to appear (accepted March 2004) in IEEE Transactions on Circuits and Systems Part I

Evidence for Self-Organized Criticality in a Time Series of Electric Power System Blackouts

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***Abstract*— We analyze a 15-year time series of North American electric power transmission system blackouts for evidence of self-organized criticality. The probability distribution functions of various measures of blackout size have a power tail and R/S analysis of the time series shows moderate long time correlations. Moreover, the same analysis applied to a time series from a sandpile model known to be self-organized critical gives results of the same form. Thus the blackout data seem consistent with self-organized criticality. A qualitative explanation of the complex dynamics observed in electric power system blackouts is suggested.**

***Index Terms*— blackouts, complex systems, time series, power system security, reliability, risk analysis.**

I. Introduction

Electric power transmission networks are complex systems that are commonly run near their operational limits. Major cascading disturbances, or blackouts of these transmission systems have serious consequences. Individually, these blackouts can be attributed to specific causes, such as lightning strikes, ice storms, equipment failure, shorts resulting from untrimmed trees, excessive customer load demand, or unusual operating conditions. However, an exclusive focus on these individual causes can overlook the global dynamics of a complex system in which repeated major disruptions from a wide variety of sources are a virtual certainty. We analyze a time series of blackouts to probe the nature of these complex system dynamics.

The North American Electrical Reliability Council (NERC) has a documented list summarizing major blackouts[1] of the North American power grid [1]. They are of diverse magnitude and of varying causes. It is not clear how complete this data is, but it is the best-documented source that we have found for blackouts in the North American power transmission system. An initial analysis of these data [6] over a period of 5 years suggested that self-organized criticality (SOC) [2], [3], [23] may govern the complex dynamics of these blackouts. Here we further examine [7], [13] this hypothesis by extending the analysis to 15 years. This extended data allows us to develop improved statistics and gives us longer time scales to explore. We compare the results to the same types of analysis of time sequences generated by a sandpile model known to be SOC. The similarity of the results is quite striking and is suggestive of the possible role that SOC plays in power system blackouts. A plausible qualitative explanation of SOC in power system blackouts is outlined in section VI.

As an introduction to the concept, a SOC system is one in which the nonlinear dynamics in the presence of perturbations organize the overall average system state near to, but not at, the state that is marginal to major disruptions. SOC systems are characterized by a spectrum of spatial and temporal scales of the disruptions that exist in remarkably similar forms in a wide variety of physical systems [2], [3], [23]. In these systems, the probability of occurrence of large disruptive events decreases as a power function of the event size. This is in contrast to many conventional systems in which this probability decays exponentially with event size.

It is apparent that large blackouts are rarer than small blackouts, but how much rarer are they? Fig. 1 shows a probability distribution of blackout size from the North American blackout data that is discussed in detail in Section II. Fig. 2 shows a probability distribution of number of line outages obtained from a blackout model that represents cascading failure and complex dynamics [11]. These data suggest a power law relationship between blackout probability and blackout size. For comparison, Fig. 2 also shows the binomial probability distribution of number of line outages and its exponential tail that would be obtained if the line outages were independent. Blackout risk is the product of blackout probability and blackout cost. Here we assume that blackout cost is roughly proportional to blackout size, although larger blackouts may well have costs (especially indirect costs) that increase faster than linearly. In the case of the exponential tail, large blackouts become rarer much faster than blackout costs increase so that the risk of large blackouts is negligible. However, in the case of a power law tail, the larger blackouts can become rarer at a similar rate as costs increase, and then the risk of large blackouts is comparable to, or even exceeding, the risk

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[1]The NERC data arises from government incident reporting requirements. The thresholds for report of an incident include uncontrolled loss of 300 MW or more of firm system load for more than 15 minutes from a single incident, load shedding of 100 MW or more implemented under emergency operational policy, loss of electric service to more than 50,000 customers for 1 hour or more, and other criteria detailed in US Department of Energy form EIA-417.

of small blackouts [11]. Thus power laws in blackout size distributions significantly affect the risk of large blackouts and the evidence for power laws in real blackout data that we address in this paper is pertinent. Standard probabilistic techniques that assume independence between events imply exponential tails and are not applicable to systems that exhibit power tails.

