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Hybrid Signal Processing and Soft Computing approaches to Power System Frequency Estimation

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Abstract- Dynamic variation in power system frequency is required to be estimated for implementing the correcting measures. This paper presents power system frequency estimation by using RLS-Adaline and KF-Adaline algorithms. In the proposed hybrid approaches the weights of the Adaline are updated using RLS/KF algorithms. Frequency of power system signal is estimated from final updated weights of the Adaline. The performances of the proposed algorithms are studied through simulations for several critical cases that often arise in a power system. These studies show that the KF-Adaline algorithm is superior over the RLS-Adaline in estimating power system frequency. Studies made on experimental data also support the superiority.

Key Words: Frequency Estimation, Adaptive Linear Neural Networks (Adaline), Discrete Fourier Transform (DFT), Least Square (LS), Recusive Least Square (RLS), Kalman Filter.

1. Introduction

Power quality allows electrical system to function in their intended manner without significant loss of performance. It deteriorates due to voltage surges, under voltage, over voltage, variation in frequency and variation in wave shape called harmonics. So for the improvement in power quality, there is a requirement of fast and accurate estimation of supply frequency and voltage for an integrated power system, which may be corrupted by noise and higher harmonics. Because of the power mismatch between the generation and load demand, there is a variation in system frequency from its normal value, which indicates the occurrence of a corrective action for its restoration to its original value. However Discrete Fourier Transforms, Least Square Error technique [1], Kalman Filter [2-6], Least Mean Square (LMS) [7-10] etc. are known signal processing techniques used for frequency measurements of power system signals, but these approaches suffer from producing inaccurate results due to the presence of noise and harmonics and other system changing conditions such as change in fault inception angle and change in fault resistance.

For better accuracy of estimation, in this paper, a combination of signal processing and soft computing techniques are used. So this paper presents combined RLS-Adaline (Recursive Least Square and Adaptive Linear Neural Network) and KF-Adaline (Kalman Filter Adaline) approaches for the estimation of frequency of a power system. The neural estimator is based on the use of an adaptive perceptron comprising a linear adaptive neuron called Adaline. Kalman Filter and Recursive Least Square algorithms carry out the weight updating in Adaline. The estimators' track the signal corrupted with noise, in presence of harmonics and in presence of sub and inter harmonics. Adaptive tracking of frequency of a power system can easily be done using these algorithms.

The tracking performances of the proposed approaches are validated taking the data generated from laboratory setup. There is an improvement in convergence and processing time on using these algorithms. In this case, leakage problem of DFT and FFT are avoided by processing data sample by sample rather than taking a window of data. Out of these two, the KF-Adaline approach of tracking the fundamental and harmonic components is better.

2. Hybrid Adaline Methods for Frequency estimation:

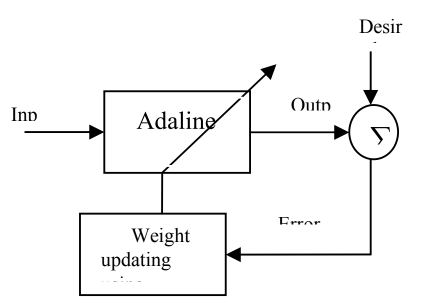

Fig. Schematic of Estimation problem

Fig. 1 Schematic of hybrid Adaline structure

Fig.1 Hybrid Adaline Estimation Scheme

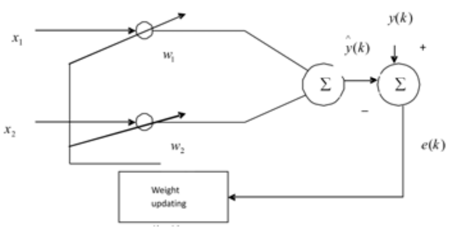

Fig. 1 shows the block diagrammatic representation of hybrid Adaline estimation scheme. First input signal is fed to Adaline structure. Output of Adaline is compared with the desired/reference output and the error so obtained is minimized by updating the weights of the Adaline using RLS/KF algorithm.

