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

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Abstract—This article 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 multilagent-based algorithm. The tool that makes the nexus between the electric generation on the physical side and consumers and prosumers on the social side the power flow algorithm. 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 dependent 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.

Index Terms—Community resilience, critical loads, cyber-physical-social system, load shedding, power flow, power systems, resilience, smart grids, social computing, social well-being.

NOMENCLATURE

| Indexes | Social Science Variables | Power Flow Variables |
|---------|--------------------------|----------------------|
| t       | Index for time.          | $\alpha_{nt}/\beta_{nt}$ Load shedding of consumers, prosumers/critical loads. |
| n/m     | Index for bus (N is the total number of buses) | $P_{nmt}$ Electricity transferred between two buses. |
| $M_{tn}^e$ | Level of emotion (fear) in each bus. | $\theta_{nt}$ Voltage angle. |
| $M_{tn}^r$ | Level of risk perception in each bus. | $P_{der}$ Electricity produced by distributed energy resources. |
| $M_{tn}^c$ | Level of cooperation in each bus. | $P_{nt}$ Electricity produced by utilities. |
| $M_{tn}^a$ | Level of empathy in each bus. | $P_{mg}$ Electricity produced microgrids. |
| $M_{tn}^p$ | Level of physical health in each bus. | $P_{cl}$ Electricity consumed by critical Loads. |
| $S_t$ | Level of social well-being of a community. | $P_{d}$ Electricity consumed by consumers and prosumers. |

Cyber Variables

$N^m_t$ Level of the related and negative news of social media.

I. INTRODUCTION

A. Motivation

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. 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 article, community resilience is defined as the ability of a community to bounce back and recover from a given class of severe disturbances [1]. One of the key factor of community resilience is social well-being, whose modeling and assessment require an interdisciplinary approach. 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, 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. Fig. 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.

B. Related Work

The national power grid, the banking and financial systems, the telecommunication and information networks and public health networks are all examples of socio-technical systems. Modeling and simulating socio-technical systems are indispensable for assisting stakeholders in predicting system behavior in rare and severe occurrences, identifying risks and vulnerabilities, and aiding in decision-making and policy development. Modeling existing socio-technical systems is difficult due to their complexity, which results from social, technical, and contextual interactions and interdependencies. Yu et al. [2] proposed a method for semantic modeling of the various components of social-technical systems, such as a holistic supply chain network. Human factors are quantified as a variable in the design and operation of technical systems. In the literature, various models of socio-technical systems have been proposed. As for the infrastructures, two basic models have been developed, namely, an integrated model that covers all elements in one framework and a linked model that combines distinct models [3]. Recently, data-driven computational models of socio-technical systems have been popular, including discrete-event simulation, agent-based models, and network models [4].

The tool that makes the nexus between the electric generation on the physical side and the consumers and the prosumers on the social side is the power flow algorithm. The latter is an essential tool for the long-term and operational planning of a power system, where ac and dc power flow analysis is performed in both transmission and distribution systems. To solve the power flow equations, a number of deterministic and probabilistic methods have been proposed [5]. Tostado-Veliz et al. [6] leveraged the Bulirsch–Stoer algorithm to solve the power flow equations for very large-scale power systems, while Tang et al. [7] employed trust-region techniques together with a least-square solution for unsolvable scenarios. Also, alternative methods, such as dc power flow models, have been advocated to find linear approximations to the ac power flow equations [8], [9]. Interestingly, Yang et al. [10] derived the linear power flow model with the minimum error. However, none of the proposed power flow methods examine consumers and prosumers’ social aspects.

In this article, we address this problem by developing and analyzing a socio-technical power flow model, which is formulated as a constrained optimization problem that maximizes the community resilience subject to power flow constraints. Zhang et al. [11] explored resilience and resilience engineering’s identity. The authors discuss how to design resilient systems. Disruptions may or may not trigger system structural changes. The system structure can be modified at both the disturbing and reconfiguration stages. In this regard, Zhang et al. [12] provided a bilevel mathematical optimization model to maximize transportation system resilience and restore its performance through two network reconfiguration schemes.

