the feeling of fear during a disaster makes agents cooperate. In fact, a high level of cooperation can positively change individual behavior.

- When people have a high level of cooperation, they share their electricity sooner than when they have a low level of cooperation. As a consequence, they have a higher level of physical health. Furthermore, due to the high level of cooperation and physical health, people experience a lower level of panic.

9.0.2 Community-Based Conclusions

The main community-based conclusions of the proposed stochastic multi-agent-based model are as follow:

- The less empathy there is among individuals, the longer other characteristics, including fear, information-seeking behavior, flexibility, cooperation converge to the same level. Additionally, people share their electricity later in the process than when the level of empathy is high.

- When two communities are empathetic to each other and a disaster occurs in one of these communities, the dynamic change of mental characteristics in these two community is roughly the same.

- The higher the population, the more resilient the society is if all individuals have a close relationship with each other.

- The society, whose individuals are closer to each other, has a higher level of community resilience than the community with a lower level of empathy.

- The relationship among the individuals of a community is so vital that the society with less population and more empathy may be more resilient than the community with more population and less empathy.

- If the community is more resilient to a specific failure class, it may be more brittle to another failure type. In other words, the society has a different amount of community resilience under different disasters. A community can be resilient to one disaster while it may not be resilient under other emergencies. Droughts, storms, floods, and terrorist attacks have a low level of community resilience at the beginning of the occurring disaster.

- When the disasters are earthquakes and terrorist attacks, the physical well-being of the community sharply drops.

9.0.3 General Conclusions

- In the social aspect, an increase in the initial value of the emotion, risk perception of the society under study because of the culture and the previous experience, to name a few, results in the decrease of the level of both the load shedding and the community resilience. On the other hand, an increase in the initial value of cooperation, empathy, and physical health results in the decrease of the level of the load shedding and an increase in the level of the community resilience.

- In the cyber aspect, an increase in the social media platform effect factor leads to a decrease in the level of both the load shedding and the community resilience.

- In the physical aspect, the larger the installed capacity of the microgrids and DERs, the smaller the level of load shedding and the larger the level of community resilience.

- The engagement of end-users in DR depends not only on incentives, such as increased rebate and sustainability but also on the degree of satisfaction, customer cooperation, and social diffusion.

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 are 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 the 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 a collective behavior, through structured simulations. Meaning, starting the modeling process from the scientific evidence in the literature, creating individual agent rules, representing the relations found in the literature. 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 understanding of which communities are more or less vulnerable during disasters, based on which combinations of factors. They help us understand the 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.

As a future work, the investment in microgrids to enhance the community resilience will be investigated. Sharing electricity is useful for both economic and resiliency aspects. this may be achieved by installing one microgrid per cluster of critical loads, such as hospitals, instead of providing each of them with a backup generator.

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Appendices

Appendix A

Human-Centered Approach in the Cyber-Physical-Social System of Power Systems for Future Developments

In this section, we elaborate the research topics needed in computational social science for power system reliability, resilience, and restoration, for future developments. For each research topic, we explain why we need social science, psychological behavior of stakeholders, and, therefore, an artificial society.

A.1 Socio-Technical Power Flow

The availability of electricity affects both the mental well-being and physical well-being of consumers, prosumers, and the community as a whole. When a disaster strikes, part of the power system may be disconnected or damaged, resulting in the shedding of generation and load. Evidently, this shedding should be achieved by minimizing its impact on the social well-being and the community resilience subject to power flow constraints. To model a socially intelligent power flow, the social behaviors of end users, primary energy companies, and secondary energy providers must be incorporated. Willingness, consensus, convenience, satisfaction, cooperation, confidence, reliability, adaptability, experience, and empathy are just a few of the social behaviors. The primary social-related objective functions that can be considered are well-being, social well-fare, equality and fairness, trust, and community capital.

A.2 Investment in Microgrids and Distributed Energy Resources

The investment in microgrids and distributed energy resources play a key role in the social, economic, and infrastructure reliability, and resilience. Annual global battery storage installations by residential, commercial, and industrial consumers are increased from 100 MW in 2017 to 10 GW in 2021. Storage capacity at the county level in the United States is depicted in Figure A.1. Numerous counties have numerous electric energy storage systems, which affect the power systems' reliability, efficiency, and resilience. End users make up a sizable portion of the owner of this storage. Due to the fact that end-users exhibit a variety of social behaviors and characteristics, their impact on the reliability and resilience of power systems varies by region. As a result, it is necessary to consider their social behavior when studying power systems. In addition, technical and economic aspects of this investment have been considered in the literature. In addition to these aspects, the social well-being and community resilience should be considered in the investment in microgrids as well.

