Adaline Based Estimation Of Synchronizing And Damping Torque Coefficients

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***Abstract* — This paper presents a neural network technique for the estimation of the synchronizing and damping torque coefficients using Adaline. The proposed technique is based on estimating the torque coefficients of a synchronous machine from the time responses of the rotor angle, rotor speed, and electromagnetic torque. The performance of the Adaline is compared with Kalman filter and least-square error techniques. The Adaline offers several advantages including significant reduction in computing time, storage, and computational complexity. The simulation results over a wide range of operating conditions show that the Adaline can be used as efficient tool for either online assessment of small-signal stability.**

***Index Terms* — Adaline, Kalman Filter, Least-Square Stability, Synchronizing and Damping Torques.**

I. Introduction

Small-signal stability analysis is concerned with the behavior of power systems under small perturbations. Its main objective is to predict the low-frequency electromechanical oscillations resulting from poorly damped rotor oscillations. The most critical types of these oscillations are the local-mode and interarea-mode oscillations [1-4]. The former occurs between one machine and the rest of the system, while the later occurs between interconnected machines. The study of these oscillations is very important to power system planning, operation, and control. The stability of these oscillations is a vital concern and essential for secure power system operation.

It is known that operating conditions change with time in real-time situations. These operating conditions affect the stability of the synchronous machine. Therefore, a small-signal stability analysis must be repeatedly conducted in system operation and control to provide estimates of stability indices on basis of the given data obtained by either measurements or computer simulation, and provide new estimates as new data are received. In terms of the synchronizing and damping torque coefficients, K_s and K_d respectively, both coefficients must be positive for a stable operation of the machine. This paper is concerned in small-signal stability assessment of local-mode oscillations. Traditionally, stability assessment of local-mode oscillations is carried out in frequency domain using modal analysis. However, it requires significantly large computational efforts, and therefore it is not suitable for online application. Alternative method based on electromagnetic torque deviation has been developed. Torque deviation can be decomposed into synchronizing and damping torques [5-7]. The synchronizing torque is responsible for restoring the rotor angle excursion. The damping torque damps out the speed deviations. The synchronizing and damping torques are usually expressed in terms of the torque coefficients K_s and K_d. These coefficients can be calculated repeatedly and this makes it suitable for online stability assessment. A least square error (LSE) minimization technique to compute K_s and K_d has been applied [7-9] The LSE technique requires the time responses of the changes in rotor angle $\Delta\delta(t)$, rotor speed $\Delta\omega(t)$, and electromagnetic torque $\Delta T_e(t)$. The LSE static estimation technique is time consuming. It requires monitoring the entire period of oscillation. An adaptive Kalman filter (KF) has been utilized to estimate K_s and K_d repeatedly to achieve less computational time [10]. However, its computational burden makes it unsuitable for online application.

Artificial neural network (ANN) based technique was proposed for online estimation of the synchronizing and damping torque coefficients K_s and K_d [11]. A static back propagation neural network (BPNN) has been used to associate the real and reactive power (P-Q) patterns with K_s and K_d. Although, the BPNN has very good learning ability, but it suffers from some drawbacks such as long offline training and the difficulty in determining the appropriate number of hidden layers and hidden neurons. Genetic algorithm (GA) and particle Swarm optimization (PSO) techniques have also been proposed for optimal estimation of K_s and K_d [12,13]. However, these techniques are not suitable for online application.

This paper presents a new technique for fast online estimation of K_s and K_d using a single adaptive linear neuron (Adaline). The technique is based on estimating K_s and K_d from online measurements of $\Delta\delta(t)$, $\Delta\omega$ (t), and $\Delta T_e(t)$. The Adaline algorithm is characterized by simple calculations, which lead to a fast execution processing time of the algorithm, a property, which is essential for online application. Time-domain simulations are conducted over wide range of P-Q loading conditions using MATLAB. The performance of the Adaline is compared with LSE and KF techniques.

II. POWER SYSTEM MODEL

In this work, the proposed method has been tested on a system comprising a single machine connected to infinite bus power system through a transmission line. The synchronous machine is equipped with an automatic voltage regulator (AVR) and IEEE ST1A static exciter. Customarily, for small-signal stability analysis, a fourth-order model is considered for the synchronous generator. The nonlinear equations describing the dynamic behavior of a synchronous generator connected to an infinite bus through an external reactance are given in Appendix A. The system parameters are given in Appendix B. The SMIBS model is linearized at a particular operating point to obtain the linearized power system model. Figure 1 shows the well-known Phillips-Hefferon block diagram of linearized model of the SMIBS, relating the pertinent variables such as electrical torque, rotor speed, rotor angle, terminal voltage, and field voltage [4].