Regarding power systems in an extremis state, islanding and fault reconfiguration actions may be taken to avoid system breakdown. For instance, Lin et al. [13] offered a tri-level defender–attacker–defender paradigm in which the system operator takes resilient operational steps, such as optimal distributed generation (DG) islanding formation and topology reconfiguration. Dehghanian et al. [14] advocated a transmission network reconfiguration with minimum additional cost for resiliency improvement. Aziz et al. [15] outline progress in network reconfiguration for power system resilience.

C. Research Goal, Contributions, and Questions

We propose a socio-technical power flow algorithm in the CPSS-PE. In this algorithm, the loads that impact the most the community resilience and that provide the highest community satisfaction are 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 as shown in Fig. 1. In reality, we face a more sophisticated power system than the example presented in that figure. Consequently, the socio-technical power flow becomes a challenging problem to solve due to the numerous technical and social constraints.

1Socio-technical system is a joint system referring to the interaction between human behavior and community’s complex infrastructure such as power systems [16].
This article is an extension of our previous work described in [17], which does not account for the power flow constraints, the load shedding, and the electricity shared during disasters that is limited by the capacity of the transmission lines. Specifically, we will address here the following question: How to maximize community resilience subject to power flow constraints in CPSS-PE? It is worth noting that the process of social behavior validation is explained in [17].

The key contributions of this article include the following.
1) A socio-technical power flow model is proposed. The power flow described in the literature only takes into account cyber-physical systems and disregards social factors. We explain how social factors might affect the power flow. In addition, we model the social media impact on power flow and the spread of news using the socio-technical framework.

2) The social behavior of consumers and prosumers as well as their influence on the availability of power are modeled. Specifically, we model consumers’ and prosumers’ levels of emotion, risk perception, empathy, and cooperation. Therefore, the proposed model captures the social behavior of power system end-users.

3) An optimization model is developed, which determines the optimal value of the load shedding based on socio-technical constraints of power systems in order to maximize community resilience. The proposed model is applied to two case studies, namely, a two-area 6-bus system and a modified IEEE RTS 24-bus system.

4) It is found that a decrease in the starting values of the emotion, the risk perception, and the social media platform effect factor is associated with an increase in load shedding, which leads to a decline in community resilience.

5) It is shown that an increase in the initial values of cooperation, empathy, the capacity of microgrids, and DERs reduces load shedding, which in turn increases community resilience.

While being developed for power systems, the method presented in this article can be applied to other critical infrastructures.

The remainder of this article 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 multiagent-based model. Section III-M 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. Section VI concludes this article.

II. SOCIAL COMPUTING AND COLLECTIVE BEHAVIOR

In our model, we consider emotion, risk perception, empathy, cooperation, and social well-being and their effects on the community resilience. Their definitions and the meaning of their numerical values are provided in Table I. There is a widely held belief that emotion is the core characteristic of group behavior; consequently, modeling group emotion is of high importance. So, we first discuss emotion and then we discuss the aforementioned social features.

A. Emotion

In addition to logical intelligence, emotional intelligence is part of human intelligence. Emotions are complex psychophysiological processes that are controlled by many internal and external factors [21]. Human emotion plays a crucial role in both human-human and human-machine interaction. Emotion in social intelligence is also important. 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.

1) Group Emotion. Barsade Theory: Barsade et al. [22] proposed 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).

When discussing group emotion, there is an important concept known as emotion diffusion. Emotion contagion or diffusion implies that the emotions of one consumer may affect the emotions of another consumer based on their proximity, friendship, and connectivity [23]. The strength with which an emotion is received by receiver R from sender S is determined by three main factors: sender emotion expression $\varepsilon_s$, channel strength $\alpha_{SR}$, and openness to receiving the emotion $\delta_R$. Sender emotion expression denotes how expressive the consumer’s emotion is. It is related to extraversion [24] and sensation seeking from Zuckerman theory [25] and Gray theory [26]. Furthermore, the strength of the channel from sender to receiver is affected by distance, attachment, type, and level of contact between two consumers [27]. Openness of the receiver of emotion, $\delta_R$, on the other hand, is the degree of susceptibility of the receiver and how emotionally flexible/persistent a consumer is. The strength with which receiver R receives an emotion from sender S is $\varepsilon_s \alpha_{SR} \delta_R$. The level of emotion that S influence on the emotion of R is equal to $\varepsilon_s \alpha_{SR} \delta_R m_t^S$. Fig. 2 depicts the consumers who interact with one another. When the level of emotion diffusion is greater than zero, the emotions of consumers eventually become the same [see Fig. 2(a)]. When there is no emotion diffusion between two consumers, implying that at least one of the Sender’s emotion expression, receiver openness, or channel strength is zero, the consumers’ emotions do not change over time [see Fig. 2(b)].

