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Exploring self-organized criticality conditions in Iran bulk power system with disturbance times series

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Abstract. Ubiquitous power-law as a fingerprint of Self-Organized Criticality (SOC) is used for describing catastrophic events in different fields. In this paper, by investigating the prerequisites of SOC, we show that SOC-like dynamics drive a correlation among disturbances in Iranian bulk power systems. The existence of power-law regions in probability distribution is discussed for empirical data using maximum likelihood estimation. To verify the results, long time correlation is evaluated in terms of Hurst exponents, by means of statistical analysis of time series, including Rescaled Range (R/S) and Scaled Windowed Variance (SWV) analysis. Also, sensitivity analysis showed that for correct inference in the existence of SOC in power systems, all disturbances should be recorded for use in statistical analyses. Greater thresholds for recording disturbances lead to underestimating the Hurst exponent.

1. Introduction

Power systems, as a critical infrastructure, play an important role in our modern society. Dependencies of other infrastructures on electricity make power grids even more vital, and, therefore, blackouts are a very challenging problem faced by power system engineers. Blackouts have direct and indirect consequences, and, therefore, quantifying associated costs is very difficult.

For hundreds of years, classic methods in different sciences have been based on the concept that problems can be understood by breaking them into smaller parts and undertaking the solutions of each separately [1]. This method is not applicable for complex systems such as large power systems. Complex systems can show catastrophic behavior, where one part of the system can affect many others in a domino-like fashion [2]. Complexity has been used to understand and describe the dynamic characteristics of systems in different fields [3]. The fact that large events follow the same path as small ones indicates that the consequences of those events are disastrous [2]. Accordingly, complex system concepts have significant usages in power systems, such as assessing the risk of blackouts [4].

SOC is a feature of complex systems used to describe rare events. It shows that despite a large number of small events, the consequences associated with large events are extremely high. Therefore, SOC can be a theoretical justification for catastrophism. As Bak, the pioneer of SOC, discussed in his book [2], by following traditional scientific methods and concentrating on an accurate description of detail, perspective may be lost. The theory of SOC must be statistical and, accordingly, cannot produce specific or deterministic details. The power-law, which occurs in an extraordinarily diverse range of phenomena, is a fingerprint of the SOC. Power-law, called heavy-tailed, means that large events (the events at the tail of distributions) are more likely to

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happen in a power-law distribution than in a Gaussian distribution [5]. Exponents of power-law, in different power transmission systems with diverse properties, are presented in [6], which indicates that blackouts follow a similar trend.

The similarity between power system behavior and a classical paradigm of SOC, known as sandpile, has been shown in [7]. Some indistinguishable statistics, such as the size of avalanches of the sandpile model and blackout size in a power system, demonstrate that SOC-like dynamics lead to correlation between events in power systems rather than power system dynamics [7]. Carreras and his coworkers argued that competitive interactions in power systems are customer load growth and engineering responses to that via planning and operating policies [3]. This idea has been the kernel of the proposed models, such as OPA, in investigating power system blackouts [8-11].

The complex behavior of a blackout time series has been studied in a considerable number of research projects. First Carreras et al. [12] showed a power-law tail for 15-year power system blackouts by means of R/S and SWV and, subsequently, the correctness of applying the SWV method to detect long term memory in a blackout time series was challenged in [13]. Reference [14] shows that a good estimate in SWV will be obtained for a series of $N \geq 2^9$ points. Therefore, in [7], only the R/S method was used for 15-year North American blackouts to demonstrate the power-law and SOC in power systems. As power system structures change with time to meet increasing energy consumption, Hines et al. [15] proposed a scaling method to adjust all blackout quantities, in order to avoid underestimating the importance of earlier blackouts. Also, statistical assessment of [15] on North American blackouts supports the power-law of previously observed blackouts. More investigations have been reported for the USA power system in [12,16,17].

Further analyses on other power systems have been undertaken to illustrate power-law. SWV and R/S methods were used in [18] to confirm the autocorrelation and power-1aw of blackout events in the time series of the Chinese power grid. Casals and Solé analyzed European power system disturbances for 7 years in [19]. Statistical analysis of Swedish power system disturbance data demonstrated that the size of large disturbances follows a power-law, and a Poisson process can be used to model such disturbances [20]. The power-law for blackouts in the Norwegian power grid was shown in [21], which proposed a model that could reproduce the power-law with global redistribution of the load, with the failure of a link in the system.

