A Discrete Filtering Algorithm for Impulse Wave Parameter Estimation

Khaled M. EL-Naggar

Abstract—This paper presents a new method for estimating the mean curve of impulse voltage waveforms that are recorded during impulse tests. In practice, these waveforms are distorted by noise, oscillations and overshoot. The problem is formulated as an estimation problem. Estimation of the current signal parameters is achieved using a fast and accurate technique. The method is based on discrete dynamic filtering algorithm (DDF). The main advantage of the proposed technique is its ability in producing the estimates in a very short time and at a very high degree of accuracy. The algorithm uses sets of digital samples of the recorded impulse waveform. The proposed technique has been tested using simulated data of practical waveforms. Effects of number of samples and data window size are studied. Results are reported and discussed.

Keyword—Digital Filtering, Estimation, Impulse wave, Stochastic filtering.

I. INTRODUCTION

UTILITIES concern much about impulse testing of high voltage electrical apparatus in order to access the overall insulation strength. Impulse waves are characterized by several parameters: Peak magnitude, front time, tail time and chopping time. The earlier methods used for impulse testing of electrical equipment were done through visual examination of the oscillographic traces. These method has problems when the impulse wave is distorted by superimposed oscillations or overshoot[1],[2].

In general, the parameters of Lightning Impulse can be determined as per IEC 60-1 if the measured impulse is smooth. However, difficulties arise if the oscillations or overshoot are superimposed on the waveform. In such cases standards require to extract the mean curve to calculate the amplitude and frequency of the impulse wave [3-7].

During the last few decades, digital waveform recorders and powerful computers have replaced the conventional methods in impulse wave testing [8],[9]. Most of the digital curve fitting methods rely on static state estimation techniques such as least error squares and least absolute value methods. Dynamic state estimation techniques such as Kalman filtering algorithm were also proposed in many references. Pereze and Martinez [10] proposed the extended Kalman filtering algorithm approach using a smooth impulse model for constructing the mean-curve of lightning impulses. Methods based on wavelet transform were also presented to measure the impulse wave parameters [11],[12].

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Recently, many techniques based on heuristic search and artificial intelligence have been proposed and used in this area. Genetic algorithms, particle swarm and artificial neural networks are all examples of these techniques [13].

This paper introduces a new method based on digital dynamic filtering algorithm for estimating the mean curveparameters of impulse voltage waveforms that are recorded during Impulse testing. The method can extract the mean curve parameters even if the waveform is contaminated with undesirable oscillations or noise. The estimation problem is presented in state space form. The proposed technique is tested using generated waveforms. Results obtained show that the algorithm can identify and measure the mean curve of any distorted impulse waveforms. The algorithm can track the curve parameters on digital bases.

II. MATHEMATICAL FORMULATION

In this paper, two different simulated impulse waveforms are generated to perform the study. Having a digitized samples of the voltage signal, the problem is to find an estimate for the mean curve parameters, namely, peak magnitude, front time, tail time and chopping time (if it exists). In the first group, different standard noise free impulses such as switching and lightning impulses are used. In the second testing group, a noisy impulse wave is utilized. In both study cases, data generated from the standard equations that simulate the recorded waveforms are analyzed using the proposed algorithm. The resultant estimated parameters of the waveforms are then compared with the exact parameters or the calculated analytically in literature. Equation 1 represents the standard noise-free impulse waveform while equation 2 represents a noisy impulse wave[4].

$$v(t) = A(e^{-\alpha t} - e^{-\beta t}) \tag{1}$$

$$v(t) = [A(e^{-\alpha t} - e^{-\beta t}) + Be^{-\delta t} sin(\omega t)](1 - e^{-\gamma t^2}) \tag{2}$$

The problem unknowns in equations 1 are the voltage amplitude A and the time constants α and β. In addition to the voltages and time constants in equation 1, the noise parameters of equation 2 (B, ω, δ and γ) are also unknowns. Considering that the noise parameters can be filtered out. Equation 2 will always reduced to 1 after filtering out the noise. Based on this, we can use Taylor expansion to write equation 1 in the following form.

$$v(t) = A\left\{1 - t\alpha + \frac{t\alpha^2}{2} - \frac{t\alpha^3}{6}..\right\} - B\left\{1 - t\beta + \frac{t\beta^2}{2} - \frac{t\beta^3}{6}..\right\} \quad (3)$$

$$v(t) = H(1,1)X_1 + H(1,2)X_2 + H(1,3)X_3 + H(1,4)X_{14} + H(1,5)X_5 \\ + H(1,6)X_6 + ...H(1,2N+4)X_{2N+4} \quad (4)$$

Now using the first four terms of the exponential function expansion, the above equation can be reduced to the following form

$$H_{(1,1)} = 1, \qquad H_{(1,2)} = -t$$
$$H_{(1,3)} = \frac{t^2}{2} \qquad H_{(1,4)} = -\frac{t^3}{6}$$
$$H_{(1,5)} = 1, \qquad H_{(1,6)} = -t \qquad (5)$$
$$H_{(1,7)} = \frac{t^2}{2}, \qquad H_{(1,8)} = -\frac{t^3}{6}$$

$$X_1 = A$$
$$X_2 = A\alpha$$
$$X_3 = A\alpha^2$$
$$X_4 = A\alpha^3 \qquad (6)$$
$$X_5 = B$$
$$X_6 = B\beta$$
$$X_7 = B\beta^2$$
$$X_8 = B\beta^3$$

