Analyzation of Electric Power Transmission System Blackouts for Evidence of Self Organized Criticality (SOC)

Subash Chandra Mishra, Saroj Kumar Rout,
Gandhi Institute of Excellent Technocrats, Bhubaneswar, India
Vedang Institute of Technology, Khordha, Odisha, India

ABSTRACT—We analyze a 15-year time series of North Americanelectric power transmission system blackouts for evidence of self-organizedcriticality(SOC).Theprobabilitydistributionfunctionsofvariousmeasuresofblackoutsizehaveapowertailandrescaledrange analysis of the time series shows moderate long-time corre-lations. Moreover, the same analysis applied to a time series froma sandpile model known to be self-organized critical gives resultsof the same form. Thus, the blackout data seem consistent withSOC.Aqualitativeexplanationofthecomplexdynamicsobservedinelectricpowersystemblackoutsissuggested**.**

I. INTRODUCTION

ELECTRICpowertransmissionnetworksarecomplexsystemsthatarecommonlyrunneartheiroperationallimits.Majorcascadingdisturbancesorblackoutsofthesetransmission systems have serious consequences. Individually,theseblackoutscanbeattributedtospecificcauses,suchaslightningstrikes,icestorms,equipmentfailure,shortsresultingfromuntrimmedtrees,excessivecustomer-loaddemand,orunusualoperatingconditions.However,anexclusivefocusontheseindividualcausescanoverlooktheglobaldynamicsofacomplexsysteminwhichrepeatedmajordisruptionsfromawidevarietyofsourcesareavirtualcertainty.Weanalyzeatimeseriesofblackoutstoprobethenatureofthesecomplex systemdynamics.

The North American Electrical Reliability Council (NERC)has a documented list summarizing major blackouts[1]oftheNorthAmericanpowergrid[1].Theyareofdiversemagnitudeandofvaryingcauses.Itisnotclearhowcompletethisdatais, but it is the best-documented source that we have found forblackouts in the North American power transmission system.An initial analysis of these data [6] over a period of five yearssuggested that self-organized criticality (SOC) [2],[3],[23]may govern the complex dynamics of these blackouts. Here,we further examine this hypothesis [7], [13] by extending theanalysis to 15 years. These extended data allow us to developimproved statistics and give us longer time scales to explore.We compare the results to the same types of analysis of timesequences generated by a sandpile model known to be SOC.The similarity of the results is quite striking and is suggestiveof the possible role that SOC plays in power system blackouts.A plausible qualitative explanation of SOC in power systemblackoutsisoutlinedinSectionVI.

As an introduction to the concept, an SOC system is one inwhich the nonlinear dynamics in the presence of perturbationsorganize the overall average system state near, but not at, thestate that is marginal to major disruptions. SOC systems arecharacterized by a spectrum of spatial and temporal scales ofthedisruptionsthatexistinremarkablysimilarformsinawidevariety of physical systems [2], [3], [23]. In these systems, theprobabilityofoccurrenceoflargedisruptiveeventsdecreasesasa power function of the event size. This is in contrast to manyconventionalsystemsinwhichthisprobabilitydecaysexponen-tiallywitheventsize.

It is apparent that large blackouts are rarer than small black-outs,buthowmuchrarerarethey?Fig.1showstheprobabilitydistributionofblackoutsizefromtheNorthAmericanblackoutdatathatisdiscussedindetailinSectionII.Fig.2showsaprob-ability distribution of number of line outages obtained from ablackout model that represents cascading failure and complexdynamics [11]. These data suggest a power law relationshipbetween blackout probability and blackout size. For compar-ison, Fig. 2 also shows the binomial probability distribution ofnumber of line outages and its exponential tail that would beobtained if the line outages were independent. Blackout risk istheproductofblackoutprobabilityandblackoutcost. Here,weassume that blackout cost is roughly proportional to blackoutsize,althoughlargerblackoutsmaywellhavecosts(especiallyindirect costs) that increase faster than linearly.

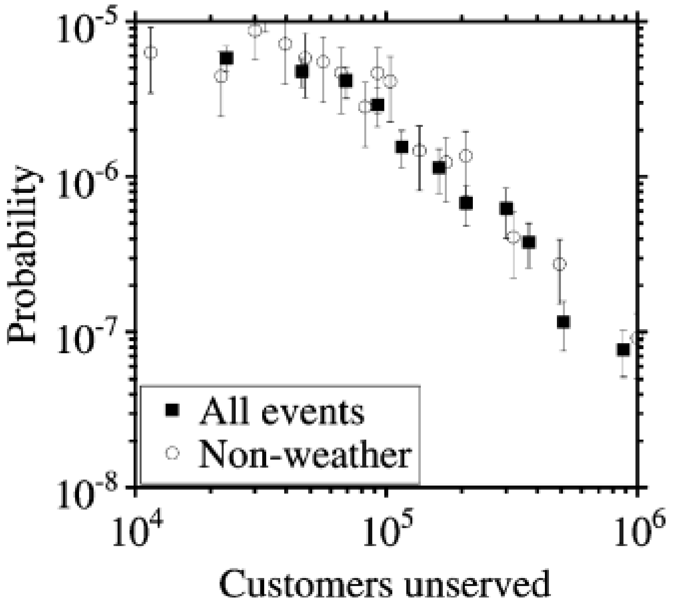


Fig. 1.Log–log plot of PDF of the number of customers unserved comparingthe totaldata set with the data excludingthe weather related events.

