Master of Science in Electrical Engineering

Data Analysis for Predicting Instabilities in Power Systems

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Introduction

Introduction

Transient Stability	Steady State Stability
A sudden, out-of-trend, high magnitude change in a state variable(s) causes blackouts.	Accumulation of several seemingly minor trends in state variables over time, ultimately leading to a critical point where a small change could cause blackouts.
Causes are generally tangible, including sudden failure of generator or transformer or transmission line or due to corrective protection mechanisms.	Causes may not be tangible. Some documented causes include: accumulation of renewable generation 'noise', measurement noise, difference in supply demand of powers in a grid after the latest power dispatch.

Introduction

While modeling every significant possible source of stochastic disturbance can be difficult or perhaps even outright impossible, at least their detection can be made through model free data-driven statistical analysis, enabling early detection of grid stability problems for a timely course-corrective action [1–3].

Introduction

Bifurcation Theory [4–7] helps explain the erratic functioning of stressed dynamical systems such as the power grid, and the theory of Critical Slowing Down [8] lists tangible quantitative analysis tools which can help us detect an impending ‘bifurcation’ (blackout) in the power grid.

Introduction

In this thesis, we first investigate various real-world grid frequency time series archives on their robustness against minor disturbances and any kind of long-standing stability problems in them, through the use of bulk distribution probability density functions and autocorrelation decay plots. We refer to this analysis as Offline/Postmortem analysis as the input data used is sampled for a long period (several months or years). Next, we investigate the effectiveness of two statistical parameters computed in real-time listed out as per the theory of Critical Slowing Down, namely Autocorrelation and Variance as Early Warning Sign Indicators of an approaching bifurcation in a power grid. We label this analysis as the Online/Real-time analysis as the input data here is only in instantaneously available from a stream of PMU data.

Literature Review

Literature Review

For offline analysis of the grids, archived frequency time-series data of several real-world grids was downloaded from these websites and/or papers: [9–17]. Schafer et al's paper [1] was referred to for the analysis of these grids. Their paper analyzes how almost all grids show a significant level of deviation from the commonly used assumption that power demand fluctuations follow the Ornstein-Uhlenbeck's Process in which the state variable follows the Gaussian distribution around a nominal mean and a bounded standard deviation. They also explain some of the causes of detected instabilities for various power grids, including measurement noise and energy trading fluctuations.

Literature Review

Most of the recent literature analyzing the effects of Critical Slowing Down on various dynamical systems including but not limited to: power grids, ecological population dynamics, predator-prey ecosystems, prediction of epileptic seizures in patients, climate systems, financial markets, prediction of conversion of vegetation area into deserts, and so on, credit the review made by Scheffer et al in [8]. The paper lists out systems in which Critical Slowing Down has been observed and provides accessible mathematical explanations behind its working, such as why is there an increase of autocorrelation and variance of state variables of real-world physical processes as the system approaches a 'critical bifurcation'.

Literature Review

The mathematical term has also been called appropriately as ‘critical transition’ or ‘tipping point’ by the author of [18], whose paper explains various normal forms of bifurcations (Fold, Hopf, Saddle Node, Transcritical, Pitchfork) via the concept of fast-slow stochastic systems. For developing a working understanding of bifurcation theory, university lecture notes by [4] and books [6, 7] were utilized.

Literature Review

For real-time/online analysis, authors in [3] have utilized PSAT [19] to simulate a steadily stressed power grid and have demonstrated that the computation of autocorrelation of detrended bus voltages and the computation of variance of detrended line currents can function as reliable Early Warning Signs of increasing instability. The detrending is required in order to filter any measurement noise from the data, which may skew the computed statistical parameters towards bogus values.

Literature Review

Adeen et al's paper [20] simulated several Stochastic Differential Equations based on the Ornstein-Uhlenbeck's Process with different values of α (autocorrelation coefficient) and analyzed their Fourier Spectrums to conclude that an increased autocorrelation does in fact lead to a greater amplitude of noise and therefore a higher risk of instability in a power system. Authors in [2] tested various power grids which were driven towards bifurcation and demonstrated that an increase of autocorrelation and variance values of bus voltages (tested in simulation) and grid frequency (tested on the time-series data measured at the Bonneville Power Administration minutes before the blackout of 10 August 1996) can reliably predict the impending bifurcation early enough for mitigating actions to be taken by the grid operator.