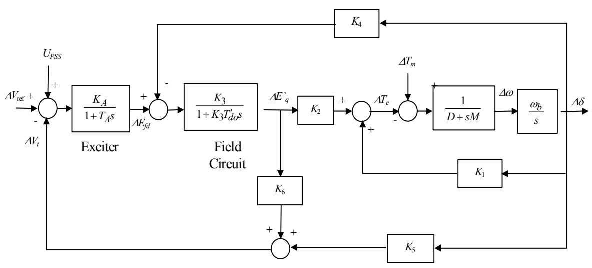

Fig. 1. Block-diagram of Phillips-Hefferon model.

From the transfer function block diagram the following state-space form is developed.

$$\dot{X} = AX + BU$$

$$= \begin{bmatrix} \dfrac{d\Delta\delta}{dt} \\ \dfrac{d\Delta\omega}{dt} \\ \dfrac{d\Delta E'_q}{dt} \\ \dfrac{d\Delta E_{fd}}{dt} \end{bmatrix} = \begin{bmatrix} 0 & \omega_b & 0 & 0 \\ \dfrac{-K_1}{M} & \dfrac{-D}{M} & \dfrac{-K_2}{M} & 0 \\ \dfrac{-K_4}{T'_{do}} & 0 & \dfrac{-K_3}{T'_{do}} & \dfrac{1}{T'_{do}} \\ \dfrac{-K_A K_5}{T_A} & 0 & \dfrac{-K_A K_6}{T_A} & \dfrac{-1}{T_A} \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta E'_q \\ \Delta E_{fd} \end{bmatrix}$$

$$+ \cdot \begin{bmatrix} 0 & 0 \\ \dfrac{1}{M} & 0 \\ 0 & 0 \\ 0 & \dfrac{K_A}{K_A} \end{bmatrix} \begin{bmatrix} \Delta T_m \\ \Delta V_{ref} \end{bmatrix} \quad (1)$$

$$Y = CX$$

$$\begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta T_e \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ K_1 & 0 & K_2 & 0 \end{bmatrix} \begin{bmatrix} \Delta\delta \\ \Delta\omega \\ \Delta E'_q \\ \Delta E_{fd} \end{bmatrix} \quad (2)$$

The system matrix A is a function of the system parameters, which depends on the operating conditions. The perturbation matrix B depends on the system parameters only. The perturbation signal U is either ΔT_m or ΔV_{ref}. The output matrix C relates the desired output signals vector Y to the state variables vector X.

The interaction among these variables is expressed in terms of the six constants K_1-K_6. These constants with the exception of K_3, which is only a function of the ratio of impedance, are function of the operating real and reactive loading as well as the excitation levels in the generator. Calculations of the K_1-K_6 parameters and variables of the SMIBS are illustrated in Appendix C.

III. LSE BASED ESTIMATION OF K_s AND K_d

The dynamic response of a single machine connected to an infinite bus comprises various modes of oscillations. These modes of oscillations can be classified into, field and rotor circuits modes and low-frequency electromechanical modes. The oscillations of the electromagnetic torque and, consequently, the rotor oscillations are dominated by the low-frequency electromechanical modes, $\lambda_i = \sigma_i \pm j\omega_i$.

Various methods have been proposed to break the electromagnetic torque variations into two components; the synchronizing torque component is in phase and proportional with $\Delta\delta(t)$, and the damping torque is in phase and proportional with $\Delta\omega(t)$ [5]. Accordingly, the estimated torque can be written as

$$\Delta\hat{T}_e(t) = K_s \Delta\delta(t) + K_d \Delta\omega(t) \quad (3)$$

For the reader convenience, the method of calculating the torque coefficients K_s and K_d using LSE technique is summarized. Following a small disturbance, the time responses of $\Delta\delta(t)$, $\Delta\omega(t)$, and $\Delta T_e(t)$, which can be obtained from either off-line simulation or on-line measurements, are recorded. The LSE technique is then used to minimize the sum of the square of the differences between the electric torque $\Delta T_e(t)$ and the estimated torque $\Delta\hat{T}_e(t)$. The error at time t_k is defined as

