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BLACKOUT MITIGATION ASSESSMENT: DISTRIBUTED GENERATION & SMART GRID

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Abstract- Electric power transmission systems are a key infrastructure and blackouts of these systems have major direct and indirect consequences on the economy and national security. Analysis of Electrical Reliability Council blackout data suggests the existence of blackout size distributions with power tails. This is an indication that blackout dynamics behave as a complex dynamical system. Here, we investigate how these complex system dynamics affects the assessment and mitigation of blackout risk. The mitigation of failures in complex systems needs to be approached with care. The mitigation efforts can move the system to a new dynamic equilibrium while remaining near criticality and preserving the power tails. Thus, In order to minimize the interruptions of power systems, it is crucially important to define the location of local generation and centralized load connection to be placed. Proper location of DGs in power systems is important for obtaining their maximum potential benefits as well as for backup purpose. By smartly applying future energy production, consumption and storage techniques, a more energy efficient electricity supply chain can be achieved using techniques like DGs and Smart Grid.

1. INTRODUCTION

Electric power transmission systems are an important element of the national and global infrastructure, and blackouts of these systems have major direct and indirect consequences on the economy and national security. Although large cascading blackouts in the power transmission system are relatively rare, their impact is such that understanding the risk of large blackouts is a high priority. In addition to the direct consequences of blackouts, the growing interconnections between different elements of the infrastructure (e.g., communications, economic markets, transportation) can cause a blackout to affect other vital infrastructures. This interconnected nature of the infrastructure begs for an even more integrated (more global) approach than we will be taking here and suggests that the "complex system" approach is likely to be even more important in understanding the entire interconnected system. While it is useful and important to do a detailed analysis of the specific causes of individual blackouts, it is also important to understand the global dynamics of the power transmission network and the frequency distribution of blackouts that they create. There is evidence that global dynamics of complex systems is largely independent of the details of the individual triggers such as shorts, lightning strikes etc. In this paper, we focus on the intrinsic dynamics of blackouts and how complex system dynamics affect both blackout risk assessment and the impact of mitigation techniques on blackout risk. It is found, perhaps counter intuitively, that apparently sensible attempts to mitigate failures in complex systems can have adverse effects and therefore must be approached with care. First, as motivation for our work we consider the properties of a series of blackouts. If blackouts were largely uncorrelated with each other, one might expect a probability distribution of blackout sizes to fall off exponentially. The probability distribution function (PDF) is empirically estimated by the frequency of blackout sizes in a short interval divided by the length of the interval and is then normalized so that the total probability is one. As an example, one measure of blackout size is load shed. Figure 1 plot on a log-log scale the empirical probability distribution of load shed in the North American blackouts. The fall-off with blackout size is approximately a power law with an exponent of about −1.1. (An exponent of −1 would imply that doubling the blackout size only halves the probability.) Thus, the NERC data suggests that large blackouts are much more likely than might be expected which has implications for risk analysis models. Additionally, power law tails, particularly with an exponent between –1 and –2 are consistent with those found in many "complex systems" models which helps motivate the use of such models to understand the electric power transmission system. The NERC blackout data are the best we have found; however, the statistics have limited resolution because the data are limited to only 15 years. Therefore, the NERC data suggest rather than prove the existence of the power tails and are consistent with complex systems models rather than conclusively validating them. However, because of the potential benefits, including risk and mitigation information that cannot be accessed without them, modeling and simulation of the complex system dynamics are clearly indicated. Progress has been made in modeling the overall forces shaping the dynamics of series of blackouts. Simulations of power networks using the Oak Ridge-Pserc-Alaska (OPA) model yield power tails that are remarkably consistent with the NERC data as shown in Figure 1.

