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Blackout Mitigation Assessment in Power Transmission Systems

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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 North American 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 impact 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, 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.

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 impact 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 counterintuitively, 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. The North American Electrical Reliability Council (NERC) has a documented list summarizing major blackouts of the North American power transmission system from 1984 to 1998 [1]. If blackouts were largely uncorrelated with each other, one might expect a probability distribution of blackout sizes to fall off exponentially (as, for example, in a Weibull distribution). However, analyses of the NERC data [2], [3], [4], [5] show that the probability distribution of the blackout sizes does not decrease exponentially with the size of the blackout, but rather has a power law tail. 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 plots 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 then 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 [6], [7], [8] yield power tails that are remarkably consistent with the NERC data as shown in Figure 1.

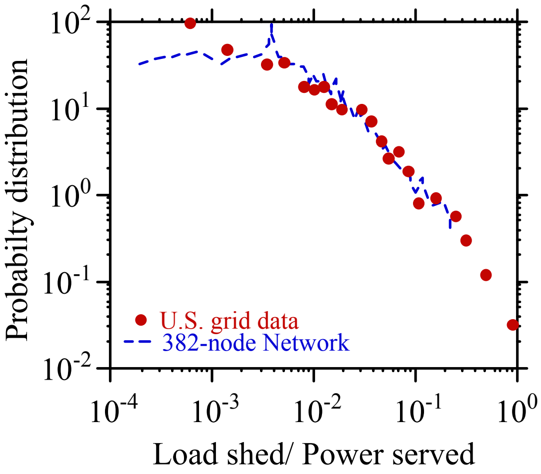

Figure 1: Blackout probability distribution vs. blackout size.

As a simple illustration of the importance of global dynamics, we apply the OPA model to an ideal transmission network of 381 lines [8] 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. A preliminary version of this paper appeared in Ref. [9].

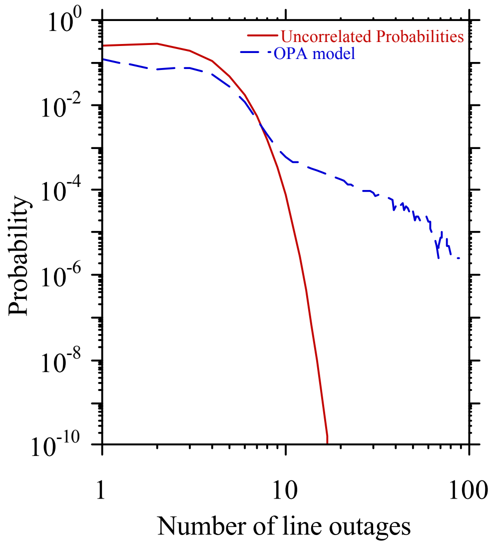

Figure 2: Blackout probability distribution vs. blackout size for uncorrelated probabilities and for the dynamical OPA model.

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 blackouts [10]. 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. Reference [11] defines 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,

$$\text{direct costs} = (\text{IEAR})\, S \quad \$ \qquad (1)$$

There are substantial nonlinearities and dependencies not accounted for in Eq. (1) [10], [12], [13], 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 [10], [14]. Also, the increasing and complicated dependencies on electrical energy of other infrastructures mentioned earlier tend to increase the costs of all blackouts [15], [16].

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 (1), then

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

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) [17], [18], [19], [20]. 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 (see Ref. [2] for an explanation in a power systems context). 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 [18].

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 [18].

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. (This seems to be the cause of the large fires in the southeastern United States in 2001.) 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.

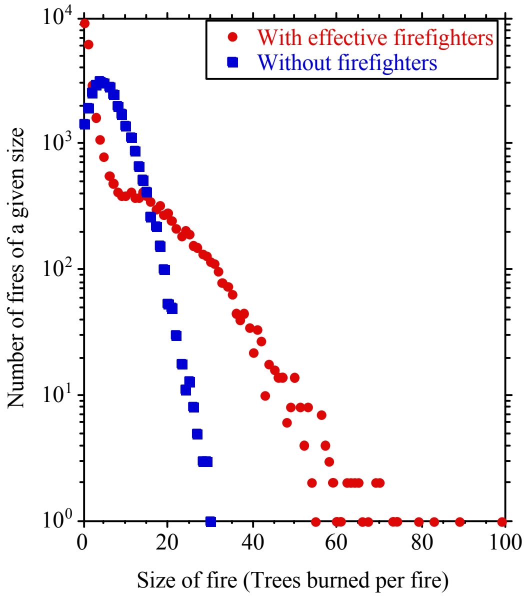

Figure 3: Frequency of forest fire sizes with and without fire fighting.