Large blackouts are typically caused by long, intricate cascading sequences of rare events. Dependencies between the first few events can be assessed for a subset of the most likely or anticipated events and this type of analysis is certainly useful in addressing part of the problem (e.g. [26]). However, this combinatorial analysis gets overwhelmed and becomes infeasible for long sequences of events or for the huge number of all possible rare events and interactions, many of which are unanticipated, that cascade to cause large blackouts. One aim of global complex systems analysis of power system blackouts is to provide new insights and approaches that could address these challenges. As a first step towards this aim, this paper analyzes observed blackout data and suggests one way to understand the origin of the dynamics and distribution of power system blackouts. Indeed, we suggest that the slow, opposing forces of load increase and network upgrade in response to blackouts shape the system operating margins so that cascading blackouts occur with a frequency governed by a power law relationship between blackout probability and blackout size. Moreover, we discuss the dynamical dependencies and correlations between blackouts in the NERC data.

II. Time series of blackout data

We have analyzed 15 years of data for North America from 1984 to 1998 that is publicly available from NERC [1]. There are 427 blackouts in 15 years and 28.5 blackouts per year. The average period of time between blackouts is 12.8 days. The blackouts are distributed over the 15 years in an irregular manner. We have detected no evidence of systematic changes in the number of blackouts or periodic or quasi-periodic behavior. However, it is difficult to determine long term trends or periodic behavior in just 15 years of data. We constructed time series from the NERC data with the resolution of a day for the number of blackouts and for three different measures of the blackout size. The length of the time record is 5479 days. The three measures of blackout size are:

1) energy unserved (MWh)
2) amount of power lost (MW)
3) number of customers affected.

Energy unserved was estimated from the NERC data by multiplying the power lost by the restoration time.

III. Analysis of the blackout time series

In order to gain an understanding of the dynamics of a system from analysis of a time series, one must employ a variety of tools beyond basic statistical analysis. Among other measures which should be employed, the tails of the Probability Distribution Function (PDF) should be investigated for normality and frequency spectra should be viewed in order to begin to look at dependencies in the time domain. The time domain is particularly important as the system dynamics are expressed in time. Periodicities and long time correlations must both be examined and compared to systems with known dynamics. We will present details of the analysis of the PDFs later; however, the first striking characteristic of the data is the power law tail of these PDFs. This power law tail is shown in Fig. 1, where we have plotted the PDF of the number of customers unserved for all events (the squares) on a log-log plot. The PDF falls off with a power of approximately –1.7 which implies a divergent variance. The PDF is clearly not a distribution with exponential tails. In this paper, the PDFs are non-cumulative probability density functions obtained by binning the data.[2] An alternative way to estimate the distribution is to plot the number of blackouts with more than n customers unserved against n to give the complementary cumulative frequency shown in Fig. 3. The empirical data in Fig. 3 falls off with a power of approximately –0.8 (all tail points considered) or –0.7 (last 7 tail points neglected due to sparse data). The relationship for an exact distribution is that a power law exponent α in a PDF yields a power law exponent of $\alpha - 1$ in the corresponding complementary cumulative frequency. Thus the power law exponents obtained from Figs. 1 and 3 are consistent.

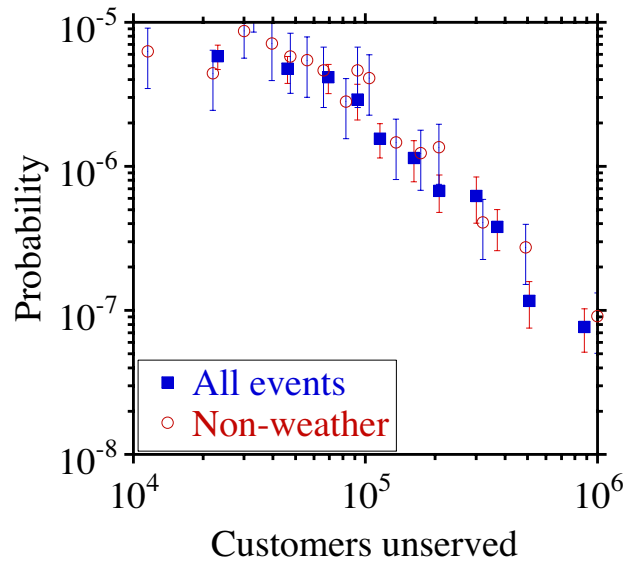

Fig. 1. Log-log plot of PDF of the number of customers unserved comparing the total data set with the data excluding the weather related events.

Looking in the time domain, a time series is said to have long range dependence if its autocorrelation function falls off asymptotically as a power law. This type of dependence is difficult to determine because noise tends to dominate the signal for long time lags. One way to address this problem is the rescaled range statistics (R/S statistics) proposed by Mandelbrot and Wallis [24] and based on a previous hydrological

[2]The bins are chosen to require a minimum number of points per bin. The minimum number of points per bin is reduced when the weather-related blackouts are excluded.