Time series analysis of four Chinese transmission and distribution systems for evidence of SOC was presented in [22]. It showed that faults in transmission systems derive their SOC from cascading outages within a power system and the SOC of atmospheric systems, while the time series of faults in distribution systems derive their SOC from that of the atmospheric system.

To continue exploring the existence of SOC in power systems, this paper investigates SOC in the Iranian bulk power system. The paper is organized as follows. The system description and classification of 4-year disturbances are presented in Section 2. SOC conditions, including power-law tail and waiting time distribution, are investigated and confirmed in Section 3. Two methods for determining the power-law are used:

i) The proposed method in [23], which is a combination of the maximum likelihood fitting method and goodness-of-fit tests based on the KS statistic and likelihood ratios,

ii) Persistent long-term correlation in disturbance data using the Hurst coefficient calculation from R/S and SWV statistical analysis.

Moreover, the exponential distribution of waiting time between disturbances is investigated in part 3 to prove SOC in the Iranian bulk power system. A discussion on results is presented in Section 4. Finally, conclusions are presented in Section 5.

2. Disturbance classification

2.1. System description

The Iranian power grid is a network with 61.5 GW of installed capacity and 45 GW of summer peak demand. IGMC as ISO is responsible for its reliability, and gathers the related data from 16 regional electric companies.

2.2. Disturbance time series

Considerable efforts have recently been undertaken in data documentation of power disturbances in Iran. Each event report includes initiating event, participating elements, starting and ending time, total lost power, operator actions, geographical area, and weather conditions. Three quantities of disturbance size for investigating power-law are: energy not supplied (MWh), load curtailed (MW), and restoration time (hrs). Unfortunately, the restoration time of some disturbances has not been recorded. Figure 1 illustrates the time series of blackouts for load curtailment in the Iranian power grid from 2008-2011.

The NERC definition for a blackout is the uncontrolled loss of more than 300 MW, taking more than 15 minutes, or load shedding of more than 100 MW under emergency conditions [24]. But, in this paper, we use disturbances instead of blackouts, which is referred to as an unplanned interruption of any size taking more than 5 minutes. Based on this definition, there were

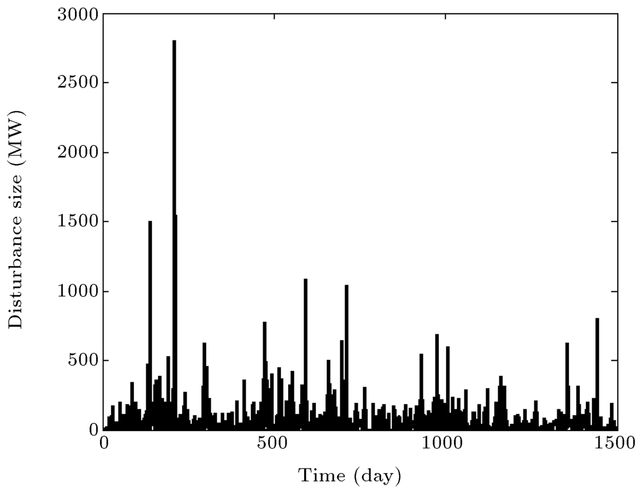

Figure 1. Time series of disturbances for Iran power grid in 2008-2011 with the resolution of a day.

935 disturbances in 4 years with curtailed load ranging from 1 to 2800 MW in the period of 2008-2011 and 19.48 disturbances per month.

According to time series definition, data points are measured at sequential time instants at uniform time intervals. Because of their stochastic characteristic, power system disturbances are scattered at non-uniform time intervals. Thus, a new time series is constructed with the resolution of a day, whose magnitude is zero, except during those instances when disturbances occur. This is the reason for using any recorded events of any size.

2.3. Types of initiating events

Initiating events of disturbances are documented in five groups, as follows:

- Protection system malfunctions;
- Weather-related events, including tornados, snow, rain, lightning, and pollution;
- Operator errors;
- Equipment failure;
- Others, including earthquakes, fires, supply shortages, external objects, and bad design.

Figure 2 summarizes the number of each category per year and total disturbances.