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 [8], this dynamical equilibrium is close to the critical points of the system [21], [22].

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 [21], [22]. 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.

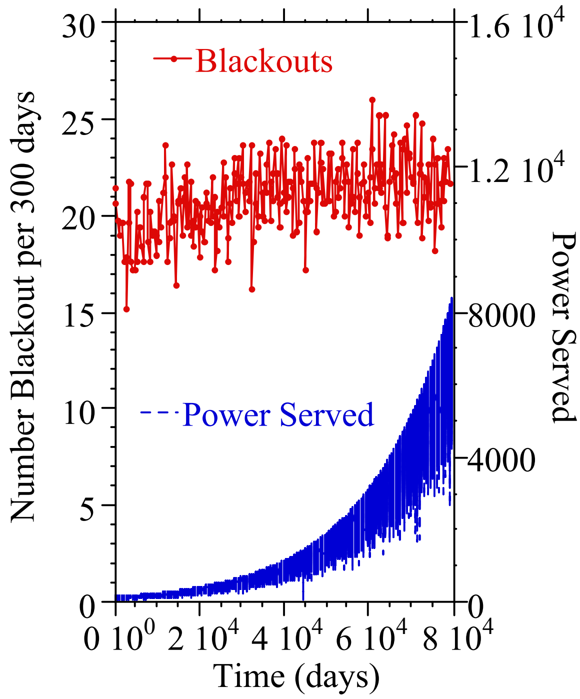

Figure 4. Time evolution of the power served and number of blackouts per year from the OPA model.

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

1) 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.
2) 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.
3) 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 [8], the IEEE 118 bus network [23] and the WSCC network. 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 [6] 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 state.

4.1. Requiring a certain minimum number of transmission lines to overload before overloaded lines outage

There are two possible sources of line outages in the OPA model. One is a random event causing a physical outage (for instance, a tree falling on top of a line). Such events happen with a prescribed probability p_0. The second cause of line outages is line overloading during a cascading event. We assume that there is a probability p_1 for an overloaded line to outage. The first type of line outage is not affected by the mitigation measure. Here we assume that operator actions can effectively resolve overloads in a few lines; therefore, we require a minimum number of transmission lines to overload before allowing those lines to outage.

We implement this measure in the OPA model by not allowing any outage unless there are $n > n_{\max}$ overloaded lines. The expected result of this mitigation measure is the reduction of the blackouts involving a small number of line outages. We have used the IEEE 118 bus network (178 lines) for these calculations. In the calculations presented here, the maximum individual load demand fluctuation is 60% and the minimum generation margin is 30%.

When we consider the base case (no mitigation measure applied), we found that only 9.7% of the blackouts had more than 10 line outages and that only 4.7% of the blackouts had no line outages. Therefore, the bulk of the blackouts, 85.6%, had 1 to 10 line outages. This suggests that the total number of blackouts would be reduced substantially if measures were implemented to ensure that there are no line outages unless, for instance, there are at least 10 overloaded lines. As we discuss below, that is not the case.

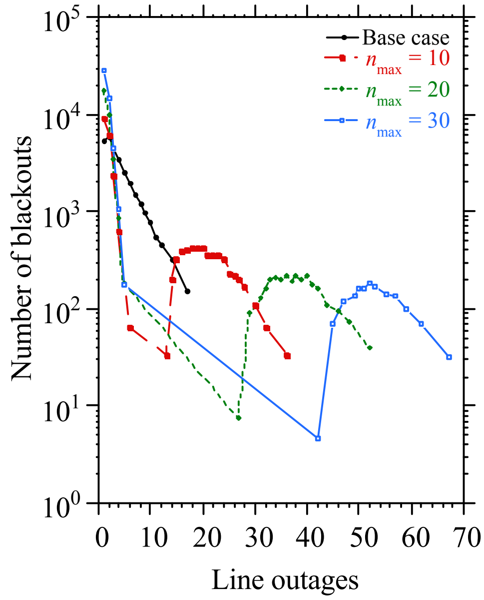

Figure 5. Logarithm of the number of blackouts as a function of the number of line outages for different values of $n_{\max}$.

