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Study about a Fast and Adaptive Signal Estimation Algorithm for Power Oscillations Component in Power Systems

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Abstract: This paper present study of the adaptive signal estimation algorithm for power oscillations component. In power system. Mainly Used in power oscillation damper controller(POD) for damp out power oscillation (low frequency oscillation .The speed of response of the signal estimation will be described which is mainly used methods are Recursive least square (RLS) algorithm and low pass filter(LPF). The effectiveness of the proposed method will described and comparison between LPF and RLS algorithm. also purposed improved modified RLS method for more fast and adaptive signal estimation in power system for POD controller .which is give more fast and accurate signal estimation

Key Words: Estimation Technique, Low-SDVVѿOWHU/3)/RZ -frequency oscillation, Power oscillation damping (POD, Recursive least square (RLS)

I.INTRODUCTION

The ability of synchronous machines of an interconnected power system to remain synchronism after being subjected to a small disturbance is known as small signal stability that is subclass of phase angle related instability problem. It depends on the ability to maintain equilibrium between electromagnetic and mechanical torques of each synchronous machine connected to power system. The change in electromagnetic torque of synchronous machine following a perturbation or disturbance can be resolved into two components ± (i) a synchronizing torque component in phase with rotor angle deviation and (ii) a damping torque component in phase with speed deviation. Lack of sufficient VFKURQ]LQWRUTXH UHVXOWV LQSHULRGLF´RUQ -oscillatory instability, whereas lack of damping torque results in low frequency oscillations. Low frequency oscillations are generator rotor angle oscillations having a frequency between 0.1 -2.0 Hz and are classified based on the source of the oscillation.

A typical example is a line fault with subsequent line disconnection, as depicted in Fig. 1. In this simple example, a synchronous generator is connected to an infinite bus through a transmission system. At *t* =20 s, a three phase fault occurs in one of the transmission lines and the fault is cleared after 100 ms. Although the system is able to maintain stability, the transmitted active power will be affected by a damped oscillatory component as it can observed in Fig. 2. The decay rate of these oscillations is mainly dependent on the mechanical damping of the generator system and on the resistance in the transmission line. However, in some cases the total damping might not be sufficient to maintain the stability of the system. For this reason, auxiliary controllers might be needed to provide effective damping in the transmitted power.

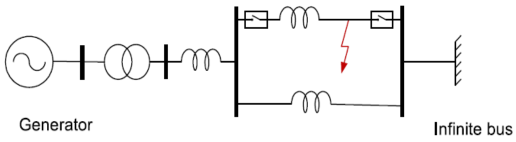

Figure 1: A simple power system to model low-frequency power oscillation

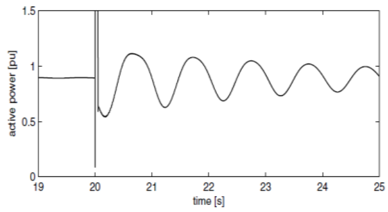

Figure 2: Transmitted active power from the generator. Fault occurred at 20 s and cleared after 100 ms

II.ESTIMATION OF POWER OSCILLATION COMPONENT

Power Oscillation Damping (POD) controllers are commonly used in the power system. The simplest way to provide POD is to include a Power System Stabilizer (PSS) in the voltage controller of the synchronous generator. The control algorithm of a PSS, as explained in [2], aims to synthesize the oscillating component of the power by using a series of wash-out and lead-lag filter links connected in cascade as in Fig. 3. However, PSS are effective only locally and often cannot provide sufficient damping action when moving away from the generation units, like in the case of inter-area oscillations. For this reason, FACTS controllers have been widely used for POD purposes [3][4]. The typical control strategy of FACTS controllers for POD is similar to the one utilized for PSS. However, this kind of control action might not be effective, due to the fact that correct phase of the controlled quantity is provided only at one specific oscillation frequency, where the design of the filter links is optimized.