If the signal is sampled at a pre-selected rate, ΔT, then m samples, for the signal would be obtained at t_1, t_2, …, t_m and we can write the following

$$\begin{bmatrix} v(t_1) \\ v(t_2) \\ .... \\ ..... \\ v(t_m) \end{bmatrix} = \begin{bmatrix} H_{(1,1)}(t_1) & H_{(1,2)}(t_1) & ... & .... & H_{(1,N)}(t_1) \\ H_{(2,1)}(t_2) & H_{(2,2)}(t_2) & ... & .. & H_{(2,N)}(t_2) \\ .... & ..... & ..... & .... & ..... \\ .... & ...... & ... & ... & ..... \\ H_{(m,1)}(t_m) & H_{(m,2)}(t_m) & & & H_{(m,2N+4)}(t_m) \end{bmatrix} \begin{bmatrix} X_1(t) \\ X_2(t) \\ .. \\ .. \\ X_{2N+4}(t) \end{bmatrix} + \begin{bmatrix} e_1(t) \\ e_2(t) \\ .. \\ .. \\ e_{2N+4}(t) \end{bmatrix} \quad (7)$$

Now define u as the number of unknowns (u=8) then we can write this system in the conventional discrete state space compact form as:

$$v(k) = H(k)X(k) + e(k) \qquad (8)$$

Where

k   *is* the discrete step number

v(k)   m * 1 measurement vector

H(k)   m * u connection matrix

X(k)   u * 1 state vector to be estimated

e(k)   u * 1 error vector to be minimized

Once the state vector for the waveform is identified, the values of problem parameters can be calculated as

$$A = X_1, \qquad \alpha = \frac{X_2}{X_1} = \frac{X_3}{X_2} = \frac{X_4}{X_3} = \sqrt{\frac{X_3}{X_1}}$$
$$B = X_5, \qquad \beta = \frac{X_6}{X_5} = \frac{X_7}{X_6} = \frac{X_8}{X_7} = \sqrt{\frac{X_7}{X_5}} \qquad (9)$$

III. DESCRIPTION OF THE PROPOSED ALGORITHM

In the first part, the on-line estimation process of the parameters described in section 2 is performed using the discrete least absolute value dynamic filtering algorithm (DDF). Although the complete derivation of the proposed filter equations is beyond the scope of this paper and given in reference [14], a short description is given next. The dynamic filter works on the discrete state space model described by the measurement equation and the state transition equation in the following form.

$$v(k) = H(k)X(k) + e(k) \qquad (10)$$

$$X(k+1) = \Phi(k)X(k) + \varpi(k) \qquad (11)$$

The state transition formulation depends on the type of reference chosen. Either stationary reference or rotating reference can be used [9]. The measurement error vector e(k) and the state error $\varpi(k)$ are assumed to be white sequence with known covariance as,

$$E\{e(k)e(j)^T\} = \begin{cases} 0 & ; \quad j \neq k \\ R(k); & j = k \end{cases} \qquad (12)$$

$$E\{\varpi(k)\varpi(j)^T\} = \begin{cases} 0 & ; \quad j \neq k \\ Q(k); & j = k \end{cases} \qquad (13)$$

The initial condition of X(0) is a Gaussian random vector with the following statistics,

$$E\{X(0)\} = \overline{X}(0) \qquad (14)$$

$$E\{[X(0) - \overline{X}(0)][X(0) - \overline{X}(0)]^T\} = \overline{P}(0) \qquad (15)$$

Where $\overline{P}(0)$ is the initial error covariance matrix of the states, with dimensions u*u. The covariance of the error at any

step (k) can be obtained by replacing $X(0)$ with $X(k)$ in equation (17).

The algorithm starts with an initial estimate for the system parameter vector $\overline{X}(0)$ and its error covariance matrix ($\overline{P}(0)$) at some point k=0. These estimates are denoted as $\overline{X}$, $\overline{P}$, where (–) means that these are the best estimations at this point, prior to assimilating the measurement at instant k. With such initial values, of both parameters and error co-variances, filter gain matrix $K(k)$ at this step is calculated as follows,

$$K(k) = \left[H(k) + R(k)Ly^T \overline{P}^{-1}(k) \right]^{-1}$$

(16)

Assuming that the state vector dimension is ux1, the vectors L and y are defined as: L is ux1 column vector $(1,1,\cdots,1)^T$; and y^T is 1xu row vector $(1,1)$ [9]. Using the filter gains, estimates are updated with measurements $Z(k)$ through equation (20), and error co-variances for update estimates are computed from equation (19).

$$\hat{X}(k) = \overline{X}(k) + K(k)\{i(k) - H(k)\overline{X}(k)\}$$

(17)

$$P(k) = [I - K(k)H(k)]P(k)[I - K(k)H(k)]^T + K(k)R(k)K^T(K)$$

(18)

Finally, error co-variances and estimates are projected ahead to repeat with k=2.

$$\overline{P}(k+1) = \Phi(k)P(k)\Phi^T(k) + Q(k)$$

(19)

$$\overline{X}(k+1) = \Phi(k)\hat{X}(k) + R(k)$$

(20)

The process is repeated until the last sample is reached. It is assumed that the co-variances and the transition matrices are known.