For simulation implementations in PSSE 34.3, the community run website run by Jervis Whitley [21] was very helpful.

Motivation and Objectives

Objectives

This thesis aims to highlight how statistical analysis can help predict/observe/detect steady state instabilities in power grids through both offline and online studies while making the least number of assumptions about the grid models themselves due to its data-driven approach. Statistical analysis can detect both lingering instability causing agents in the grids through Offline/Postmortem Analysis as well as predict any impending blackout/'bifurcation' in the grid through Online/Real-time Analysis.

Objectives

Typical power grid state variables such as Bus Voltages, Line Currents/MVAs and Grid Frequencies obtainable from a stream of PMU data may be used as inputs for such data-driven analysis. Tools used for Offline/Postmortem Analysis are visual inspection of bulk-distribution PDFs and estimating grid damping constants from autocorrelation decay curves. Tools used for Online/Real-time Analysis involve computing fixed-lag autocorrelation and variance of the filtered detrended fluctuations.

Objectives

All simulations were done in Siemens PSSE 34.3 in conjunction with Python 2.7 (for writing automation scripts). All data analysis was conducted in MATLAB 2022a. A working implementation for anyone interested may be downloaded via [Simulation, Offline Analysis, Online Analysis]

Theory

Bifurcations and Critical Slowing Down

Bifurcation: A qualitative change in the 'motion' of a dynamical System due to a quantitative change in one of its parameters. Serious bifurcations, called Critical Bifurcations, cause the system to become unstable from stable.

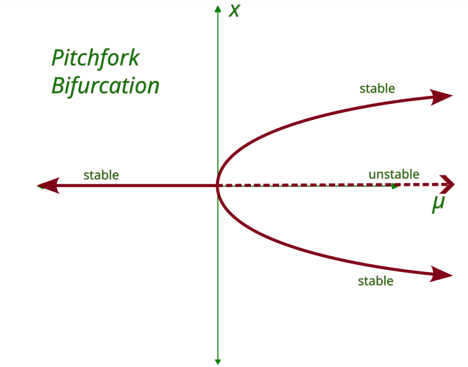


Figure 1: Bifurcation Diagram showing the Normal form of Pitchfork Bifurcation

$$\frac{dx}{dt} = \mu x - x^3 \tag{1}$$

Bifurcations and Critical Slowing Down

Critical Slowing Down: Dynamical Systems exhibit early statistical warning signs before collapsing, i.e. before a critical bifurcation, they exhibit these signs:

- Increased recovery times from perturbations.
- Increased signal variance from the mean trajectory.
- Increased flicker and asymmetry in the signal

The above three properties can be identified by increasing variance and autocorrelation in time-series measurements taken from the system.

AR1 and Variance

$$d[k] = a_1 d[k-1] + e[k] \tag{2}$$

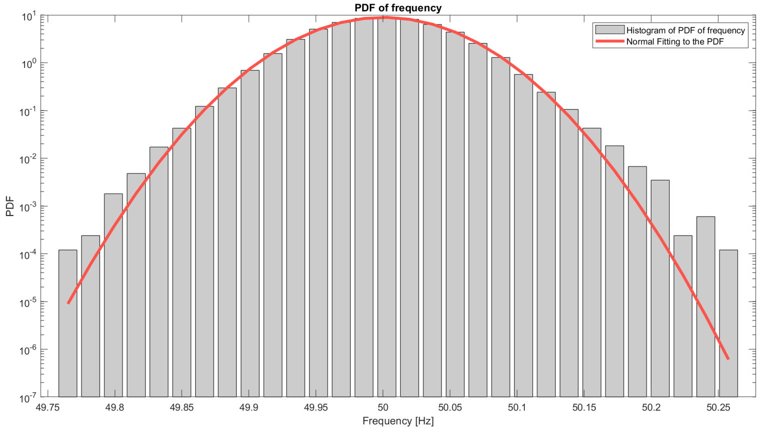
Autoregressive Model of Order 1 on detrended voltages.

