Non-stationary Autoregressive Model for On-line Detection of Inter-area Oscillations in Power Systems

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Outline

- Power Systems Monitoring. Problem Statement
- State-of-the-art Techniques
- Stabilized Forgetting Approach for On-line Oscillations Detection
- Key Steps of the Proposed Algorithm
- Testing on Simulated Data
- Testing on Real World Data (500kV Power Grid)
- Conclusions

Introduction

Detailed modelling of oscillations

Factors influencing oscillations:

- the position of the subsystem in the whole power system.
- the distribution of the natural damping elements such as series resistance of the lines, and shunt resistance of the loads.
- the number and position of special damping controllers.

Blind oscillation detection

- all variables are monitored on-line,
- oscillation is a result of unknown cause,
- detection algorithm is designed to warn the operators as early as possible.

State-of-the-art Techniques

1. the observed process is locally approximated by a linear system
   - locality: window shapes (square, triangle, exponential).
2. parameters of the linear system are estimated
   - Kalman filter: requires the noise variance to be known
   - RLS: variance can be estimated
3. poles of the system are computed from the estimates
   - typically only the point estimates are considered
4. stability and oscillatory behavior is analyzed
   - setting thresholds on closeness to stability border

Our approach:

1. Exponential window
2. Autoregressive model with unknown variance
3. Full posterior density on parameters
4. Probability of stabable poles computed

Model of the signal

Model

$$y_t = a_t y_{t-1} + b_t y_{t-2} + c_t + \sigma_t e_t \tag{1}$$

where y_t is the observed signal, a_t, b_t, c_t, σ_t are its unknown parameters, and e_t is Gaussian noise with zero mean and unit variance, $e_t = \mathcal{N}(0, 1)$.
which defines PDF of the observed random variable y_t:

$$p(y_t|y_{t-1}, y_{t-2}, a_t, b_t, \sigma_t) = \mathcal{N}(a_t y_{t-1} + b_t y_{t-2}, \sigma^2). \tag{2}$$

Bayesian treatment

- Estimation of time-invariant system is RLS (Gauss-inverse-Wishart posterior).
- Can be extended to time-invariant system by model of parameter evolution
- Alternatively, we may choose to model the parameters as random walk, leading to a method known as forgetting.

Stabilized Forgetting

Regularized exponential forgetting is formalized as follows:

$$p(a_t, b_t, \sigma_t | y_1, \ldots, y_t) \propto p(y_t | y_{t-1}, y_{t-2}, a_t, b_t, \sigma_t) \\ \times p(a_{t-1}, b_{t-1}, \sigma_{t-1} | y_1, \ldots, y_{t-1})^{\phi} \\ \times \bar{p}(a_{t-1}, b_{t-1}, \sigma_{t-1} | y_1, \ldots, y_{t-1})^{1-\phi}. \tag{3}$$

Here, $\bar{p}(\cdot)$ denotes an *alternative* probability of the parameters.
It preserves posterior density of the Normal-inverse-Gamma type,

$$p(a_t, b_t, \sigma_t) = \mathcal{N}i\mathcal{G}(V_t, \nu_t), \tag{4}$$

the statistics of which are as follows:

$$V_t = \phi V_{t-1} + [y_t, y_{t-1}, y_{t-2}, 1]'[y_t, y_{t-1}, y_{t-2}, 1] + (1 - \phi)\bar{V}, \tag{5}$$

and $\nu_t = \phi \nu_{t-1} + 1 + (1 - \phi)\bar{\nu}$. Here, $\bar{V}, \bar{\nu}$ denote statistics of the alternative pdf.

Probability of oscilations

The poles of the system are:

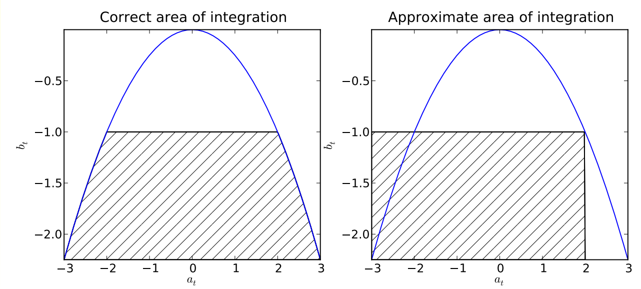
$$p_{1,2} = \frac{a_t \pm \sqrt{a_t^2 + 4b_t}}{2}.$$

The system is oscillating when:

$$a_t^2 < -4b_t$$

and the system is unstable when $|p_{1,2}| > 1$, i.e.

$$|p_{1,2}| = \left| \left(\frac{a_t}{2}\right)^2 - \frac{a_t^2 + 4b_t}{4} \right| = |b_t| > 1.$$



Detection Algorithm

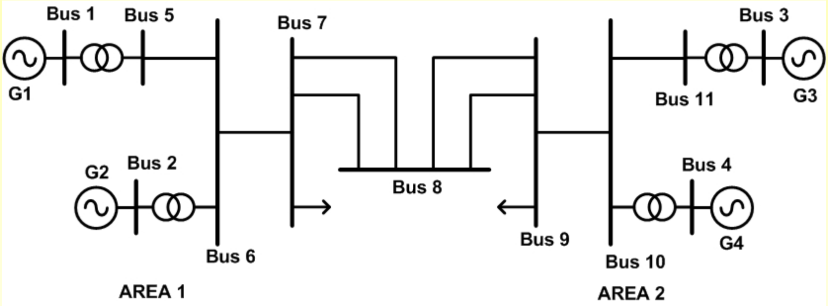
Key Steps of the Algorithm:

Off-line: choose initial alternative statistics, $\bar{V}, \bar{\nu}$ and forgetting factor ϕ.
On-line: at each time t do:

1. update statistics V, ν,
2. compute posterior marginal estimates of parameters $\hat{a}_t, \hat{b}_t, \mathrm{var}(a), \mathrm{var}(a)$,
3. compute probability of unstable oscillations as follows

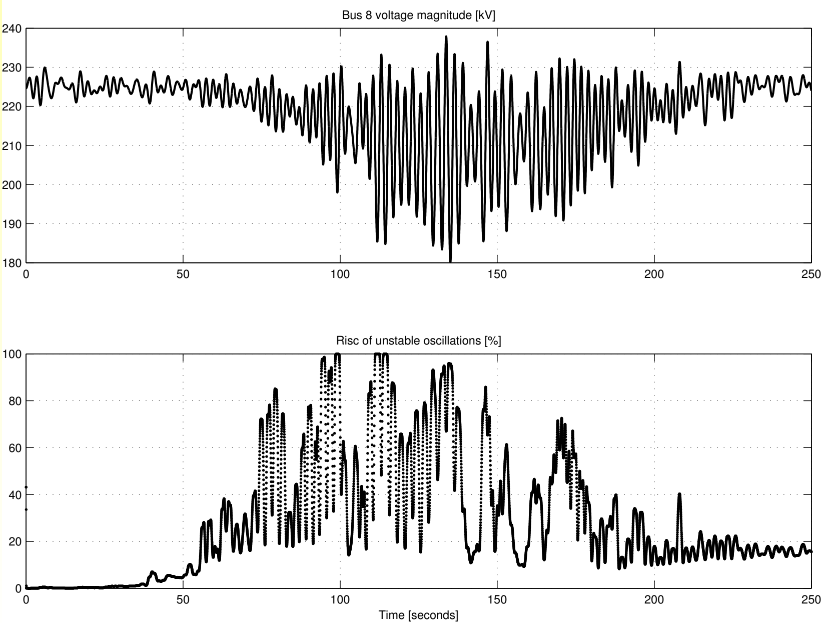
$$
\begin{aligned}
Pr(unstab.oscil.) &= Pr(a_t < 2)Pr(b_t < -1) \\
&= \frac{1}{2}\left(1 - \mathrm{erf}\frac{\hat{a}_t - 2}{\sqrt{2}\mathrm{var}(a_t)}\right)\frac{1}{2}\left(1 - \mathrm{erf}\frac{\hat{b}_t + 1}{\sqrt{2}\mathrm{var}(b_t)}\right) \qquad (6)
\end{aligned}
$$

Simulation studies

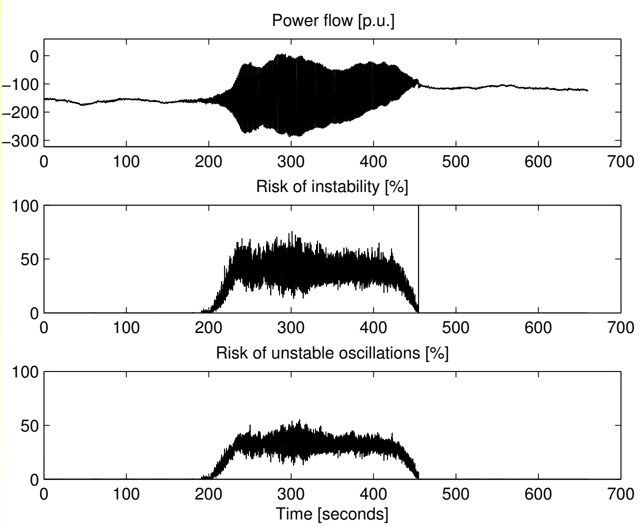


- Area 1 and Area 2 are sending and receiving subsystems accordingly.
- From 50 to 115 second, increase of active power output of G2 from 500 MW to 660 MW. Active power increase rate 2.5 MW per second;
- From 165 to 230 second, decrease of active power output of G2 from 660 MW to 500 MW. Active power decrease rate 2.5 MW per second.
- Bus 8 is monitored.

Simulation studies



Real data


Power flow [p.u.]
0
−100
−200
−300
0
100
200
300
400
500
600
700
Risk of instability [%]
100
50
0
0
100
200
300
400
500
600
700
Risk of unstable oscillations [%]
100
50
0
0
100
200
300
400
500
600
700
Time [seconds]

Conclusions

1. Oscillation detection algorithm is based on autoregressive model
    1. universal black-box model for oscillations
    2. more detailed modelling would yield more informative models
    3. allows estimation of the noise variance
    4. forgetting factor is the only tuning parameter
2. Statistical approach
    1. full posterior density is evaluated, posterior risk of oscillations
    2. allows hypotheses testing: what is more likely cause of oscillations
    3. more detailed modelling of the forgetting factor is being developed