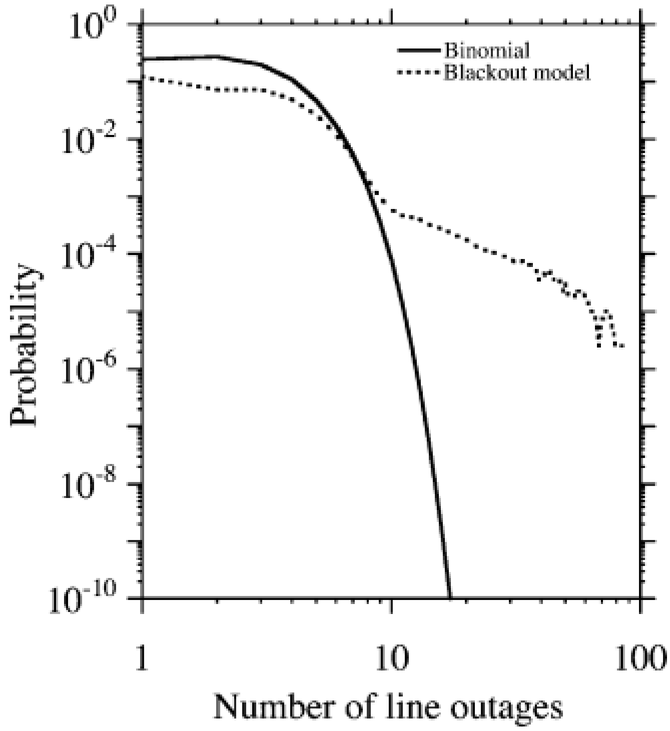


Fig. 2.Log–log plot of PDF of number of line outages from blackout modelcomparedwith binomialrandomvariablewithexponentialtail.

In the case ofthe exponential tail, large blackouts become rarer much fasterthan blackout costs increase, so that the risk of large blackoutsis negligible. However, in the case of a power law tail, the largerblackouts can become rarer at a similar rate as costs increase,and then the risk of large blackouts is comparable to, or evenexceeding,theriskofsmallblackouts[11].Thuspowerlawsinblackout size distributions significantly affect the risk of largeblackoutsandtheevidenceforpowerlawsinrealblackoutdatathatweaddressinthispaperispertinent.Standardprobabilistic techniquesthatassumeindependencebetweeneventsimplyex-ponential tails and are not applicable to systems that exhibitpowertails.

Large blackouts are typically caused by long, intricate cas-cading sequences of rare events. Dependencies between the firstfew events can be assessed for a subset of the most likely oranticipated events and this type of analysis is certainly usefulin addressing a part of the problem (e.g., [26]). However, thiscombinatorial analysis gets overwhelmed and becomes infea-sibleforlongsequencesofeventsorforthehugenumber ofallpossible rare events and interactions, many of which are unantic-ipated,thatcascadetocauselargeblackouts.Oneaimof globalcomplexsystemsanalysisofpowersystemblackoutsistopro-videnewinsightsandapproachesthatcouldaddressthesechal-lenges. As a first step toward this aim, this paper analyzes ob-served blackout data and suggests one way to understand theoriginofthedynamicsanddistributionofpowersystemblack-outs. Indeed, we suggest that the slow, opposing forces of loadincrease and network upgrade in response to blackouts shapethesystemoperatingmarginssothatcascadingblackoutsoccurwithafrequencygovernedbyapowerlaw relationshipbetweenblackout probability and blackout size. Moreover, we discussthe dynamicaldependencies and correlations between blackoutsintheNERCdata.

I. TIMESERIESOFBLACKOUTDATA

We have analyzed 15 years of data for North America from1984 to 1998 that is publicly available from NERC [1]. Thereare 427blackouts in 15years and 28.5blackouts peryear.The average period of time between blackouts is 12.8 days.The blackouts are distributed over the 15 years in an irregularmanner. We have detected no evidence of systematic changes inthenumberofblackoutsorperiodicorquasi-periodicbehavior.However, it is difficult to determine long term trends or periodicbehavior in just 15 years of data. We constructed time seriesfromtheNERCdatawiththeresolutionofadayfor thenumberof blackouts and for three different measures of the blackoutsize. The length of the time record is 5479 days. The threemeasuresofblackoutsizeare:

1) energyunserved(MWh);
2) amountofpowerlost(MW);
3) numberofcustomersaffected.

Energy unserved was estimated from the NERC data by multi-plyingthepowerlostbytherestorationtime.

II. ANALYSISOFBLACKOUTTIMESERIES

In order to gain an understanding of the dynamics of a systemfrom analysis of a time series, one must employ a variety oftools beyond basic statistical analysis. Among other measureswhich should be employed, the tails of the probability distri-butionfunction(PDF)shouldbeinvestigatedfornormalityandfrequencyspectrashouldbeviewedinordertobegintolookatdependencies in the time domain. The time domain is particu-larly important as the system dynamics are expressed in time.Periodicities and long-time correlations must both be exam-ined and compared to systems with known dynamics. We willpresentdetailsoftheanalysisofthePDFslater;however,the

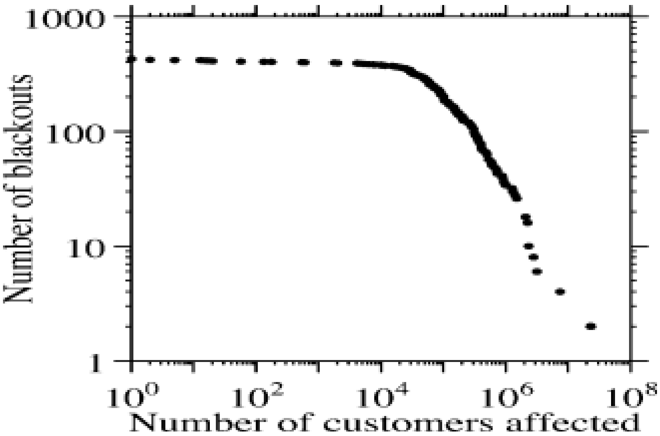


Fig.3.Complementarycumulativefrequencyofthenumberofcustomersunserved.