An estimation algorithm based on a combination of low-pass filters (LPF) has been proposed in [5]. Although this algorithm presents good selectivity in the estimation, its speed of response is tightly dependent on the frequency of the oscillations to be estimated.
In this section, the LPF-based and RLS algorithms for estimation of power oscillation component will be described. Assume that the input signal for the estimation algorithm is the transmitted active power p(t). As described in Fig. 2, the active power can be modeled as the sum of a constant and an oscillatory term

$$p(t) = p_{avg}(t) + p_{osc}(t) = p_{avg}(t) + A_{osc(t)}(t)\cos[\omega_{osc}t + \varphi(t)] \quad (1)$$

where p_{avg} is the average transmitted active power, while the oscillatory component, p_{osc}, is expressed in terms of its amplitude $A_{osc(t)}$ frequency ω_{osc} and phase φ.It is of importance to stress that the validity of the performed analysis should not be restricted to power oscillations only, but is valid in the generic case of signal estimation.

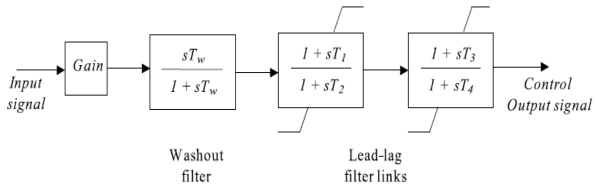

Figure 3: Conventional filter set up to create a damping control signal

III.LOW- PASS FILTER ESTIMATION ALGORITHM

Denoting $\overline{P_{ph}} \quad A_{osc} e^{jM}$ as the complex phasor of the oscillatory component and $_{osc}(t) \; I \; _{osc} t$ as the oscillation angle, the active power in (1) can be rewritten as

$$p(t) \quad p_{avg}(t) \quad real\{\overline{p_{ph}}(t) e^{jT_{osc(t)}}\} \quad p_{avg(t)} \quad \frac{1}{2}\overline{p_{ph}}(t) e^{jT_{osc(t)}} \quad \frac{1}{2}\overline{p_{ph^*}}(t) e^{\;jT_{osc(t)}} \tag{2}$$

The expression in (2) separates the input signal into three frequency components (0, &osc, and-&osc)where the average p_{avg} and the phasor $\tilde{p}_{ph}$ are slowly varying signals. By rearranging (2) and apply in low-pass filtering, the estimate for the average $\overline{p_{avg}}(t)$ the phasor $\tilde{p}_{ph}(t)$ and the oscillatory component $p_{osc}(t)$ can be extracted from the input signal as [5][6]

$$\overline{p_{avg}}(t) \quad H_0\{p(t) \quad p_{osc}(t)\} \tag{3}$$

$$\tilde{p}_{ph}(t) \quad H_{Ph}\{[2p(t) \quad 2\tilde{p}_{avg}(t) \quad \overset{\#}{p}_{ph}(t) e^{\;j\;\;osc(t)}] e^{\;T\;osc(t)}\} \tag{4}$$

$$p_{osc}(t) \quad \frac{1}{2}\overline{p_{ph}}(t) e^{j\;\;osc(t)} \quad \frac{1}{2}\overline{p_{ph^*}}(t) e^{\;T\;osc(t)} \tag{5}$$

where $H0$ and Hph represent the transfer function of low-pass filters to extract the average and the phasor component, respectively. The block diagram of this method is shown in Fig. 4.

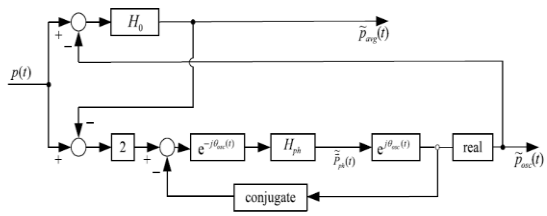

Figure 4: Block diagram of the LPF-based estimation algorithm

IV. RECURSIVE LEAST SQUARE ESTIMATION ALGORITHM

The complex phasor $\tilde{p}_{ph}$ can be expressed in terms of its real, $p_{ph.d}$ and imaginary component, $p_{ph.q}$ yielding

$$p(t) = p_{avg}(t) + p_{ph.d}\cos(\theta_{osc}(t)) + p_{ph.q}\sin(\theta_{osc}(t)) \quad (6)$$

