On-line Detection of Inter-Area Oscillations Using Forgetting Approach for Power Systems Monitoring

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Abstract— **This paper addresses on-line early detection of inter-area electro-mechanical oscillations in power systems using dynamic data such as currents, voltages and angle differences measured across transmission lines in real time. The collected data are evaluated in real-time with the main objective to give the transmission operator qualitative information regarding stability margins. In our approach an oscillating systems have been modelled by second order autoregressive system using forgetting approach. The stability margins are proposed to define by poles analysis. The approach is demonstrated using real retrospective voltage data registered in 500 kV power grid.**

Keywords – power systems monitoring; inter-area-oscillations; Kalman filter; forgetting; stability

I. INTRODUCTION

Power systems characterized by many modes of electro-mechanical oscillations caused by interactions of its components. During such oscillations, mechanical kinetic energy is exchanged between synchronous generators as electric power flows through the network. For example one generator rotor could swings relative to one another. The inter-area modes are usually associated with groups of machines swinging relative to other groups across a relatively weak transmission line. These impacts cause oscillations in state variables of the electric system such as voltage, current, power and frequency are conventionally measured by PMU devices (Phasor Measurement Units).

The amplitudes of the swinging state variables are mainly determined by the following factors:

• 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, e.g. Power System Stabilizer (PSS) and Static Var Compensators (SVC) such as Thyristor Controlled Reactor (TCR) and Thyristor Switched Capacitor (TSCs) which are intrinsic parts of Flexible Alternating Current Transmission System (FACTS) technology.

PSS controllers are among the most effective and robust solutions [9], SVCs are also widely used for stabilization by modulating voltage at strategic locations of the power system (see e.g. the example of Mexico System [9, 7]).

There are two distinct types of oscillations causing problems in power systems: local mode oscillations and inter-area oscillations. Local mode oscillations occur when a generator (or group of generators) under voltage regulator control at a station is swinging against the rest of the system. Inter-area oscillations involve combinations of many machines on one part of a system swinging against machines on another part of the system. It is to be noted that the local mode of oscillations are well damped by the traditional PSS controllers, but normally fails the inter-area ones [10]

In this paper we address the problem of robust detection of inter-area oscillations which needs more sophisticated approaches in order to ensure accurate monitoring of system dynamics and reliable detection of dangerous oscillations with noise-polluted PMU measurements. It is to be noted that oscillations themselves could not be dangerous as long as they do not become unstable [1]. The key objective of this paper is to design algorithm to establish stability margins.

The paper is organized as follows. In Section 1 we provide the motivation of our studies, next we briefly discuss the related techniques employed for on-line oscillations prediction. Section 2 presents oscillations detection algorithm based on regularized exponential forgetting suitable for non-stationary data analysis of power systems. In Section 3 we present application of the designed technique for real retrospective data corresponding to inter-area oscillations event recorded in 500kV power grid. The concluding remarks and possible ways for improvements of the proposed techniques are briefly listed in Section 4.

II. PROBLEM STATEMENT

A. State-of-the-art Techniques

The deregularization of power market causes the substantial demand for development of new tools for electro-mechanical oscillations prediction. Many classical non-adaptive algorithms such as Yule-Walker, Burgs, lattice and Prony's methods (see e.g. [5], [6] and [3]) have been applied in the field. Also recursive least squares (RLS) and least mean squares (LMS) methods are among typical solutions.

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Recently, Kalman filtering techniques has been employed by Korba et al [2] for on-line oscillations prediction.

B. Techniques Comparisions

These methods are typically based on treatment of the underlying process as a linear system. Detection of the oscillations is based on two basic results of linear systems theory:

1. poles of oscillating linear systems have non-zero imaginary part,
2. poles of unstable linear systems are greater than one in absolute value.

Application of these facts to detection of oscillations is as follows: (i) the observed process is locally approximated by a linear system, (ii) parameters of the linear system are estimated, (iii) poles of the system are computed from the estimates, and (iv) stability and oscillatory behavior is analyzed.