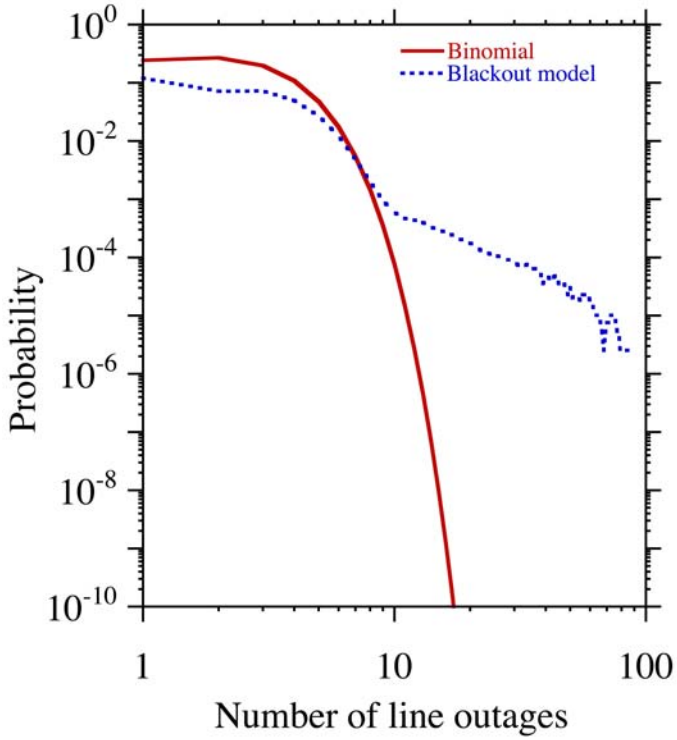

Fig. 2. Log-log plot of PDF of number of line outages from blackout model compared with binomial random variable with exponential tail.

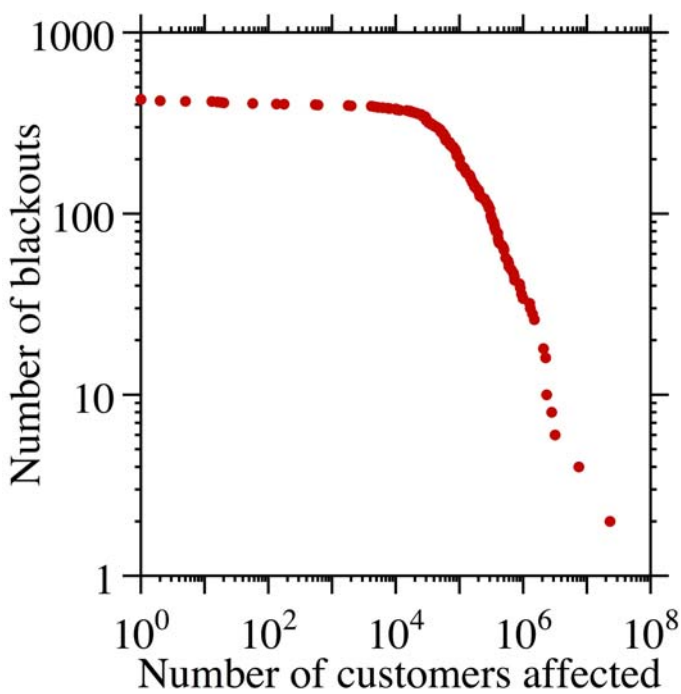

Fig. 3. Complementary cumulative frequency of the number of customers unserved.

analysis by Hurst [21]. The R/S statistics considers blocks of m successive points in the integrated time series and measures how fast the range of the blocks grows as m increases. The calculation of the R/S statistics is further described in the Appendix.

It can be shown that in the case of a time series X with an autocorrelation function that has an algebraic tail, the R/S statistic scales proportionally to m^H, where H is the Hurst exponent. Thus H is the asymptotic slope on a log-log plot of the R/S statistic versus the time lag. If $1 > H > 0.5$, there are long range time correlations, for $0.5 > H > 0$, the series has long range anticorrelations, and if $H = 1.0$, the process is deterministic. Uncorrelated noise corresponds to $H = 0.5$. A constant H parameter over a long range of time lag values is consistent with self-similarity of the signal in this range [32] and with an autocorrelation function that decays as a power of the time lag with exponent $2 - 2H$.