From an REVHUYDWLRQ PDWUL[- DQ PHDVXUHG LQSXW VLJQDO SW WKH HVWLPDWHG VWDWH
derived using the RLS algorithm in discrete time as [6][7]

$$h(n) = h(n-1) + k(n)[p(n) - \varphi(n)h(n-1)] \quad (7)$$

With

$$h(n) = [p_{avg}(n)\, p_{ph.d}(n)\, p_{ph.q}(n)]^T, \quad \varphi(n) = [1\ \cos(\theta_{osc}(n))\ \sin(\theta_{osc}(n))]$$

Calling **I** the identity matrix, the gain matrix **K** and covariance matrix **R** are given by

$$K(n) = R(n-1)\varphi^T(n)[\lambda + \varphi(n)R(n-1)\varphi^T(n)]^{-1} \quad (8)$$

$$R(n) = [I - K(n)\varphi(n)]R(n-1)/\lambda \quad (9)$$

With T_s representing the sampling time, the steady state bandwidth of the RLS, ω_{RLS}, is given by(10) where $0 < \lambda \leq 1$ [8]. The estimation error at the time instant $t = nT_s$, $e(n)$ is given by.(11)

$$\omega_{RLS} = \frac{1-\lambda}{T_S} \quad (10)$$

$$e(n) = p(n) - \varphi(n)h(n-1) \quad (11)$$

V.LPF VERSUS RLS ESTIMATION ALGORITHM

In order to compare the described estimation algorithms, a first order low-pass filter with cut-off frequency $\omega_{LPF} = \omega_{RLS}$ is used for the filters in (3) - (4) for the LPF-based estimation algorithm.

$$H_0(s) = H_{ph}(s) = \frac{\omega_{LPF}}{s + \omega_{LPF}} \quad (12)$$

The state-space models for the LPF-based and the RLS-based (steady-state model) estimation algorithms are reported in the Appendix. When low bandwidth in the estimation (i.e. when the bandwidth of the estimator is much lower than the oscillation frequency to be estimated) is acceptable, the two methods present similar dynamic performance [8]. If fast estimation is needed, the LPF-based method presents poor dynamic performance unlike the RLS-based method. As an example, consider a power oscillation frequency of 1 Hz. The cut off frequencies for the filters *H*0 and *H*ph is varied from 0 Hz to 1 Hz in steps of 0.05 Hz. The bandwidth of the RLS estimator is varied accordingly. The poles for the transfer function from the input *p* *WRWKHHVWLPDWHRIWKHRVFLOODWLRQDPSOLWXGH* *P*osc is shown in Fig. 5 for the two estimation methods. As shown ,the distance of the poles from the origin starts to decrease for *D*LPF > 0.4Zosc (marked in red colour in Fig. 5 for clarity) when using the LPF-based method, indicating that estimation speed starts to decrease .Opposite behaviour can be observed when using the RLS-based method, thus making faster estimation possible. Therefore, the RLS algorithm can be used to obtain faster estimation during rapid changes of the input signal and hence will be the preferred method for this work. In the following section, a novel method to improve the dynamic performance of the RLS-based estimation method will be presented.

VI. IMPROVED RLS-BASED ESTIMATION

$VGHVFULEHGLQWKHSUHYLRXVVHFWLRQWKHIRUJHWWLQJIDFWRULVGLUectly related to the bandwidth *D*RLS,see (10). The selection of *D*RLS is typically a trade-off between a good selectivity for the estimator and its speed of response. From analysis of (8) and (9), it is possible to observe that when steady state is reached, the gain matrix K will be independent of the input and the dynamic performance of algorithm depends on the forgetting factoURQ\PDNLQJWKH5/6DOJRULWKPDWLPH-invariant system. To increase the speed of response of the algorithm in case of rapid variation in the input signal, it is necessary to force the matrix K to change [7]. In order to maintain the needed selectivity and to enhance the dynamic performance in case of input variation, a two-step estimation is proposed in this paper. Immediately after a rapid change in the input signal, fast estimation is favoured, followed by the steady state estimation that aims to higher seOHFWLYLW\RIWKHHVWLPDWRU 7KLV UHTXLUHV WKH XVH RI which depends on the input signal. A novel resetting method to temporarily vary the forgetting factor to increase speed of estimation will be described in this section.

