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ESTIMATING INSTANTANEOUS VOLTAGE FLICKER USING KALMAN FILTER AND FUZZY LOGIC TUNING NOISE LEVELS

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ABSTRACT
This paper presents a novel technique for tracking voltage flicker occurring in electric power systems. Voltage flicker tracking is essential for electric power quality analysis. The instantaneous voltage flicker magnitude, frequency and phase are estimated using Kalman filtering technique. This approach is based on expressing voltage flicker as a discrete time linear dynamic system model using flicker parameters as the system parameters. An extended state space model is adapted for the Kalman filter to estimate the parameters. Fuzzy rule-based logic is used to tune-up the system-noise and measurement-noise levels by adjusting their covariance matrices using flicker measurements.

KEY WORDS
Power quality, Voltage flicker, Kalman Filter, and Fuzzy logic.

1. Introduction

A major problem in electric power quality is voltage flicker. It is defined as repetitious variation in the electric voltage supply that results in a repetitious fluctuation in the luminance of a light source which is inconvenient to the human eyes. Voltage flicker has a detrimental effect on electrical and electronic devices. It may result in malfunction, failure or mis-operation of sensitive equipment such as computers, electronic control and protection devices, and equipment used for medical purposes. Moreover, frequent exposure of electric and electronic devices to voltage flicker results in reduction of the life span of such devices.

Voltage flicker is produced by large non-linear loads that cause repetitious variation in the system voltage envelope. There are many sources of voltage flicker ranging from severe load changes due to arc furnaces, or arc welders, to mild variation caused by factors like starting an industrial motor, pumps, elevators, fans, etc [2]. Such severe changes of load cause a small recurring voltage variation of about ±10% in amplitude and 1-50% in frequency of the system voltage envelope. IEEE has established flicker standards [1] which demonstrate that frequencies from two to ten fluctuations which result in approximately 0.5% voltage amplitude modulation will produce irritation to the observer. Different types of devices are currently used to mitigate the effect of sensitive equipment to the voltage flicker [2]. Effective design and implementation of mitigation devices require accurate estimation of the voltage flicker levels.

In the literature several techniques have been developed to track and evaluate voltage flicker. A general survey of flicker analysis and methods for electric arc furnace is presented in [3]. Fast Fourier transform (FFT) techniques are used to measure voltage flicker levels of stationary signals [4, 5]. For non-stationary signals, two techniques are used to track and measure instantaneous flicker level. These are: the least absolute value (LAV) state estimation technique [6] and the Kalman filtering technique (KF) [7]. The LAV technique assumes the flicker frequency is known in advance; however, in practice, this assumption is not necessarily true. The KF technique suffers from heavy computational burden, and it does not provide an accurate adjustment of its model parameters. The wavelets transform technique is also used to analyze voltage flicker [8, 9]. However, like the KF technique, this technique suffers from excess computation. It also has extensive difficulties with deciding upon candidate wavelets. The Teager energy operator and the Hilbert transform are both used to track voltage flicker in the presence of the deviation of supply frequency [10]. However, the technique suffers from instability when the input voltage maintains high frequency components.

This paper proposes a new and effective technique for tracking and estimating voltage flicker for power quality analysis and implementation of flicker mitigation and compensation devices. A combined fuzzy-Kalman Filter approach is developed in this paper. A flicker voltage is modeled as a discrete time linear difference equation that has flicker amplitude, frequency and phase as parameters. An extended discrete time state space model that extends the state vector with the system parameters as additional states is adapted for the Kalman filter in order to estimate the parameters. Fuzzy rule-based logic is employed to tune-up the system-noise and measurement-noise levels by adjusting their covariance matrices using flicker measurements. The model considers measurements as fuzzy values, each belonging to a fuzzy set of values represented by a triangular membership function.

The rest of the paper is organized as follows: Section 2 presents fuzzy load modeling. Kalman Filter formulations for fuzzy parameter estimation along with fuzzy IF-THEN rule based logic for coefficient estimation error are developed in Section 3. The fuzzy rule-based inference is introduced in Section 4. Model validation and results are discussed in Section 5. The conclusion is presented in Section 6.