Figure 5 plots the logarithm of the number of blackouts as a function of the number of line outages. The logarithmic vertical scale emphasizes the rarer large blackouts, but this is appropriate, given the risk analysis presented above. We can see that with no mitigation, there are blackouts with line outages ranging from zero up to 20. When we suppress outages unless there are $n > n_{\max}$ overloaded lines, there is a clear increase in the number of blackouts with line outages greater than $n_{\max}$. There is also an increase in the number of blackouts with no line outage. In particular for $n_{\max} = 10$, blackouts with 1 to 10 outages are reduced by 40%. However, blackouts with no line outage or with more than 10 line outages increase by 110%. The overall result is only a reduction of 15% of the total number of blackouts. Furthermore, as the number of large blackouts has increased, this reduction in blackouts may not lead to any overall benefit to the consumers.

As there is a significant increase in the rare but very large blackouts, this mitigation may have a negative economic effect on the system. If we measure the economic impact of a blackout as being proportional to the power loss [11], we can make an estimate of the blackout cost reduction due to the reduction in the frequency of outages. If the minimum number of transmission lines $n_{\max}$ is kept below 10, there is a decrease in the cost of the blackouts. However, $n_{\max}$ larger than 10 has a negative impact in the blackout cost. The change in the blackout cost is at most an increase of 60%.

To better see the impact of the rare large blackouts, it is more useful to look for extreme value statistics than to analyze all the events. The way we approach this analysis is by compiling the statistics of the worst yearly blackouts. For a period of 360 days, we select the blackouts with the largest number of outages and the largest power load shed. In Figure 6, we have plotted the PDF of the yearly worst blackout for different values of n_{max}. It is clear that, regardless of the value of n_{max}, this type of mitigation method makes the larger blackouts worse.

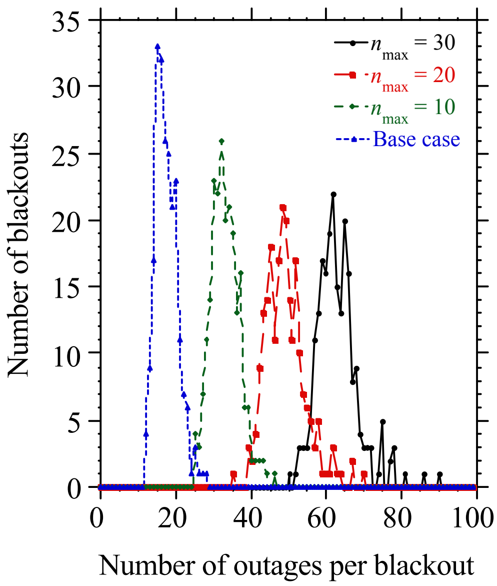

Figure 6. Distribution of the worst yearly blackouts for different level of mitigation.

It is interesting to explore in more detail the consequences of implementing such a mitigation measure. To do so, we can look in detail at the time evolution of the system after the measure has been applied. In Figure 7, we plot the number of outage lines during a blackout as a function of time. We start with the base case and can see that during this initial phase the number of outages per blackout oscillates between 0 and 20, as expected from the PDF in Figure 5. At time t = 10,000 days, the mitigation goes into effect and we require 30 transmission lines to overload before any overloaded line outages can occur. There is an instantaneous improvement, and the number of line outages per blackout is reduced. There is a reduction of the frequency of blackouts just as the measure is applied, but the frequency start to slowly increase to its steady-state value.

In Figure 7, we see that the expected improvement resulting from the mitigation method is happening right away. It is only over a longer time scale (a few years) that very large blackouts become more frequent. First there are only very few blackouts with a high number of line outages, but their frequency increases until it reaches the expected value from the steady-state calculation. It is because of the dynamics induced by the growth of the demand that the system self-organizes to a new dynamical state in which improvements introduced by the mitigation fail and an overall situation worse than that with no mitigation emerges.