We have determined the long range correlations in the 15 year blackout time series using the R/S method. The time series has 5479 days and 427 blackouts. The calculated Hurst exponents [21] for the different measures of blackout size are shown in Table I. The H values are obtained by fitting over time lags between 100 and 3000 days. In this range, the behavior of the R/S statistic is power-like (Fig. 7). The values of H obtained for all the time series are close to 0.6. This seems to indicate that they are all equally correlated over the long range. These values of H are somewhat lower than the previously obtained values [6], but still significantly above 0.5. Note that the "events" in the time series are the events that have produced a blackout and not all the events that occurred. The latter are supposed to be random ($H = 0.5$); however, the events that produce a blackout may indeed have moderate correlations because they depend on the state of the system.

TABLE I

HURST PARAMETER H FROM R/S ANALYSIS OF BLACKOUT SIZE TIME SERIES

	H
Events	0.62
Power lost	0.59
Customers	0.57
MWh	0.53

A method of testing the independence of the triggering events has been suggested by Boffetta et al. [4]. They evaluated the times between events (waiting times) and argued that the PDF of the waiting times should have an exponential tail. Such is clearly the case for the waiting times of sandpile avalanches (Fig. 4). In the case of waiting times between blackouts, we also have observed the same exponential dependence of the PDF tail (Fig. 5). This observation is confirmed in [13]. This strengthens the contention that the apparent correlations in the events come from SOC-like dynamics within the power system rather than from the events driving the power system dynamics.

Examining the R/S results in more detail, Fig. 6 shows the R/S statistic for the time series of the number of customers affected by blackouts. The average period of time without blackouts is 12.8 days, hence, in looking over time lags of this order we typically find either one blackout or none. For the shorter time lags less than 50 days, we are unable to get information on correlations between blackouts because the time intervals are too short to contain several blackouts. We see a correlation between absences of blackouts, and

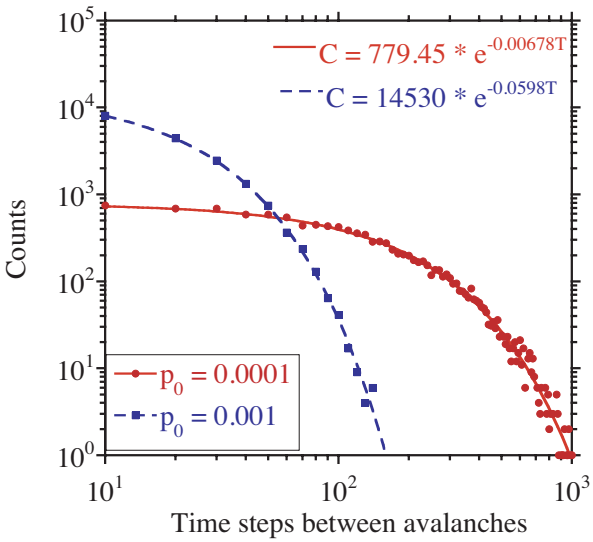

Fig. 4. Distribution of waiting times between avalanches in a sandpile for two values of the probability of adding grains of sand.

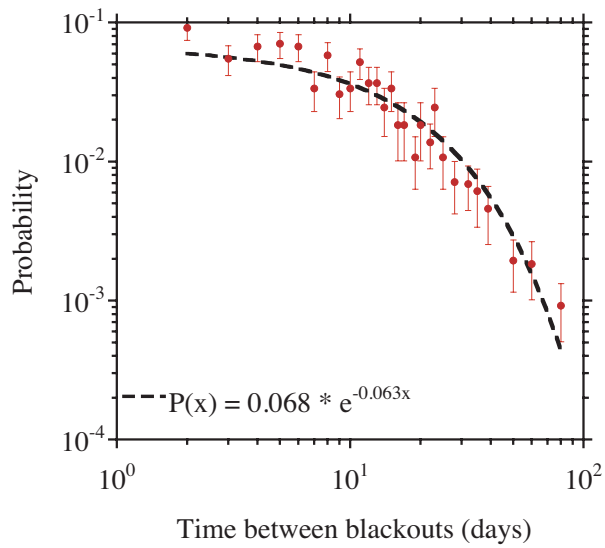

Fig. 5. PDF of the waiting times between blackouts

because these time intervals tend to only contain absences of blackouts, we see H close to 1 (trivially deterministic). For time lags above 50 days, the R/S shows a power behavior and gives a correct determination of blackout correlation. The R/S calculation is sensitive to this change in regime and there is an obvious change of behavior for time intervals around 50 days. An alternative method of determining correlations is the scaled window variance method. We do not use the scaled window variance method in this paper because in this method, the correlations between absences of blackouts skew the correlations between blackouts at larger time lags [7].