firststrikingcharacteristicofthedataisthepowerlawtailofthesePDFs.ThispowerlawtailisshowninFig.1,wherewehaveplottedthePDFofthenumberofcustomersunservedforallevents(thesquares)onalog–logplot.ThePDFfallsoffwithapowerofapproximately 1.7 ,whichimpliesadivergentvari-ance.ThePDFisclearlynotadistributionwithexponentialtails.Inthispaper,thePDFsarenoncumulativePDFsobtainedbybinningthedata.2Analternativewaytoestimatethedistributionistoplotthenumberofblackoutswithmorethan n customersunservedagainst n togivethecomplementarycumulativefre-quencyshowninFig.3.TheempiricaldatainFig.3fallsoffwithapowerofapproximately 0.8 (alltailpointsconsidered)or (lastseventailpointsneglectedduetosparsedata).Therelationshipforanexactdistributionisthatapowerlawexpo-nent α inaPDFyieldsapowerlawexponentof $\alpha - 1$ in thecorresponding complementary cumulative frequency. Thus thepowerlawexponentsobtainedfromFigs.1and3areconsistent.Lookinginthetimedomain,atimeseriesissaidtohavelong-rangedependenceifitsautocorrelationfunctionfallsoffasymptoticallyasapowerlaw.Thistypeofdependenceisdiffi-culttodeterminebecausenoisetendstodominatethesignalforlongtimelags.Onewaytoaddressthisproblemistherescaledrange(R/S)statisticsproposedbyMandelbrotandWallis[24]andbasedonapreviousHydrologicalanalysisbyHurst[21].TheR/Sstatisticsconsiderblocksof m successivepointsintheintegratedtimeseries X andmeasurehowfasttherangeoftheblocksgrowsas m increases.ThecalculationoftheR/Ssta-tisticsisfurtherdescribedinthe Appendix. Itcanbeshownthatinthecaseofatimeseries withanautocorrelationfunctionthathasapowerlawtail,theR/S

TABLEI

HURSTPARAMETERHFROMR/SANALYSISOFBLACKOUTSIZETIMESERIES

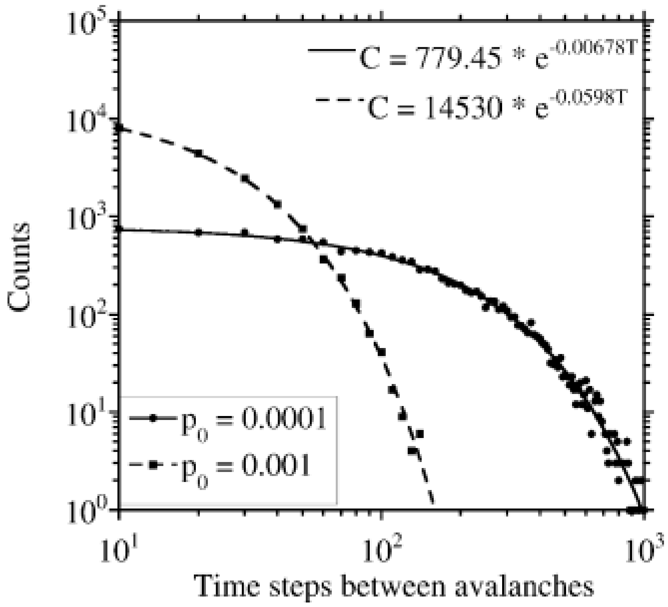
	H
Events	0. 62
Power lost	0.59
Customers	0.57
MWh	0.53

statistic scales proportionally to m^H, whereis the Hurst ex-ponent. Thus, H is the asymptotic slope on a log–log plot oftheR/Sstatisticversusthetimelag.If $1 \geq H > 0.5$,therearelong-rangetimecorrelations,for $0.5 > H \geq 0$,theserieshaslong-rangeanticorrelations,andif $H = 1.0$,theprocessisdeterministic.Uncorrelatednoisecorrespondsto $H = 0.5$ .A constant parameter H over a long range of time-lag valuesis consistent with self-similarity of the signal in this range [32]and with an autocorrelation function that decays as a power ofthetimelagwithexponent $2 - 2H$.

We have determined the long-range correlations in the 15 yearblackout time series using the R/S method. The H time series has5479daysand427blackouts.TheCalculatedHurstexponents [21]forthedifferentmeasuresofblackoutsizeareshowninTableI.The H valuesareobtainedbyfittingovertimelagsbetween100and3000days.Inthisrange,thebehavioroftheR/Sstatisticispowerlike. Thevaluesof H obtained for all thetimeseriesareclosetoo0.6.Thisseemstoindicatethat theyareallequallycorrelatedoverthelongrange.These valuesofaresomewhatlowerthanthepreviouslyobtainedvalues[6],butstillsignificantlyabove0.5.Notethatthe“events”inthetimeseriesaretheeventsthathaveproducedablackoutandnotalltheeventsthatoccurred.Thelatteraresupposedtoberandom($H = 0.5$);however,theeventsthatproduceablackout mayindeedhavemoderatecorrelationsbecausetheydependonthestateofthesystem.

A method of testing the independence of the triggering eventshas been suggested by Boffettaet al. [4]. They evaluated thetimes between events (waiting times) and argued that the PDFof the waiting times should have an exponential tail. Such isclearly the case for the waiting times of sandpile avalanches(Fig.4).Inthecaseofwaitingtimesbetween blackouts,wealsohaveobservedthesameexponential dependenceofthePDFtail(Fig.5).Thisobservationisconfirmedin[13].Thisstrengthensthecontentionthattheapparentcorrelationsintheeventscomefrom SOC-like dynamics within the power system rather thanfromthe events drivingthe powersystemdynamics.

