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Early warning signals for critical transitions in power systems

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ABSTRACT

Several episodes of sudden large scale disruptions in electrical service deeply impacted both the social stability and economic development in affected countries. The prevention of such catastrophic incidents poses huge challenges for reliability study and operational practices in power systems. Studies in other scientific fields show that, upon reaching a tipping point, complex dynamical systems can experience sudden transitions into a contrasting state. These transitions may be predicted through behavioral changes in some statistical measures of the system state. Inspired by these studies, this paper proposes an analysis of the *critical transition* in power systems from a long-term perspective. The evolution of the operational "stress" and its cyclical variation due to a slowly increasing demand and system expansions is simulated on a test system. The disturbances and the resulting failures under different stress levels are studied. Our analysis identifies the statistical trends known as *flickering* and *critical slowing down* in the operational and the recorded outage data along the simulation. These statistical changes can be used as early warning signals of the upcoming operational state which is more prone to a catastrophic blackout. The development of such early warning signals is the key to reaching higher levels of reliability in the energy supply infrastructure that society requires today.

1. Introduction

Critical infrastructures have become the central nervous system of the economy in every nation [1] and tremendous effort and investment have been made in their protection in Europe and the United States [1,2]. Electricity infrastructure stands in the center and is essential to the operation of others [3].

Several large scale disruptions in electrical service, like in Canada and the U.S. (August 2003), Germany, Belgium, Italy, France, Spain and the Netherlands (November 2006), and Brazil (November 2009) [2], have deeply impacted both the social stability and economic development in the aforementioned countries. To counter this effect, effort has been made by researchers from various disciplines with different focuses. Insightful results have been gained into understanding [4–6], predicting and mitigating large catastrophic blackouts [7], also new perspectives have been formulated [8,9]. Major challenges still exist to facilitating the on-line prediction and mitigation of large blackouts in the accuracy and scalability of the models, especially regarding the computation efficiency [7,10]. These obstacles detain the application of most of the research results in the power industry as a supplementation of the $N-1$ and $N-t$ contingency criteria for reliability analysis.

Recent advances in other fields on *critical transition* have shown a promising potential in the prediction of sudden collapse of complex systems because of the computational efficiency. Previous researches [11–15] proved the existence of critical transition in a fixed power grid as the load demand continuous growing by observing the changes of "mean blackout size (expected energy not served)", "mean number of failed components" and "probability of cascading failures with certain size". References [16–20] extended the general mathematical description of fast-slow system into power system application on transient stability and derived autocorrelation functions for better understanding the early warning signals and the prediction of the transient instability. A study of transient instability on real power system is performed in [18] based on about 10 min of measured bus voltage frequency data from the Bonneville Power Administration territory provided by the WSCC (now WECC) disturbance study committee.

Besides being directly related to the operational state and the structural characteristics of a power grid, the system robustness against cascading failures is the accumulative outcome of decades of design choices of engineering systems under the guidance of

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reliability requirements, as well as financial, economic [21] and other social constraints and principles. A study of an evolving power system is then necessary for a better understanding of how the vulnerability of the system changes over time. Among all the references addressing the risk of power system cascading blackouts, the ORNL–PSerc–Alaska (OPA) model and its modification [22–24] stand out because of describing the interaction between long-term evolutions of the system (which are consistent with planning practices) and short-term systemic response to the disturbances. Therefore, based on OPA and its modification, in this paper we investigate the characteristics of the system along the complex evolution by considering all factors affecting the system's robustness. The objective is to detect early warning signals for a critical transition of the "stress" of the system from a long-term perspective rather than focusing on any single transient instability scenario [19,18]. The proposed method is built on the research in the area of nonlinear stochastic dynamical systems. Through the research, we show that recorded outage data and fractional overload are the most valuable variables in the assessment of the stress level in power systems. The constant tracking and analysis of these data could provide early warning signals for the changing of the system states. Ultimately, our results could be a useful complement to other studies on the prevention of large-scale catastrophic blackouts and could be included in planning decision models to mitigate catastrophic blackout risk.

The paper is organized as follows: Section 2 provides a brief summary of researches on critical transition in complex systems and insights of its application in power systems. Section 3 describes the research method. Section 4 analyzes the simulation results and discusses the effect of modeling details regarding the detection of early warning signals for critical transitions of the test system. Section 5 summarizes the key findings of this paper and the focuses of future work.