2) **Upward Emotional Well-Being, Fredrickson Theory:** One important question that is pivotal for the social network emotion is the following: How do positive and negative emotions influence the agents? Fredrickson et al. [28] answered this question by proposing a broaden-and-build theory, also known as 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. In contrast, in downward spirals theory, negative status, such as anxiety, depression, and failure, anticipate local prejudices according to narrowed focus.

3) **Absorption Model—A Multiagent-Based Model for Group Emotion:** To model the emotion of a social network, computational models are used. According to social neuroscience, emotion can be considered as a collective feature of the group since the emotion of an agent forms the feelings, thoughts, and behavior of other agents.

In the absorption model, the bottom-up conception based on Barsade theory is utilized [29]. This model assumes that group emotion is equal to the sum of the emotions of all the agents within the group and that it is determined by the homogeneity, heterogeneity, and the mean emotion of the agents within the group. This model is appropriate in some situations, where the emotion dynamics of the agents have to be simulated.

As stated previously, the level of social diffusion between two consumers is $\varepsilon_s \alpha_{SR} \delta_R$. After interaction, the influence of group emotion on the consumer is $A = \sum \varepsilon_s \alpha_{SR} \delta_R m_t^S$. The emotion change of each consumer for each $\Delta t$ is equal to $\Delta M_t^R = \gamma (A - M_t^R) \Delta t$, where $\gamma$ is the group emotion’s rate of change. Interestingly, Bosse et al. [29] stated five theorems for the absorption model, which are: 1) No change when $\gamma = 0$; 2) Equilibrium when $\gamma > 0$ for all consumers; 3) Monotonicity Conditions; 4) Preservation of overall emotion; and 5) Closure property.

Let us now discuss some simulation results using the absorption model applied to a group of three consumers whose emotion levels are assumed to be 0.1, 0.3, and 0.9, where 0 and 1 are the minimum and maximum levels. The results of two cases are displayed in Fig. 3. As observed in Fig. 3(a), when the level of social diffusion between the consumers is 1, all consumers’ emotions converge to the same emotion level, which is the group’s emotion. In contrast, as observed in Fig. 3(b), when the level of social diffusion between consumers 1 and 3 is 1 while there is no social diffusion between consumer 2 and consumers 1 and 3, the emotions of consumers 1 and 3 converge over time while the emotions of consumer 2 remains constant. Note that in this case, the group emotion is different from that of each consumer.

4) **Amplification Model:** The amplification model of the emotion of a social network is based on Fredrickson theory, i.e., the broaden-and-build theory, including upward and downward emotional spirals.

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**Fig. 2.** Consumers’ emotional state before and after interaction. (a) With social diffusion. (b) Without social diffusion.