Examining the R/S results in more detail, Fig. 6 shows the R/Sstatisticforthetimeseriesofthenumberofcustomersaffectedbyblackouts.Theaverageperiodoftimewithoutblackoutsis 12.8days,hence,inlookingovertimelagsofthisorderwetyp-icallyfindeitheroneblackoutornone.Fortheshortertimelagsless than 50 days, we are unable to get information on correla-tionsbetweenblackoutsbecausethetimeintervalsaretooshortto contain several blackouts. We see a correlation between ab-sence of blackouts, and because these time intervals tend to onlycontainabsencesofblackouts,weseeclosetoo1(trivially de-terministic). For time lags above 50 days, the R/S shows a powerbehaviorandgivesacorrectdeterminationofblackoutcorrela-tion.TheR/Scalculationissensitivetothischangeinregime



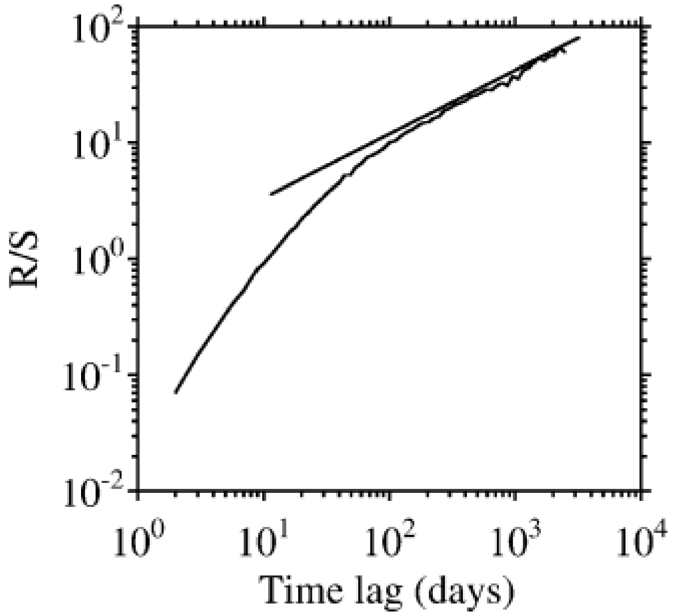


Fig.4.Distributionofwaitingtimesbetweenavalanchesinasandpilefortwovaluesoftheprobabilityofaddinggrainsofsand.

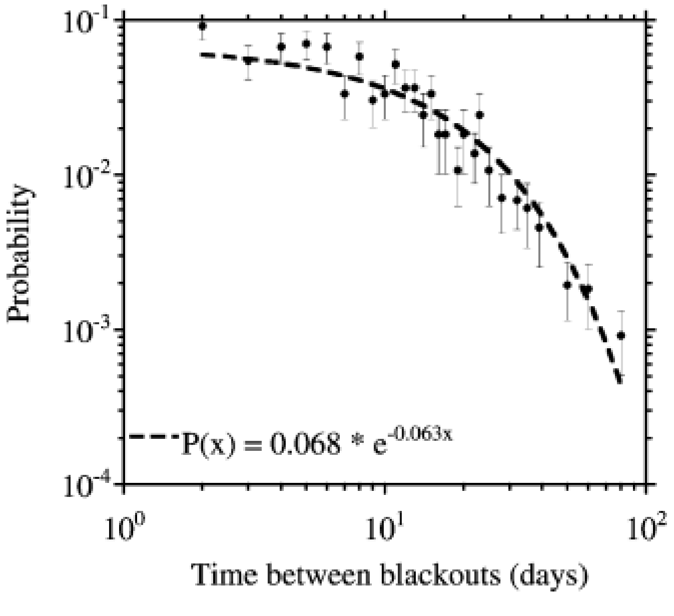


Fig. 5.PDFofthewaiting timesbetweenblackouts.

and there is an obvious change of behavior for time intervalsaround 50 days. An alternative method of determining correla-tionsisthescaledwindowvariancemethod.Wedonotusethescaled window variance method in this paper because in thismethod, the correlations between absences of blackouts skewthecorrelationsbetween blackoutsatlarger timelags [7].

III. EFFECTOFWEATHER

Approximatelyhalfoftheblackouts(212blackouts)are char-acterizedasweatherrelatedintheNERCdata.Inattemptingtoextractapossibleperiodicityrelatedtoseasonalweather,weconsiderseparatelythetimeseriesofallblackoutsandthetimeseriesofblackoutsthatarenotweatherrelated.Animportant

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

TABLEII
HURSTPARAMETERHFORMEASURESOFBLACKOUTSIZECOMPARINGALLDATAWITHDATA EXCLUDINGBLACKOUTSTRIGGEREDBYWEATHER

	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

issue in studying long-range dependencies is the possible pres-enceofperiodicities.BothR/Sanalysisandspectralanalysisofthisdatadonotshowanyclearperiodicity.However,sincetheweatherrelatedeventsmayplayanimportantroleintheblack-outs,onemaysuspectseasonalperiodicities.However, thedatacombinesbothsummerandwinterpeakingregionsofNorthAmerica.Becauseofthelimitedamountof data,itisnotpos-sibletoseparatetheblackoutsbygeographicallocationandredotheanalysis.Whatwehavedoneistoreanalyzethedataex-cludingtheblackoutstriggeredbyweatherrelatedevents.TheresultsaresummarizedinTableII.Ascanbeseen,theexclu-sionoftheblackoutstriggeredbyweatherrelatedevents doesnotsignificantlychangethevalueof H .Whenlookingsolelyattheblackoutstriggeredbyweatherrelatedevents,thevalueofisclosertoo0.5(randomevents), althoughtheavailabledata istoosparsetobesure ofthesignificanceofthisresult. Another question to consider is the effect of excluding theweather related events on the PDF. We have recalculated thePDFforallthemeasuresofblackoutsizewhentheweatherre-lated events are not included. The PDFs obtained are the samewithin the numerical accuracy of this calculation. This is illus-trated in Fig. 1, where we have plotted the PDFs of the number ofcustomers unserved for all events and for the nonweather relatedevents.Therefore,forbothlong-rangedependenciesandstruc-ture of the PDF, the blackouts triggered by weather events do notshowanyparticularpropertiesthatdistinguishthem fromthe