IV. The effect of weather

Approximately half of the blackouts (212 blackouts) are characterized as weather related in the NERC data. In attempting to extract a possible periodicity related to seasonal weather, we consider separately the time series of all blackouts and the time series of blackouts that are not weather related. An important issue in studying long range dependencies is the possible presence of periodicities. Both R/S analysis and spectral analysis of this data do not show any clear periodicity. However, since the weather related events may play an important role in the blackouts, one may suspect seasonal periodicities. However, the data combines both summer and winter peaking regions of North America. Because of the limited amount of data, it is not possible to separate the blackouts by geographical location and redo the analysis. What we have done is to reanalyze the data excluding the blackouts triggered by weather related events. The results are summarized in Table II. As can be seen, the exclusion of the blackouts triggered by weather related events does not significantly change the value of H. When looking solely at the blackouts triggered by weather related events, the value

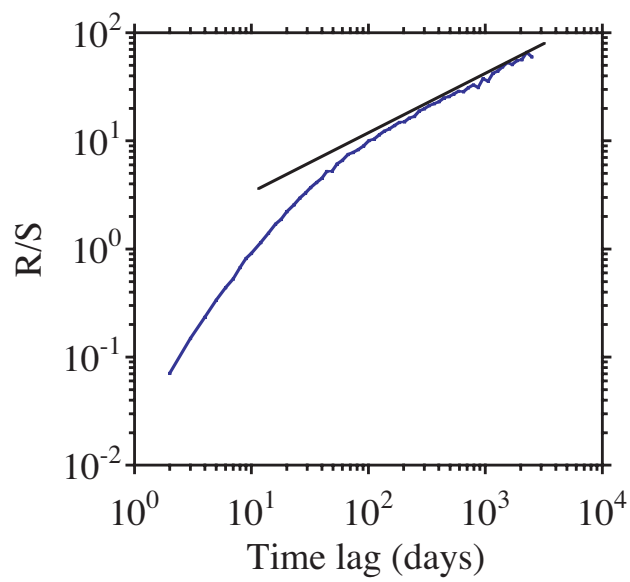

Fig. 6. R/S for the number of customers affected by blackouts.

of H is closer to 0.5 (random events), although the available data is too sparse to be sure of the significance of this result.

Another question to consider is the effect of excluding the weather related events on the PDF. We have recalculated the PDF for all the measures of blackout size when the weather related events are not included. The PDFs obtained are the same within the numerical accuracy of this calculation. This is illustrated in Fig. 1, where we have plotted the PDFs of the number of customers unserved for all events and for the non-weather related events. Therefore, for both long range dependencies and structure of the PDF, the blackouts triggered

TABLE II

HURST PARAMETER H FOR MEASURES OF BLACKOUT SIZE COMPARING ALL DATA WITH THE DATA EXCLUDING BLACKOUTS TRIGGERED BY WEATHER

	H all events	H non weather events
Events	0.62	0.62
Power lost	0.59	0.64
Customers	0.57	0.58
MWh	0.53	0.57

by weather events do not show any particular properties that distinguish them from the other blackouts. Therefore, both the long time correlations and the PDFs of the blackout sizes remain consistent with SOC-like dynamics.

In addition to weather effects, one might expect spatial structure of the grid to have an effect on the dynamics. However, analysis of the NERC data by Chen and Thorp in [13] suggests that similar results are obtained when data for the eastern and western North American power systems is analyzed separately. Since the eastern and western power systems have different characteristics, this interesting result tends to support the notion that there are some underlying common principles for the system dynamics.

V. COMPARISON TO A SOC SANDPILE MODEL

The issue of determining whether the power system blackouts are governed by SOC is a difficult one. There are no unequivocal determining criteria. One approach is to compare characteristic measures of the power system to those obtained from a known SOC system. The prototypical model of a SOC system is a one-dimensional idealized running sandpile [22]. The mass of the sandpile is increased by adding grains of sand at random locations. However, if the height at a given location exceeds a threshold, then grains of sand topple downhill. The topplings cascade in avalanches that transport sand to the edge of the sandpile, where the sand is removed. In the running sandpile, the addition of sand is on average balanced by the loss of sand at the edges and there is a globally quasi-steady state or dynamic equilibrium close to the critical profile that is given by the angle of repose. There are avalanches of all sizes and the PDF of the avalanche sizes has an algebraic tail. The particular form of the sandpile model used here is explained in [25] and the sandpile length used in the present calculations is L = 800. We are, of course, not claiming that the running sandpile is a model for power system blackouts. We only use the running sandpile as a black box to produce a time series of avalanches characteristic of an SOC system.