**Fig. 3.** Consumers’ emotional state before and after interaction using the absorption model applied to a group of three consumers: a) The level of social diffusion between all three consumers is 1; b) Consumers 1 and 3 have a social diffusion of 1 between themselves and no social diffusion with consumer 2.
The upward spiral (US) equals $1 - (1 - M^*tR)(1 - M^*tR)$, and the downward spiral (DS) equals $M^*tRM^*tR$. Here, US and DS, respectively, indicate the positive and negative effects that an event or other consumers have on an agent’s emotion. As for the parameter $R$, it defines the total impact as a weighted combination of upward and downward spirals. If $R = 1$, the consumer, as the recipient, is only susceptible to positive effects. If $R$ equals zero, the consumer is only susceptible to negative effects. If $R = 0.7$, the US and DS have 70% and 30% impact on consumers, respectively. The emotion change of each consumer for each $\Delta t$ is equal to $M^*tR = \gamma(RU/S + (1 - R)DS - M^*tR)\Delta t$, where $\gamma$ represents the rate at which the emotion is evolving. Fig. 4 depicts numerical examples of the application of the amplification model to a group of three consumers. In the first example depicted in Fig. 4(a), there are three consumers with initial emotions of 0.9. When we set all $R$ to 0, indicating that the consumers are only susceptible to negative effects, the level of emotion felt by the consumers declines over time. When all $R$ are set to 1, the emotions of all the consumers reach a state of equilibrium at the value of 1. The prevalence of these patterns is stated in [30, Th. 2]. In contrast, if we follow the absorption model, the consumers’ emotions will remain stable over time. In the second example, however, there are three consumers with initial emotions of 0.3, 0.6, and 0.7 as depicted in Fig. 4(b). Now, let us assume that the level of $R$ for each of the three consumers is 0, 1, and 0.8. As time passes, the emotion of the consumer with $R = 0$ diminishes, while the emotion of the consumer with $R = 1$ increases faster than the emotion of the consumer with $R = 0.8$.

Theorems 1–4 of the amplification model are stated in [30]. These theorems include the following cases: 1) Equilibria when some Rs are equal to 0 or 1; 2) Equilibria when all $R$ are either equal to 0 or to 1; 3) Equal equilibrium values for all members; 4) The case of two consumers.

**B. Cooperation**

We use a multiagent-based model to examine the social behavior of a group of agents. In a multiagent system, the success or failure in accomplishing an objective is highly dependent on the cooperation between the agents [31]. According to the World Peace Through Technology Organization (WPTTO), cooperation between agents induces much more benefits than competition [32]. Hence, modeling cooperation and its effect on social behavior are of high importance. Guan et al. [33] proposed a cooperation model from the multiple social networks. Shao et al. [34] discussed the simultaneous impact of cooperation and competition. Besides, different factors influence the level of cooperation among the social groups. The main feature for teamwork cooperation is trust between agents [31]. De et al. [19] emphasized 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 [35].

**C. Empathy**

The key element in establishing meaningful and effective social relationships is empathy. Emotional support needs to be an empathetic communication where one understands the emotional state of other people. 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 [32], [36]. 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, 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. As described in the absorption model, the level of empathy is determined by the level of social diffusion and the level of attachment among consumers. As observed in Fig. 3(b), when the level of empathy among customers is 1, the emotional state of all consumers will converge over time. In addition, when consumers lack empathy for one another, their level of emotions will become consistent throughout time.

**D. Risk Perception**

One of the natural behaviors of people when they face disaster is the feeling that they are in danger due to their dynamic interaction with the environment. This helps them to take actions aimed at dealing with the situation and the incident. With an increase in the uncertainty of a disaster, people tend to perceive a higher risk than it is in reality. This is because they may be at greater risk otherwise. People without previous experience, they cannot unusually evaluate the risk of a hazard as reliably as someone with prior experience. Consequently, they are exposed to greater danger. 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 [37], [38]. Based on the discussion in [39], the variable $R$ proposed in the amplification model is the level of consumer risk perception.

**E. Social Well-Being and Community Resilience**

Social well-being requires an interdisciplinary approach, integrating knowledge and ideas from disciplines, such as neuroscience, social and cognitive psychology, artificial intelligence, and other fields. The development of technologies to enhance social well-being and community resilience should be viewed as a fundamental requirement in the age of social media.

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Footnote:

2Peace software are tools and platforms that aim to make peace in the community and to increase the awareness of global interdependency [32].
cognition, multimedia development, engineering, and healthcare [40]. The social well-being includes the mental and physical well-being. In our model, we consider the inverse of the level of emotion (fear) of a society as mental well-being. This means that the less concern, the more mental well-being. On the other hand, we hold the physical health of the community as a physical well-being. When a society faces a disaster or an extreme event, its social well-being is affected, especially when there are losses. The reader is referred to Section III for further details.