3. Exploring SOC in disturbance time series

Necessary and (perhaps) sufficient criteria for determining a SOC system are [25]:

- Statistical independency events in time series;
- Nonlinear coherent growth;
- Random duration of rise times.

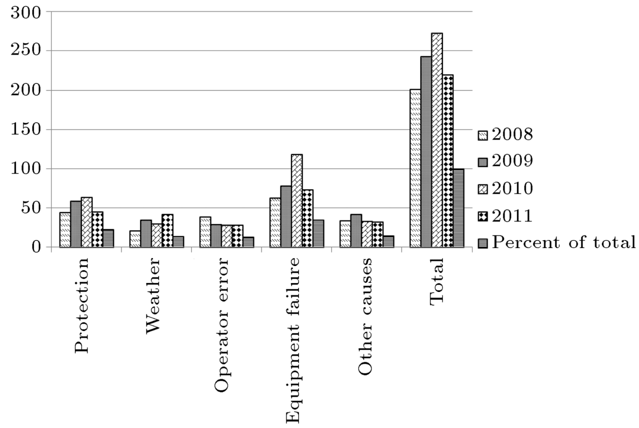

Figure 2. Initiating events of disturbances in Iran bulk power system for 4 years.

The first and second criteria lead to a power-law distribution as a necessary, but not sufficient, condition for SOC processes, while the third criterion is used to verify or disprove SOC in a system. In this section, these conditions for three quantities of disturbances in the Iranian bulk transmission system are investigated.

3.1. Existence of power-law

Detection of a power-law is complicated because there are large fluctuations occurring at the tail of the distribution. It is worth noting that simply plotting a simple histogram on log scales and fitting a straight line is not an appropriate method. Power-law distribution is not easily realized on a logarithmic curve. In [23], a principled statistical framework for quantifying power-law behavior in empirical data is presented. The approach combines maximum-likelihood fitting methods with goodness-of-fit tests based on the KS statistic and likelihood ratios. This method is used in this section.

Suppose that x represents a quantity of time series. The first tool needed for investigating power-law distribution in a time series is a histogram, which can be constructed easily by means of the following equation:

$$p(X=x)dx=\Pr(x\leq X\leq x+dx)=Cx^{-\alpha},$$

$$x\geq x_{\min}, \tag{1}$$

where, X is the observed value, C is normalization constant, and α is a scaling parameter. There are also some occasional exceptions, α, typically, lies in the range [23]. Moreover, $x_{\min}$ is the lower bound of the power-law region.

When $dx\rightarrow 0$, $p(X)$ will be the PDF of the time series. However, analyses of blackout size in North America show that the probability distribution has a power-law tail with an exponent between -2 and -1 [26].

The following three steps are appropriate for determining the parameters of power-law distribution. More details can be found in [23]:

1. Estimating the parameters, α and $x_{\min}$, using a maximum likelihood estimator.

   Assume that the PDF for $x \geq x_{\min}$ exactly follows power-law distribution. Then, maximum likelihood estimators can be used for estimating the scaling parameter, as follows:

$$\hat{\alpha} = 1 + n\left[\sum_{i=1}^{n} \ln \frac{x_i}{x_{\min}}\right]^{-1}, \tag{2}$$

   where, x_i for $i = 1, 2, \cdots, n$ are the empirical data, which are greater than $x_{\min}$, and $\hat{\alpha}$ denotes the estimated α, which is derived from data.

   Now, the best fitted power-law is derived from the following optimization:

$$\min \mathrm{KS}, \tag{3}$$

   where, KS is the maximum distance between two time series, namely; the original data ($D(x)$) and the fitted power-law ($F(x)$), as follows:

$$\mathrm{KS} = \max_{x \geq x_{\min}} |F(x) - D(x)|. \tag{4}$$

2. Calculating the goodness-of-fit between the original data and the fitted power-law using p-value.

   For calculating the p-value, numerous synthetic data sets, according to the desired distribution, are generated, and the KS criterion for each of them is calculated. Then, the p-value is the fraction of the synthetic data sets for which KS is larger than that of empirical data.

   The power-law is rejected if the p-value is smaller than 0.1. Parameters of the fitted power-law for the aforementioned quantities are listed in Table 1. It contains $x_{\min}$, α, KS, and p-value for 2500 synthetic sets. As seen in this table, all data sets are consistent with power-law distribution.