2. Voltage Flicker Model

Eq.(1) shows a system signal Eq.(2) modulated with a random flicker signal Eq.(3).

$$y(t) = (A_0 + A_f \cos(\omega_f t + \theta_f)) \cos(\omega_0 t + \theta_0) \quad (1)$$

$$y_s(k) = A_0 \cos(\omega_0 t + \theta_0) \quad (2)$$

$$y_f(k) = A_f \cos(\omega_f t + \theta_f) \quad (3)$$

Where A_0, ω_0, and θ_0 are constant system parameters representing system amplitude, frequency and phase angle, respectively. A_f, ω_f, and θ_f are the voltage flicker amplitude, frequency and phase angle, respectively. A typical waveform is shown in Fig. 1 with $y(t) = 1.0 \cos(2\pi(50) + \pi/6)[1 + 0.05\cos(2\pi(2.5) + \pi/4)]$, t is in msec.

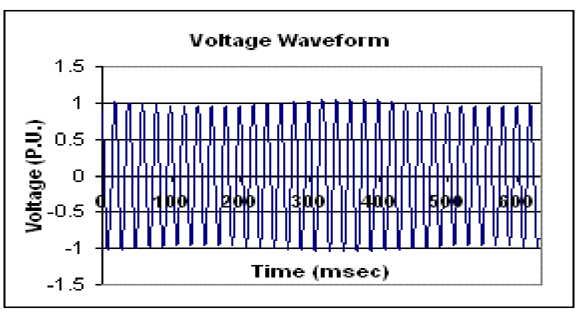

Fig. 1 Typical Flicker Voltage Waveform *y(t)*.

2.1 Linear State Space Estimation Model

The essence of the voltage flicker estimation problem is to estimate the voltage flicker envelope such as the one given in Fig. 1. The voltage flicker envelope is modeled as amplitude modulated voltage waveform Eq. (1) with the sinusoid voltage flicker waveform Eq. (3) as an amplitude modulating signal. The system voltage waveform Eq. (2) parameters are know and constant. Hence, the estimation problem reduces to estimate the voltage flicker parameters of Eq. (2). These are the voltage flicker amplitude A_f, frequency ω_f and phase φ_f. For the purpose of voltage flicker parameter estimation, a discrete z-transform linear time model for Eq. (3) is given in Eq. (4), [12].

$$\frac{Y_f(z)}{U(z)} = \frac{z^2 b_2 + z b_1 + b_0}{z^2 - z a_1 - a_0} \quad (4)$$

Where:

T is the sampling period

a_0 = -1

a_1 = $2\cos(\omega_f T)$

b_0 = 0

b_1 = $-A_f (\cos\varphi_f \cos\omega_f T - \sin\varphi_f \sin\omega_f T)$

b_2 = $A_f \cos\varphi_f$

The sampling period, T, must be at least twice the system frequency; $Y_f(z)$ is the z-transform of the $y_f(k)$, and $U(z)$ is the z-transform of a unit impulse function ($u(k)$ = 1 for k=0, zero otherwise) exciting input. The discrete time difference equation of Eq. (4) is described in Eq. (5).

$$\begin{aligned} y_f(k) = {} & a_1 y_f(k-1) + b_1 u(k-1) + \\ & a_0 y_f(k-2) + b_0 u(k-2) + b_2 u(k) \end{aligned} \quad (5)$$

By proper choice of dynamic system states, a state space model for Eq. (5) is derived as follows:

$$\begin{aligned} x_1(k+1) &= a_0 y_f(k) + b_0 u(k) \\ x_2(k+1) &= a_1 y_f(k) + b_1 u(k) + x_1(k) \\ y_f(k) &= b_2 u(k) + x_2(k) \end{aligned} \quad (6)$$

An extended state space model is formulated with parameters as additional states, [11]:

$$\begin{bmatrix} x_1(k+1) \\ x_2(k+1) \\ a_0(k+1) \\ a_1(k+1) \\ b_0(k+1) \\ b_1(k+1) \\ b_2(k+1) \end{bmatrix} = \begin{bmatrix} 0 & 0 & y_f(k) & 0 & u(k) & 0 & 0 \\ 1 & 0 & 0 & y_f(k) & 0 & u(k) & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ a_0(k) \\ a_1(k) \\ b_0(k) \\ b_1(k) \\ b_2(k) \end{bmatrix} \quad (7)$$

$$y_f(k) = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & u(k) \end{bmatrix} \begin{bmatrix} x_1(k) \\ x_2(k) \\ a_0(k) \\ a_1(k) \\ b_0(k) \\ b_1(k) \\ b_2(k) \end{bmatrix}$$

In the following Section, the Kalman Filter algorithm is used to obtain optimal estimates of the states of the model in Eq.(7). After introducing the necessary basic Kalman Filter formulation, fuzzy logic is used to tune-up system-noise and measurement-noise levels covariance matrices of the unknown system parameters.