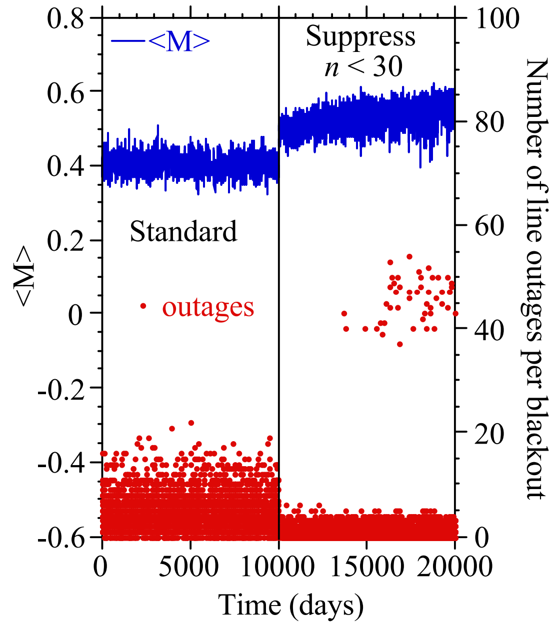

Figure 7. Time evolution of the number of outages per blackout and <M> before and after the mitigation action has been applied.

In Figure 7, we have also plotted a measure $<M>$ of the amount of overloading of the network. $M_{ij} = F_{ij} / F_{ij}^{max}$ is the fraction of overloading of the line connecting the nodes i and j. (Here F_{ij} is the power flow through this line and F_{ij}^{max} is the power flow limit.) The averaged value of M_{ij} over all the lines of the system, $<M>$, gives a measure of how close to its transmission limits the system is operated. In the example plotted in Figure 7, we can see a jump in the value of $<M>$ as soon as the mitigation measure is implemented. This jump is followed by a slow evolution toward a higher fraction of overloading. As the operators have learned to deal with up to 30 overloaded lines without line outages, the system has been operated with more and more lines closer to their limits. When an incident happens that triggers a blackout, this higher level of overloading makes a large blackout more likely.

Because of the time taken to reach to the new steady state with large blackouts, it is clear that in a real system it will be difficult to determine that the mitigation introduced at time t = 10,000 days is the cause of the situation at a time t = 15,000 days, more than 13 years later. The transition time is a function of how drastic the mitigation is. For instance, for $n_{max} < 10$, the transition time to larger blackout is barely detectable, although the largest blackouts also appear a few years later.

An important issue in understanding these results is the relation between the mitigation and the slow time dynamics of upgrade and repair. For the results presented here, upgrading of the transmission lines is done on outage lines after a blackout. However, if the upgrade is done on the overloaded lines, we can expect the effect to be weaker because line outages are not so directly involved in the feedback loop of the dynamics. Therefore, when we change the dynamics by upgrading overloaded lines after a blackout, the negative results of applying the mitigation should be less dramatic.

In Figure 8, we compare the distribution of worst yearly blackouts over a period of 222 years in steady state for the standard case and for n_{max} = 10.

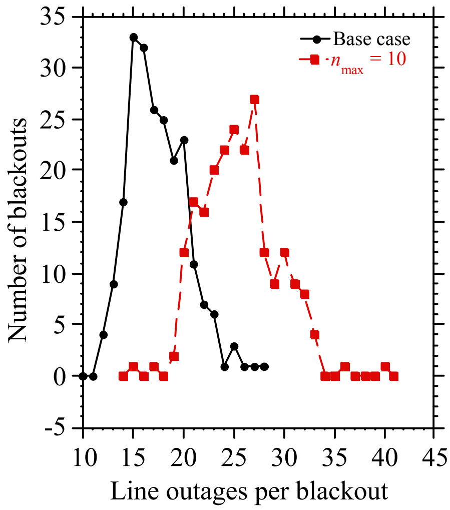

Figure 8. Distribution of the worst yearly blackouts for the base case and for n_{max} = 10.