III. COMMUNITY RESILIENCE OPTIMIZATION SUBJECT TO POWER FLOW CONSTRAINTS

A. Defining the Objective Function on Community Resilience

The social well-being of a CPSS-PE consists 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

$$\text{Max} \sum_t S_t \quad (1)$$

subject to

$$\begin{align*}
S_t &= \frac{1}{N} \left( \sum_n \eta (\zeta^e (1 - M^e_{tn}) + \zeta^{\text{ecl}} (1 - M^{\text{ecl}}_{tn})) \\
&+ \sum_n (1 - \eta) (\zeta^p M^p_{tn} + \zeta^{\text{pcl}} P^{\text{pcl}}_{tn}) \right),
\end{align*} \quad (2)$$

and 11 other equality or inequality constraints that are defined next. The first term of the summation given by (2) 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 $\{\eta, \zeta^e, \zeta^{\text{ecl}}, \zeta^p, \zeta^{\text{pcl}}\}$. 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

$$\begin{align*}
M^{\text{ecl}}_{tn} &= \omega^e (1 - \beta_{tn}) \quad (3) \\
P^{\text{ecl}}_{tn} &= \omega^p \beta_{tn} \quad (4)
\end{align*}$$

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

B. Dynamical Changes of the Level of Emotion of Consumers and Prosumers

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

$$M^e_{(t+1)n} = \gamma^e_{tn} \left( f(M^e_{tn}, M^{pc}_{tn}) - M^e_{tn} \right) \omega^e + M^e_{tn} \quad (5)$$

where $\omega^e$ denotes the time coefficient such that $\omega^e \leq \frac{1}{n-1}$ as indicated in [29] and where

$$\begin{align*}
\gamma^e_{tn} &= \sum_{m} \gamma^e_{tnm} M^e_{tnm} \\
f(M^e_{tn}, M^{pc}_{tn}) &= \eta^e (1 - M^e_{tn}) (1 - M^{pc}_{tn}) \\
&+ (1 - M^e_{tn}) (1 - M^{pc}_{tn}) + (1 - \eta^e) M^e_{tn}
\end{align*} \quad (6)$$

$$\begin{align*}
M^e_{tn} &= w^e \left( \sum_{m} \gamma^e_{tnm} M^e_{tnm} \right) + W^e (1 - M^e_{tn}) \\
&+ W_{\text{pc}} (1 - M^p_{tn}) + W_{\text{pcl}} \\
&\times (1 - \alpha_{tn}) + W_{\text{m}} N^m_{tn}
\end{align*} \quad (7)$$

$$M^e_{(t=0)n} = M^{eini}_{n} \quad (8)$$

where $\alpha_{tn}$ denotes the load shedding variable, which is constrained to take values between 0 and 1, that is, $0 \leq \alpha_{tn} \leq 1$, and where $\gamma^e_{tn}$ 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 $f(M^e_{tn}, M^{pc}_{tn})$, 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, $M^e_{tn}$ denotes the amount of emotion of an agent influenced by the emotion of the other consumers and prosumers, which account for the interagent impacts [41]. Here, the term $M^e_{tn}(1 - (1 - M^e_{tn})(1 - M^{pc}_{tn})) + (1 - M^e_{tn})(M^e_{tn}, M^{pc}_{tn})$, 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 $L_W = \{W^e, W_{\text{pc}}, W_{\text{pcl}}, W_{\text{m}}\}$.

Note that $M^e_{tn}$ is influenced by the social-social dependence including the emotion of the other agents ($w^e \left( \sum_{m} \gamma^e_{tnm} M^e_{tnm} \right)$), its cooperation ($W^e (1 - M^e_{tn})$), and agent’s physical health ($W_{\text{pc}} (1 - M^p_{tn})$). 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 ($W_{\text{m}} (1 - \alpha_{tn})$) and the cyber-social dependence, i.e., the social media ($W_{\text{m}} N^m_{tn}$) [39]. In (10), $M^{eini}_{n}$ represents the initial values of the emotion of consumers and prosumers at time 0.

C. Dynamic Change of the Level of the Related and Negative News of Social Media

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 [21, 42]. They use these social media services to share their emotions and thoughts. The dynamic change of the level of the related and negative news of the social media is given by

$$N^m_{tn} = \zeta^m [\zeta^e (1 - \alpha_{tn}) + \zeta^{\text{ecl}} (1 - \beta_{tn})] \quad (10)$$
where $\zeta_n$ is the effect coefficient. Here, the social media news are directly related to the load shedding of consumers, prosumers, and critical loads. 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.