3. Fuzzy Parameter Estimation Using Kalman Filtering

The Kalman Filter Algorithm is a well-established technique for estimating the parameters of stationary random processes [11]. It is suitable for estimating stochastic processes producing optimal estimates in the presence of noise. It formulates the parameter estimation problem as state-space dynamic equations that include system as well as measurement uncorrelated Gaussian white noises. The estimates produced are optimized in the least square sense by minimizing error equations containing covariance matrices of both noises. Only necessary derivations of the filter and its recursive equations that are suited for the voltage flicker state model in Eq. (7) are presented.

3.1 The Basic Kalman Filter

A discrete time-varying state-space dynamic model is considered for implementing the Kalman Filter for the rule-based fuzzy voltage flicker parameter estimation problem. The detailed derivation of Kalman filtering can be found in various references in the literature [11]. Given the discrete state equations Eq.(8):

$$x(k+1) = A(k)\,x(k) + w(k)$$
$$y(k) = C(k)\,x(k) + v(k) \qquad (8)$$

Where:

$x(k)$ is n x 1 system states.
$A(k)$ is n x n time varying state transition matrix.
$y(k)$ is m x 1 measurement vector.
$C(k)$ is m x n time varying output matrix.
$w(k)$ is n x 1 system error.
$v(k)$ is m x 1 measurement error.

The noise vectors *w(k)* and *v(k)* are uncorrected white noises that have:

1. Zero mean: $E[w(k)] = E[v(k)] = 0$
2. No time correlation:
   $E[w(i)\,w^T(j)] = E[v(i)\,v^T(j)] = 0, \quad for\ i \neq j$
3. Known covariance matrices (noise levels):
   $E[w(k)\,w^T(k)] = Q(k)$
   $E[v(k)\,v^T(k)] = G(k)$

where *Q(k)* and *G(k)* are positive semi-definite and positive definite matrices, respectively.

The basic discrete time-varying Kalman Filter algorithm is given by the following set of recursive equations. Given an initial estimate of the state vector $\hat{x}_0 = \hat{x}(0)$ and its covariance error matrix, $\boldsymbol{P_0} = \boldsymbol{P(0)}$, set $k=0$, then recursively compute:

Kalman gain:

$$K(k) = \left[A(k)P(k)C^T(k)\right]\left[C(k)P(k)C^T(k)+G(k)\right]^{-1} \qquad (12)$$

Estimate new state with new measurement *z(k)* :

$$\hat{x}(k+1) = A(k)\hat{x}(k) + K(k)\left[y(k) - C(k)\hat{x}(k)\right] \qquad (13)$$

Covariance error update:

$$P(k+1) = \left[A(k) - K(k)C(k)\right]P(k)\left[A(k) - K(k)C(k)\right]^T + K(k)G(k)K^T(k) + Q(k) \qquad (14)$$

An intelligent choice of the initial estimate of the state $\hat{x}_0$ and its covariance error P_0 enhances the convergence characteristics of the Kalman Filter. A few samples of measurement *y(k)* can be used to get a weighted least square as initial values for $\hat{x}_0$ and P_0:

$$\hat{x}_0 = \left[H^T G_0^{-1} H\right]^{-1} H^T G_0^{-1} z_0$$
$$P_0 = \left[H^T G_0^{-1} H\right]^{-1} \qquad (15)$$

where z_0 is (m m_1) x 1 vector of m_1 measured samples and H is (m m_1) x n matrix.

$$z_0 = \begin{bmatrix} z(1) \\ z(2) \\ \vdots \\ z(m_1) \end{bmatrix} \quad and \quad H = \begin{bmatrix} C(1) \\ C(2) \\ \vdots \\ C(m_1) \end{bmatrix} \qquad (16)$$

3.2 Kalman Filter Estimation Algorithm

The dynamic system of Eq. (8) is used with the following definitions:

1. State transition matrix, *A(k),* defined in Eq.(7).
2. The covariance error matrices, *Q(k)* and *G(k)*, are diagonal positive semi-definite and positive definite matrices, respectively. They are adjusted using the rule-based fuzzy logic described in Section 4.
3. The state vector, *x(k)*, consists of the seven variables described in Eq. (7). They are two system states and five flicker voltage parameters. (9)
4. The output matrix *C(k)* is the 1 x 7 time varying vector, described in Eq. (7). It relates the measurement flicker voltage to the system states. (10)

(11)

4. Fuzzy Rule Based Inference

The fuzzy set theory was first introduced by Zadeh 1956 [13]. Measured data and input signals are inevitably loaded with errors due to measuring instrument and human collection errors. The *theory of fuzzy sets* describes variables in a range of values rather than as a single crisp value, thus enabling efficient description of unreliable and inaccurate data.