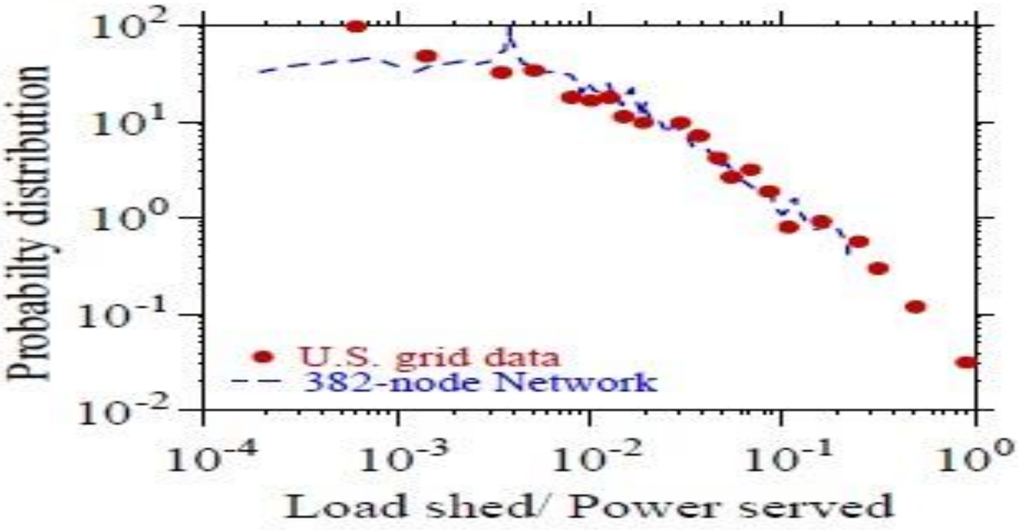

Fig. 1.1 Blackout Probability Distribution vs. Blackout Size

As a simple illustration of the importance of global dynamics, we apply the OPA model to an ideal transmission network and investigate the probability distribution of blackout sizes in two different ways. First, the blackouts governed by the global system dynamics were generated by the OPA model, and the resulting probability distribution of line outage sizes was plotted (dashed line in Figure 2). Next, the probability of any one line failing at a given time was also computed from the OPA results and this probability was then used to construct the PDF of the blackout sizes, assuming that the probabilities of outage for each line are independent of each other. This result, which is of course a binomial distribution with an exponential tail, is then compared with the OPA results in Figure 2. The distribution of the smaller events is similar for the two calculations. However, above the size of approximately 10 line outages, the OPA model distribution diverges from the exponential and exhibits the power law tail characteristic of many complex systems. According to the independent probability model, the probability of a blackout of, say, size 20 is more than 6 orders of magnitude lower. This discrepancy gets even larger for larger sizes. The absolute probability of the large blackouts is still very low which is in good agreement with the observed probability (Figure 1); however, because it is many times higher than the independent probability, it plays a much larger role in the overall impact. In fact, the presence of power tails has a profound effect on risk and cost analysis for larger blackouts, particularly in the case in which the power law exponent is between –1 and –2. In this case, the large blackouts are the major contributors to the overall impact. This bolsters the need to develop an understanding of the frequency of large blackouts and how to affect it. The main purpose of this paper is to outline some of these effects and to suggest ideas toward quantifying and mitigating the risks of larger blackouts from a complex systems perspective.