3. Comparing the power-law with alternative distributions, which might give a better fit for the present time series, via a likelihood ratio test.

The principal of a likelihood ratio test is to calculate the likelihood of two alternative distributions. The higher likelihood shows the better fit. It is possible to calculate the logarithm of the ratio of these two likelihoods, which may be positive or negative. Positive likelihood values support the power law hypothesis, and p-values lower than 0.1 indicate no significant effect on results [19]. This step strengthens the power-law hypothesis. There are more descriptions in [23].

Numerous synthetic data from exponential and Weibull distributions were generated using appropriate parameters for each quantity. Table 2 shows the p-value and the likelihood ratio for these distributions. Therefore, these distributions are ruled out.

The CDF is more robust than PDF against fluctuations. Therefore, Figure 3 illustrates the CDF

Table 1. Parameters of fitting power-law to CDF of disturbance time series.

Quantity	$x_{\min}$ (MW)	α	KS	p-value
Load curtailed	89	2.46	0.0322	0.5623
Energy not supplied	251	2.04	0.0273	0.9412
Restoration time	6.1	2.91	0.0621	0.8318

Table 2. Likelihood ratios for other distributions.

Distribution	Exponential		Weibull	
	LR	p-value	LR	p-value
Load curtailed	-1.23	0.0185	1.23	0.4425
Energy not supplied	-0.23	0.0248	3.45	0.5525
Restoration time	-2.05	0.0194	1.65	0.6235

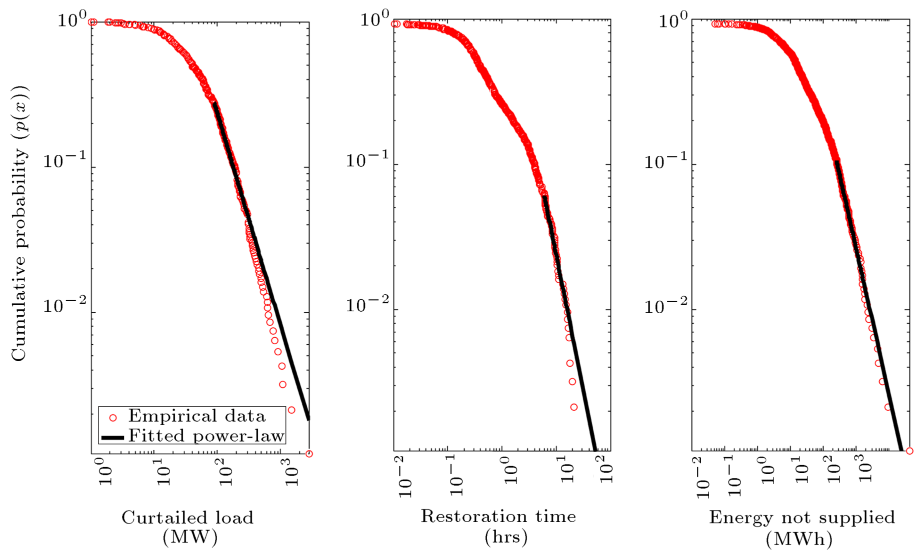

Figure 3. CDF of disturbances and its power-law tail in 2008-2011 for Iran power grid.

of blackouts for the Iranian power grid in 2008-2011, and its power tail for bins equals 1 MW. Power-law distribution in power system blackout data is applied for the tail of the distribution, which means for values greater than $x_{\min}$. Note that in a real power system, the upper limit of the power-law region is a finite cutoff, which is consistent with the largest possible blackout [17] and equal to the peak demand of the system.

3.2. Long memory in blackouts

There are several alternative definitions of long memory functions that are mathematically investigated in [27]. Generally speaking, a time series has long memory when a past event has a decaying effect on future events. Thus, some memory of past events will be forgotten as time differences increase. An autocorrelation function is used to describe long term memory. Dobson argued that the dependency of failures in blackouts creates the power-law region. Thus, as a power system experiences more stress, further failures become more likely [17]. This means that autocorrelation and smaller blackouts will change into larger ones.