Electric voltage flicker depends on a collection of unpredictable operating and load conditions. When it occurs, it produces nonlinear behavior on the system voltage and frequency which is manifested as the voltage flicker. Moreover, any parametric model that strives to track voltage flicker is affected by inevitable sudden load conditions that are modeled as sudden varying random noise. In this section, the state space flicker model parameters Eq. (7) are estimated using the Kalman filter with white noises Eqs. (9-11). However, fuzzy rule-based logic is used to tune the level of the flicker model noises *Q(k)* and *G(k)*. No matter how much effort is applied to strive for an accurate flicker model, un-modeled factors or uncertainties exist, that affect the dynamics of the state model. Such factors are compensated for by introducing system and measurement white noises, *w(k)* and *v(k)*, respectively. However, these noises change in magnitude according to the variations in the power system conditions and load. Fuzzy logic is used to tune-up noises levels by adjusting the covariance matrices *Q(k)* and *G(k)*, respectively. The inputs of the fuzzy logic machine are the measurements of the flicker voltage $y_f(k)$ and its rate of change $\dot{y}_f(k)$. The outputs of the fuzzy machine are the diagonal elements of the covariance matrices *Q(k)* and *G(k)*.

4.1 Fuzzy Rule Based Logic

In the measurement equation of state model Eq. (7), $y_f(k)$ has a direct relation to $x_2(k)$ and $b_2(k)$. Therefore, sudden noises in $x_2(k)$ and $b_2(k)$ are compensated for using q_{22} and q_{22}, respectively. Moreover, the second state equation is relates $x_2(k+1)$ to $a_1(k)$ and $b_1(k)$. Hence q_{44}, q_{66} and q_{77} are use to adjust $a_1(k)$, $b_1(k)$, and $b_2(k)$, respectively. The fuzzy rules for tuning q_{ii}, i= 2, 4, 6 and 7, according to $|y_f(k)|$ are summarized in Fig. 2.

If ($|y_f(k)|$ is Small) then (q_{ii} is Small).
If ($|y_f(k)|$ is Medium) then (q_{ii} is Medium).
If ($|y_f(k)|$ is Large) then (q_{ii} is Large).

Fig. 2. Inference fuzzy rules for Covariance *Q(k)* affected by magnitude of flicker voltage.

Similarly, the rate of change of the flicker voltage, $\dot{y}_f(k)$, is related to $x_1(k)$. Thus, sudden noise in $x_1(k)$ is compensated for using q_{11}. The first state equation relates $x_1(k+1)$ with to $a_0(k)$ and $b_0(k)$. Hence q_{33} and q_{55} are use to adjust $a_0(k)$ and $b_0(k)$, respectively. The fuzzy rules for tuning q_{ii}, i= 1, 3 and 5, according to $|\dot{y}_f(k)|$ are summarized in Fig. 3.

If ($|\dot{y}_f(k)|$ is Small) then (q_{ii} is Small).
If ($|\dot{y}_f(k)|$ is Medium) then (q_{ii} is Medium).
If ($|\dot{y}_f(k)|$ is Large) then (q_{ii} is Large).

Fig. 3. Inference fuzzy rules for Covariance *Q(k)* affected by magnitude of rate of change of flicker voltage.

The covariance of the system states error *Q(k)* is increased according to the noise level of the flicker signal and its rate of change. Sudden peak level noise in measurement is compensated for using the measurement covariance matrix *G(k)*. The fuzzy rules for tuning g_{ii}, i= 1, 2, …, 9, according to $|y_f(k)|$ and $|\dot{y}_f(k)|$ are summarized in Table 1.

Table 1. Input-Output Fuzzy Logic Rules for g_{ii}.

		$\|\dot{y}_f(k)\|$		
		S	**M**	**L**
$\|y_f(k)\|$	**S**	VS	M	L
	M	S	L	L
	L	M	L	VL

The above rules are formed and reflect our experimental experiences with the voltage flicker waveforms and their noises. Typical voltage flicker envelopes such as the one presented in Fig. 1 show that there is a greater dependency of sudden noises on the rate of change of measured flicker waveforms than on the changes in the flicker voltage itself. Accordingly, the fuzzy rules of Table 1 are established emphasizing $|y_f(k)|$ over $|\dot{y}_f(k)|$.

4.2 Fuzzy Logic Inference Machine

Inference in the noise covariance is formed using a rule-based fuzzy logic inference machine Fig. 4 described below.