It is clear from Figure 8 that the worst yearly events have become worse by applying this mitigation measure. However, because the frequency of the rare events decreases as n_{max} increases, the benefit of this mitigation measure appears for large enough values of n_{max}. When n_{max} is close to 20, there are many years with no large blackouts. When n_{max} > 20, the tail of large blackouts has been significantly reduced, but the frequency of blackouts has only been reduced by a 32%.

Therefore, only by going to large values of n_{max} we can observe some benefits from the implementation of the mitigation. However, the benefits are limited and it is not clear that they are commensurate with the technological and economic investments required to implement the mitigation.

In practice, we can expect that the dynamics of real networks will be somewhat between the two dynamical models discussed in this section, and we can consider the results of the assessment given above to be an optimistic evaluation of the mitigation. Very similar results have been obtained for the WSCC 179 bus network when applying this mitigation.

4.2. Reducing the probability that an overloaded line suffers an outage

Increasing reliability of the transmission lines can be represented by a reduction in the probability that an overloaded line outages. The expectation from this mitigation method is an overall decrease in the frequency of the blackouts. Furthermore, multiple blackouts are also expected to be less likely because of the decreased probability of failure of each of the components. In Figure 9, we show a plot of the distribution of the number of blackouts as a function of the load shed for different values of the probability of line outage, p_1. The results are for the tree network with 190 nodes.

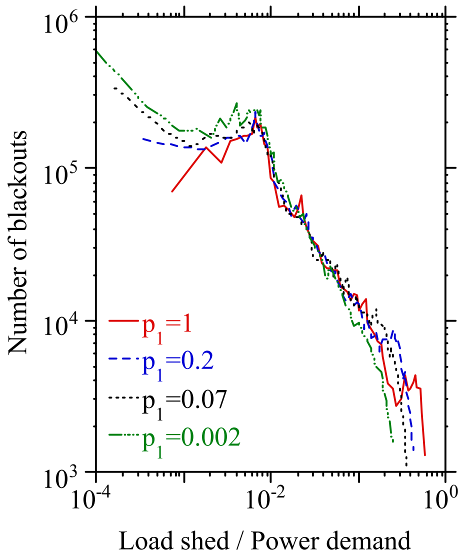

Figure 9. Frequency distribution of blackouts for different values of the probability for an overload line to outage.

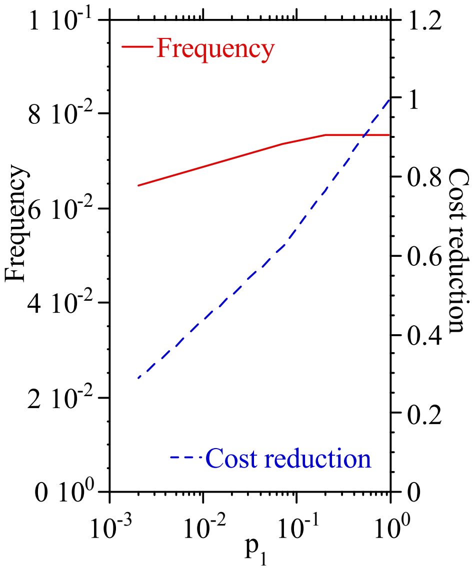

Figure 10. frequency of blackouts and their estimated cost as a function of the probability for an overload line to outage.

As expected, we see that reducing p_1 reduces the probability of large blackouts. However, this is not the only change observed in the dynamics. With the decrease of large blackouts, there is a concomitant increase in the number of small blackouts. The overall result is that there is hardly any change on the frequency of blackouts (Figure 10).

In the intermediate range, where the probability distribution of the load shed varies inversely proportional to the size of the blackout, there is not much change. The functional form remains algebraic with exponent close to –1. This robustness of the algebraic tail of the PDF is characteristic of self-organized critical system [19]. Using the same approach as in the previous section, we can evaluate the economic impact of mitigation. For the same cases shown in Figure 9, we have done the evaluation of the blackout cost and have normalized all costs to the case with $p_1 = 1$. The results are shown with the frequency of the blackout in Figure 10.

There is a reduction in the overall cost of blackouts because the probability of large blackouts has been reduced and because of the assumptions about the cost. However, the reduction of the blackout cost scales as the logarithm of the probability of outage.