### D. Dynamic Change of the Level of Risk Perception of Consumers and Prosumers

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

$$M_r^c(t+1)_n = (\eta^c + (1 - \eta^c)N_t^m_n) \left( \frac{1}{1 + e^{-\sigma^c(M_{tn} - \phi^n)^T}} \right)$$

$$- (1 - M_{tn}^p) (1 - M_{tn}^r_n)((1 - \alpha_{tn} - M_{tn}^r) \sigma + M_{tn}^r)_{n}$$

$$M_r^c(t=0)_n = M_r^{m, c}.$$  \hspace{2cm} (11)

It is affected by load shedding, social media, and the cooperation, the physical health, and the emotion of the consumers and prosumers. If the emotion ($M_r^c$) is lower than the fear or the threshold ($\phi^n$), it has no impact on the risk perception [43]. According to the narrowing hypothesis of Fredrickson’s broaden-and-build theory [39], the factor, $((1 - \alpha_{tn} - M_{tn}^r)$, measures the tendency of risk perception to be more or less positive. In (13), $M_r^{m, c}$ represents the initial values of risk perception of consumers and prosumers at time 0.

### E. Dynamic Change of the Level of Cooperation of Consumers and Prosumers

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

$$M_r^c(t+1)_n = (\eta^c + (1 - \eta^c)N_t^m_n) \left( \frac{1}{1 + e^{-\sigma^c(M_{tn} - \phi^n)^T}} \right)$$

$$- (1 - M_{tn}^p) (1 - M_{tn}^r_n)((1 - \alpha_{tn} - M_{tn}^r) \sigma + M_{tn}^r)_{n}$$

$$M_r^c(t=0)_n = M_r^{m, c}.$$  \hspace{2cm} (13)

It is affected by the emotion, load shedding, and the physical health of consumers and prosumers. Here, the factor $((1 - \alpha_{tn} - M_{tn}^r)$ is based on the narrowing hypothesis of Fredrickson’s broaden-and-build theory. The relationship between fear and cooperation is provided in [44], [45], [46], and [47]. The relation between cooperation and physical health is discussed in [48] and [49]. According to [50], [51], [52], social media influence the level of cooperation among the individuals of a group. In (15), $M_r^{m, c}$ represents the initial values of cooperation of consumers and prosumers at time 0.

### F. Dynamic Change of the Level of Physical Health of Consumers and Prosumers

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

$$M_r^{p}(t+1)_n = \eta^p \left( \frac{1}{1 + e^{-\sigma^p(M_{tn} - \phi^n)^T}} \right)$$

$$- (1 - M_{tn}^p) \alpha_{tn} - P_{nt} \right) \sigma + M_{tn}^p$$

$$M_r^{p}(t=0)_n = M_r^{m, p}.$$  \hspace{2cm} (15)

It is affected by fear among consumers and the load shedding of consumers and prosumers. The set of $L_{MP} = (\eta^f, \eta^c, \eta^p)$ includes the mental and physical coefficients. All of the above-mentioned features are assumed to take values in the interval [0, 1]. In (17), $M_r^{m, p}$ represents the initial values of physical health of consumers and prosumers at time 0.

### G. Topology Control and Adjustment of the System

The optimization given by (1) is subject to a sixth set of inequality constraints, which are the power flow equations using a dc model. It is possible to use the concept of topology control optimizations in system emergency scenarios in order to recover from critical disruptions with load outages [14], [53] and mitigate the potential grid-scale violations, such as transformer overloads, line over flows, and over/under voltage conditions [54]. Here, we propose to optimize the resilience-based corrective topology control based on direct current optimal power flow (DCOPF). They are given by

$$\frac{\theta_{nt} - \theta_{nt}^-}{X_{nm}} - P_{nt} + (1 - \Lambda_{nm}) \cdot M_K \geq 0 \hspace{2cm} (17)$$

$$\frac{\theta_{nt} - \theta_{nt}^-}{X_{nm}} - P_{nt} - (1 - \Lambda_{nm}) \cdot M_K \leq 0. \hspace{2cm} (18)$$

An integer variable, i.e., $\Lambda_{nm}$, determines the status of any transmission line in the system. $M_K$ is a large integer specified by the user that is used to make the constraints nonbinding.