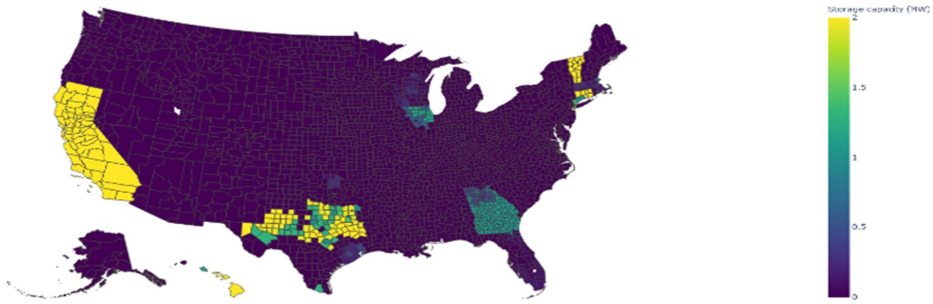

Figure A.1: The US County-level Storage capacity (MW).

A.3 Socially Intelligent Transactive Energy

Another application of computational social science in power systems is transactive energy, where stakeholders such as wholesale and retail sellers, prosumers, and buyers of energy services interact with one another by leveraging the concept of interoperability and using the value signals. The modeling of the decision-making of the latter relies heavily on the modeling of their social behavior. The United States' electricity system is moving toward a future full of DERs located everywhere and in all shapes and sizes, raising the value of utility-customer relations. The Energy Flexibility Platform and Interface, GridWise Olympic Peninsula Project, and the Pacific Northwest Demonstration Project as examples of using transactive energy show the importance of engagement and cooperation of costumers in the double auction market.

A.4 Socially Intelligent Electricity Markets

Power market, similar to any other market, should consider the psychological aspects of the investors, such as trust and satisfaction. In turn, the culture of each community can influence these psychological aspects. The winner of this electric market is the stakeholder who takes the consumers and their social behavior into account. During and after a disaster, due to the scarcity of electric energy, its price should be set up in fair manner, not by the electric market; see for example the ice storm in Texas in February 2021 where the price of electricity skyrocketed. To model a socially intelligent electricity markets, the social behaviors of end users, retailers, GENCOSs, TRANSCOs, Distributed generators' owners must be incorporated. Price-Information-seeking, Energy-Information-seeking, confidence, learning, privacy, risk perception, collaboration and experience, are just a few of the social behaviors. The primary social-related objective functions that can be considered are community resilience, social well-fare, equality and fairness, trust, and community capital.

A.5 Electrified Transportation System with Large Penetration of Electric Vehicles

Long charging time may make an electric vehicle's owner anxious. Indeed, the limited distance to drive per each charge can increase the owner's concern. By driving until discharging the electric vehicle battery following the vehicle-to-grid program, the owner may face problems to reach a destination. Furthermore, when using a blockchain for electric vehicles, the owners may be anxious about their privacy and information. This anxiety and concern regarding the charging, discharging, and privacy affect the owner's actions and decision to experience a large variability. An effective way to address this problem is to enhance the active demand side management to participate in the vehicle to grid program. The participation of the owner also depends on the level of cooperation, flexibility, and trust to the aggregator.

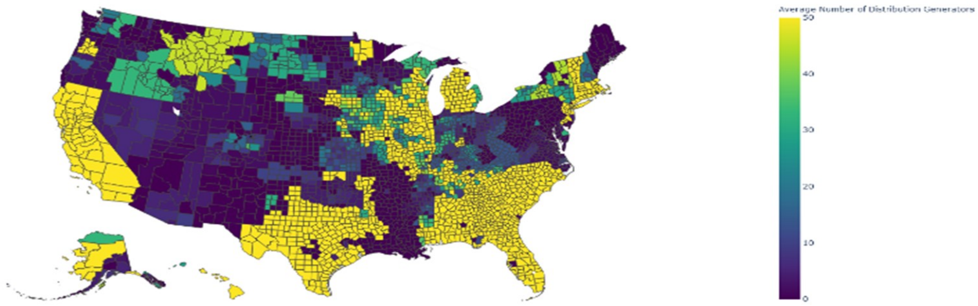

Figure A.2: The US County-level Average Number of Distribution Generators.

