GRID RESILIENCY AGAINST CLIMATE CHANGE: NEED FOR CONNECTING SOCIAL INDEX TO RESILIENCY PLANNING

1st Ramesh Doddaiah
Dell Technologies
Hopkinton, USA
ramesh.doddaiah@dell.com

2nd Aurongzeb Deeder
Dell Technologies
Texas, USA
deeder_aurongzeb@dell.com

***Abstract*—Climate change is here and its impact on extreme weather events is undeniable. Power is an overly critical part of our functional structure. Understanding power resiliency is critical but at the same time, our perception and information assimilation and local social structure can impact how actionable the resiliency tools are adopted and recovery process takes in effect. In this paper, we propose the need for social index on resiliency planning followed by a few recent developments in grid infrastructure resilience under extreme weather conditions.**

***Index Terms*—Climate Change, Power Grid Resiliency, Social Index**

I. INTRODUCTION

A general definition of resilience was raised by United Nations in 2009 as "The ability of a system, community or society which is exposed to hazards in order to resist, absorb, accommodate to and recover from the effects of a hazard in an efficient manner, through the preservation and restoration of its essential basic structures and functions" [1]. As climate change is driving lot of uncertain and stochastic failures in overall human infrastructure, we focus on electrical power grids.

Severe weather events such as hurricanes and storms have been occurring more frequently in America in recent years, each of which resulted in a half to several million customers without electricity for days [2]. Power distribution was often impacted the most, as a compound effect of severe weather and degraded infrastructure. Distribution networks lie at the edge of the grid with many components across a wide geographical span. Those components can be either aging or not well-hardened and are thus susceptible to severe weather. A fundamental research issue pertaining to this real problem is the resilience of power distribution to large-scale external disruptions from severe weather [3]. Resilience here corresponds to the ability of the grid to withstand external disturbances and to recover rapidly from failures [4]. Out of 679 power outages caused by extreme weather in U.S. in 2003-2012, 80% were due to failure in distribution systems [5]. According to the U.S. Department of Energy [6], hardening refers to physically changing the infrastructure to make it less susceptible to damage from extreme wind, flooding, or flying debris. Resiliency refers to the ability of an energy facility to recover quickly from damage to any of its components or to any of the external systems on which it depends. The review paper is organized in 3 areas. We will look at human perception [7], narrow the problem to extreme weather resilience [8] and an example industry solution which uses dynamic modeling [9].

II. EXTREME EVENT AND SOCIAL INDEX

Extreme events are challenging because the probabilities are hard to measure and because decisions about rare events with important consequences pose special challenges. Profound uncertainty makes rational responses difficult and makes it easier for irrational approaches to take hold. In some cases probabilities may be fundamentally unknowable, due to the complex interactions between human and environmental systems. The probability is obviously unknown for completely new events, such as the emergence of a particular new disease. However, probabilities may be poorly known even for events that have occurred only occasionally in the past. In the tails of probability distributions, data points are rare and therefore data are sparse for fitting any reasonable existing models. Therefore, trends in extreme events are hard to discern. For example, large data sets and extensive analysis are needed to establish trends in extreme rainfall events, flood damages or sizes of forest fires. Where sparse noisy data make it hard to measure the probability of a certain kind of extreme event and assessing a trend. Some classes of extreme events, such as flood damages, earthquake magnitudes, and wildfire sizes, have 'fat-tailed' probability distributions. In fat-tailed distributions the probability densities of extreme events are much larger than in more familiar distributions such as the normal distribution. Sometimes two or more kinds of extreme events co-occur, for example if flooding causes landslides in a watershed previously denuded by fire. In ecology such multiple impacts are called compound disturbances. Fat-tailed distributions tend to magnify the correlations of extreme events and thereby increase the probability of compound disturbances. The design and allocation of resiliency information is critical so that the aggregate decision creates more good outcomes for the group.

These (and other) behavioral phenomena inevitably affect societal decision making about extreme environmental events. In this case, human perception will become more critical how information about resiliency is handled [7]. In this case, the authors argue that that perception-based resilience is a problem domain for social computing as lot more people are connected and information quickly. If social computing dynamically model and understand aspects of online interactive behaviors, it may therefore include capturing the dynamics of human perceptions towards achieving resilience. A key aspect here is conflicting perception of resiliency. Based on the location, the perception the authors propose new model to improve grid resiliency so that all users work toward common goal with common set of information. Social computing can help design platforms for diverse (i.e., in terms of disciplines, methodologies, experience, and cultural background, among others) problem solvers to collaborate and to facilitate the exchange of perceptions of experts and "non-experts" (only because they lack formal education) who are rich in experiential knowledge, which can lead to actionable information for resilience. In this case perception centric information fusion from rural to city dwellers can increase grid resiliency. Currently, there are only few models in this area. Connecting social vulnerability to resiliency is a critical part of resiliency design in the face of climate change.