other blackouts. Therefore, both the long time correlations andthePDFsoftheblackoutsizesremainconsistentwithSOC-likedynamics. Inadditiontoweathereffects,onemightexpectspatialstruc-ture of the grid to have an effect on the dynamics. However, anal-ysisoftheNERCdatabyChenetal.in[13]suggeststhatsim-ilar results are obtained when data for the eastern and westernNorth American power systems is analyzed separately. Sincethe eastern and western power systems have different charac-teristics, this interesting result tends to support the notion thatthere are some underlying common principles for the systemdynamics.

IV. COMPARISONTOSOCSANDPILEMODEL

The issue of determining whether power system blackoutsare governed by SOC is a difficult one. There are no unequiv-ocal determining criteria. One approach is to compare charac-teristic measures of the power system to those obtained from aknown SOC system. The prototypical model of a SOC systemisaone-dimensionalidealizedrunningsandpile[22].Themass ofthesandpileisincreasedbyaddinggrainsofsandatrandomlocations. However, if the height at a given location exceeds athreshold, then grains of sand topple downhill. The topplingscascade in avalanches that transport sand to the edge of the sand-pile, where the sand is removed. In the running sandpile, theaddition of sand is on average balanced by the loss of sand atthe edges and there is a globally quasi-steady state or dynamicequilibriumclosetothecriticalprofilethatisgivenbytheangleof repose. There are avalanches of all sizes and the PDF of theavalanchesizeshasapowerlawtail.Theparticularformofthesandpile model used here is explained in [25] and the sandpilelengthusedinthepresentcalculationsis. We are, ofcourse, not claiming that the running sandpile is a model forpowersystemblackouts.Weonlyusetherunningsandpileasablack box to produce a time series of avalanches characteristicofaSOCsystem. Itisconvenienttoassumethatevery timeiterationofthesand-pilecorrespondstooneday.Whenanavalanchestarts,weinte-grateoverthenumberofsitesaffectedandthenumberof stepstakenandassignthemtoasingleday.Thusweconst ructatimeseriesoftheavalanchesizes.Thesandpilemodelhasafreepa-rameter ,whichistheprobabilityofagrainofsandbeingaddedatalocation. ischosenso thattheaveragefrequencyofavalanchesisthesameastheaveragefrequencyofblackouts.Inevaluatingthelong-rangetimedependenceoftheblack-outs,weusetherescaledrangeorR/S[24]techniquedescribedearlier.Asstatedbefore,theR/Stechniqueisusefulindeter-miningtheexistenceofapowerlawtailintheautocorrelationfunctionandcalculatingtheexponentofthedecayofthetail(seeAppendixfordetails).ThesameR/Sanalysisusedfortheblackouttimeseries isappliedtotheavalanchetimeseries.Fig.7showstheR/Sstatisticforthetimeseriesofavalanchesizes from the sandpile and for the time series of power lost bytheblackouts.Thesimilaritybetweenthetwocurvesisremark-able.AsimilarlygoodmatchoftheR/Sstatisticsbetweentheblackoutandsandpiletimeseriesisobtainedfortheothermea-suresofblackoutsize.

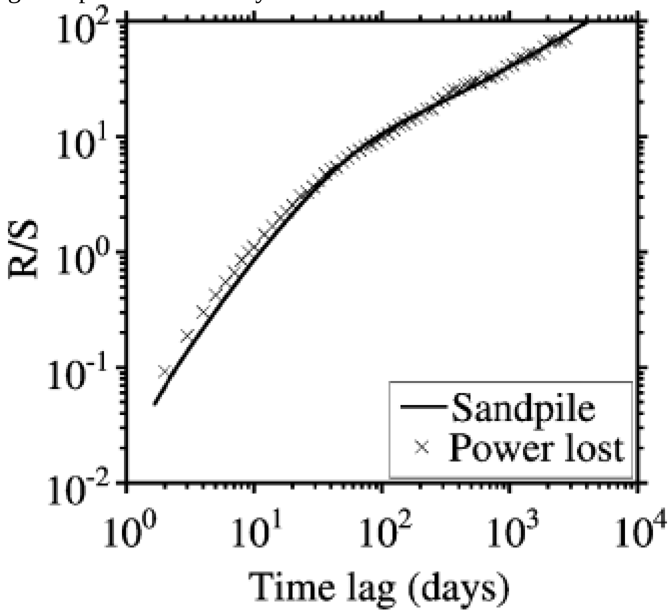


Fig.7.R/Sforavalanchesizesinarunningsandpilecomparedto R/Sforpowerlostinblackouts.

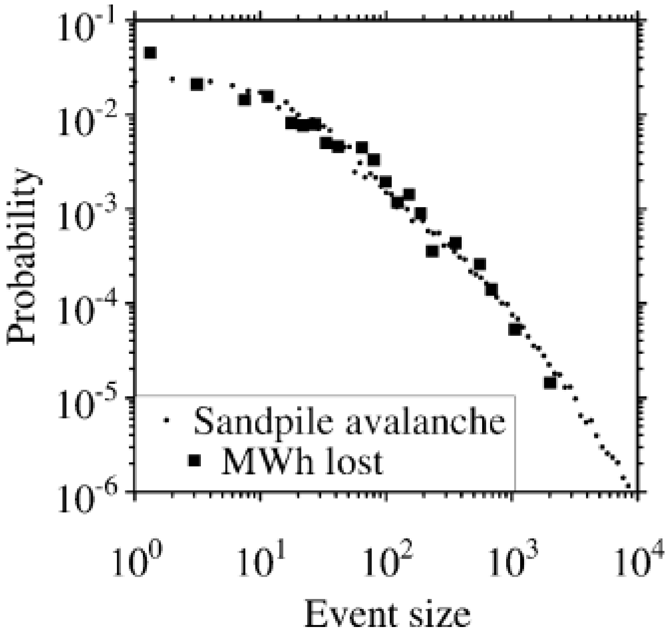


Fig.8.RescaledPDFofenergyunservedduringblackoutssuperimposedonthePDFoftheavalanchesizeintherunningsandpile.