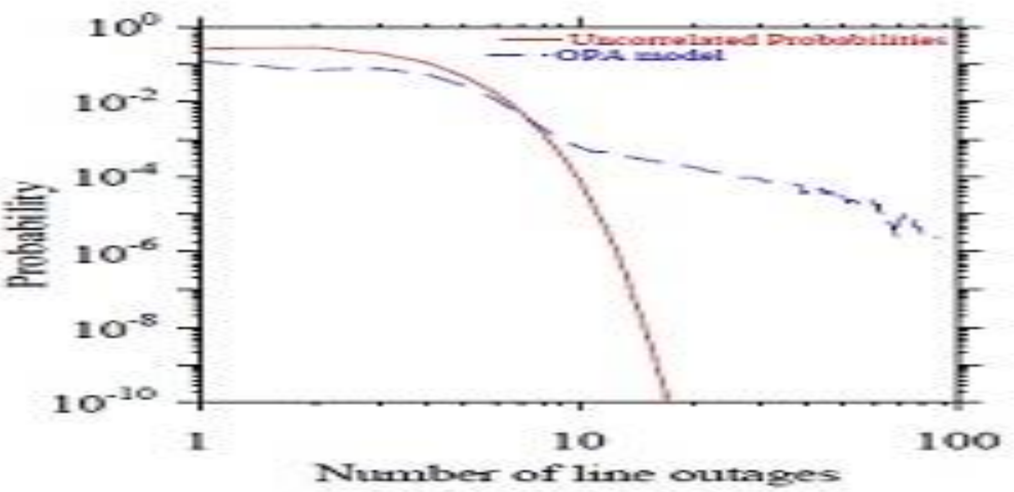

Fig. 1.2 Blackout Probability Distribution vs. Blackout Size for Uncorrelated Probabilities and for the Dynamical OPA Model

2. BLACKOUT RISK ANALYSIS AND POWER TAILS

To evaluate the risk of a blackout, we need to know both the frequency of the blackout and its costs. It is difficult to determine blackout costs, and there are several approaches to estimate them, including customer surveys, indirect analytic methods, and estimates for particular blackout. The estimated direct costs to electricity consumers vary by sector and increase with both the amount of interrupted power and the duration of the blackout. An interrupted energy assessment rate IEAR in dollars per kilowatt-hour that is used as a factor multiplying the unserved energy to estimate the blackout cost. That is, for a blackout with size measured by unserved energy S

$$\text{Direct costs} = (\text{IEAR})\ S\ \text{rs} \qquad 2.1$$

There are substantial nonlinearities and dependencies not accounted for in Eq. (2.1), but expressing the direct costs as a multiple of unserved energy is a commonly used crude approximation. However, studies of individual large blackouts suggest that the indirect costs of large blackouts, such as those resulting from social disorder, are much higher than the direct costs. In addition, the increasing and complicated dependencies on electrical energy of other infrastructures mentioned earlier tend to increase the costs of all blackouts.

For our purposes, let the frequency of a blackout with unserved energy S be F(S) and the cost of the blackout be C(S). The risk of a blackout is then the product of blackout frequency and cost:

$$\text{risk} = F(S)\ C(S)$$

The NERC data indicate a power law scaling of blackout frequency with blackout unserved energy as

$$F(S) \sim S^{\alpha}$$

Where α ranges from −0.6 to −1.9. If we take $\alpha = -1.2$, and only account for the direct costs in C(S) according to (2.1), then

$$\text{risk} \sim S^{\bullet 0.2}$$

This gives a weak decrease in risk as blackout size increases, which means that the total cost of blackouts is very heavily dominated by the largest sizes. If we also account for the indirect costs of large blackouts, we expect an even stronger weighting of the cost for larger blackouts relative to smaller blackouts. From this one can clearly see that, although large blackouts are much rarer than small blackouts, the total risk associated with the large blackouts is much great than the risk of small blackouts. In contrast, consider the same risk calculation if the blackout frequency decreases exponentially with size so that