VII. STEADY STATE ESTIMATION

During steady state operations, the bandwidth of the RLS is set to a low value, meaning that the forgetting factor will be close to unity. For example, assuming that the oscillating frequency is equal to 1

Hz, the steady state forgetting factor will bHHTXDOWR O_{ss} = 0.9997, corresponding to a bandwidth of 0.4Hz for a sampling time Ts = 0.1 ms. This gives the performance of the estimator to be selective, less sensitive to noise and at the same time adaptive to slow changes in the input signal.

VIII. TRANSIENT ESTIMATION

A large forgetting factor makes the estimation to be slow. Likewise, a small value of the forgetting factor as suggested in [9], makes the estimator to be fast but less selective. Therefore, to achieve fast estimation when a rapid change occurs in the input signal, the gain matrix of the RLS algorithm K in (8) must be increased for a short time. One way to cope with this problem is to reset the covariance matrix R to a high value, as described in [10]. Although effective in the cases presented in the reference, by using this technique the speed of the estimation during the transient period is not known. Furthermore, the covariance matrix to be used for the reset is chosen by trial and error and has to be selected case by case. An alternative solution is to use a variable forgetting factor. The benefit of this PHWKRG LV WKDW LV YDULHG LQ FRQWUROOHG ZD\ GHSHQGLQJ RQ WKH LQSXW OHDGLQJ WR D NQRZOHG HVWLPDWRU¶V VSHHG DOVR GXULQJ WUDQVLHQWV. When the RLS is in steady state, its bandwidth is GHWHUPLQHG E\ VV, If a rapid change is detected in the input (i.e. if the error en exceeds a pre-defined WKUHVKROG WKH ZLOO EH PRGLILHG WR D VPDOOHU YDOXH KHUH GHQRWHG DV WUDQVLHQW IRUJ Thus, by using the properties of the step response for a high-pasV ILOWHU ZLOO EH VORZO\ LQFUHDVHG ED WR LWV VWHDG\ VWDWH YDOXH VV DV VKRZQ LQ)LJ 7KH SDUDPHWHUV VV WU DV ZHOO DV WKH WLP the high-SDVV ILOWHU 2 GHWHUPLQH WKH SHUIRUPDQFH RI WKH 5/6 DOJRULWKP LQ WKH WUDQVLH shows the time variation of the forgetting factor when a rapid variation is detected in the input signal ZLWK VV WU DQG 2 V 2QH WKH YDOXH RI VV LV FKRVHQ EDVHG RQ WKH VWHDG\ VWDWH performance requirement of the algorithm as descrLEHG SUHYLRXVO\ WKH YDOXH RI WU DQG 2 FDQ EH determined based on the transient estimation speed required. One ideal and one noisy input signals are XVHG WR HYDOXDWH WKH SHUIRUPDQFH RI WKH DOJRULWKP IRU GLIIHUHQW FKRLFH RI WKH SDUDPH DVVXPHG RVFLOODWLRQ IUHTXHQF\ RI +] WKH VHWWOLQJ WLPH IRU WKH HVWLPDWRU DV D IXQFWLRQ RI VKRZQ LQ)LJXUH 7V PV V 7KH WUDQVLHQW EDQGZLGWK RI WKH HVWLPDWRU .WU LV YDULHG between 5 Hz and 100 Hz in steps of 5 Hz, wKLOH 2 LV YDULHG EHWZHHQ PV DQG PV LQ VWHSV RI PV)RU DQ LGHDO LQSXW VLJQDO KLJKHU .WU LH ORZHU WU DQG KLJKHU 2 UHVXOW LQ D VWHUU UHVSRQVH 2Q hand, in the case of noisy input signal, the estimation speed starts to decrease beyond some values.