$$\sigma^2 = \frac{1}{n_k} \sum_{k=1}^{n_k} d[k]^2 \tag{3}$$

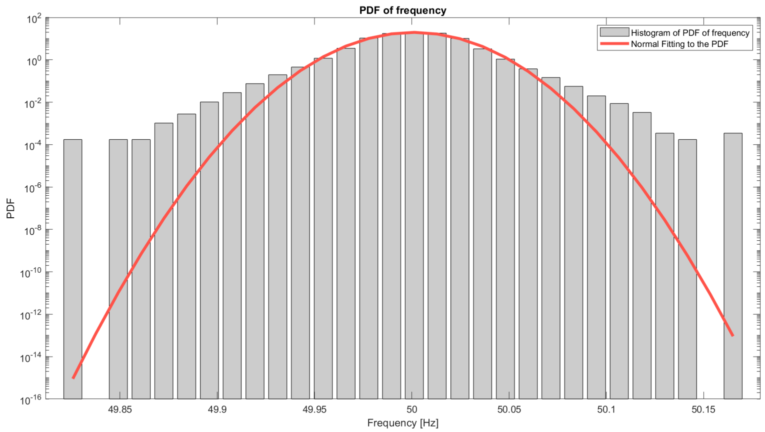
Sample variance on detrended voltages.

Offline Analysis

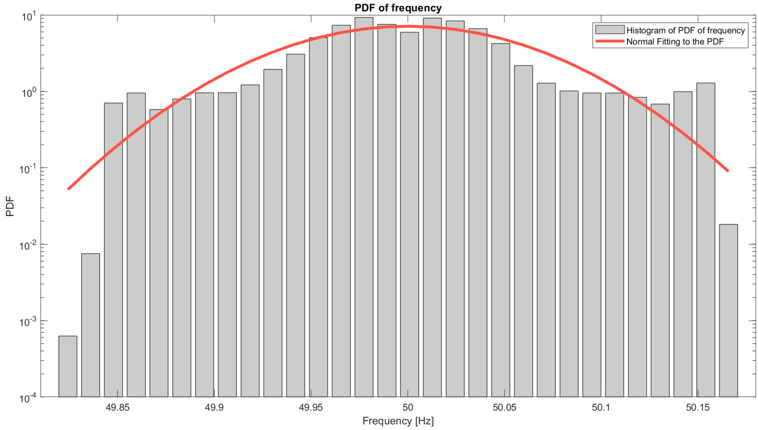
Nordic Grid


PDF of frequency
Histogram of PDF of frequency
Normal Fitting to the PDF
PDF
Frequency [Hz]
49.75
49.8
49.85
49.9
49.95
50
50.05
50.1
50.15
50.2
50.25

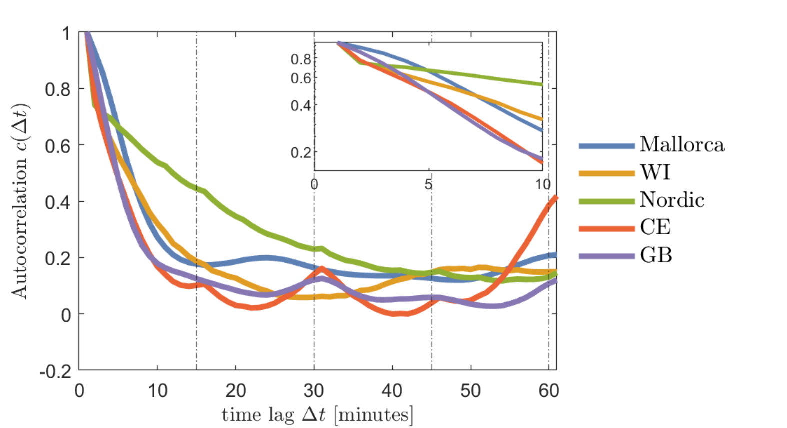
Continental European Grid



Spanish Mallorcan Grid



Offline Analysis



Online Analysis

Online Analysis

- Created and simulated the IEEE 9 Bus System in PSSE 34.
- Added stochastic disturbance to the loads (at Bus 5, 6 and 8) via white noise modeled as

$$(P_L)_i[k] = (P_L)_i[k-1] + N(0, \sigma^2) \tag{4}$$

  for load bus i at discrete sample k. $\sigma = 0.01$ pu.
- In order to drive the power grid towards bifurcation, steadily increased the three loads at different rates, between 20% to 30% per minute.
- Ran a time analysis simulation until critical bifurcation attained.
- Extracted the bus voltages.