$$F(S) = A^{-S}$$

With the simple accounting for direct costs only, one gets

$$\text{risk} \sim S\ A^{-S}$$

for which the risk peaks for blackouts of some intermediate size and decreases exponentially for larger blackouts. Then, unless one deals with an unusual case in which the peak risk occurs for blackouts comparable to the network size, one expects the risk of larger blackouts to be much smaller than the peak risk. This is likely to remain true even if the indirect blackout costs are accounted for unless they are very strongly weighted (exponentially, for example) toward the large sizes. While there is some uncertainty in assessing blackout costs, and especially the costs of large blackouts, the analysis above suggests that, when all the costs are considered, power tails in the blackout size frequency distribution will cause the risk of large blackouts to exceed the risk of the more frequent small blackouts. This is strong motivation for investigating the global dynamics of series of blackouts that can lead to power tails. If one were able to develop a model for the probability distribution function based on the complex systems dynamics by normalizing the PDF to the observed frequency of the more common small blackouts, one could construct the frequency distribution. This would allow the evaluation of realistic frequencies of the occurrence of rare large blackout events that are so important in risk analysis. Additionally, by comparing the width and shape of the small blackout region of the PDF, one might be able to determine how close to the critical point the system is. We now put the issue of power tails in context by discussing other aspects of blackout frequency that impact risk. The power tails are of course limited in extent in a practical power system by a finite cutoff near system size corresponding to the largest possible blackout. More importantly, the frequency of smaller blackouts and hence the shape of the frequency distribution away from the tail impacts the risk. Also significant is the absolute frequency of blackouts. When we consider the effect of mitigation on blackout risk, we need to consider changes in both the absolute frequency and the shape of the blackout frequency distribution.

3. MITIGATING FAILURES IN COMPLEX SYSTEMS

Large disruptions can be intrinsic to the global system dynamics as is observed in systems displaying Self Organized Criticality (SOC). A SOC system is one in which the nonlinear dynamics in the presence of perturbations organize the overall average system state near to a critical state that is marginal to large disruptions. These systems are characterized by a spectrum of spatial and temporal scales of the disruption that exist in remarkably similar forms in a wide variety of different physical systems. Systems that operate near criticality have power tails; the frequency of large disruptions decreases as a power function of the disruption size. This is in contrast to Gaussian systems or failures following a Weibull distribution, in which the frequency decays exponentially with disruption size. Therefore, the application of traditional risk evaluation methods to such systems can underestimate the risk of large disruptions. The success of mitigation efforts in SOC systems is strongly influenced by the dynamics of the system. One can understand SOC dynamics as including opposing forces that drive the system to a "dynamic equilibrium" near criticality in which disruptions of all sizes occur. Power tails are a characteristic feature of this dynamic equilibrium. Unless the mitigation efforts alter the self-organization forces driving the system, the system will be pushed to criticality. To alter those forces with mitigation efforts may be quite difficult because the forces are an intrinsic part of our society. If they do not change the self-organization processes, the mitigation efforts can move the system to a new dynamic equilibrium while remaining near criticality and preserving the power tails. Thus, while the absolute frequency of disruptions of all sizes may be reduced, the underlying forces can still cause the relative frequency of large disruptions to small disruptions to remain the same. Moreover, in some cases, efforts to mitigate small disruptions can even increase the frequency of large disruptions. This occurs because the large and small disruptions are not independent but are strongly coupled by the dynamics. Before discussing this in the more complicated case of power systems, we will illustrate this phenomenon with a forest fire model. The forest fire model has trees that grow with a certain probability, lightning that strikes (and therefore lights fires) with a certain probability, and fires that spread to neighboring trees (if there are any), also with a given probability. The opposing forces in the forest are tree growth and fires, which act respectively to increase and decrease the density of trees. The forest settles to a dynamic equilibrium with a characteristic average density of trees. The rich dynamics of this model system have been extensively studied. In our version of the forest fire model, there are two types of forests. The first type is an uncontrolled forest in which the fires are allowed to burn themselves out naturally. The second type of forest has an efficient fire-fighting brigade that can extinguish small fires with a high probability. At first, this appears to be a good thing; after all, we want to decrease damaging fires. However, in the longer run the effect of the fire fighting is to increase the density of flammable material (trees). Therefore when one fire is missed or a few start at once (from multiple lightning strikes), the fire brigade is overwhelmed and a major conflagration results. The enhanced probability of large fires can be seen in Figure 3, in which the frequency distribution of fire sizes is plotted for the two different situations. In the case where the small fires are efficiently extinguished, the large fire tail of the distribution is significantly increased over the case with no mitigation. This type of behavior is typical because, in a complex system, there is a strong nonlinear coupling between the effect of mitigation and the frequency of the occurrence. Therefore, even when mitigation is effective and eliminates the class of disruptions for which it was designed, it can have unexpected effects, such as an increase in the frequency of other disruptions. As a result, the overall risk may be worse than the case with no mitigation.