Fig. 8 shows the PDF of the avalanche sizes from the sandpiledata together with the rescaled PDF of the energy unserved fromthe blackout data. The resemblance between the two distribu-tionsisagainremarkable.Therescalingisnecessarybecauseofthedifferentunitsusedtomeasureavalanchesizeandblackoutsize. That is,weassumeatransformationof the form

(1)

isthevariablethatweareconsidering, isthecorre-spondingPDF,andistherescalingparameter.Ifthetransfor-mation(1)works, istheuniversalfunctionthatdescribesthe

PDFforthedifferentparameters.Transformation(1)is usedtooverlaythesandpileandblackoutPDFs.

We can consider PDFs of the other measures of blackout sizeand use transformation (1) to plot each of these PDFs with thesandpileavalanchesizePDF.Inallcases,theagreementisverygood. Of course, the rescaling parameter differs for each mea-sure of blackout size. The exponents obtained for these PDFstailsarebetween -1.5 and -2.Theseexponentsimplydiver-gence of the variance, one of the characteristic features of sys-temswithSOCdynamics.Infact,divergenceofthevarianceisageneralfeatureofsystemsnearcriticality.ThiscomparisonofthePDFs ofthemeasuresofblackoutandavalanchesizesisuseful in evaluating the possible errors in the determination ofthepowerlawdecayexponentofthePDFs.Onecanseethatforthe large size events where the statistics are sparse, there maybe deviations from the curve. These deviations can influence thecomputed value of the exponent, but they are probably of littlesignificanceforthepresentcomparisons.

V. POSSIBLEEXPLANATIONOFPOWERSYSTEMSOC

To motivate comparisons between power system blackoutdata and SOC sandpile data, we suggest a qualitative descrip-tion of the structure and effects in a large-scale electric powertransmission system which could give rise to SOC dynamics.The power system contains many components such as gener-ators, transmission lines, transformers and substations. Eachcomponent experiences a certain loading each day and whenall the components are considered together, they experiencesome pattern or vector of loadings. The pattern of componentloadings is determined by the power system operating policyand is driven by the aggregated customer loads at substations.The power system operating policy includes short term actionssuch as generator dispatch as well as longer term actions suchas improvements in procedures and planned outages for main-tenance. The operating policy seeks to satisfy the customerloadsatleastcost.Theaggregatedcustomerloadhasdailyandseasonal cycles and a slow secular increase of about 2% peryear.

Events are either the limiting of a component loading $P(X) = \lambda F\left(\frac{X}{\lambda}\right)$ to amaximumorthezeroingofthecomponentloadingifthatcom-ponent trips or fails. Events occur with a probability that de-pends on the component loading. For example, the probabilityof relay misoperation[13] or transformer failure generally in-creaseswithloading.Anotherexampleofaneventcould be anoperator redispatching to limit power flow on a transmission lineto its thermal rating and this could be modeled as probabilityzero when below the thermal rating of the line and probabilityone when above the thermal rating. Each event is a limiting orzeroing of load in a component and causes a redistribution ofpower flow in the network and hence a discrete increase in theloadingofothersystemcomponents.Thuseventscancascade.Ifacascadeofeventsincludeslimitingorzeroingtheloadatsub-stations,itisablackout.Astressedpowersystemexperiencinganeventmusteitherredistributeloadsatisfactorilyorshedsomeloadatsubstationsinablackout.Acascadeofeventsleadingto blackoutusuallyoccursonatimescaleofminutestohoursandiscompletedinlessthanoneday.

It is customary for utility engineers to make prodigious effortsto avoid blackouts and especially to avoid repeated blackoutswith similar causes. These engineering responses to a blackoutoccuronarangeoftimescaleslongerthanoneday.Responsesinclude repair of damaged equipment, more frequent mainte-nance,changesinoperatingpolicyawayfromthespecificcon-ditions causing the blackout, installing new equipment to in-crease system capacity, and adjusting or adding system alarmsor controls. The responses reduce the probability of events incomponents related to the blackout, either by lowering theirprobabilities directly or by reducing component loading by in-creasing component capacity or by transferring some of theloadingtoothercomponents.Theresponsesaredirectedtowardthe components involved in causing the blackout. Thus the prob-ability of a similar blackout occurring is reduced, at least untilload growth degrades the improvements made. There are sim-ilar, but less intense responses to unrealized threats to systemsecurity such as near missesand simulated blackouts.

Thepatternorvectorofcomponentloadingsmaybethoughtof as a system state. Maximum component loadings are drivenup by the slow increase in customer loads via the operatingpolicy.Highloadingsincreasethechancesof cascadingeventsand blackouts. The loadings of components involved in theblackout are reduced or relaxed by the engineering responsesto security threats and blackouts. However, the loadings ofsome components not involved in the blackout may increase.These opposing forces driving the component loadings up andrelaxing the component loadings are a reflection of the stan-dard tradeoff between satisfying customer loads economicallyand security. The opposing forces apply over a range of timescales. We suggest that the opposing forces, together with theunderlying growthin customerloadanddiversity give riseto a dynamic equilibrium and conjecture that this dynamicequilibrium could be SOC-like. It is important to note that thistypeofsystemorganizesitselftoanoperatingpointneartobutnot at a critical value. This could make the system intrinsicallyvulnerable to cascading failures from unexpected causes as therepair and remediation steps taken to prevent a known failuremodearepartofthesystemdynamics.