III. Power grid extreme event-topological case

In the context of power systems, resilience can be defined as the grid's ability to withstand extraordinary and high-impact low-probability events that may have never been experienced before, such as extreme weather events, rapidly recover from such disruptive events, and adapt its operation and structure to prevent or mitigate the impact of similar events in the future. The concept introduced in this regard for extreme event [8] is a severity risk index. Using the influence and probability of the specific failure scenarios, a Severity Risk Index (SRI) is given by

$$SRI = \sum_{k=1}^{k=\mathbf{K}} P_k * Im_k \tag{1}$$

Here, P_k is the probability of scenario k, Im_k is the impact of scenario k and $\mathbf{K}$ the set of selected failure scenarios. The risk assessment flow extreme weather related event uses the vulnerable branches with $\mathbf{K}$ failure scenarios using the vulnerable branches and solves for power flow. The rating in this case is based on an emergency setting. It should be noted that no operator's actions take place during the risk assessment procedure, and the SRI depends on the failure probability for given loading and topology of the system. Based on the topology the authors propose a defensive islanding system. Defensive islanding drives recovery by disconnecting the vulnerable components to avoid cascading outages. The scheme involves dynamic preventive control, which allows for variable weather condition at the various phases of the post-event degraded state. Once islanding solution converged, the next vulnerable component is identified due to extreme event. In this case, the weather-dependent failure probabilities obtained by the fragility curves are compared with a uniformly distributed random number. Once a component outage takes place, the time to repair (TTR) is generated using exponential distribution. This assumption works as this is a simple static case. For increasing, TTR for higher component damage as a result of weather events with higher intensity, the TTR under normal weather is multiplied with a uniformly distributed random number. This type of simulation and proposed methodology can also be applied to any weather event (e.g., floods). During a cascading failure once can run both simulation where extreme weather can drive grid failure in cities and flood in rural areas of same extreme event zone. In this case connecting social index can be used to support rapid recovery to the people who needs the recovery the most.

IV. Power grid extreme event-Temporal case

In recent years, with more computational power and sensor data, static models are being developed for various communities and solution can be combination of manual and controls feed-back, however, dynamic models and resilience planning are becoming easier as characterizing the time-varying nature of weather-induced large-scale failure and recovery becomes feasible with financial resources [9]. The first challenge is stochasticity arriving extreme events where failures and recoveries occur randomly and dynamically. Failure stochasticity results from spatial-temporal evolution of external weather [9]. Recovery stochasticity results from environmental conditions of the aftermath of a severe weather event. In addition, failures and restorations exhibit non-stationarity, i.e., contextual behaviors at varying time and locations. The work [9] includes the effect of network structures through a new notion of dynamic neighborhood which is characterized by weather-induced failures impacting a typical network structure. The work in this case [9], defines dynamic resilience metric as the spatial temporal model derived that encompasses dynamic network neighborhoods and weather-induced failures. The dynamic spatial temporal model requires a novel resilience metric for power distribution with bi-modal recovery model (fast and slow)[9] with following equation with a sub-network in region Z with m number of disruptions:

$$s\,(t,\,z) = 1 - \frac{1}{m}\int_{\tau=0}^{t}\left(\sum_{w=f,0}\sum_{i(\tau)\in Z}\lambda_{i(\tau)}^{w}\,(\tau)\,\Pr\left\{D_{i(\tau)}^{w}\tau > t-\tau+d_0\right\}\right)d\tau \tag{2}$$

The second term calculates the expected percentage of aging recoveries at time t. The aging recoveries which correspond to disruptions at time t that would not recover for at least additional set duration thus the integral adds up all aging recoveries in duration [0, t]. Thus, S(t, Z) is the expected percentage of nodes in area Z at time t which are either in normal operation or recover within additional set duration thus reflecting temporal evolution of a network in response to unstable severe event. As we build model and tools for disruption and recovery, connecting community resiliency index to recovery model is very critical and it can be tied to probabilistic definition for better planning and policy making.

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