Also, self-similarity and scale-invariance are indicative of long memory. The decay of the auto covariance function in a long memory time series exhibits power-law, and so decays slower than exponentially [27]. For large time differences, noise dominates the signal. Therefore, it is difficult to calculate the auto covariance function. An alternative method is to estimate H, which is a measure of the degree of long-range dependence in a time series.

Estimation of H in the time series was originally developed in hydrology by Harold Edwin Hurst. Since then, H estimation has been applied to various fields, including biology, biophysics, computer networking, financial markets, seismic activity, and climate change. H ranges from 0 to 1 for which the closer H is to 1, the greater the degree of persistence or long-range dependence. $H = 0.5$ corresponds to independent events, which is the boundary of anti-persistent and persistent behavior [28]. Two famous statistical analysis methods for estimating H are R/S and SWV. The following subsections investigate these methods for the Iranian power system blackout time series.

3.2.1. R/S Analysis

The method for analysis of long records in a time series was first proposed by Harold Edwin Hurst, and named R/S analysis, which is the range of partial sums of deviations of a time series from its mean, rescaled by its standard deviation. A short explanation of the R/S method is presented in this subsection from [7]. Consider the time series:

$$\{X_t : t = 1, 2, \cdots, n\}. \tag{5}$$

Then, construct a new series as follows:

$$\{Y_t : t = 1, 2, ..., n\}, \tag{6}$$

where:

$$Y_t = \sum_{i=1}^{t} X_i. \tag{7}$$

Now, a new series with m elements is constructed as follows:

$$Y^m = \left\{ Y_u^{(m)}; 1, 2, \cdots, \frac{n}{m} \right\}, \tag{8}$$

where,

$$Y_u^{(m)} = \{Y_{um-m+1}, \cdots, Y_{um}\}. \tag{9}$$

The range of each series (R_m^i) and its standard deviation (σ_m^i) must be calculated for the n/m series. Accordingly, the R/S statistic is a function of (m):

$$R/S = \frac{m}{n} \sum_{i=1}^{n/m} \frac{R_m^i}{\sigma_m^i}. \tag{10}$$

More details can be found in [1]. A package was developed to estimate H and tested for reliable results. The estimated H for 1000 Brownian motion with $H = 0.5$ was 0.53, with standard deviation of 0.0817.

R/S analysis for curtailed load in the Iranian power system is illustrated in Figure 4.

Table 3 demonstrates the H for blackout quantities based on R/S analysis. For all quantities, H is significantly greater than 0.5, which shows its persistent behavior.

3.2.2. SWV analysis

The SWV analysis was developed by Cannon and his coworkers in 1997, in [14]. There are three SWV methods, namely, standard, linear regression detrended, and

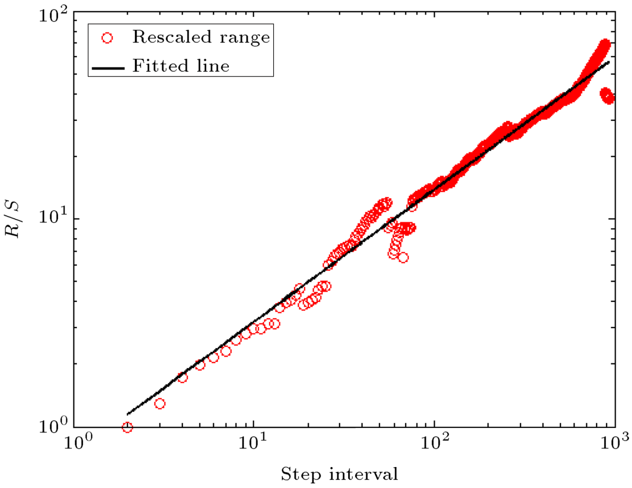

Figure 4. R/S analysis for the curtailed load in disturbances for Iran power grid.

Table 3. Hurst exponent for disturbance quantities based on R/S analysis.

