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Evidence for Self-Organized Criticality in Electric Power System Blackouts

B. A. Carreras
Oak Ridge National Laboratory
Oak Ridge TN 37831
carrerasba@ornl.gov

D. E. Newman
Physics Dept.
University of Alaska
Fairbanks AK 99775
ffden@uaf.edu

I. Dobson
ECE Department
Univ. of Wisconsin
Madison WI 53706
dobson@engr.wisc.edu

A. B. Poole
Oak Ridge National Laboratory
Oak Ridge TN 37831
pooleab@ornl.gov

Abstract

We analyze a 15-year time series of North American electric power system blackouts for evidence of self-organized criticality. Scaled window variance and R/S analysis of the time series shows moderate long time correlations. The probability distribution functions of various measures of blackout size have a power tail. 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 is consistent with self-organized criticality. Self-organized criticality, if fully confirmed in power systems, would suggest new complex systems approaches to understanding and possibly controlling blackouts.

1. Introduction

Electric power transmission networks are complex systems that are commonly run near their operational limits. Such systems can undergo non-periodic major cascading disturbances, or blackouts, that 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 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 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 [2] over a period of 5 years suggested that self-organized criticality (SOC) [3-5] may govern the complex dynamics of these blackouts. Here, we further examine this hypothesis by extending the analysis to 15 years. These data give us improved statistics and longer time scales to explore. We compare the results to the same analysis of time sequences generated by a sandpile model known to be SOC. The similarity of the results is quite striking and is strongly suggestive of the possible role that SOC plays in power system blackouts.

In evaluating the long-range time dependence of the blackouts, we use both the R/S˚[6] and the SWV˚[7] techniques. These techniques are useful in determining the existence of an algebraic tail in the autocorrelation function and calculating the exponent of the decay of the tail.

2. Time series of blackout data

We have analyzed the full 15 years of data 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 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 5477 days. The three measures of blackout size are:

1. energy unserved (MWh)
2. the 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.

3. 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 statistics 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 [8]. The mass of the sandpile is increased by adding grains of sand at random locations. However, if the height at a 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 [9]. 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.

The same R/S and SWV analyses used for the blackout time series (see section 4 for details) are applied to the avalanche time series. It is useful to recall that for a time series with an autocorrelation function with an algebraic tail, the R/S or SWV statistic scales as m^H where m is the time lag and H is the Hurst parameter. Thus H is the asymptotic slope on a log-log plot of the R/S or SWV 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 $H = 0.5$.

Fig. 1 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. In Fig. 2, we show the same comparison using the SWV technique. In both cases, the similarity between the two curves is remarkable.

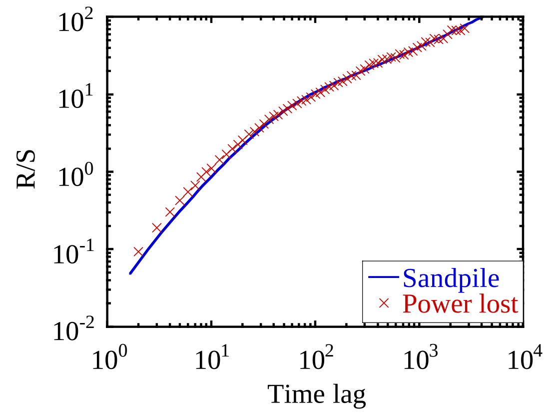

Fig. 1. R/S for avalanche sizes in a running sandpile compared to R/S for power lost in blackouts.

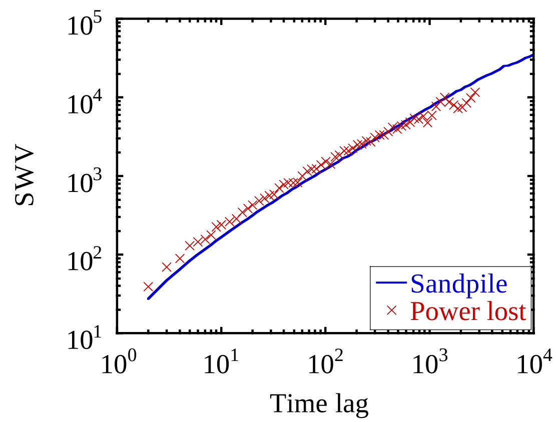

Fig. 2. SWV for avalanche sizes in a running sandpile compared to SWV for power lost in blackouts.