2.1Recursive Least Square-Adaptive Linear Neural Network (RLS-Adaline) approach for frequency estimation:

From the discrete values of the three-phase voltage signal of a power system, a complex voltage vector is formed using the well-known $\alpha-\beta$ transformation [7]. A non-linear state space formulation is then obtained for this complex signal and Recursive Least Square (RLS) approach is used to compute the true state of the model. As frequency is modeled as a state, the estimation of the state vector yields the unknown power system frequency. The discrete representation of three phase voltages of a power system can be expressed as

$$V_a(k) = V_m \cos(\omega k\Delta T + \phi) + \varepsilon_a(k)$$

$$V_b(k) = V_m \cos(\omega k\Delta T + \phi - \frac{2\pi}{3}) + \varepsilon_b(k)$$

$$V_c(k) = V_m \cos(\omega k\Delta T + \phi + \frac{2\pi}{3}) + \varepsilon_c(k)$$

(1)

where V_a, V_b and V_c are three phase voltage signals. V_m is the amplitude of the signal, ω is the angular frequency, $\varepsilon_a(k), \varepsilon_b(k), \varepsilon_c(k)$ are the noise terms, ΔT is the sampling interval, k is the sampling instant, ϕ is the phase of fundamental component. The complex form of signal derived from the three-phase voltages is obtained by transform as mentioned below

$$V_\alpha(k) = \sqrt{\frac{2}{3}}(V_a(k) - 0.5V_b(k) - 0.5V_c(k))$$

V [illegible] $5V_c(k))$

(2)

A complex voltage can be obtained from above equation as follows

$$V(k) = V_\alpha(k) + jV_\beta(k)$$

$$= Ae^{j(\omega k\Delta T + \phi)} + \varepsilon(k)$$

(3)

where A is the amplitude of the signal and ε is the noise component.

The observation signal V_k can be modeled in a state space form as

$$\begin{bmatrix} w_1(k+1) \\ w_2(k+1) \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & w_1(k) \end{bmatrix} \begin{bmatrix} w_1(k) \\ w_2(k) \end{bmatrix}$$

(4)

$$y(k) = V(k) = \begin{bmatrix} 0 & 1 \end{bmatrix} \begin{bmatrix} w_1(k) \\ w_2(k) \end{bmatrix} + \varepsilon(k)$$

(5)

Fig. 2 Block diagram of Adaline for frequency estimation

Fig.2 shows the block diagram of Adaline containing states, actual and estimated signal.

where the states w_1 and w_2 are

$$w_1(k) = e^{j\omega\Delta T} = \cos k\omega\Delta T + j\sin k\omega\Delta T$$

(6)

$$w_2(k) = Ae^{j(\omega k\Delta T + \phi)}$$

(7)

$$W(k) = \begin{bmatrix} w_1(k) & w_2(k) \end{bmatrix}^T$$

(8)

From equation (3.5)

$$X = \begin{bmatrix} x_1 & x_2 \end{bmatrix} = \begin{bmatrix} 0 & 1 \end{bmatrix}$$

(9)

so $$y(k) = XW(k)$$

(10)

Using the RLS estimation technique to (3.5), the parameters are estimated using the formula given by

$$\hat{W}(k) = \hat{W}(k-1) + K(k)\varepsilon(k)$$

(11)

where $\hat{W}(k) =$ current value of estimate

$\hat{W}(k-1) =$ Past value of estimate

$K(k) =$ Gain

The error in the measurement is given by

$$\varepsilon(k) = y(k) - X^T \hat{W}(k-1)$$
(12)

The gain K is updated using the following expression

$$K(k) = P(k-1)X[\lambda I + X^T P(k-1)X]^{-1}$$
(13)

where $P(k) =$ Error Covariance matrix

$\lambda (0 < \lambda < 1) =$ Forgetting factor

The covariance matrix updatation is as follows

$$P(k) = [I - K(k)X^T]P(k-1)/\lambda$$
(14)

Equations (3.9) to (3.12) are initialized at $k = 0$. The choice of initial covariance matrix $P(0)$ is large, usually a value i.e $P = \alpha I$, where α is a large number and I is a square identity matrix.

After the convergence of state vector is attained, the frequency is calculated from equation (6) as

$$\hat{f} = \frac{1}{2\pi \Delta T} (\sin^{-1} \mathrm{Im}(\hat{W}_1))$$
(15)

$\hat{f}$ is the estimated frequency of the signal

where Im ( ) stands for the imaginary part of a quantity.

2.2 Kalman Filter-Adaptive Linear Neural Network (KF-Adaline) approach for frequency estimation:

The discretized voltage signal as described in 2.1 is considered. The equations (1) to (10) are taken into account.

Using the Kalman Filtering estimation technique to (10), the parameters are estimated using the formula given by

$$K(k) = \hat{P}(k/k-1)X^T(X\hat{P}(k/k-1)X^T + Q)^{-1}$$
(16)

where K is the Kalman gain, X is the observation vector, P is the covariance matrix, Q is the noise covariance of the signal.