The above mentioned methods differ typically in (i) and (ii). For example, detection methods based on fixed window assume that all data in the window were generated by the estimated linear system with identical weight. An alternative is represented by RLS with discounting which assumes exponential decrease of importance of older data records. The difference in (ii) is typically in the assumption whether the variance of the measurement noise is known (Kalman filter) or unknown (RLS-type methods). However, the methods rarely differ in (iii) and (iv) where a point estimate of the poles is being analyzed. We aim to address mainly this issue.

The traditional point estimate approach provides a single option for all poles for given time. Without any uncertainty bounds on the result. Thus, it is hard to assess reliability of this value. In this paper, we are concerned with Bayesian approach, i.e. we develop full posterior density of the parameters of the linear system and transform this density to density on poles.

III. Oscillations Detection Algorithm

We consider the signal to be represented by a second-order linear system with unknown time-variant parameters:

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

where y_t is the observed signal, a_t, b_t, σ_t are its unknown parameters, and e_t is Gaussian noise with zero mean and unit variance, $e_t = N(0,1)$. In probabilistic formulation, (1) defines probability density function (pdf) of the observed random variable y_t:

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

Estimation of system (2) with stationary parameters is a well known task in statistics, with posterior density of Normal-inverse-Gamma type. Extension of this approach to non-stationary system can be achieved by specification of the parameter evolution model, $p(a_t, b_t, \sigma_t \mid a_{t-1}, b_{t-1}, c_{t-1})$. Specific choice of such model yields a task of Bayesian filtering, which can be solved in some cases by the Kalman filter.

However, we consider a simpler alternative, known as forgetting or discounting. In this approach, the time-variant system is treated similarly to the time-invariant system, but the resulting sufficient statistics is multiplied by a constant ϕ smaller then one. In effect, delayed data records, y_{t-k} are weighted by ϕ^k which correspond to application of exponential window. This simple approach has however some shortcomings such as numerical instability when data are not informative.

We will apply an improved version of forgetting, [11] where regularized exponential forgetting is formalized as follows:

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

Here, $\bar{p}(\cdot)$ denotes an *alternative* probability of the parameters. This probability expresses an alternative (prior) knowledge about location of the parameters. However, in our case, we have no extra information and thus, we will choose a flat non-informative alternative.

One advantage of (3) is that for system (1) it preserves posterior density of the Normal-inverse-Gamma type,

$$p(a_t, b_t, \sigma_t) = NiG(V_t, \nu_t), \tag{4}$$

the statistics of which are recursively computed as follows:

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

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

Important moments of this posterior density are mean value,

$$\begin{bmatrix} \hat{a}_t \\ \hat{b}_t \end{bmatrix} = \begin{bmatrix} V_{2,2} & V_{2,3} \\ V_{3,2} & V_{3,3} \end{bmatrix}^{-1} \begin{bmatrix} V_{2,1} \\ V_{3,1} \end{bmatrix}, \tag{6}$$

which is equivalent to the result of RLS with discounting (under the choice of $\bar{V} = 0$).

Since the main parameters of interest are parameters $[a_t, b_t]$ we marginalize (4) to obtain marginal density of Student-t type. An important property of this density is that it is not as sharply concentrated as a Gaussian, hence it assigns higher probability to values distant from the mean. The difference is greatest for $\nu_t < 20$, which arise for $\phi < 0.95$. For more details, see [12].

Transformation of this density to density on the poles is a non-trivial task due to their nonlinear mapping. As a first step, we transform the density numerically, using Monte Carlo sampling technique. The probability of unstable oscillations is then evaluated as expected value of poles being complex with absolute value greater than one.

Final oscillation detection algorithm is then following:

Off-line: choose initial alternative statistics, $\overline{V}, \overline{\nu}$ and forgetting factor ϕ, and number of samples, n.