### H. Power Balance Between Generation and Load

Using 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. Their behavior may be viewed as one single group behavior by using a bottom–up approach [22].

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

$$\sum_m P_{nt} + P_{nt}^{mg} + P_{nt}^{der} + P_{nt}^{w} = \alpha_{nt} P_{nt}^{cl} + \beta_{nt} P_{nt}^{cl}. \hspace{2cm} (19)$$

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.
I. Power Flow Limitations of the Transmission Lines

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

\[ -T_{nm}^j \Lambda_{nm} \leq P_{ntm} \leq T_{nm}^j \Lambda_{nm}. \]  

(20)

J. Limitations of the DERs

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

\[ 0 \leq P_{nt}^{der} \leq M_{tn} P_{n}^{der}. \]  

(21)

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.

K. Capacities of the Microgrids to Generate Electricity

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

\[ 0 \leq P_{nt}^{mg} \leq P_{n}^{mg}. \]  

(22)

Here, the microgrids and the DERs connected to a bus are assumed to share their electricity with 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.

L. Power Plants’ Capacities to Generate Electricity

The optimization given by (1) is subject to an 11th set of inequality constraints, which are the power plant capacities to generate electricity. They are given by

\[ 0 \leq P_{nt}^{w} \leq P_{n}^{w}. \]  

(23)

M. Voltage Angle Bounds

The optimization given by (1) is subject to a 12th set of inequality constraints, which are the voltage angle bounds given by

\[ -\pi \leq \theta_{nt} \leq \pi. \]  

(24)

In the proposed model, the severity level of the 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 \( L_M, P \), the weighting factors in \( L_W \), and the well-being coefficients in \( L_W \).

IV. Case Study. Two-Area 6-Bus System

The first case study is a two-area 6-buses system, as shown in Fig. 5. This case study aims to provide the results related to the sensitivity analysis of different cyber, physical, and social factors shaping community resilience. It is assumed that all buses have access to the internet and social media platforms.

A. Soft Validation of the Proposed CPSS-PE Model

We make a soft validation of the proposed CPSS-PE model by comparing the obtained socio-technical power flow results with those of Case Study 1 provided by [41]. 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 used in the CPSS-PE. To do so, we consider the cooperation, the empathy, social media, the physical well-being of the agents along with the power flow constraints.

B. Numerical Explanations

Let us assume that the initial level of emotion is 0.5, that is, \( ME = [0.5, 0.5, 0.5, 0.5, 0.5, 0.5] \), since there are six nodes. Also, let us assume that the initial value of risk perception and cooperation is 0.1, \( MC = [0.1, 0.1, 0.1, 0.1, 0.1, 0.1] \) and \( MC = [0.1, 0.1, 0.1, 0.1, 0.1, 0.1] \), respectively, that the physical health is \( MP = [0.5, 0.5, 0.5, 0.5, 0.5, 0.5] \), and that the overall DER capacity is 200, which results in \( P_{n}^{der} = [100, 100] \) and \( P_{n}^{mg} = [50] \) for the entire microgrid capacity. Note that equal DER capacity was assumed for each node. The initial values of the social elements rely on a variety of variables, including past experience, geography, culture, current circumstances, among others. After solving the optimization model for 24 h, the social behavior for each hour is calculated for each bus. For instance, the average levels of emotion at all buses during each hour are: 0.500, 0.489, 0.491, 0.501, 0.508, 0.513, 0.524, 0.536, 0.546, 0.556, 0.564, 0.518, 0.513, 0.519, 0.527, 0.537, 0.549, 0.560, 0.570, 0.579, 0.588, 0.596. In the outputs, we indicate that the 24 h average for emotion is 0.660. In addition, the amount of load shedding at each of the six buses are 0.042, 0.042 0.737, 1.00, 0.988, 0.944. In the outputs, the average of these six buses, or \( L^a = 0.625 \), is displayed.
C. Sensitivity Analysis of Various CPSS-PE Factors in 24 Scenarios

Table II of the appendix displays the sensitivities of different social, cyber, and physical factors influencing the community resilience as demonstrated in Scenarios 1–24 listed as follows. The social factors consist of the level of emotion (fear), cooperation, risk perception, empathy, and physical health. The cyber factor includes the social media effect factor ($\zeta_{m}$). The physical factors consist of the capacities of the microgrid and of the DERs. Table III illustrates the effect of multiple factors concurrently as demonstrated in Scenarios 25–49.