It is convenient to assume that every time iteration of the sandpile corresponds to one day. When an avalanche starts, we integrate over the number of sites affected and the number of steps taken and assign them to a single day. Thus we construct a time series of the avalanche sizes. The sandpile model has a free parameter p_0, which is the probability of a grain of sand being added at a location. p_0 is chosen so that the average frequency of avalanches is the same as the average frequency of blackouts.

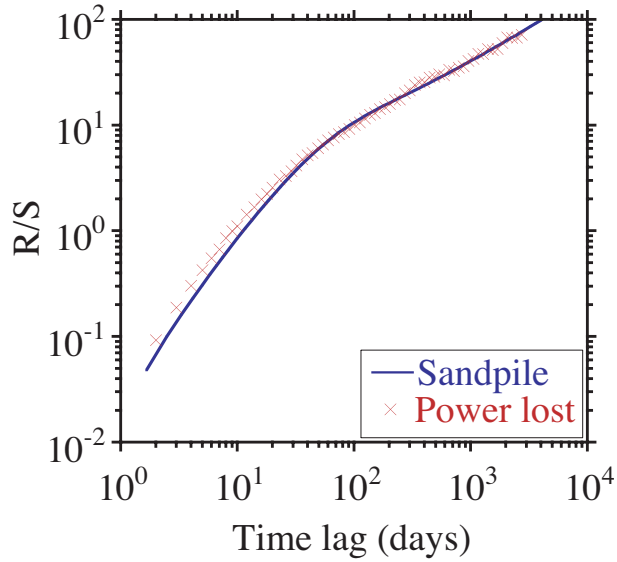

Fig. 7. R/S for avalanche sizes in a running sandpile compared to R/S for power lost in blackouts.

In evaluating the long range time dependence of the blackouts, we use the rescaled range or R/S [24] technique described earlier. As stated before, the R/S technique is useful in determining the existence of an algebraic tail in the autocorrelation function and calculating the exponent of the decay of the tail (see Appendix for details). The same R/S analysis used for the blackout time series is applied to the avalanche time series. Fig. 7 shows the R/S statistic for the time series of avalanche sizes from the sandpile and for the time series of power lost by the blackouts. The similarity between the two curves is remarkable. A similarly good match of the R/S statistics between the blackout and sandpile time series is obtained for the other measures of blackout size.

Fig. 8 shows the PDF of the avalanche sizes from the sandpile data together with the rescaled PDF of the energy unserved from the blackout data. The resemblance between the two distributions is again remarkable. The rescaling is necessary because of the different units used to measure avalanche size and blackout size. That is, we assume a transformation of the form

$$P(X) = \lambda F(X/\lambda) \tag{1}$$

X is the variable that we are considering, $P(X)$ is the corresponding PDF, and λ is the rescaling parameter. If the transformation (1) works, F is the universal function that describes the PDF for the different parameters. Transformation (1) is used to overlay the sandpile and blackout PDFs.

We can consider PDFs of the other measures of blackout size and use transformation (1) to plot each of these PDFs with the sandpile avalanche size PDF. In all cases, the agreement is very good. Of course, the scaling parameter differs for each measure of blackout size. The exponents obtained for these PDFs tails are between –1.3 and –2. These exponents imply divergence of the variance, one of the characteristic features

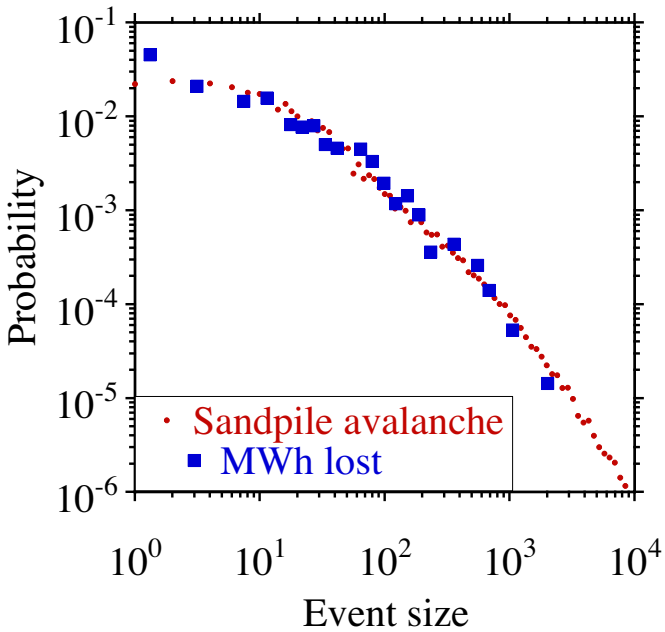

Fig. 8. Rescaled PDF of energy unserved during blackouts superimposed on the PDF of the avalanche size in the running sandpile.