A.6 Renewable Energy

The electric generation of renewable energy units, such as wind turbine and photovoltaic units, experience random intermittences. This makes their productions highly uncertain and difficult to predict. Figure A.2 shows the US county-level average number of distribution generators. As we can see, renewable energy has a high penetration level in the power grid these days. Due to the high rate of distributed generator insertion, the level of generation uncertainty increases, posing a challenge for power system operators. For instance, during the Texas blackout, some wind turbines became frozen, as forecasters were unable to account for these uncertainties. Thus. active end-users appropriate social behavior, e.g., a high level of adaptability, empathy, and cooperation, can assist power system stakeholders in addressing the challenges posed by this type of uncertainty. As a result, the power system's frequency may enhance due to increased consumer cooperation. Additionally, the owners of distributed generators' participation in supporting critical loads during a disaster are contingent on their level of collaboration.

A.7 Socially Intelligent Power System Planning

Power system planners should consider enhancing community resilience, social welfare, equality, fairness, and community capital as main objectives when planning the investment in new generating units, transmission lines, and charging stations for electric vehicles. Socially intelligent power system expansion consists of social traits various stakeholders, e.g., prosumers, consumers, electrical vehicle owners, DERs, retailer, utilities, GENCOs, TRANSCOs, DISCOs, MG, load serving entities, aggregator, ISOs, regional transmission organizations, coal industry, natural gas industry, and critical infrastructures. These social features include emission-information-seeking, reliability, confidence, learning, cooperation, privacy, institutional efficiency, risk perception, emotion, flexibility, collaboration, and experience, to name a few.

A.8 Economic Dispatch and Unit Commitment

Figure A.3 and Figure A.4 show the US county-level photovoltaic and wind capacity, respectively. As we can see, the photovoltaic and wind turbine capacity in the US power grid is quite high. Thus, collaboration between owners of photovoltaic and wind turbines and power system operators can contribute to the reliability, sustainability, and efficiency of the power system. In addition, active end-users can supply some parts of the electricity to the load as part of the grid's real-time operation. Hence, the prosumers' high level of cooperation and flexibility can increase the economic dispatch and unit commitment efficiency if it is properly modeled.

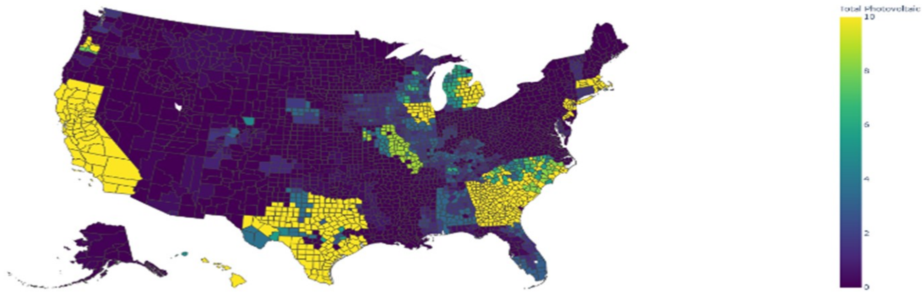

Figure A.3: The US County-level Photovoltaic capacity (MW)

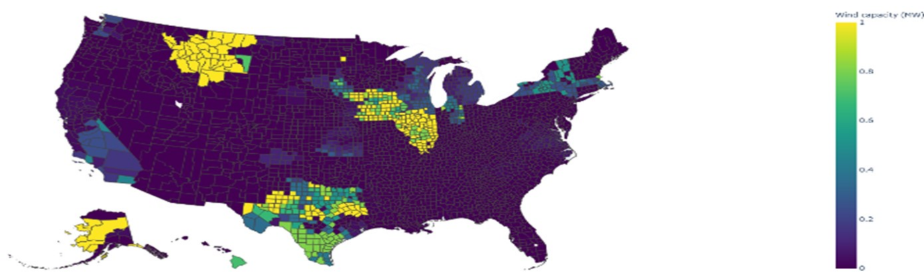

Figure A.4: The US County-level Wind capacity (MW)

A.9 Socially Intelligent Demand response

Figure A.5 and Figure A.6 show the US county-level number of customers enrolled in demand response and resulted average energy savings (MWh). These figures emphasize three points: 1- This figure demonstrates the widespread participation of consumers in demand response. Thus, end users exert a significant influence on the operational power balance through their social behavior. 2- Consumer participation varies by county. This implies that each of these counties, with their unique social characteristics, has its own set of social needs. 3- Demand response can result in a variety of benefits, including profit. We can speculate on why one state is able to conserve more energy than others. One of the primary reasons is that the magnitude of these benefits is directly related to their psychological behavior. The study of demand response in the literature is limited to the economic and sustainability aspects. Most of demand response models ignore the social science aspect despite its great importance. Participation in demand response scheduling depends directly on the level of flexibility,