IV. TESTING

In this section, three study cases are considered to examine the behavior of the proposed algorithm. The first case represents a standard lightning impulse wave. The second waveform is a standard switching impulse. In the third study case, a practical noisy signal is considered from the literature.

A. Standard Lightning Impulses

To represent a standard 1.2/50 lightning impulse, equation 1 is used to generate the necessary data. The constants used are, A=207.45292274 KV , α and β equals 14659.3 and 2468000 sec.-1 respectively[13].

Table I shows the effect of varying the number of samples on the accuracy of the estimated parameters. Results recorded in this table show that most results are accurate. Examining

these results reveals that the maximum error in estimating the amplitude is about 0.5 % and the maximum error in estimating time constants are, 0.1% and 0.35 % respectively. It is notable that starting from 200 samples, the accuracy is very high.

TABLE I
ESTIMATED PARAMETERS (CASE 1)

Number of samples	A	α	β
10	206.346610	14643.44	2468044.22
100	207.129943	14649.75	2468041.02
200	207.450224	14657.59	2467843.8
300	207.451005	14657.27	2467885.38
400	207.451000	14657.73	2467888.40

B. Standard Switching Impulses

In this test, a standard 250/2500 switching impulse is simulated [13]. Equation 1 is used to generate the required samples. Parameters used to generate the signal are; A=250 KV., α = 316.85 , β = 16005 sec.-1. Table II shows some of the results obtained.

As in the case of lightning impulse, errors are very small. Maximum errors recorded for the amplitude, and the two time constants are, 0.75%, 0.95% and 0.5 %respectively. It was observed that the error starts to be very small once the number of samples reaches 1000. Therefore, the recommended number of samples is 1000 in this case.

TABLE II
ESTIMATED PARAMETERS (CASE 2)

Number of samples	A	α	β
50	248.762	313.11	15876.97
100	248.553	316.31	15981.13
1000	249.849	316.80	16005.44
1500	249.901	316.80	16003.51
2000	249.901	316.80	16003.11

C. Practical Case Study

In this test the generated wave is a simulated one that is typical when impulse testing performed on a low inductance winding of a transformer. The equation of the waveform is given as [12]

$$v(t) = V_1 e^{-\alpha t} \sin(\omega_1 t + \phi_1) + V_2 e^{-\beta t} \sin(\omega_2 t + \phi_2)$$

This waveform has a characteristic overshoot on the front and an oscillating under-swing. The purpose of choosing this waveform is to illustrate that such complicated waveforms can be handled by the algorithm. Parameters to be estimated here are the basic wave parameters V_1=101.9, V_2=115, in KV , α=0.00355, β=0.977 (time constants are in 1/(micro sec.)) and the noise parameters ω_1=0.0138, ω_2=1.636, Φ_1=1.815, Φ_2=4.177 (phase angles are in radians).

In this case the proposed filtering algorithm is hybrid with simple genetic based algorithm (GA). The GA is used to extract the noise signal parameters (frequencies and phase angles) [12]. Once these parameters are estimated the characteristic time constants and peak voltage can be

estimated, as in the previous cases, using the proposed method. Table III gives the results obtained for the noise parameters [12] while table IV shows samples of the results obtained for the main estimated parameters. Results displayed are for the best sampling rate observed which was 1000 samples while the data window size was 35 micro seconds. These tables indicate that the proposed method not only estimates the mean curve, but can also determine the noise level very accurately. The GA filter can be used also to initialize the DDF.

TABLE III
ESTIMATED NOISE PARAMETERS

Parameter	ω_1	ω_2	,1	,2
Estimated	0.0135	1.639	1.750	4.190
Exact	0.0138	1.636	1.815	4.177

TABLE IV
ESTIMATED MEAN CURVE PARAMETERS

Parameter	V_1	V_2	α	β
Estimated	102.05	114.87	0.00346	0.979
Exact	101.9	115	0.00355	0.977

V. CONCLUSIONS

This paper presents a new method for filtering the impulse wave forms superimposed by noise is presented. The method is based on optimal filtering algorithm. The problem is formulated and presented in the state space form. The goal is to minimize the sum of absolute error in the measurement equations. The proposed technique is then used to solve the formulated problem. The method is tested using different simulated data, including pure and noisy waveforms. The results of this paper show that the proposed algorithm can identify and measure the impulse parameters of any distorted impulse wave in a power system. The algorithm can estimate the mean-curve of the impulse wave on digital bases. The method has also the advantage of self-tuning when dealing with non stationary waveforms.

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