A fit to the numerical results for p_1 from Figure 10 in the range (10^{-3}, 1) gives

$$\text{Cost} = 1 + \frac{1}{4}\log(p_1)$$

To get a reduction of a factor 2 in the cost of the blackouts, the probability must be reduced by a factor of 100. Such a high improvement in the reliability of the system seems technologically difficult and very costly.

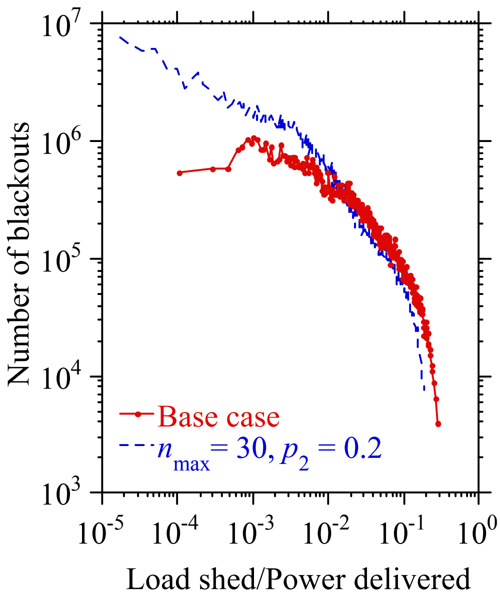

Figure 11 Distribution of the normalized load shed during blackouts for a case combining two mitigation methods and the same distribution for the base case.

If one considers both the results of this section and the previous section, one could conclude that combining these two mitigation measures would be a good way of successfully controlling the blackouts. One could implement a measure requiring a certain minimum number of transmission lines, let us say 30, to overload before any line outages can occur. This reduces the probability of blackouts with less than 30 line outages. At the same time, one could reduce the probability p_1 that overloaded lines outage. This reduces the number of blackouts with a large number of line outages. In this way one could expect to reduce both the small and large blackouts. In Figure 11 we compare the distribution of the normalized load shed during blackouts for this case with the same distribution for the standard case. We see practically no change. There is a reduction of the largest blackouts but that is compensated for by an increase of the blackouts with no line outages. The distribution keeps the power tail, and there is no significant change. As a result, there is no economic impact of the two measures applied simultaneously, except for the cost of implementing such measures.

4.3. Increasing the generation margin

In the OPA model the maximum generator power is increased as a response to the load demand. We have limited the model to increases in maximum generator power at the same nodes that initially had generators. The increase in power is quantized. This may reflect the upgrade of a power plant or adding generators. The increase is taken to be a fixed ratio to the total power, $\Delta P_a \equiv \kappa(P_T/N_G)$. Here, P_T is the total power demand, N_G is the number of generator nodes, and κ is a parameter that we have taken to be a few percent. To be able to increase the maximum power in node j, the sum of the power flow limits of the lines connected to j should be larger than the existing generating power plus the addition at node j. A second condition to be verified before any maximum generator power increase is that the mean generator power margin has reached a threshold value. That is, we define the mean generator power margin at a time t as

$$\Delta P/P = \left(\sum_{j\in G} P_j - P_0 e^{\lambda t}\right) \Big/ P_0 e^{\lambda t} \qquad (2)$$

where P_0 is the initial power load demand.

After power has been added to a node, we use Eq. (2) to recalculate the mean generator power margin and continue the process until $\Delta P/P$ is above the prescribed quantity, $(\Delta P/P)_c$. This is motivated by the fact that utilities are in general likely to build a power plant where the transmission capacity already exists.

To increase the minimal generator power margin $(\Delta P/P)_c$ is possibly the simplest mitigation approach, and we expect a reduction in the overall number of blackouts. We find that the frequency of blackouts decreases as the capacity margin increases. We have carried out these calculations for several ideal tree networks. In Figure 12, we have plotted the frequency of blackouts as a function of $(\Delta P/P)_c$ for a tree network with 46 nodes. The frequency decrease with increasing $(\Delta P/P)_c$ only happens when this margin is greater than the standard deviation of the load demand fluctuations. When they are comparable, there are no simple mitigation measures that are effective in reducing the blackout frequency. Also, the mean blackout size (measured by the number of line outages) increases as blackout frequency decreases in Figure 12. When we increase the generator margin, the character of the blackouts changes. When the generator margin is small the blackouts are small with mostly no line outages. However, at a high generation margin, they became considerably less frequent but have a large size with many line outages. This is illustrated in Figure 13, where we have plotted the number of blackouts for a given number of line outages for different values of $(\Delta P/P)_c$. This suggests that the increases on generator margin need to be associated with upgrades of the transmission grid.