We briefly indicate the roughly analogous structure and ef-fectsinanidealizedsandpilemodel.Eventsarethetopplingofsandandcascadingeventsareavalanches.Thesystemstateisavector of maximum gradients at all the locations in the sand pile.The driving force is the addition of sand, which tends to increasethemaximumgradient,andtherelaxingforceis gravity,whichtopples the sand and reduces the maximum gradient. SOC is adynamicequilibriuminwhichavalanchesofallsizesoccurandin which there are long time correlations between avalanches.Theroughanalogybetweenthesandpileandthepowersystemisshownin TableIII.Therearealsosomedistinctionsbetweenthe two systems. In the sand pile, the avalanches are coinci-dentwiththerelaxationofhighgradients.Inthepowersystem,eachblackoutoccursonfasttimescale(lessthanoneday),buttheknowledgeofwhichcomponentscausedtheblackoutdeter-mineswhichcomponentloadingsarerelaxedbothimmediatelyafter theblackout and forsometime after the blackout.

TABLEIII
ANALOGYBETWEENPOWERSYSTEMANDSANDPILE

	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

II. CONCLUSION

We have calculated long time correlations and PDFs forseveral measurements ofblackout size in the NorthAmer-ican power transmission grid from 1984 to 1998. These longtime correlations and PDFs seem consistent with long-rangetime dependencies and PDFs for avalanche sizes in a runningsandpile known to be SOC. That is, for these statistics, theblackoutsizetimeseriesseemindistinguishablefromthesand-pile avalanche size time series. This similarity suggests thatSOC-like dynamics may play an important role in the globalcomplexdynamicsofpowersystems.

We have outlined a possible qualitative explanation of thecomplex dynamics in a power system which proposes some ofthe opposing forces that could give rise to a dynamic equilib-rium 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 black-outs strengthening parts of the system. Here we are suggestingthat the engineering and operating policies of the system are im-portant and integral parts of the system long-term complex dy-namics. Carlson and Doyle have introduced a theory of highlyoptimized tolerance (HOT) that describes power law behaviorin a number of engineered or otherwise optimized applications[5]. After this paper was first submitted, Stubna and Fowler [33]publishedanalternativeviewbasedonHOToftheoriginofthepowerlawintheNERCdata.[3]

The PDFs of the measures of blackout size have power tailswithexponentsrangingfrom -1.5 to -2 andthereforehavedivergent variances. Thus large blackouts are much more fre-quent than might be expected. In particular, the application oftraditional risk evaluation methods can underestimate the risk oflarge blackouts. R/S analysis of the blackout time series showsmoderate($H \approx 0.8$)longtimecorrelationsforseveralmeasuresofblackoutsize.Excludingtheweatherrelatedblackoutsfrom the time series has little effect on the results. The expo-nentialtailofthePDFofthetimesbetweenblackoutssupportsthe contention that the correlations between blackouts are duetothepowersystemglobaldynamicsratherthancorrelationsintheeventsthattriggerblackouts.

The strength of our conclusions is naturally somewhat limitedby the short time period (15 years) of the available blackout dataand the consequent limited resolution of the statistics. To furtherunderstand the mechanisms governing the complex dynamics ofpowersystemblackouts,modelingofthepowersystemisindi-cated. There is substantial progress in modeling and analyzingtheapproachinspiredby SOCoutlined inSection VI[8]–[12], [17] and in modeling blackouts and cascading failure from otherperspectives[14]–[16],[18]–[20],[27], [29]–[31],[34].

If the dynamics of blackouts are confirmed to have some char-acteristics of SOC, this would open up possibilities for moni-toringstatisticalprecursorsoflargeblackoutsorcontrollingthepower system to modify the expected distribution of blackoutsizes [11]. Moreover, it would suggest the need to revisit the tra-ditionalriskanalysisbasedonrandomvariableswithexponen-tialtailssincethesecomplexsystemshavestatisticswithpowertails.