$$E(t_k) = \Delta T_e(t_k) - \Delta\hat{T}_e(t_k) \quad (4)$$

The torque coefficients K_s and K_d are calculated to minimize the sum of the error squared over the entire interval of oscillation T, as given in (4), where, $T = N\Delta T$ (N is the number of samples and ΔT is the sampling period). In matrix notation, the above problem can be described by over-determined discrete system of linear equations as follows

$$\Delta\boldsymbol{T}_e(k) = \boldsymbol{A}(k)\boldsymbol{x} + \boldsymbol{E}(k) \quad (5)$$

where $\boldsymbol{A} = [\Delta\delta(k) \quad \Delta\omega(k)]$, and $\boldsymbol{x}$=[K_s K_d]^T. The estimated vector $\boldsymbol{x}$ can be calculated using the left pseudo inverse of matrix $\boldsymbol{A}$. Solving (6) gives the values of K_s and K_d for the corresponding operating point

$$\boldsymbol{x} = \boldsymbol{A}^{\dagger} \bullet \Delta\boldsymbol{T}_e \tag{6}$$

IV. ADALINE BASED ESTIMATION OF K_s AND K_d

The Adaline is introduced in [14] as a powerful harmonics tracking technique. It produces a linear combination of its input vector $X(k) = [x_1, x_2, ..., x_n]$ at time k. After, the input vector is multiplied by the weight vector $W(k) = [w_1, w_2, ..., w_n]$, the weight inputs are combined to produce the linear output $\hat{y}(k) = W(k)^T.X(k)$. The weight vector is adjusted by an adaptation rule so that the output from the Adaline algorithm $\hat{y}(k)$ is close to the desired value $y(k)$. The least mean square (LMS) algorithm, known as the modified Widrow-Hoff delta rule, is usually used as the adaptation rule. This rule is given by

$$W(k+1) = W(k) + \frac{\alpha e(k)\,\mathrm{sgn}(X(k))}{\lambda + X(k)^T\,\mathrm{sgn}(X(k))} \tag{7}$$

where $e(k) = y(k)\text{-}\hat{y}(k)$ is the prediction error at time k, $\hat{y}(k)$ is the estimated signal magnitude, and α is the learning parameter (reduction factor), and λ is a parameter to be suitably chosen to avoid division by zero. The sgn function is given by

$$\mathrm{sgn}(x_i) = \begin{cases} +1 & if\ x_i > 0 \\ -1 & if\ x_i < 0 \\ i = 1,2,\cdots\cdots,N \end{cases} \tag{8}$$

Perfect training is attained when the error is brought to zero. The numerical values of α and λ greatly affects the performance of the estimation, which is demonstrated in the simulation.

V. ADALINE TRAINING

The Adaline algorithm is utilized in this study to approximate the torque deviation $\Delta\hat{T}_e(k)$ as a linear combination of the synchronizing torque $K_s\Delta\delta(k)$ and the damping torque $K_d\Delta\omega(k)$ [5,7]:

$$\begin{aligned} \Delta\hat{T}_e(k) &= [K_s \quad K_d]\begin{bmatrix} \Delta\delta(k) \\ \Delta\omega(k) \end{bmatrix} \\ &= [w_1(k) \quad w_2(k)]\begin{bmatrix} \Delta\delta(k) \\ \Delta\omega(k) \end{bmatrix} \end{aligned} \tag{9}$$

Figure 2 shows the block diagram of the Adaline based estimator of K_s and K_d, where $\Delta\delta(k)$ and $\Delta\omega(k)$ are given as inputs to the single neuron, $\Delta\hat{T}_e(k)$ is the output of the Adaline and $\Delta T_e(k)$ is desired output torque developed by the SMIBS.

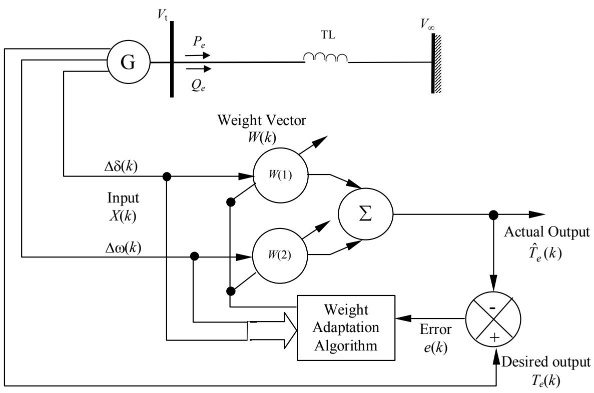

Fig. 2. Adaline estimator of K_s and K_d of a SMIBS.