**Scenarios 1–3. Changes in the Initial Value of Emotion:** In these scenarios (shown in Table II), 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 social media platforms.

**Scenarios 4–6. Changes in the Initial Value of Cooperation:** In these scenarios (shown in Table II), 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 infrastructure is decreased. An increase in the cooperation reduces the average level of the load shedding. Therefore, less negative news are reported in the social media platforms.

**Scenarios 4–6. Changes in the Initial Value of Cooperation:** In these scenarios (shown in Table II), 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 infrastructure is decreased. An increase in the cooperation reduces the average level of the load shedding. Therefore, less negative news are reported in the social media platforms.
loads is decreased. Hence, there is less negative news reported in the social 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 19–21. Change in the Total DER Capacity: In these scenarios (shown in Table II), 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 social 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 25–29. Change in the Initial Value of Emotion and Cooperation: These scenarios (shown in Table III) are related to the changes in social factors, i.e., emotion and cooperation. The values of emotion and cooperation are [0.5,0.1,0.9,0.1,0.9] and [0.5,0.1,0.9,0.1,0.9], respectively, while the values of the other components are fixed. Community resilience grows when the initial degree of emotion drops and the level of cooperation increases. According to the results, high levels of emotion and cooperation are associated with greater community resilience than low levels of emotion and cooperation.

Scenarios 45–49. Change in the Social Media Effect Factor, Total DER Capacity, and the Initial Value of Cooperation: These scenarios (shown in Table III) are associated with the changes in cyber-physical-social variables, such as social media impact factor, total DER capacity, and cooperation. These parameters receive the values [1,0.1,0.1,0.1,1], [60,200,0,200,0], and [0.5,0.9,0.1,0.1,0.1] while the values of the other variables remain constant. Community resilience increases as the initial level of cooperation and total DER capability grow while the social media effect factor decreases. Among all analyzed scenarios, a high degree of cooperation and total DER capacity and a low value of the social media effect factor results in the best level of community resilience.

Remember that the optimization model’s control variable is the level of load shedding for consumers, prosumers, and critical loads. In order to maximize community resilience, we should determine how to shed various network loads given the limited amount of generation. With suboptimal load shading at the network level, community resilience is decreased. This will increase the end-users dissatisfaction and decrease their level of cooperation. It can result in additional community losses.

D. Topology Control and Adjustment of the System

Based on the optimization model, Line 1–2 is disconnected when the emotion is at 0.90, the cooperation is at 0.10, and the total DER capacity amounts to 200 MW. Here, we do not include the cost of generation in the model. The outcomes may differ if the cost of generation and other objectives are included as the objective function of the optimization model.

V. 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 Fig. 6. 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 social media effect factor. 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 agents at two buses connected by a transmission line. The socio-technical power flow algorithm is executed for 24 h. 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.

Figs. 7 and 8 provide the result of the socio-technical power flow in CPSS-PE. Fig. 7 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
because some generating units are turned off during peak hours, which increases the levels of fear of the consumers and the prosumers. The level of emotion fluctuates from hour 1 to hour 14. Afterward, the load shedding, and physical health, to name a few. The level of the emotion contagion, cooperation, and resiliency aspects. This may be achieved by installing one or more generators in the community. Therefore, the 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.

Fig. 8 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 loads at Bus 8 and 19 amount to 0.275 and 0.013, respectively, yielding a total average load shedding of 0.288.

The average levels of load shedding experienced by the consumers and the prosumers amount to 0.401.

VI. CONCLUSION

In this article, we developed a community resilience optimization method subject to power flow constraints in CPSS-PE. The results show that the prosumers cooperate to share electricity since they face a power shortage. 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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