Online Analysis

Passed the voltage signals through a Low Pass Filter in order to capture the slow changing trends not an effect of CSD. Eg. Change in bus voltages due to the gradual increasing of loads. Gaussian Kernel Smoothing Filter was used for the same.

$$h(n, \sigma_f) = \frac{1}{\sqrt{2\pi}\sigma_f} \exp^{\frac{-n^2}{2\sigma_f^2}} \tag{5}$$

where σ_f can be varied between 5 to 10 .
The detrended signal is obtained by subtracting the filtered signal from the original signal.

$$d[x] = x[k] - GKS(x[k]) \tag{6}$$

Online Analysis: Applying AR1 and Variance

Windows length of $W = 15$ seconds was used for computing autocorrelations and variances. The windows were moved by $W_{moving} = 1.5$ seconds after every computation.

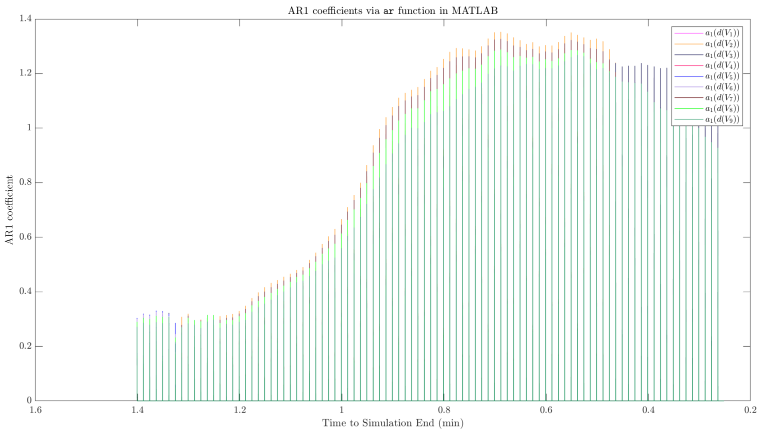
For every window, Autoregressive Model of Order 1 was fitted onto the detrended voltages using least squares of error approach.

$$d[k] = a_1 d[k-1] + e[k] \tag{7}$$

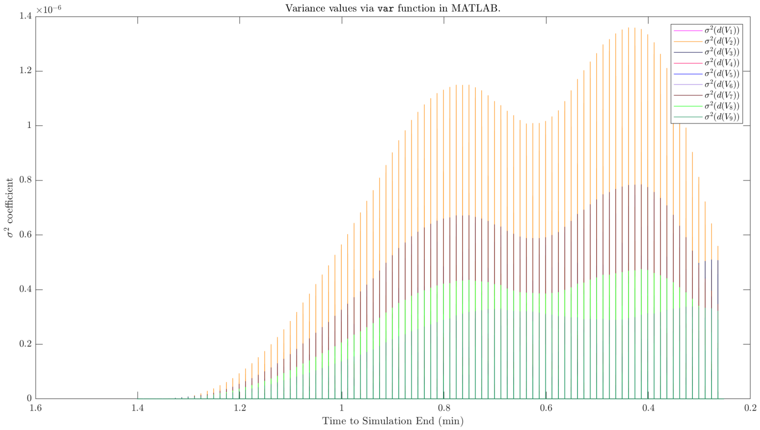
Variances were also computed for every window.

$$\sigma^2 = \frac{1}{n_k} \sum_{k=1}^{n_k} d[k]^2 \tag{8}$$

Autocorrelations



Variances


Variance values via var function in MATLAB.
$\times 10^{-6}$
1.4
1.2
1
0.8
0.6
0.4
0.2
0
σ^2 coefficient
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
Time to Simulation End (min)
$\sigma^2(d(V_1))$
$\sigma^2(d(V_2))$
$\sigma^2(d(V_3))$
$\sigma^2(d(V_4))$
$\sigma^2(d(V_5))$
$\sigma^2(d(V_6))$
$\sigma^2(d(V_7))$
$\sigma^2(d(V_8))$
$\sigma^2(d(V_9))$

Conclusions

Conclusions i

Offline/Postmortem Analysis

- Frequency time-series for months/years of data obtained from various real-world grids were converted into probability distribution function plots and autocorrelation decay plots ($c(\tau)$ vs τ plots).
- Visual inspection of the probability distribution function plots provided many insights into the presence of long-standing steady-state instabilities in the grid as well as the grid's resilience against any additional instability causing agents. Generally the PDFs of the more robust grids such as the RTE (France) and Continental European grids were mostly Gaussian except that they had heavier tails, whereas the smaller or island grids, such as the Mallorcan (Spain) grid had multiple peaks,

Conclusions ii

skewed distributions and thus an overall visible deviation from Gaussianity which explains their higher susceptibility to steady-state deviations and thus a greater degree of vulnerability to grid failures.