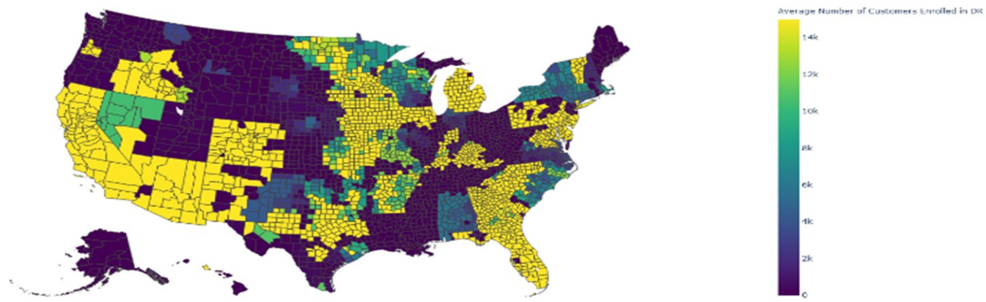

Figure A.5: The US County-level Average Number of Customers Enrolled in Demand Response.

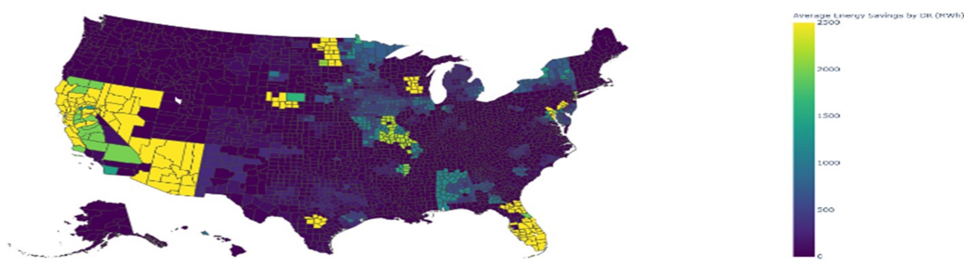

Figure A.6: The US County-level Average Energy Savings by Demand Response (MWh)

cooperation, empathy, emotional status, and habits of the community. Hence, there is a need to consider them in the demand response modeling, which involves the achievement of trade-offs between various objective functions, i.e., social well-being, sustainability, and cost.

A.10 Cascading Failures

Cascading failures in power systems, e.g., the blackout that the USA and Italy experienced in 2003, can induce failures in other critical infrastructures such as transportation, water supply, health care systems, financial services, and communication systems. The utilities and end-users' role is to take appropriate actions to minimize the economic losses that may result, which is dependent on human activity and the mental states, habit, and culture. For example, if a blackout occurs, microgrids can provide electricity to critical loads such as hospitals, gas stations, police stations, data centers, to name a few. Overloading is one of the triggers for a cascading failure in power systems, leading to equipment outages and blackouts. It turns out that active demand side management can mitigate this risk. Furthermore, the detrimental consequences of electric power outages on a community can be alleviated via enhancing the level of cooperation, flexibility, and empathy. If power outages occur, we must put critical loads as a priority to supply to enhance community resilience. The prosumers within the community can share their electricity with vulnerable people, e.g., elderly and handicapped and sick people, as a priority. Besides, the consumers within the community can reduce their loads.

A.11 Socially Intelligent Rolling Blackout and Load Shedding

Rolling blackouts affect the power system end-users. To reduce community vulnerability and increase power system resilience, rolling blackouts should be carried out fairly. The levels of cooperation and flexibility of the end-users can help the utilities to enhance both the infrastructure and the community resilience. These levels are influenced by the levels of satisfaction, trust, experience, risk perception, willingness, collaboration, and learning of the end-users, to name a few. To model socially intelligent rolling blackout and load shedding, it is necessary to integrate computational social science into conventional cyber-physical power systems through the use of social and cyber-psychological science and theories, as well as social sensing.