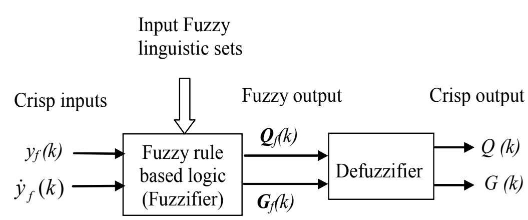

Fig. 4. Fuzzy Logic Inference Machine.

The fuzzy logic inference machine accepts fuzzified linguistic fuzzy variables as input. The two inputs are the voltage magnitude $|y_f(k)|$ (in p.u.) and the magnitude of its rate of change $|\dot{y}_f(k)|$. The outputs of the Fuzzifier are fuzzy covariance matrices $\boldsymbol{Q}_f(k)$, $\boldsymbol{G}_f(k)$ which have fuzzy linguistic variables on their diagonal according to the rules of Section 4.1. The fuzzy covariance matrices are fed to the Defuzzyfier which converts them to crisp covariance matrices that are used in the Kalman filtering parameter estimation.

4.2.1 Fuzzifier

Each input and output fuzzy linguistic variable belongs to a set of values that are represented by a triangular membership function in the range [0, 1], which corresponds to the degree to which the input belongs to the linguistic class. Input and output linguistic variables and their membership functions are defined in Fig. 5. The abbreviations in the Figures refer to: VS = Very Small, S = Small, M = Medium, L = Large and VL = Very Large.

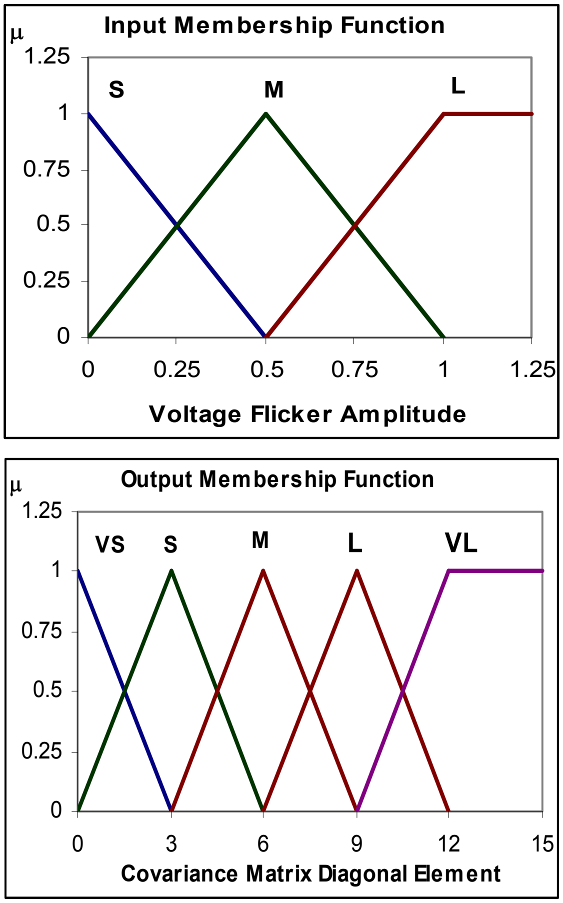

Fig. 5. Input and Output Membership Functions.

The max-min composition based on the Mamdani Implication Method of inference is used to implement the fuzzy rules. For a set of r disjunctive rules, the aggregated output membership function is given by:

$$\mu_{\underline{B}k}(q) = \max_{k}\ [\min\{\ \mu_{\underline{A_1 k}}(y_1),\ \mu_{\underline{A_2 k}}(y_2)\}],\quad i = 1, 2, \cdots, r \qquad (17)$$

where $\mu_{\underline{Bk}}, \mu_{\underline{Ak_1}}$ *and* $\mu_{\underline{A_2k}}$ are output, first input, second input membership functions, respectively; q, y_1 *and* y_2 are the output and first input, second input, respectively.

Applying Eq. (17) to the fuzzy rules in Table 1 is best illustrated by a simple graphical example. The two inputs are taken to be: $|y_f(k)| = 0.4$ p.u. and $|\dot{y}_f(k)| = 0.7$ p.u., as illustrated in Fig. 6. The first and second rows of Fig. 7 refer to the two inputs and their minimum (min) fuzzy output of Rule 2 and Rule 6, respectively. The last row shows the maximum (max) of the two (min) fuzzy outputs. The extension for more than two rules is straightforward as given by Eq. 17. Up to this point, it should be noted that the aggregate output membership function in Fig. 7 defines a set of values [3, 12] for the output, but it does not define the outputs crisp (center) value.