2. Insights from research on critical transition in complex system

Complex dynamical systems, which range from ecosystems to financial markets, can undergo *phase transition* (*critical transition*), in which a sudden shift to a contrasting dynamical regime may occur [25]. There are various sources or drivers for such systemic risks in complex systems, and one of them is *Self-organization* [26]. From the standpoint of thermodynamics all self-organization phenomena can be viewed as phase transitions [27], through which the complex system enters a critical state [26]. *Bifurcations*, *critical fluctuations* (*flickering*) and *critical slowing down* are characteristics of these phase transitions [27]. Work in different scientific fields has proved that the aforementioned characteristics can be observed and captured as indicators of the approaching of the system to a critical threshold [25]. Therefore, these could work as "early warning signals" of the critical transition. *Critical slowing down* leads to three possible early-warning signals: slower recovery from perturbations (if it can be measured directly), increased autocorrelation (AR) and increased variance of the time series of the observed parameter. *Flickering* is reflected in relatively low-resolution time series as bimodality and increasing variance, coupled to a decrease in AR and skewness [28].

Power system provides a good example of self-organized complex system. Previous research by model (OPA being the leading one) and historical outage data provided the evidence of self-organization in power systems [22]. As any complex system designed with a certain degree of connectivity and homogeneity, power systems are robust to small perturbations. However, the connectivity makes it easier for a local failure to propagate out and cause cascading events [27]. From a long-term point of view, power systems are evolving under the complex dynamics among load increase, random failures and upgrade practices to meet their requirements for reliability and economic benefits. As the grid upgrades, the pattern of maximum power flow limits of lines is changing [29], resulting in an increase in the inhomogeneity of the transmission system. This is part of the self-organization in power systems. However, the increasing inhomogeneity has another effect. A failure in a highly upgraded part of the system more easily propagates out, hence causing an over-critical failure with much larger amounts of load-shedding. This is one kind of the events that are capable of triggering systemic failures [27]. The inhomogeneity in the transmission system increases along the evolution. Eventually, power systems will enter a new state in which large scale cascades can happen more frequently. This new state is the "complex systems steady state" studied in [29]. The complex reaction between cascading overloads and the resulting transmission pattern from upgrades may aggravate the inhomogeneity and accelerate the transition of the system into a new state. How abrupt the transition is depends on the local reliability and the detailed self-organization mechanism of the system. We will further explain these phenomena of *critical transition* and the related *critical slowing down* and *flickering* in Section 4 together with the simulation results.

3. Simulation models

The models used in this research are the OPA model [22,30] and one of its modifications (EconOPA) [23]. IEEE 118-bus test system is taken as an example and applied to each model.

3.1. Model description

OPA and EconOPA simulate the evolution of the "stress" of the system with a constant load increase as well as the upgrades of the transmission capacity and generation capacity over time. However, they shape the system differently because of the integration of different driving forces for system evolution. EconOPA imbeds the economic force in generation upgrade and optimal power flow with quadratic cost functions for the decision of the operational state.

Above the Monte Carlo Simulation, two modules, *cascading overload tripping* and *system growing*, are added (these are indicated by the shaded grey area in Fig. 1). The main modeling details of OPA and EconOPA are briefly introduced below on the modeling of demand (load increase and variation), supply and market.

3.1.1. Load increase and variation [30]

In both the OPA and EconOPA, the load demand grows according to a specified trend (2% annual increase) using a model of daily constant growth (0.005%) plus a deviation from the trend. This deviation represents the daily load variation. In the simulation, each iteration represents an instance of the operation of one day. Demand P_i^{t+1} at node i in the $(t+1)$th simulation iteration can be calculated by (1) and (2), where γ represents a selected realization of the daily load curve of the area (different load node could belong to different area and follows different variation behavior). $\bar{\lambda} = 1.00005$ corresponds to a 0.005% daily increase. The simulation has 30,000 to 50,000 iterations, thus simulating a long-term evolution of the system.

$$\bar{P}_{t+1} = \bar{P}_t \times \bar{\lambda} \tag{1}$$

$$P_i^{t+1} = \bar{P}_{t+1} \times \gamma \tag{2}$$

One single load instance is chosen each day to be a representative sample of 24 h of the day. The value of the load could be randomly from heavily loaded instance to light loading one. The