of systems with SOC dynamics. In fact, divergence of the variance is a general feature of systems near criticality. This comparison of the PDFs of the measures of blackout and avalanche sizes is useful in evaluating the possible errors in the determination of the algebraic decay exponent of the PDFs. One can see that for the large size events where the statistics are sparse, there may be deviations from the curve. These deviations can influence the computed value of the exponent, but they are probably of little significance for the present comparisons.

VI. Possible Explanation of Power System Self-Organized Criticality

To motivate comparisons between power system blackout data and SOC sandpile data, we suggest a qualitative description of the structure and effects in a large scale electric power transmission system which could give rise to SOC dynamics. The power system contains many components such as generators, transmission lines, transformers and substations. Each component experiences a certain loading each day and when all the components are considered together they experience some pattern or vector of loadings. The pattern of component loadings is determined by the power system operating policy and is driven by the aggregated customer loads at substations. The power system operating policy includes short term actions such as generator dispatch as well as longer term actions such as improvements in procedures and planned outages for maintenance. The operating policy seeks to satisfy the customer loads at least cost. The aggregated customer load has daily and seasonal cycles and a slow secular increase of about 2% per year.

Events are either the limiting of a component loading to a maximum or the zeroing of the component loading if that component trips or fails. Events occur with a probability that depends on the component loading. For example, the probability of relay misoperation [13] or transformer failure generally increases with loading. Another example of an event could be an operator redispatching to limit power flow on a transmission line to its thermal rating and this could be modeled as probability zero when below the thermal rating of the line and probability one when above the thermal rating. Each event is a limiting or zeroing of load in a component and causes a redistribution of power flow in the network and hence a discrete increase in the loading of other system components. Thus events can cascade. If a cascade of events includes limiting or zeroing the load at substations, it is a blackout. A stressed power system experiencing an event must either redistribute load satisfactorily or shed some load at substations in a blackout. A cascade of events leading to blackout usually occurs on a time scale of minutes to hours and is completed in less than one day.

It is customary for utility engineers to make prodigious efforts to avoid blackouts and especially to avoid repeated blackouts with similar causes. These engineering responses to a blackout occur on a range of time scales longer than one day. Responses include repair of damaged equipment, more frequent maintenance, changes in operating policy away from the specific conditions causing the blackout, installing new equipment to increase system capacity, and adjusting or adding system alarms or controls. The responses reduce the probability of events in components related to the blackout, either by lowering their probabilities directly or by reducing component loading by increasing component capacity or by transferring some of the loading to other components. The responses are directed towards the components involved in causing the blackout. Thus the probability of a similar blackout occurring is reduced, at least until load growth degrades the improvements made. There are similar, but less intense responses to unrealized threats to system security such as near misses and simulated blackouts.

The pattern or vector of component loadings may be thought of as a system state. Maximum component loadings are driven up by the slow increase in customer loads via the operating policy. High loadings increase the chances of cascading events and blackouts. The loadings of components involved in the blackout are reduced or relaxed by the engineering responses to security threats and blackouts. However, the loadings of some components not involved in the blackout may increase. These opposing forces driving the component loadings up and relaxing the component loadings are a reflection of the standard tradeoff between satisfying customer loads economically and security. The opposing forces apply over a range of time scales. We suggest that the opposing forces, together with the underlying growth in customer load and diversity give rise to a dynamic equilibrium and conjecture that this dynamic equilibrium could be SOC-like. It is important to note that this type of system organizes itself to an operating point near to but not at a critical value. This could make the system intrinsically vulnerable to cascading failures from unexpected causes as the repair and remediation steps taken to prevent a known failure mode are part of the system dynamics.