VI. SIMULATION RESULTS

In this study, performance evaluation of the Adaline for the estimation of K_s and K_d is compared with LSE and KF estimation techniques. The evaluation is carried out by conducting several offline simulation cases on the linearized model of the SMIBS. Either the state-space model or the Phillips-Hefferon block diagram implemented in SIMULINK can be used for offline simulation. The system input is a 0.1 pu mechanical torque pulse (ΔT_m) for 10 ms. The system output vector comprises the rotor speed, rotor angle, and electromagnetic torque. A sampling rate of 100 samples per second, over a window size of 10 seconds, is set for all simulation cases. Starting with zero initial weighs $W(k)$, the rotor angle $\Delta\delta(k)$ and rotor speed $\Delta\omega(k)$ are fed to the Adaline as input signals, whereas the developed torque $\Delta T_e(k)$ is introduced to the Adaline as the desired signal. The output of the Adaline is given as $\Delta\hat{T}_e(k) = w_1(k)\Delta\delta(k) + w_2(k)\Delta\omega(k)$.

Figures 3 and 4 show the performance of the Adaline and KF estimations in comparison with LSE estimation. A fast convergence and accurate estimation of K_s and K_d by both techniques are obvious. Kalman filter gives faster convergence and rigid tracking without overshoot compared to the Adaline. However, the light computational burden of the Adaline algorithm makes its implementation easier than KF. It is crucial to tune the parameters α and λ for the Adaline using trial and error to achieve a high online tracking accuracy of K_s and K_d. The final estimated of K_s and K_d for a stable and unstable operating points are given in Table 1. The values of α and λ are set to α=0.90 and λ=0.005.

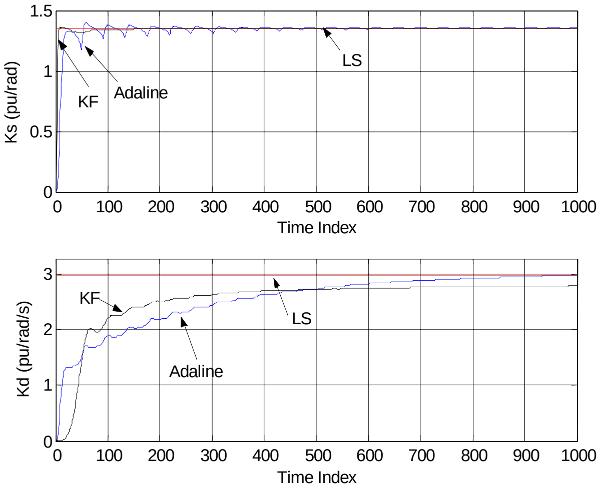

Fig. 3. Adaline and KF Estimation of K_s and K_d. V_{to}=1.05 pu; P_e=0.8 pu;Q_e=-0.6 pu

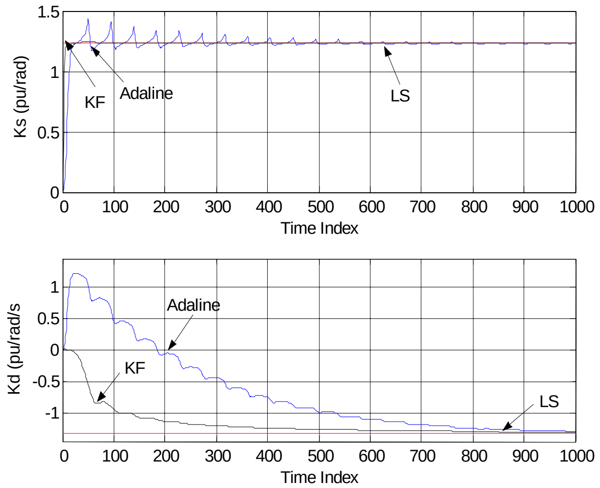

Fig. 4. Adaline and KF estimation of K_s and K_d. V_{to}=1.05 pu; P_e=0.8 pu;Q_e=0.60 pu

TABLE 1

FINAL ESTIMATES OF K_s AND K_d

Rotor Mode	Estimates of Torque Coefficients			
	K_i	LSE	KF	Adaline
-0.1677± *j*7.4255 stable	K_s	1.3502	1.3502	1.3557
	K_d	2.9847	2.7857	2.9821
0.0720± *j*7.0756 unstable	K_s	1.2301	1.2301	1.2296
	K_d	-1.3254	-1.3116	-1.3033

VII. CONCLUSION

An online adaptive technique for accurate estimation of the synchronizing and damping torque coefficients, K_s and K_d, using Adaline is presented in this paper. The performance of the technique has been compared with KF and LSE techniques. Simulation results have shown that Adaline technique is accurate and can be implemented with small computing time and storage. It is believed, that Adaline is a good candidate for online estimation of small signal stability indices.