4.2.2 Defuzzifier

We next demonstrate the computation of the crisp output. After obtaining the output membership function using the max-min method, the output crisp (center) value is evaluated using the "defuzzification" process. Refer to Fig. 4. The centroid defuzzification method is used to convert the fuzzy output to a crisp one [14].

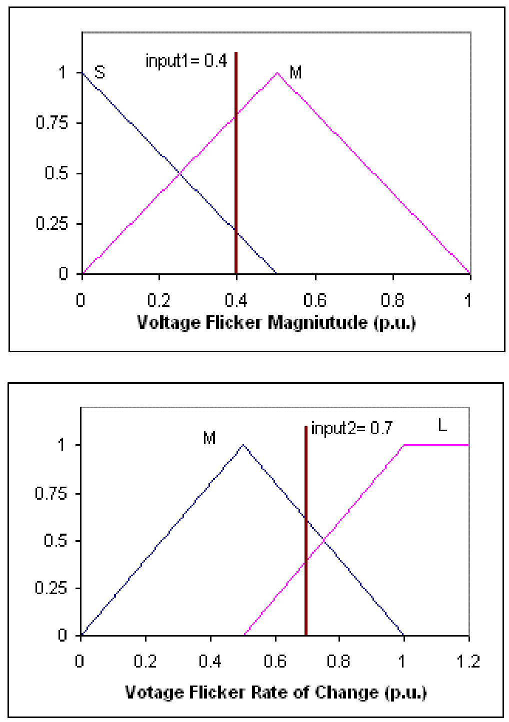

Fig. 6. Fuzzifier Inputs

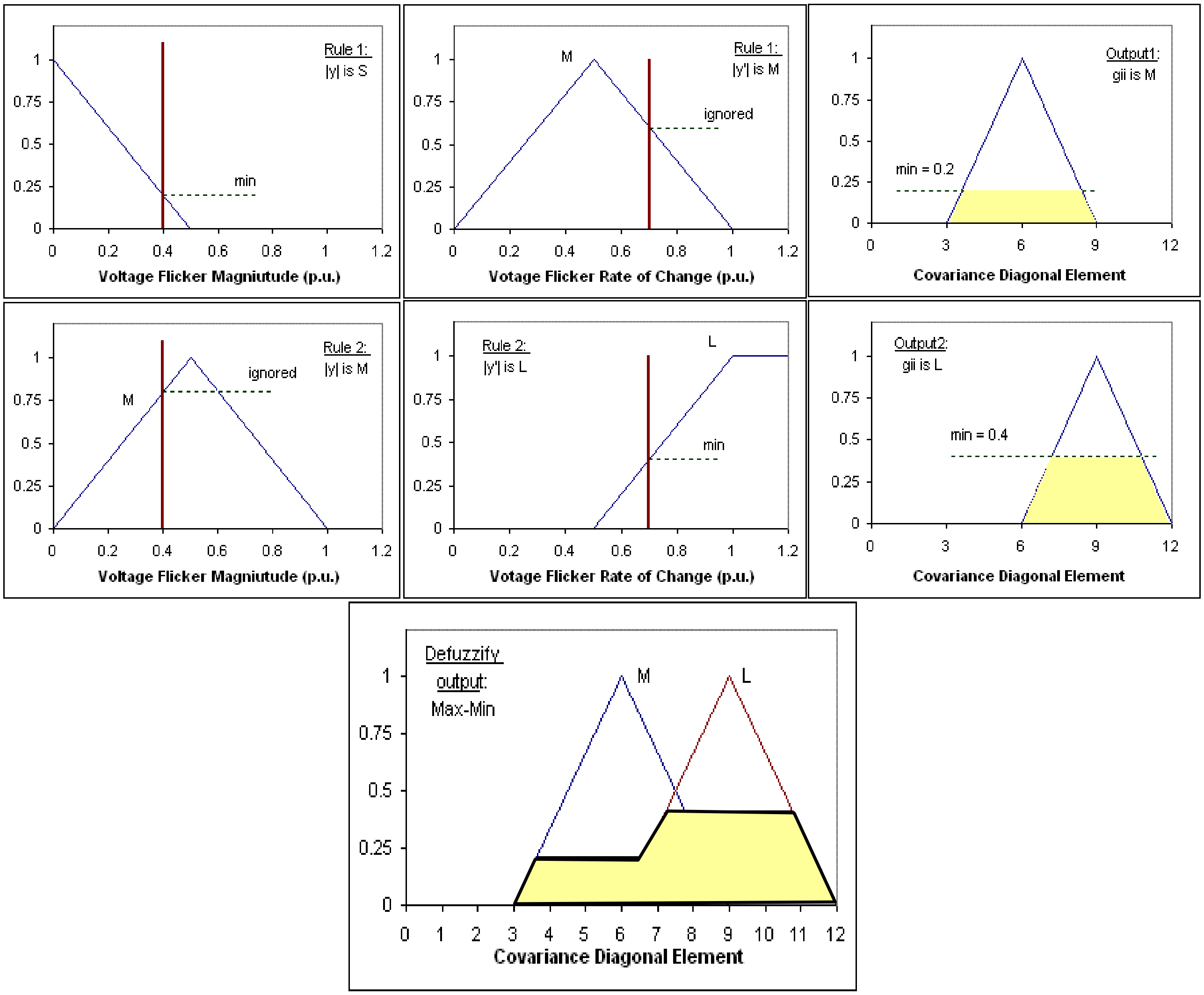

Fig. 7. Illustration of graphical (max-min) inference method.

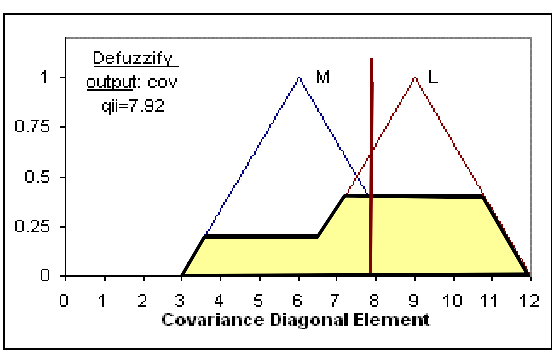

Fig. 8. Crisp value using the centroid defuzzification method.

To illustrate the point, the crisp value of the fuzzy output in Fig. 8 is the centroid (center of area) of the graph. The centroid is computed to be q_{ii} = 7.92 and illustrated in Fig. 8.

5. Testing Proposed Technique and Results

To illustrate the proposed flicker model of Section 2.1 and the fuzzy ruled-based Kalman filter technique of Section 4, we use a simulated flicker waveform Eq. (18) having a 50 Hz system frequency, a 240 volts amplitude, and a π/4 radians phase angle. The aforementioned parameters are known constant system parameters. The chosen modulating flicker signal has a 5 Hz frequency, a 10 volts amplitude and a π/6 (≈5.236) radians phase angle.

$$y_f(t) = 10\ \cos(2\pi(2.5) + \pi/6)] \qquad (18)$$

Table 2. Sample of the Kalman Filter Iterations for Parameter Estimation.							
k	**x1**	**x2**	**a0**	**a1**	**b0**	**b1**	**b2**