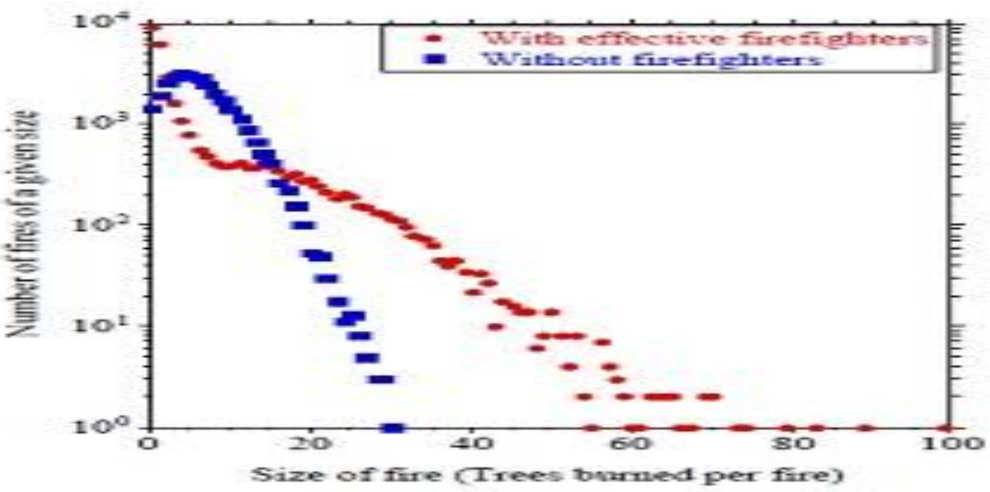

Fig. 3.1Frequency of Forest Fire Sizes With and Without Fire Fighting

4. ASSESSMENT OF MITIGATION MEASURES

To study the real impact on the system of different mitigation measures, we use the OPA model. In the OPA model, the dynamics of blackouts involve two intrinsic time scales. There is a slow time scale in the model, of the order of days to years, over which load power demand slowly increases and the network is upgraded in response to the increased demand. The upgrades are done in two ways. Transmission lines are upgraded as engineering responses to blackouts, and maximum generator power is increased in response to the increasing demand. These slow, opposing forces of load increase and network upgrade self-organize the system to a dynamic equilibrium. As discussed elsewhere, this dynamical equilibrium is close to the critical points of the system. In this model, there is also a fast time scale, of the order of minutes to hours, over which cascading overloads or outages may lead to blackout. Cascading blackouts are modeled by overloads and outages of lines determined in the context of LP dispatch of a DC load flow model. A cascading overload may start if one or more lines are overloaded in the solution of the linear programming problem. In this situation, we assume that there is a probability, p 1, that an overloaded line will suffer an outage. When a solution is found, the overloaded lines of the solution are tested for possible outages. If an outage is found, a new solution is calculated. This process can lead to multiple iterations, and the process continues until a solution is found with no more line outages. The overall effect of the process is to generate a possible cascade of line outages that is consistent with the network constraints and optimization. The OPA model allows us to study the dynamics of blackouts in a power transmission system. This model shows dynamical behaviors characteristic of complex systems and has a variety of transition points as power demand is increased. In particular, we can assess some generic measures that may be taken for blackout mitigation and it provides guidance on when and how such mitigation methods may be effective.