Quantity	Unit	H
Load curtailed	MW	0.6865
Energy not supplied	MWh	0.5959
Restoration time	hrs	0.5977

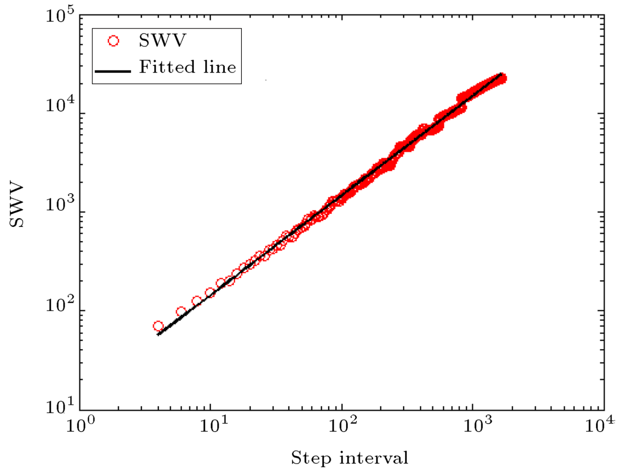

Figure 5. SWV analysis for the curtailed load in disturbances for Iran power grid.

bridge detrended. For all these methods, both the bias and standard deviation of estimates are less than 0.05 for a series having $N \geq 2^9$ points [14]. In this paper, the standard method is used. Here, a brief description of this method is presented, which is duplicated from [3]. Consider Eqs. (5)-(9). The standard deviation series of $Y_u^{(m)}$ is calculated by:

$$\sigma_m = \frac{\sum_{u=1}^{n/m} \sigma_m^{(u)}}{n/m}, \tag{11}$$

where, the standard deviation of $Y_u^{(m)}$ is represented by $\sigma_m^{(u)}$.

Reference [13] shows that if series X has a power law tail, so does the standard deviation series, σ_m. Therefore:

$$\sigma_m \propto m^H. \tag{12}$$

Similar to the previous section, the estimated H for 1000 Brownian motion with $H = 0.5$ was obtained. Its mean value was 0.51, with standard deviation equal to 0.0963. SWV analysis for a curtailed load is illustrated in Figure 5.

As shown in Table 4, H, for blackout quantities based on SWV analysis, for all quantities, are significantly greater than 0.5, which shows their persistent behavior.

3.2.3. R/S and SWV Comparison

Carreras and his colleagues did not use the SWV method in their paper, as they believe that in this

Table 4. Hurst exponent for disturbance quantities based on SWV analysis.

Quantity	Unit	Hurst exponent
Load curtailed	MW	0.8958
Energy not supplied	MWh	0.8644
Restoration time	hrs	0.6806

method, at larger window sizes, the correlations between blackouts are affected by the correlations between absences of blackouts [3]. This is because a series partitioned into large windows has fewer average standard deviations. Thus, as proposed in [14], large time lags can be excluded. On the other hand, Lo pointed out that the statistical R/S test used by Mandelbrot is too weak and is unable to distinguish between long and short memory [29]. However, Hurst exponents estimated in two methods are sufficiently greater than 0.5. One could conclude that there is long-term persistent correlation, which, therefore, confirms the power-law region in the Iranian disturbance time series.

3.3. Waiting time distribution

Waiting time is the time interval between subsequent events in a time series. It must be noted that the duration of an event and the waiting time between two subsequent events are different. Therefore, the statistical distribution of waiting time intervals and event durations are not identical [25].

Events in a SOC system are unpredictable and thus exhibit a random time scale. Waiting times follow a straight line on a semi-log curve that means exponential distribution. Thus, if a blackout as a catastrophic event has occurred, the occurrence of the next one gradually slows down. Some physical processes might produce similar power-law distributions to SOC processes. However, they can be distinguished from their different waiting-time distributions. Waiting time distributions were often used to verify or disprove a SOC system [25]. Distribution of waiting times in a blackout time series is presented on a semi-log curve in Figure 6. Clearly, the waiting time distribution of disturbances in the Iranian bulk power system obeys exponential distribution, which confirms SOC in this system.