due to the estimators tendency to follow the noise, leading to an increase of the settling time. The optimum value in this case lies in the middle. Depending on the estimation speed and a noise rejection performance required, an optimum YDOXH IRU WU DQ 2 FDQ EH FKRVHQ IRU WKLV ZRUN D YDOXH RI WU FRUUHVSRQGLQJ WR.WU DQ2 VKDYHEHHQVHOHFWHG

IX. FREQUENCY ADAPTATION

7KH LQYHVWLJDWHG PHWKRG DVVXPHV DFFXUDWH NQRZOHGJH RI WKH RVFLO
However, this frequency is dependent on the system parameters and its operating conditions. To cope with this problem,the investigated estimation method has been further improved in order to be able to deal with inaccuracy in the estimated oscillation frequency. For DQ DVVXPHG RVF WKH VWHDG\ VWDWH IUHTXHQF\FKDUDFWHULVWLF RI WKH HVWLPDWRU¶V WUDQVIHU IXQFWLRQ IURP WKH LQSXW RVFLOODWRU\FRPSRQHQW LV VKRZQ LQ)LJ7KH WUDQVIHU IXQFWLRQV KDYH SXUH SKDVH VKLIW DW WKH estimated frequency component and 0 pu gain at the other frequency component. This results in a correct extraction of the average and oscillatory components in steady state for accurate knowledge of the oscillation frequency. If the frequency content

Figure 9: Bode diagram of the steady state RLS-based estimator transfer function. Left: from input to estimate of the average component; Right: from input to estimate the oscillatory component.

Figure 10: Block diagram of the RLS estimator with frequency adaptation by a PLL

of the input changes, the estimator will give rise to a phase and amplitude error in the estimated TXDQWLWLHV RZHYHU WKH IUHTXHQF\ VSHFWUD RI WKH LQSXW ZLOO EH SUHVHUYHG LQ WKH HVV Therefore, using the rotating phasor of the estimate (Pph), a Phase Locked Loop (PLL) can be used to track the true oscillation frequency of the input. Figure 10 shows the block diagram of the modified estimation algorithm. Observe that the output of the PLL will be limited and fed back to the RLS algorithm. The bandwidth of the PLL to use is limited by the oscillation frequency.

To avoid operation of the PLL when no oscillation is observed, it will only be active when magnitude of detected oscillatory component by the RLS estimator is greater than a given threshold value. When a rapid change in the input is observed and the the high-pass filter is triggered (see Fig. 7), the PLL will be temporarily freezed, until the RLS algorithm stabilizes. For a PLL with bandwidth 0.5 Hz and an assumed oscillation frequency of 1.2 Hz, Fig. 11 shows the estimated oscillation frequency. The PLL activates at 5.2 s. Observe that although the PLL requires about 4 s to stabilize, the impact of the small oscillations in the estimate of the oscillation frequency &×RVF RQ WKH estimated oscillation angle ©&osc is negligible.)

X. APPENDIX

The state space representation of the LPF-based and the steady state RLS-based estimation PHWKRGV LV JLYHQ EHORZ ZKHUH *×D VLQ RUWKRJRQDO WR WKH RVFLOODWRU\ FRPSRQHQW* *P*osc.This orthogonal component is used by the PLL for the update of the oscillation frequency.

XI. CONCLUSION

In this paper, a fast RLS-based estimation algorithm for low-frequency oscillations in the power system is treated. At first, a LPF and RLS estimation algorithms are compared and the problem of the LPF based method to obtain high speed of estimation is highlighted. An improved fast estimation based on the RLS algorithm with a novel resetting method to temporarily vary the forgetting factor is described .The effectiveness of the proposed method in terms of estimation speed and selectivity is shown.

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