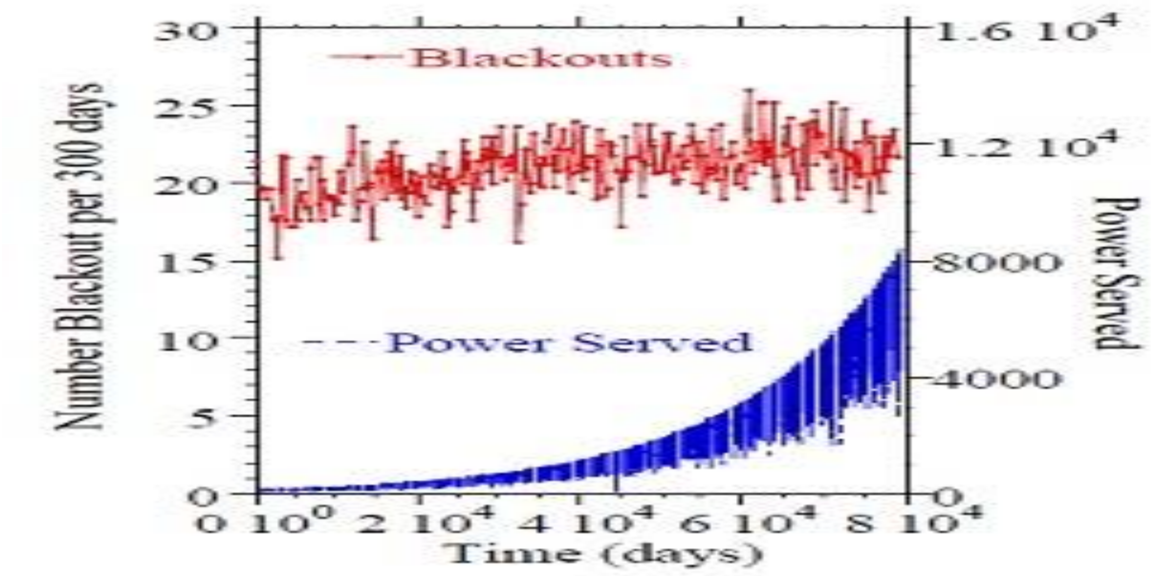

Fig.4.1 Time Evolution of the Power Served and Number of Blackouts per Year From the OPA Model

To experiment with possible mitigation effects, we consider three types of mitigation measures:

- Requiring a certain minimum number of transmission lines to overload before any line outages can occur. This could represent operator actions that can effectively resolve overloads in a few lines but that are less effective for overloads in many lines.
- Reducing the probability that an overloaded line outages. This strengthens the transmission lines. For example, this could roughly represent the effect of increased emergency ratings so that an overloaded line would be more likely to be able to operate while the operators resolve the line overload.
- Increasing the generation margin. This implies having greater power backup around the network to respond more effectively to fluctuations in the power demand. Clearly, an increase in available generator power should reduce the chances of blackouts.

In what follows, we discuss each of these three options from the perspective of the OPA model. The strong dynamical correlations observed in the results of the model will manifest in several unpredicted consequences of these mitigation techniques. In these studies, we have used the ideal tree network configuration. In what follows, we will present a few examples for those networks. We collect the data for our statistical studies during the steady-state regime in the dynamical calculation. Here "steady state" is defined with relation to the dynamics of the blackouts because the power demand is constantly increasing, as shown in Figure 4. The time evolution in the OPA model shows two distinct stages; depending on the details of the initial conditions, there is a transient period, followed by steady-state evolution. This is illustrated in Figure 4, where we have plotted the number of blackouts in 300 days as a function of time. We can see slight increase in the average number of blackouts during the first 40,000 days. This transient period is followed by a steady state where the number of blackouts in an averaged sense is constant. The properties in the slow transient are not very different from those in the steady state. However, for statistical analysis, it is better to use the steady-state information. The length of this transient depends on the rate of growth in power demand. In the calculations presented here, this rate has been fixed to 1.8% per year. In the following calculations, we evaluate the statistics on blackouts by neglecting the initial transients and doing the calculations for a time period of 80,000 days in steady state. Of course, the use of steady-state results is driven by the need for large statistical samples. It is arguable whether the real electric power grid reaches steady.