0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1	0.0000	-6.9920	0.0000	0.0000	0.0000	4.2768	4.3301
2	0.0000	12.7388	0.0000	1.6392	0.0000	5.4606	5.4714
3	-4.4179	5.6847	-0.6602	1.6164	-0.0762	5.8045	5.7790
4	-3.6996	4.2602	-0.6793	1.6167	0.0048	5.8076	5.7814
5	-2.8053	2.8264	-0.6897	1.6185	0.0433	5.6865	5.7034
6	-1.8133	1.3499	-0.7006	1.6225	0.0746	5.5630	5.6594
7	-0.7460	-0.1427	-0.7136	1.6305	0.1000	5.4978	5.6952
8	0.3818	-1.6230	-0.7295	1.6441	0.1160	5.5075	5.8117
9	1.5551	-3.0688	-0.7479	1.6643	0.1174	5.5828	5.9885
10	2.7487	-4.4612	-0.7670	1.6899	0.1006	5.7053	6.2008
11	3.9194	-5.7771	-0.7839	1.7173	0.0672	5.8563	6.4277
12	5.0102	-6.9802	-0.7961	1.7417	0.0252	6.0209	6.6544
13	5.9685	-8.0253	-0.8031	1.7600	-0.0157	6.1884	6.8714
14	6.7597	-8.8697	-0.8060	1.7718	-0.0490	6.3515	7.0731
15	7.3665	-9.4825	-0.8064	1.7783	-0.0725	6.5053	7.2564
16	7.7820	-9.8455	-0.8057	1.7812	-0.0872	6.6471	7.4199
17	8.0042	-9.9511	-0.8048	1.7823	-0.0948	6.7749	7.5632
18	8.0331	-9.8000	-0.8044	1.7824	-0.0973	6.8875	7.6861
19	7.8710	-9.3992	-0.8047	1.7824	-0.0961	6.9842	7.7891
20	7.5225	-8.7615	-0.8058	1.7827	-0.0924	7.0650	7.8730
…	…	…	…	…	…	…	…
555	-9.0115	9.6479	-0.9864	1.9617	-0.0055	7.7433	8.6289
556	-9.5283	9.9368	-0.9864	1.9617	-0.0055	7.7434	8.6290
557	-9.8105	9.9811	-0.9865	1.9617	-0.0055	7.7435	8.6291
558	-9.8510	9.7796	-0.9865	1.9617	-0.0055	7.7436	8.6292
559	-9.6489	9.3373	-0.9865	1.9617	-0.0055	7.7437	8.6293
560	-9.2093	8.6651	-0.9865	1.9617	-0.0055	7.7438	8.6294
…	…	…	…	…	…	…	…