Similar results are obtained for the other tree configurations. However, the frequency of the blackouts is somewhat higher when the size of the network increases. There is a weak scaling of the frequency with size given by $f \propto N_N^{1/4}$.

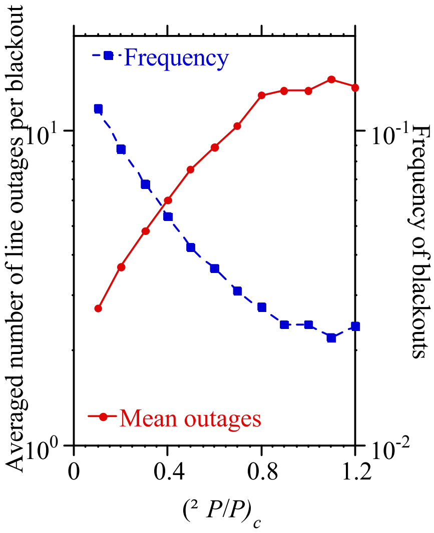

Figure 12 . Frequency of blackouts and averaged number of outages per blackout as a function of $(\Delta P/P)_c$ for a tree network with 46 nodes.

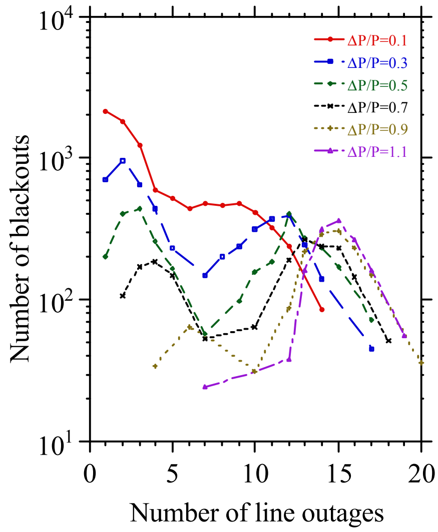

Figure 13. Frequency of blackouts as a function of number of line outages for different values of $(\Delta P/P)_c$

The overall effect of the generation margin on the cost of the blackouts is rather subtle. As the frequency decreases but the average size of the blackout increases, there is compensation of the beneficial effects of this measure. For the tree 46 node network there is a reduction in the cost of the blackouts, but the reverse happens for larger tree networks. This is illustrated in Figure 14, where we have plotted the normalized cost of the blackouts as a function of $(\Delta P/P)_c$. In any case, for the tree 46 node network, the decrease is only by a factor of 2 after a tenfold increase on the minimum generator margin. Naturally, if the blackout cost is not a linear cost with power loss, the cost impact may be quite different.

5. Conclusions

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.

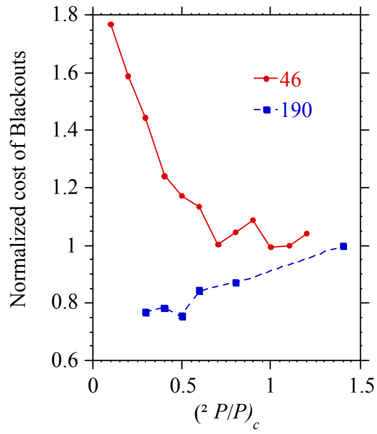

Figure 14. Normalized cost of the blackouts as a function of $(\Delta P/P)_c$ for two different tree networks.

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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6. References

[1] Information on electric system disturbances in North America can be downloaded from the NERC website at http://www.nerc.com/dawg/database.html.

[2] B. A. Carreras, D. E. Newman, I. Dobson, A. B. Poole*, Initial evidence for self organized criticality in electric power system blackouts*, Thirty-third Hawaii International Conference on System Sciences, Maui, Hawaii, January 2000.