So the covariance matrix is related with Kalman gain with the following equation.

$$\hat{P}(k/k) = \hat{P}(k/k-1) - K(k)X\hat{P}(k/k-1)$$
(17)

So the updated estimated state is related with previous state with the following equation.

$$\hat{W}(k/k) = \hat{W}(k/k-1) + K(k)(y(k) - X\hat{W}(k/k-1))$$
(18)

After the state vector is converged, the frequency is calculated from equation (3.15).

3. Simulation results

3.1. Sinusoidal Signal in presence of noise

A 50 Hz signal with constant frequency but with random noises is generated with a 1-millisecond sampling interval.

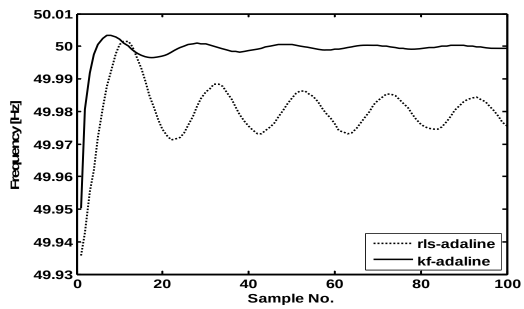

Fig. 3 Estimation of frequency at SNR 40 dB

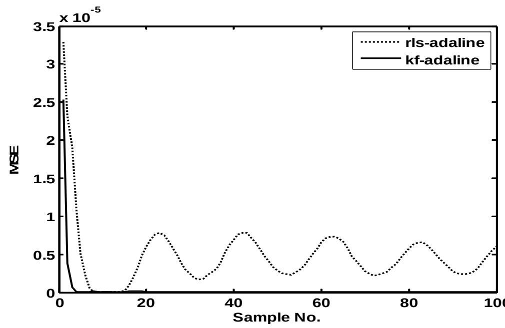

Fig. 4 Mean Square Error in the estimation of Frequency

In the analysis, we consider only the 40 dB SNR case since in the other cases the errors using the existing algorithms are quite large. Fig. 3 shows the comparison of estimation performance using RLS-Adaline and KF-Adaline algorithms. Fig. 4 shows MSE values using different methods. These figures show that the error is less in case of KF-Adaline algorithm.

3.2. Jump in frequency in the signal

The next case is considered to be the performance of the algorithm in presence of jump in frequency. For this, we consider that the frequency changes from

50 Hz to 49 Hz. Fig. 5 shows the estimation of frequency during sudden change in frequency at SNR 40 dB. Both the algorithms estimates frequency accurately but performance of KF-Adaline is little better than RLS-Adaline.

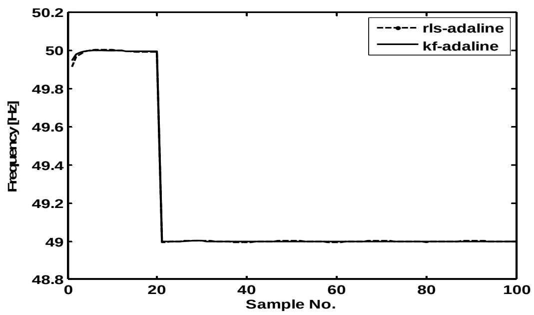

Fig. 5 Estimation of frequency during frequency jump (SNR 40 dB)

3.3. In the presence of Harmonics

Next we consider the problem of estimating fundamental frequency from signals having harmonics content in them. The common case of 3rd harmonic is considered. Fig.6 shows the estimation of frequency using different algorithms from the signal with harmonics. It is found that a comparatively better performance is obtained in case of KF-Adaline algorithm

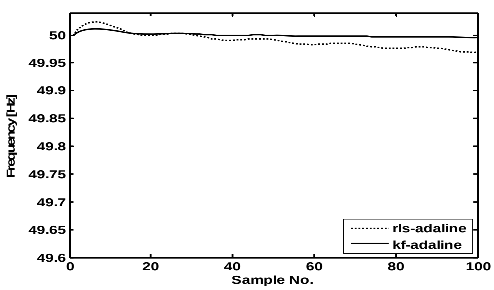

Fig. 6 Estimation of Frequency in presence of harmonics

4. Experimental results (Data generated from Laboratory Setup)

The data is obtained in laboratory from the supply on normal working day as per the experimental setup shown in Fig. 7