REFERENCES

[1] InformationonBlackoutsinNorthAmerica[Online].Available:http://www.nerc.com/~dawg/database.html
[2] P.Bak,C.Tang,andK.Wiesenfeld,“Self-organizedcriticality:Anex-planationof 1=fnoise,” Phys.Rev.Lett., vol.59,pp. 381–4,1987.
[3] P.Bak,HowNatureWorks:TheScienceofSelf-OrganizedCriti-cality.NewYork:Copernicus,1996.
[4] G.Boffetta,V.Carbone,P.Guliani,P.Veltri,and A.Vulpiani,“Powerlawsinsolarflares:Self-organizedcriticalityorturbulence?,”Phys.Rev. Lett.,vol.83,pp.4662–4665,1999.
[5] J. M. Carlson and J. Doyle, “Highly optimized tolerance: A mecha-nism for power laws in designed systems,” Phys. Rev. E, vol. 60, pp.1412–1427,1999.
[6] B.A.Carreras,D.E.Newman,I.Dobson,andA. B.Poole,“Initialevi-denceforself-organizedcriticalityinelectricpowerblackouts,”inProc.33rdHawaiiInt. Conf. SystemSciences, Maui, HI, Jan. 2000.
[7] , “Evidence for self organized criticality in electric power systemblackouts,”in Proc.34thHawaiiInt. Conf.SystemSciences,Maui,HI,Jan.2001.
[8] B. A. Carreras, V. E. Lynch, M. L. Sachtjen, I. Dobson, and D. E.Newman, “Modeling blackout dynamics in power transmission net-works with simple structure,” in Proc. 34th Hawaii Int. Conf. SystemSciences,Maui,HI,Jan.2001.
[9] B. A. Carreras, V. E. Lynch, I. Dobson, and D. E. Newman, “Dynamics,criticality and self-organization in a model for blackouts in powertransmissionsystems,”inProc.35thHawaiiInt.Conf.SystemSciences,Maui,HI,Jan.2002.
[10] , “Critical points and transitions in an electric power transmissionmodel for cascading failure blackouts,” Chaos, vol. 12, no. 4, pp.985–994,2002.
[11] B. A. Carreras, V. E. Lynch, D. E. Newman, and I. Dobson, “Blackoutmitigation assessment in power transmission systems,” in Proc. 36thHawaii Int.Conf. SystemSciences, Maui,HI, Jan.2003.
[12] B. A. Carreras, V. E. Lynch, I. Dobson, and D. E. Newman, “Complexdynamics of blackouts in power transmission systems,” Chaos, to bepublished.
[13] J. Chen, J. S. Thorp, and M. Parashar, “Analysis of electric powersystemdisturbancedata,”inProc.34thHawaiiInt.Conf.SystemSciences,Maui,HI,Jan.2001.
[14] J.ChenandJ.S.Thorp,“Areliabilitystudyoftransmissionsystempro-tectionviaahiddenfailureDCloadflowmodel,” inProc.5thInt.Conf.PowerSystem Managementand Control,2002,pp.384–389.
[15] J. Chen, J. S. Thorp, and I. Dobson, Power Systems Engineering Re-searchCenter,CornellUniv.,Ithaca,NY,PSERCRep.03–09[Online].Available:http://www.pserc.org,2003.
[16] C. L.DeMarco, “Aphasetransitionmodelforcascadingnetworkfailure,”IEEE ControlSyst.Mag.,pp. 40–51, Dec.2001.
[17] I. Dobson, B. A. Carreras, V. E. Lynch, and D. E. Newman, “An initialmodel for complex dynamics in electric power system blackouts,” inProc.35thHawaiiInt.Conf.SystemSciences, Maui,HI,Jan.2001.
[18] I.Dobson,J.Chen,J.S.Thorp,B.A.Carreras,and D.E.Newman,“Ex-aminingcriticalityofblackoutsinpowersystem

modelswithcascadingevents,”inProc.35thHawaiiInt.Conf.SystemSciences,Maui,HI,Jan.2002.

[19] I.Dobson,B.A.Carreras,andD.E.Newman,“A probabilisticloading-dependentmodelofcascadingfailureandpossibleimplicationsfor blackouts,” in Proc. 36th Hawaii Int. Conf. System Sciences, Maui,HI,Jan.2003.

[20] ——, “A branching process approximation to cascading load-dependentsystemfailure,”inProc.37thHawaiiInt.Conf.SystemSciences,Maui,HI,Jan.2004.

[21] H. E. Hurst, “Long-term storage capacity of reservoirs,” Trans. Amer.Soc.CivilEng.,vol.116,p.770,1951.

[22] T. Hwa and M. Kardar, “Avalanches, hydrodynamics, and dischargeevents in models of sandpiles,” Phys. Rev. A, vol. 45, no. 10, pp.7002–7023,1992.

[23] H.J.Jensen,Self-OrganizedCriticality.Cambridge,U.K.:CambridgeUniv.Press,1998.

[24] B. B. Mandelbrot and J. R. Wallis, “Noah, Joseph, and operational hy-drology,”WaterResources Res.,vol.4, pp.909–918,1969.

[25] D. E. Newman, B. A. Carreras, P. H. Diamond, and T. S. Hahm, “Thedynamicsofmarginalityandself-organizedcriticalityasaparadigmtur-bulent transport,” Phys. Plasmas, pt. 2, vol. 3, no. 5, pp. 1858–1866, May1996.

[26] M.Ni,J.D.McCalley,V.Vittal,andT.Tayyib,“Onlinerisk-basedse-curityassessment,”IEEETrans.PowerSyst.,vol.18,pp.258–265,Feb.2003.

[27] P.A.Parrilo,S.Lall,F.Paganini,G.C.Verghese, B.C.Lesieutre,and J. E. Marsden, “Model reduction for analysis of cascading failuresin power systems,” in Proc. Amer. Control Conf., vol. 6, 1999, pp.4208–4212.

[28] D.L.Pepyne,C.G.Panayiotou,C.G.Cassandras,andY.-C.Ho,“Vul-nerability assessment and allocation of protection resources in powersystems,”inProc.Amer.ControlConf.,vol.6,2001,pp.4705–4710.

[29] M. A. Rios, D. S. Kirschen, D. Jawayeera, D. P. Nedic, and R. N. Allan,“Value of security: Modeling time-dependent phenomena and weatherconditions,” IEEE Trans. Power Systems, vol. 17, pp. 543–548, Aug.2002.

[30] S. Roy, C. Asavathiratham, B. C. Lesieutre, and G. C. Verghese, “Net-workmodels:Growth,dynamics,andfailure,”inProc.34thHawaiiInt.Conf.SystemSciences, Maui,HI,Jan.2001.

[31] M. L. Sachtjen, B. A. Carreras, and V. E. Lynch, “Disturbances in apowertransmissionsystem,”Phys.Rev.E,vol. 61,no.5,pp.4877–4882,2000.

[32] G.SamorodnitskyandM.S.Taqqu,StableNon-GaussianRandomPro-cesses: Stochastic Models with Infinite Variance.New York: ChapmanandHall,1994.

[33] M. D. Stubna and J. Fowler, “An application of the highly optimizedtolerance model to electrical blackouts,” Int. J. Bifurc. Chaos, vol. 13,no.1,pp.237–242,2003.