[3] B. A. Carreras, D. E. Newman, I. Dobson, and A. B. Poole, *Evidence for Self-Organized Criticality in Electric Power System Blackouts*, 34th Hawaii International Conference on System Sciences, Maui, Hawaii, Jan. 2001.

[4] J. Chen, J.S. Thorp, M. Parashar*, Analysis of electric power system disturbance data,* 34th Hawaii International Conference on System Sciences, Maui, Hawaii, Jan. 2001.

[5] B. A. Carreras, D. E. Newman, I. Dobson, and A. B. Poole, *Evidence for self-organized criticality in a time series of electric power system blackouts*, preprint, submitted to IEEE Transactions on Circuits and Systems.

[6] I. Dobson, B. A. Carreras, V.E. Lynch, D. E. Newman, *An initial model for complex dynamics in electric power system blackouts*, 34th Hawaii International Conference on System Sciences, Maui, Hawaii, Jan. 2001.

[7] B.A. Carreras, V.E. Lynch, M. L. Sachtjen, I. Dobson, D. E. Newman, *Modeling blackout dynamics in power transmission networks with simple structure*, 34th Hawaii International Conference on System Sciences, Maui, Hawaii, Jan. 2001.

[8] B.A. Carreras, V.E. Lynch, I. Dobson, D. E. Newman, *Dynamics, Criticality and Self-organization in a Model for Blackouts in Power Transmission Systems,*35th Hawaii International Conference on System Sciences, Hawaii, Hawaii, Jan. 2002.

[9] I. Dobson, D.E. Newman, B.A. Carreras, and V.E. Lynch, An initial complex systems analysis of the risks of blackouts in power transmission systems, Power Systems and Communications Infrastructures for the future, Beijing, China, September 2002.

[10] R. Billinton, R.N. Allan*, Reliability evaluation of power systems*, second edition, Chapter 13, Plenum Press, New York, 1996.

[11] R. Billinton, J. Otengadjei, R. Ghajar, *Comparison of 2 alternate methods to establish an interrupted energy assessment rate*, IEEE Transactions Power Systems, vol. 2 no 3, pp. 751-757 August 1987.

[12] D.W. Caves, J.A. Herriges, R.J. Windle, Customer demand for service reliability, A synthesis of the outage costs literature, Electric Power Research Institute report P-6510, September 1989.

[13] K.K. Kariuki R.N. Allan*, Evaluation of reliability worth and value of lost load*, IEE Proceedings-Generation transmission and distribution, vol. 143 no. 2, pp. 171-180, March 1996.

[14] J.L. Corwin, W.T. Miles, *Impact assessment of the 1977 New York City blackout*, U.S. Department of Energy, Washington DC 1978.

[15] S.M. Rinaldi, J.P. Peerenboom, T.K. Kelly, *Identifying, understanding and analyzing critical infrastructure dependencies*, IEEE Control Systems magazine, vol. 21, no 6, December 2001, pp. 11-25.

[16] North American Electricity Reliability Council Working group forum on critical infrastructure protection, *An approach to action for the electricity sector*, Appendices E and F, June 2001.

[17] P. Bak, C. Tang and K. Weisenfeld, *Self-Organized Criticality: An Explanation of 1/f Noise,* Phys. Rev. Lett. 59, 381 (1987).

[18] B. Drossel and F. Schwabl, *Self-organized critical forest-fire model*, Phys Rev. Lett. **69**, 1629 (1992).

[19] P. Bak, "How Nature Works: The Science of Self-Organized Criticality," Copernicus books, 1996.

[20] H. J. Jensen, *Self-organized criticality*, Cambridge University Press, 1998.

[21] B. A. Carreras, V.E. Lynch, I. Dobson and D. E. Newman, *Critical Points and Transitions in a Power Transmission Model*, to appear in Chaos.

[22] I. Dobson, J. Chen, J.S. Thorp, B. A. Carreras, and D. E. Newman, *Examining criticality of blackouts in power system models with cascading events*, 35th Hawaii International Conference on System Sciences, Hawaii, Hawaii, Jan. 2002.

[23] The IEEE 118 bus network model is a standard test system; see http://www.ee.washington.edu/research/pstca/.