The Kalman algorithm is used to estimate the three flicker signal parameters (A_f, f_f, and ω_f).

The state space model of Eq. (7) is used to estimate the parameters. Starting with zero initial conditions, a sample of the Kalman filter iterations is illustrated in Table 2. Figs. 9-11, illustrate the convergence of the system states and parameters. Table 3 contains the steady state values of the parameters. The estimated three flicker parameters (A_f, f_f, and ω_f) are computed as defined in Eq. (4) to be (9.984, 5.018, 0.521).

Table 3. Converged Parameters

a0	a1	b0	b1	b2
-0.9999	1.9752	-0.0001	-7.7729	8.6603

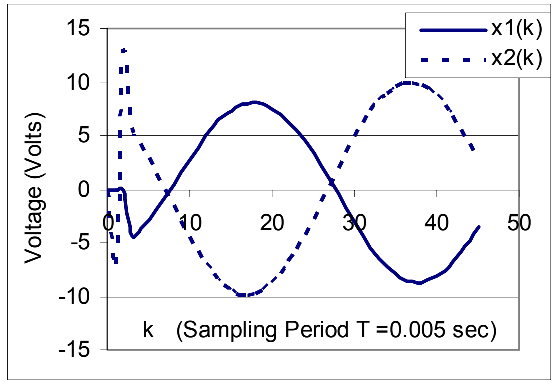

Fig. 9. Convergence of x_1 and x_2

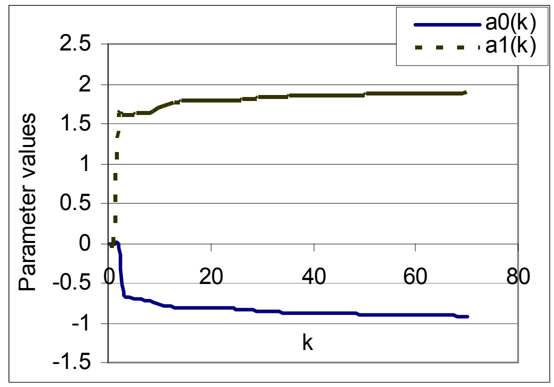

Fig. 10. Convergence of a_0 and a_1

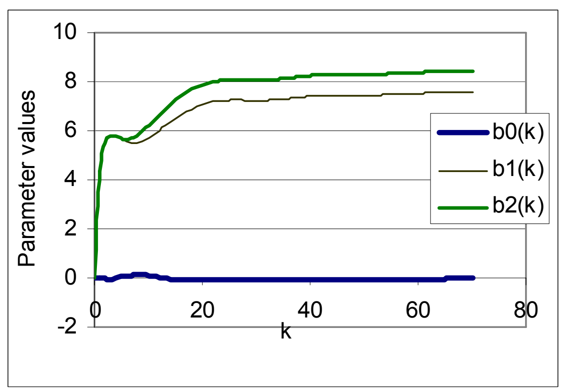

Fig. 11. Convergence of b_0, b_1 and b_2

6. Conclusion

The paper presented a new technique for tracking the voltage flicker envelope. The voltage flicker signal was modeled as a discrete time linear dynamic system with flicker voltage parameters. An extended state space model is adapted for the Kalman filter to estimate the parameters. Fuzzy rule-based logic is used to tune-up the system and measurement noise levels by adjusting their covariance matrices using flicker voltage and its rate of change measurements. The simulation results show the convergence of the estimated parameters using Kalman filter iterations. The resulted estimated parameters values are very close to the original values.

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