- For most grids, the autocorrelation functions exponentially decayed with respect to time lag τ for smaller values of τ but certain grids showed significant deviation from the expected norm. For example the Continental European and UK grids showed a spike in autocorrelation decay function at time lags of every 15 minutes. This spike, which indicates an inherent instability causing agent in the grid systems, can be attributed to their 15 minute power trading intervals. Unlike the amount of transacted power which is suddenly varied every 15 minutes, the power grids, being dynamical systems cannot instantly adjust to the new power settings and thus the sudden imbalance of supply and demand leads to transients in the grid state variables.

- Autocorrelation decay curves of other grids (Nordic, Japan, US-Western Interconnection) initially decreased exponentially but later followed between a very slowly decaying or almost constant curve with respect to τ. This can be attributed to measurement noise in the frequency detection.
- From the initial exponential decay of the curves, semi-log graphs were plotted and their inverse correlation times ${t_{corr}}^{-1}$ were obtained. As per the Ornstein-Uhlenbeck Process this inverse correlation time can be likened to the damping constant α of the grids. As per our theoretical expectations, the bigger and

Conclusions iv

more robust grids had higher values of α compared to the smaller, islanded grids.

Conclusions i

Online/Real-time Analysis

- The IEEE 9 Bus System was progressively stressed in a time-domain simulation until ‘bifurcation’ was achieved [2]. In terms of implementation, ‘bifurcation’ was concluded to have taken place when the simulation solver could no longer converge to a solution without violating convergence thresholds. PSSE 34.3 simply calls out this occurrence as ‘Network Not Converged’.
- The bus voltages were detrended with the help of a low pass filter, and their variance σ^2 as well as autocorrelations $c(t, \tau)$ with a fixed time lag $\tau = 1$ instance were computed over a running window.

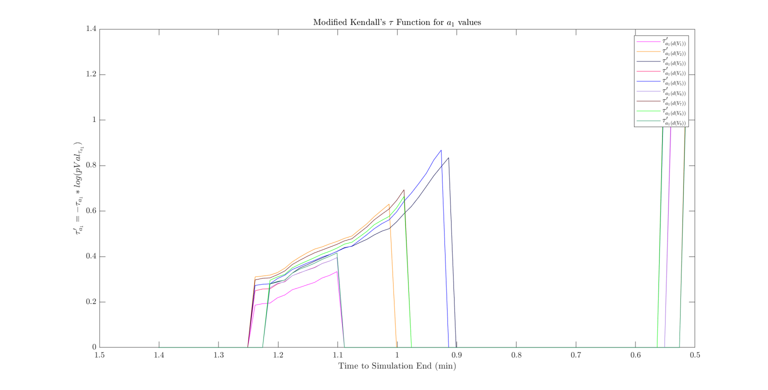
Conclusions ii

- A new statistical parameter, called the Modified Kendall's τ Correlation Coefficient (MKTCC) was employed to check if the increase in the autocorrelations and variances was statistically significant. The reason for using a modified version of the normally used Kendall's τ Correlation Coefficient was to accommodate for the degree of certainty/confidence in predicting the correlation apart from the absolute value of correlation itself.
- Both autocorrelation and variance were found to be appropriate Early Warning Sign Indicators for an impending bifurcation, predicting the event minutes earlier.

Future Work

Future Work

The grid analyzed for online/real-time analysis should be bigger, in order to demonstrate spatial variation in the early warning sign indicators for different buses/areas and for singling out areas which are more vulnerable to steady state instabilities.



Future Work

Despite the successful application of statistical analysis to detect symptoms of Critical Slowing Down in various phenomena [8], autocorrelation and variance are not certain indicators for the same, at least by themselves [22]. In order to tackle that, statistical parameters other than autocorrelation and variance can be investigated for their feasibility as Early Warning Signal indicators. Even for the same statistical indicators, changing the length of the running window, time lag τ, sampling rate etc. can have a significant effect on their effectiveness. Thus an 'optimal' set of parameters could be researched for, which may be different for different grids, but shouldn't vary for a particular grid once computed. On similar lines, grid state variables other than bus voltages, line current/MVAs, grid frequencies may be investigated.

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