4. Discussion on the results

In this section, the importance of lower limits of recorded data is investigated. It was shown that quantities of disturbances obey the power-law for values greater than $x_{\min}$. Suppose that disturbances with consequences smaller than a threshold are ignored. This threshold was changed and H was estimated for the obtained time series of disturbances using

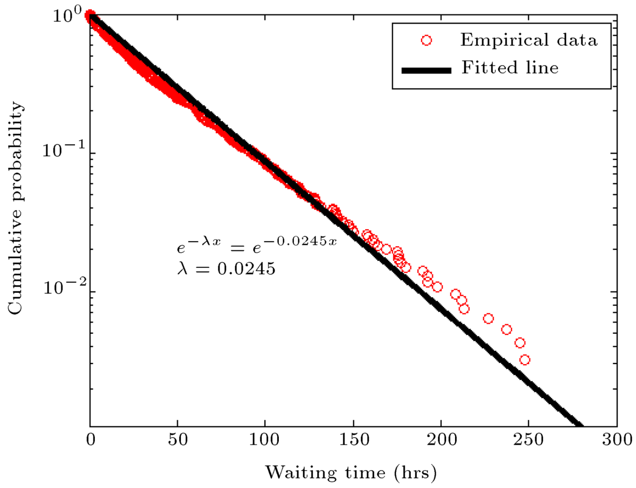

Figure 6. Waiting time between disturbances in hours for Iran power grid.

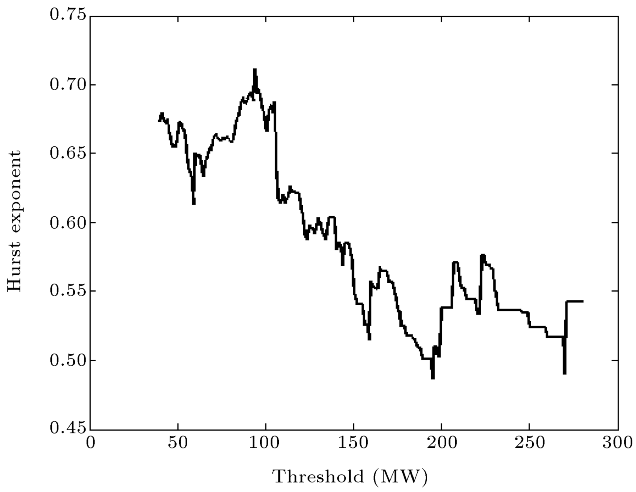

Figure 7. Sensitivity analysis of H for different values of $x_{\min}$ in curtailed load.

R/S analysis. This sensitivity analysis for curtailed load is undertaken and the results are illustrated in Figure 7. As can be seen, greater thresholds lead to underestimate H. Thus, for confidence in results, it is better that the time series of disturbances contains all disturbances, as treated in this paper. It should be noted that underestimating $x_{\min}$ leads to a smaller scaling exponent. For instance, blackout distribution of the North American power system, according to [23], using maximum-likelihood fitting, obeys $x_{\min} = 1016$ MW and $\alpha = 1.19$, whereas, using other methods, the parameters of the power-law are $x_{\min} = 500$ MW and $\alpha = 0.97$ [15].

5. Conclusion

Further research into other empirical data from various power systems with different properties would resolve the present doubts on the existence of power-law regions in blackouts. Despite the existing differences between Iran and the above-mentioned countries in culture, continent, and in the structure of the power grids, such as dimensions and regulations, SOC is a good universal theorem for justifying blackouts in power systems.

This paper extends previous investigations done on the empirical data of power system blackouts. It demonstrates that the distribution probability for three quantities of disturbances in the Iranian bulk power system obeys the power-law as a fingerprint of SOC. Also, the estimated Hurst exponent in the disturbance time series was significantly greater than 0.5, which indicates persistent long-term memory and, therefore, confirms the existence of the power-law. Exponential distribution of waiting time between disturbances proved SOC in the Iranian bulk power system. The power-law exponent for this system is in a typical range between -3 and -2, which means that the occurrence of catastrophic blackouts is more likely.

It has been shown that for assurance in estimating the Hurst exponent, all disturbances should be recorded for use in statistical analyses. Greater thresholds lead to underestimating the Hurst exponent and, therefore, incorrect inferences.

Acknowledgment

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Abbreviations

CDF	Cumulative Distribution Function
H	Hurst exponent
IGMC	Iran Grid Management Company
ISO	Independent System Operator
KS	Kolmogorov-Smirnov
LR	Likelihood Ratio
NERC	North American Electrical Reliability Council
OPA	Oak Ridge National Laboratory, Power systems engineering research center and university of Alaska (institutions that developed this model)
PDF	Probability Density Function
R/S	Rescaled range
SOC	Self-Organized Criticality
SWV	Scaled Windowed Variance

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