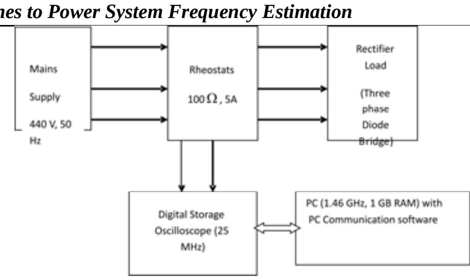

Fig.7 Experimental setup for online data generation

Specifications of the Instruments used are:

1. Rheostats: 100 Ω , 5 A (3 in no.)
2. Non-linear load: 3 Phase diode bridge rectifier with a 5 Ω resistor in series with a 100 mH inductor at the d.c side.
3. Digital Storage Oscilloscope (Make-Falcon): Band Width-25 MHz, Sample rate-100 MS/s, Channels-2, Record length-5000 data points, PC Connectivity- USB Port and PC Communication software.
4. PC: 1.46 GHz CPU and 1GB RAM, Notebook PC

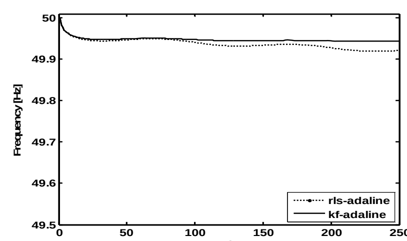

Fig. 8 Estimation of Frequency of real data

The voltage waveform is stored in a Digital Storage Oscilloscope and then through PC Communication software, data is acquired to the personal computer. The used PC had a 1.46 GHz CPU and 1GB RAM. The sampling time in this case is fixed at 0.04ms.

Fig. 8 shows the estimation of frequency of signal using both the algorithms from the real data obtained from the experiment. From this Fig.8, it is found that the performance in estimation using KF-Adaline is better (less estimation error i.e. 0.1632) as compared to RLS-Adaline.

5. Conclusions

Two new hybrid algorithms (RLS-Adaline and KF-Adaline) for power system frequency estimation are suggested. Initial choice of weight vector and Covariance matrix determines performance of RLS-Adaline and KF-Adaline algorithms. After the adaptation of the weight vector using RLS/KF algorithms, frequency of signal is estimated from updated weights of Adaline. KF-Adaline performs better than RLS-Adaline at different level of noises and different signal changing conditions of power system.

References

[1] M.S. Sachdev, M.M. Giray "A Least Square technique for determining power system frequency" IEEE Trans. Power Apparatus Syst. Vol. 104, No.2, pp. 437-443, 1985

[2] P.K.Dash, A.K.Pradhan and G.Panda, "Frequency estimation of distorted power system signals using extended complex Kalman Filter." IEEE Trans. on Power Del., vol. 14, no. 3, pp. 761-766, 1999.

[3] Chien-Hung Huang, Chien-Hsing Lee, Kuang-Jung Shih and Yaw-Juen Wang "Frequency Estimation of Distorted Power System Signals Using a Robust Algorithm" IEEE Transactions on Power Delivery, vol.23, no.1, pp.41-51, 2008.

[4] A. Routray, A. K. Pradhan and K. P. Rao "A Novel Kalman Filter for Frequency Estimation of Distorted Signals in Power Systems" IEEE Transactions on Instrumentation and Measurement, Vol.51, No.3, pp.469-479, 2002.

[5] P.K.Dash, R.K.Jena, G.Panda and A. Routray "An Extended Complex Kalman Filter for Frequency Measurement of Distorted Signals" IEEE Transactions on Instrumentations and Measurement, Vol.49, No.4, pp.746-753, 2000.

[6] Chien-Hung Huang, Chien-Hsing Lee, Kuang-Jung Shih and Yaw-Juen Wang "Frequency Estimation of Distorted Power System Signals Using a Robust Algorithm" IEEE Transactions on Power Delivery, vol.23, no.1, pp.41-51, 2008.

[7] A. K. Pradhan, A. Routray and Abir Basak "Power System Frequency Estimation Using Least Mean Square Technique." IEEE Trans. Power Del., vol. 20, no. 3, pp.1812-1816, 2005

[8] Bernard Widrow "Thinking about Thinking: The Discovery of the LMS Algorithm" IEEE Signal Processing Magazine, pp.100-103, 2005.

[9] Bernard Widrow, John McCool, and Michael Ball "The Complex LMS Algorithm" Proceedings of the IEEE, vol.63, no.4, pp.719-720, 1975.

[10] Raymond H. Kwong, Edward W. Johnston "A Variable Step Size LMS Algorithm" IEEE Trans. on Signal Processing, vol. 40, no.2, pp.1633-1642, 1992.