We briefly indicate the roughly analogous structure and effects in an idealized sand pile model. Events are the toppling of sand and cascading events are avalanches. The system state is a vector of maximum gradients at all the locations in the sand pile. The driving force is the addition of sand, which tends to increase the maximum gradient, and the relaxing force is gravity, which topples the sand and reduces the maximum gradient. SOC is a dynamic equilibrium in which avalanches of all sizes occur and in which there are long time correlations between avalanches. The rough analogy between the sand pile and the power system is shown in Table III. There are also some distinctions between the two systems. In the sand pile, the avalanches are coincident with the relaxation of high gradients. In the power system, each blackout occurs on fast time scale (less than one day), but the knowledge of which components caused the blackout determines which component loadings are relaxed both immediately after the blackout and for some time after the blackout.

TABLE III

ANALOGY BETWEEN POWER SYSTEM AND SAND PILE

	power system	sand pile
system state	loading pattern	gradient profile
driving force	customer load	addition of sand
relaxing force	response to blackout	gravity
event	limit flow or trip	sand topples

VII. CONCLUSIONS

We have calculated long time correlations and PDFs for several measurements of blackout size in the North American power transmission grid from 1984 to 1998. These long time correlations and PDFs seem consistent with long range time dependencies and PDFs for avalanche sizes in a running sandpile known to be SOC. That is, for these statistics, the blackout size time series seem indistinguishable from the sandpile avalanche size time series. This similarity suggests that SOC-like dynamics may play an important role in the global complex dynamics of power systems.

We have outlined a possible qualitative explanation of the complex dynamics in a power system which proposes some of the opposing forces that could give rise to a dynamic equilibrium with some properties of SOC. The opposing forces are, roughly speaking, a slow increase in loading (and system aging) weakening the system and the engineering responses to blackouts strengthening parts of the system. Here we are suggesting that the engineering and operating policies of the system are important and integral parts of the system long-term complex dynamics. Carlson and Doyle have introduced a theory of highly optimized tolerance (HOT) that describes power law behavior in a number of engineered or otherwise optimized applications [5]. After this paper was first submitted, Stubna and Fowler [33] published an alternative view based on HOT of the origin of the power law in the NERC data.[3]

The PDFs of the measures of blackout size have power tails with exponents ranging from –1.3 to –2 and therefore have divergent variances. Thus large blackouts are much more frequent than might be expected. In particular, the application of traditional risk evaluation methods can underestimate the risk of large blackouts. R/S analysis of the blackout time series shows moderate ($H \approx 0.6$) long time correlations for several measures of blackout size. Excluding the weather related blackouts from the time series has little effect on the results. The exponential tail of the PDF of the times between blackouts supports the contention that the correlations between blackouts are due to the power system global dynamics rather than correlations in the events that trigger blackouts.

The strength of our conclusions is naturally somewhat limited by the short time period (15 years) of the available blackout data and the consequent limited resolution of the statistics. To further understand the mechanisms governing the complex dynamics of power system blackouts, modeling of the power system is indicated. There is substantial progress in modeling and analyzing the approach inspired by SOC outlined in Section VI [8], [9], [10], [11], [12], [17] and in modeling blackouts and cascading failure from other perspectives [14], [15], [16], [18], [19], [20], [27], [29], [30], [31], [34].

If the dynamics of blackouts are confirmed to have some characteristics of SOC, this would open up possibilities for monitoring statistical precursors of large blackouts or controlling the power system to modify the expected distribution of blackout sizes [11]. Moreover, it would suggest the need to revisit the traditional risk analysis based on random variables with exponential tails since these complex systems have statistics with power tails.

VIII. ACKNOWLEDGEMENTS

We thank J.S. Thorp and R. Weron for useful discussions. Ian Dobson thanks H-D. Chiang and the School of Electrical Engineering at Cornell University for their generous hospitality during a sabbatical leave.

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APPENDIX

Consider the time series $X = \{X_t; t = 1, 2, ..., n\}$. We construct the series $Y = \{Y_t; t = 1, 2, ..., n\}$ that is the original series integrated in time: $Y_t = \sum_{s=0}^{t} X_s$. For the series Y and for each $m = 1, 2, ..., n$ a new series $Y^{(m)} = \{Y_u^{(m)}; u = 1, 2, ..., n/m\}$ is generated. The elements of the series $Y^{(m)}$ are blocks of m elements of Y so that $Y_u^{(m)} = \{Y_{um-m+1}^{(m)}, ..., Y_{um}\}$. We then calculate the range R_m^i and standard deviation S_m^i within each of the n/m blocks of m elements of $Y^{(m)}$, and compute for each block R_m^i/S_m^i. The R/S statistic as a function of the time lag m is then the average $\frac{m}{n}\sum_{i=1}^{n/m} R_m^i/S_m^i$.

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