Fig. 3 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 functions is again surprising. 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

$$P(X) = \lambda F(X/\lambda)$$

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

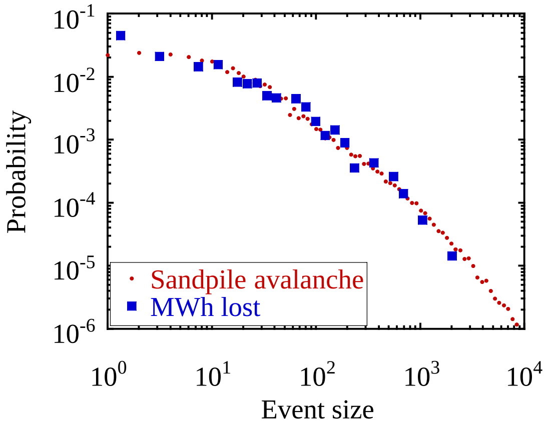

Fig. 3. Rescaled PDF of energy unserved during blackouts superimposed on the PDF of the avalanche size in the running sandpile.

We can do the same transformation for the other measures and plot the various PDFs with the 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 of systems with SOC dynamics.

This comparison of the PDFs of the measures of the blackouts and the 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 may be of little significance for the present comparisons.

4. Analysis of the blackout time series

We have determined the long-range correlations in the blackout time series using both R/S [6] and SWV [7] methods. The calculated Hurst exponents [10] 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 both R/S and SWV is power-like (Figs. 1 and 2).

The time sequence for the events has $H \approx 0.6$ for all cases. In our previous analysis over a five-year period [2], H for the events was closer to 0.5. For the R/S calculation, the values of H obtained for all sequences are close to 0.6. This seems to indicate that they are all equally correlated over the long range. Note that the "events" in the time series is the list of events that have produced a blackout. It is not the list of all possible events. 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 for blackout size time series.

	H (R/S)	H (SWV)
Events	0.62	0.62
Power lost	0.59	0.60
Customers	0.57	0.78
MWh	0.53	0.71

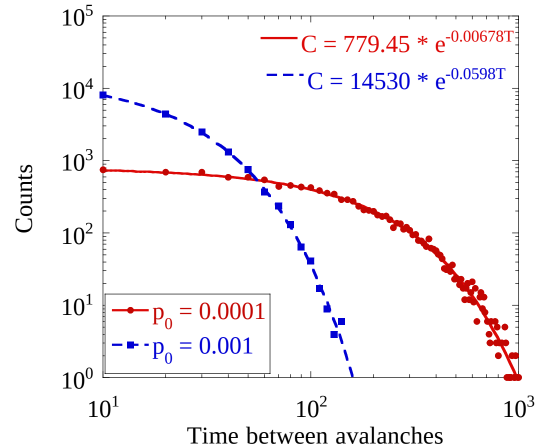

Fig. 4. Distribution of waiting times between avalanches in a sandpile for two values of the probability of adding grains of sand.

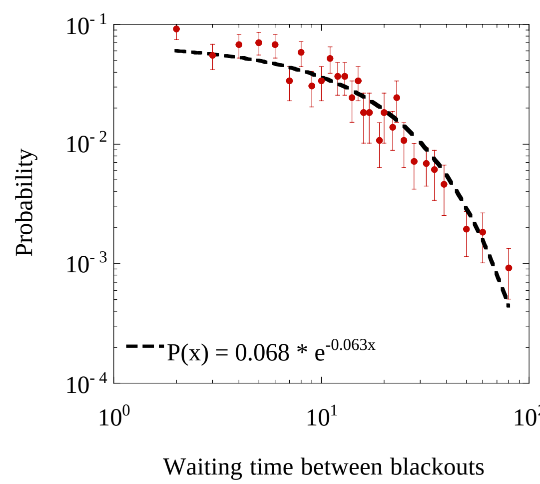

Fig. 5. Probability distribution function of the waiting times between blackouts.

A better way of testing the independence of the triggering events has been suggested by Boffetta et al [11]. 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 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.