On-line: at each time t do:

1. update statistics V, ν using (5),
2. generate n samples, $\{a_t^{(i)}, b_t^{(i)}, \sigma_t^{(i)}\}_{i=1}^n$ from (4),
3. for each sample compute roots of polynomial $x^2 - a_t^{(i)} x - b_t^{(i)} = 0$, and their angle, θ_i, and absolute value, ρ_i.
4. compute probability of unstable oscillations as follows

$$p(unstability) = \frac{1}{n}\sum_{i=1}^{n}(\theta_i > 0) AND (\rho_i > 1)$$

Remarks:

Sampling based computation of the pdf of the roots is rather computationally expensive and can be replaced by simpler techniques, such as evaluation of deterministic points at (3) standard deviations from the mean. However, we present Monte Carlo in the simulation part since it is the most accurate method.

Once a physically based model of parameter estimation is constructed, the forgetting operator (3) will be replaced by proper Bayesian filtering algorithm.

In our opinion, the forgetting approach has the advantage over the approach based on Kalman filtering [2] in being able to estimate covariance of the observation, σ_t (1).

IV. Results Analysis

In order to verify the designed techniques, the time-synchronized retrospective data has been employed. In particular, the time series of voltage (see Fig. 1 Top higher), active and reactives powers have been used. The time series has been registered using PMU devices from 500kV power grid [4] with one millisecond sampling period. The total duraction of the registered event is less then 1 minute.

It is to be noted that oscillations are easily detectable to a human. However, correct assessment where they start is non-trivial. For example, oscillatory behavior was detected relatively early, as is documented by non-zero angle of the pole computed from point estimates (6), Fig. 1 Middle higher. However, the absolute value of the pole is lower than 1, indicating stable oscillations. When the oscillations become unstable is quite difficult to estimate. On the other hand, the computed probability of oscillations marks the start of the oscillations quite clearly and can be easily adopted to give the transmission operator qualitative information regarding stability margins.

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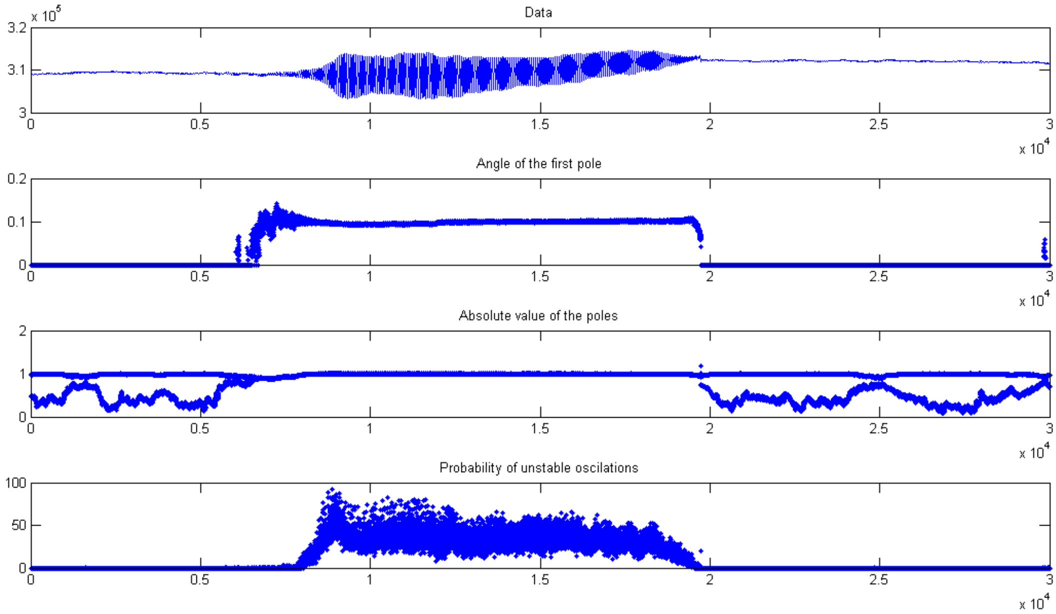

Figure 1. Results for voltage amplitude data. **Top**: observed data. **Middle higher**: angle of the first pole. **Middle lower**: absolute values of both poles, respectively. **Bottom**: computed probability of unstable oscillations.