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APPENDIX A

The dynamical nonlinear differential equations of the SMIBS are given below [4]

$$\frac{d\omega}{dt} = \frac{1}{M}\left(T_m - T_e\right) \quad \text{(A-1)}$$

$$\frac{d\delta}{dt} = \omega_b(\omega - 1) \quad \text{(A-2)}$$

$$\frac{dE'_q}{dt} = \frac{1}{T'_{do}}\left[E_{fd} - E'_q - (x_d - x'_d)i_d\right] \quad \text{(A-3)}$$

$$\frac{dE_{fd}}{dt} = \frac{1}{T_A}\left[K_A(V_{ref} - v_t + u_{PSS}) - E_{fd}\right] \quad \text{(A-4)}$$

where T_m and T_e are the mechanical input and electrical output torques of the generator, respectively; M is inertia constant. E_{fd} is the field voltage; T'_{do} is the open circuit field time constant; x_d and x'_d are the d-axis and transient reactances of the generator, respectively. K_A and T_A are the gain and time constant of the excitation system, respectively. V_{ref} is the reference voltage.

APPENDIX B

The parameters of the synchronous generator and transmission line are given below [4].

Machine Parameters (pu):

$x_d = 0.973$, $x_q = 0.550$, $x'_d = 0.190$

$M = 9.26$, $T'_{do} = 7.76$ s, $D = 0$, ω_b=377 rad/s

Exciter:

$K_A = 50$, $T_A = 0.05$ s

Transmission Line (pu)

$r_e = 0.0$, $x_e = 0.40$

Nominal Operating Point (pu)

$P_{eo} = 0.9$, $Q_{eo} = 0.1$, $V_{to} = 1.05$

APPENDIX C

For a SMIBS the following relationships apply with all the variables with subscript o are calculated at their pre-disturbance steady-state operating values corresponding to the operating conditions P_o, Q_o, and V_{to}.[5]:

$$i_{qo} = \frac{P_o V_{to}}{\sqrt{(P_o x_q)^2 + (V_{to}^2 + Q_o x_q)^2}} \quad \text{(C-1)}$$

$$v_{do} = i_{qo} x_q \quad \text{(C-2)}$$

$$v_{qo} = \sqrt{V_{to}^2 - v_{do}^2)} \quad \text{(C-3)}$$

$$i_{do} = \frac{Q_o + x_q i_{qo}^2}{v_{qo}} \quad \text{(C-4)}$$

$$E_{qo} = v_{qo} + i_{do} x_q \quad \text{(C-5)3}$$

$$E_o = \sqrt{(v_{do} + x_e i_{qo})^2 + (v_{qo} - x_e i_{do})^2} \quad \text{(C-6)}$$

$$\delta_o = \tan^{-1}\left(\frac{v_{do} + x_e i_{qo}}{v_{qo} - x_e i_{do}}\right) \quad \text{(C-7)}$$

For the case $r_e = 0$, K_1-K_6 are calculated as follows:

$$K_1 = \frac{x_q - x'_d}{x_e + x'_d} i_{qo} E_o \sin\delta_o + \frac{1}{x_e + x_q} E_{qo} E_o \cos\delta_o \quad \text{(C-8)}$$

$$K_2 = \frac{E_o \sin\delta_o}{x_e + x'_d} \quad \text{(C-9)}$$

$$K_3 = \frac{x_e + x'_d}{x_e + x_d} \quad \text{(C-10)}$$

$$K_4 = \frac{x_d - x'_d}{x_e + x'_d} E_o \sin\delta_o \quad \text{(C-11)}$$

$$K_5 = \frac{x_q}{x_e + x_q}\frac{v_{do}}{V_{to}} E_o \cos\delta_o - \frac{x'_d}{x_e + x'_d}\frac{v_{qo}}{V_{to}} E_o \sin\delta_o \quad \text{(C-12)}$$

$$K_6 = \frac{x_e}{x_e + x'_d}\frac{v_{qo}}{V_{to}} \quad \text{(C-13)}$$