4.1 Sample Benefits of Distributed Generation Systems

- Shorter construction times
- Reduced financial risk of over- or under-building
- Reduced project cost-of-capital over time due to better alignment of incremental demand and supply
- Lower local impacts of smaller units may qualify for streamlined permitting or exempted permitting processes, reducing fixed costs per kW
- Significantly reduced exposure to technology obsolescence
- Local job creation for manufacturing, technician installers/operators
- Higher local, small-business development and taxes vs. overseas manufacturing
- Lower unit cost, automated manufacturing processes shared with other mass-production enterprises (i.e., automotive industry)
- Shorter lead times reduce risk of exposure to changes in regulatory climate
- Significant reduction in fuel disruption risk (portfolio of locally produced fuels and “fuel-less” technologies—solar, wind)

4.2 Possible Negative Impacts of Distributed Generation on Reliability

In light of the many potential benefits associated with DG, there has been a large body of work devoted to addressing a number of concerns with regard to the impact of DG on system stability and safety. Standards agencies, such as the IEEE, have promulgated interconnection standards to protect both the grid and the DG equipment. Some states have instituted interconnection rules that serve the same purpose. However, some of the equipment required to meet these standards or other utility-imposed rules can be costly, especially if used for smaller scale DG projects. Research is on going to find better solutions and to optimize the use of DG in the grid.

Some researchers are also examining possible common cause failure modes that could become important if the use of DG grows. One DG failure mode, the loss of local natural gas supply, is also important for central generation as more central station power plants use that relatively clean fuel.

CONCLUSION

Complex system dynamics in the power transmission system have important implications for mitigation efforts to reduce the risk of blackouts. As expected from studies of general self-organized critical systems, the OPA model shows that apparently sensible efforts to reduce the risk of smaller blackouts can sometimes increase the risk of large blackouts. This is due to the nonlinear interdependence of blackouts of different sizes caused by the dynamics. The possibility of an overall adverse effect on risk from apparently sensible mitigation efforts shows the importance of accounting for complex system dynamics when devising mitigation schemes. When we apply mitigation measures that tend to reduce the probability of small blackouts, we normally see an increase in the frequency and/or the size of large blackouts. Conversely, when we try to eliminate the large blackouts, there is an increase in frequency of the small ones. When we combine both types of mitigation, we see very little net effect on the number or distribution of blackouts. The negative effects of some mitigation measures may not necessarily appear right away. They can cause a slow worsening of system performance over an extended period of time. That may increase the difficulties in assessing the effectiveness of a measure and in identifying the cause of worsening of operational conditions. In this discussion, we have made estimates of the economic impact of the blackouts under very simplified assumptions. In these evaluations, we have not included the cost of implementing the mitigation measures. The cost of these measures is likely to be high because they imply considerable and sustained investments in both generation and transmission. Such investments may not be guaranteed in a deregulated open electricity market. Moreover, it is not clear to what extent the industry, regulators, or the public are prepared to spend money to avoid rare events, even if the risk and consequent economic impact of these rare events are high. Our complex system approach, which implies interdependence between large and small blackouts, should be contrasted with an approach in which large and small blackouts occur independently as uncorrelated events. The difference between the two approaches cannot be deduced from a frequency distribution of blackout sizes (these could be the same in both approaches), but from assumptions about the dynamics governing the system that produce these statistics. The present version of the OPA model includes very simple representations of the parts of the power transmission system but as a combined model can nevertheless yield complicated complex system behaviors. We intend to improve the modeling and understanding of the dynamics so that effective blackout mitigation measures can be devised and assessed from a complex systems perspective.

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