In evaluating *H* for the blackout series, we found significant differences between *H* calculated using R/S and SWV for the time series of customers and MWh. To better understand this, let us compare the R/S and SWV results in detail. In Fig. 6, we have plotted the R/S and SWV statistics for the time series of the number of the customers affected by blackouts.

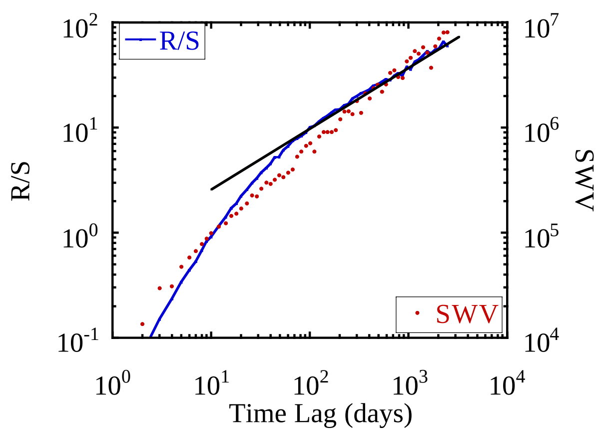

Fig. 6. R/S and SWV statistics for the number of customers affected by blackouts.

The average period of time without blackouts is 12 days, hence, in looking over time lags of this order we either capture one event or none. Therefore, for the region below 50 days, we can expect a very different behavior than for 1 year. For the shorter times, we are unable to get information on correlations between events because the time intervals are too short to contain several events. We see a correlation between non-events, and because these time intervals tend to only contain non-events, we see *H* close to 1 (trivially deterministic). The *R/S* calculation is always more sensitive to changes in regimes than the SWV method. That is why there is a more obvious change of behavior for time intervals around 50 days. The SWV method tends to give a more uniform power over all scales, and it does not see the two regimes. In the SWV results, the long-range dependencies are polluted by the short-range dependencies. For time lags above 50 days, the *R/S* shows a power behavior and gives the correct determination over those scales. The SWV has a higher sensitivity to correlations, but because of this it can be more easily polluted. The *R/S* results lead to values of *H* that are somewhat lower than the previously obtained values [2], but still significantly above 0.5.

5. 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. Spectral analysis for this data does 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 weather-related events. The results are summarized in Table II. In this table, the column marked Non-W has the results of the analysis when the events triggered by weather are excluded. As can be seen, the exclusion of the weather events does not significantly change the value of *H*. When looking solely at the weather related events, the value 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.

Table II. Hurst parameter *H* for measures of blackout size comparing the total data set with the data excluding the events triggered by weather.

	H (total) R/S	*H* (non W) R/S
Events	0.62	0.62
Power lost		0.64
Customers	0.57	0.58
MWh	0.53	0.57

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 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. 7, 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 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.

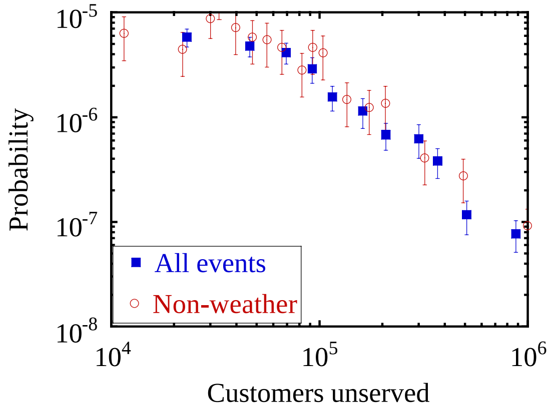

Fig. 7. PDF of the number of customers unserved comparing the total data set with the data excluding the weather related events.

6. 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 are consistent with long-range dependencies and PDFs for avalanche sizes in a running sandpile known to be SOC. That is, for these statistics, the blackout size time series is indistinguishable from the avalanche size time series. This similarity strongly suggests that SOC dynamics may play an important role in the global complex dynamics of power systems.

R/S analysis of the blackout time series shows moderate ($H \approx 0.6$) long time correlations for several measure of blackout size. The probability distribution functions of the measures of blackout size have power tails with exponents ranging from -1.3 to -2 and divergent variances. 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 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 dynamics of power system blackouts, modeling of the power system from a SOC perspective is indicated and is underway [12,13].

7. Acknowledgements

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