A.12 Recovery

to a Specific Disaster A line, a tower, a transformer, a substation have different times to repair, typically from small to large. To estimate these times to repair, there is a need for social neuroscience model to account for the past experience and the level of cooperation and flexibility and the level of satisfaction of the utility workforce, as well as the level of information and resources available to them. Pre-event prevention and mitigation of the impact of the hurricane on the power system and the emergency services are event modifiers between the event and post-event time period. We propose to leverage an artificial society to model workforce behavior that influences power system vulnerability. The 2021 Texas winter storm made more than 4.5 million homes, businesses, and event critical loads lose electricity. Furthermore, the market-oriented system in the Energy Reliability Council of Texas (ERCOT) electrical grid results in bills of up to $17,000 for less than one month of service. The power outage, high electricity prices, and difficulty in recovering from the Texas storm crisis result from a lack of community capital, such as cooperation and empathy, and adequate winterization of power infrastructure. These factors made the Texas storm crisis one of the most expensive disasters in history, with an estimated cost loss of $195 billion.

A.13 Active Demand Side Management and Direct Load Control

Figure A.7 shows the US county-level average number of customers with direct load control. Frequency regulation is of high importance to power system stability. Active consumers in smart grids can play a significant role in providing ancillary services for power system transient stability. Although frequency regulation is important in normal power system

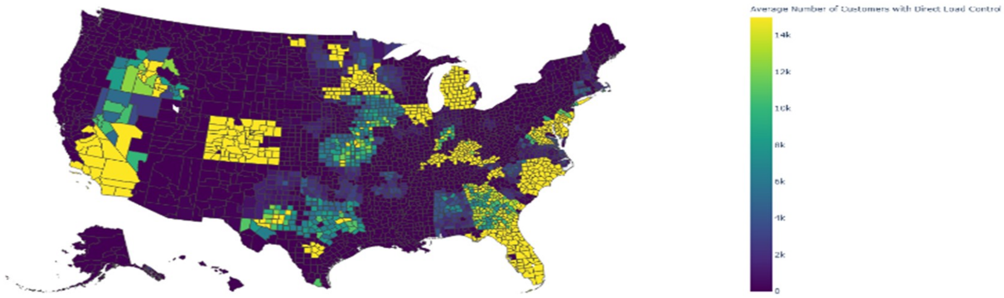

Figure A.7: The US County-level Average Number of Customers with Direct Load Control

operation, it is more crucial and challenging during a disaster. The consumers who receive signals by smart meters can decrease the risk of electricity outage by participating in an active demand side management. They can turn off unnecessary electric devices for a few hours as soon as they receive a signal about the disaster from the emergency services or utilities. The participation of consumers in active demand side management to provide ancillary services for frequency regulation is entwined with their social behavior.

A.14 Impact of an Epidemic on Power System Operation

An epidemic, e.g., COVID19 induces a decrease in industrial and commercial loads and a possible increase in residential loads. It may produce an increase in the harmonic voltage levels at specific frequencies. This in turn increases the vulnerability of the power system to voltage and frequency instabilities. The cooperation and flexibility of the end-users who are willing to engage in the demand response program is essential to enhance power system stability margins in real-time.

A.15 Pandemic Planning

An infectious outbreak such as a pandemic influenza impacts the primary energy and, in turn, the electric supply chain. Consequently, it affects the electric generation and decreases the resiliency of the power system. In fact, a pandemic makes a disconnection between the fuel supply chain (the primary energy) and the electric sector (the secondary energy). Hence, the normal operation of the bulk power system is disturbed. This is the reason why studying the impact of the pandemic on electric power systems is emphasized by European electricity, gas, and oil coordination groups, and selected US Federal agencies such as Health and Human Services (HHS), Department of Homeland Security (DHS), Department of Energy (DOE), Department of Transportation (DOT), and Department of the Interior (DOI). The outbreak of influenza or other infectious diseases, e.g., coronavirus or 2003 outbreak of SARS, can negatively influence power systems from coal supply chin to fuel transportation to electricity production.

A.16 Environmental Protective Policies and Regulations

End users may promote investment in energy hub resources to improve environmental conservation programs. As one course of action, consumers can shift their load to the hour that environmentally friendly energy sources, e.g., wind turbines, solar thermal panels, generate electricity. These consumers' motivations are to reduce air emissions and water pollution, which are critical issues in the use of conventional energy, in order to protect the environment.

A.17 Restoration

Restoration of a power system following a blackout induced by various extreme events is a complex process. It consists of phases, i.e., planning to restart and reintegration of the bulk power system, retaining critical sources of power (degraded level), and restoration after stabilizing at some degraded level. The level of experience, knowledge, learning rate, the cooperation of the workforce, experts, and operators influence the quality of restoration.