Time-varying Harmonic Synchrophasors Estimation based on Recursive Filtering Techniques

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***Abstract*—This paper aims to evaluate the effectiveness of different recursive filtering techniques in order to extract harmonic synchrophasors from PMU (Phasor Measurement Unit) input signals for real-time data processing considering time-varying aspects of the measurements. For the case studies, a PMU signal measured during a sustained sag is used in order to evaluate the performance of each recursive filter. From the results, it can be concluded that the estimation errors associated to the average filter indicates that it is not suitable for time-varying harmonic components estimation. The moving average and the low pass filter are capable of estimating harmonic components minimizing the difference between measured and filtered values. However, their effectiveness depends on the tuning of their parameters. The Kalman filter has the capability of reducing measurement noise and estimation errors, representing a viable solution for estimating time-varying harmonic synchrophasors.**

***Index Terms*—Power quality, data processing, time-varying harmonics, PMUs, voltage sags.**

I. Introduction

PMUs (Phasor Measurement Units) are devices which measure electrical waveforms at high sampling rates (more than 2880 samples per second for 60Hz systems) using a common time source for synchronization provided by Global Positioning System (GPS) [1]. The analogue alternating current waveforms are then digitalized by an analogue-to-digital (A/D) converter and the information collected from various PMUs installed in a power grid can be transmitted to local or remote receiver, also known as PDC (Phasor Data Concentrator) [2].

Once the PMUs are capable of measuring electrical waveforms, it is possible to analyse harmonic components from PMU measured data as deeply discussed by various literature references [1], [3]. Extracting harmonic components is often done by Fourier analysis using FFT (Fast Fourier Transform). It then becomes possible to get all the amplitude (magnitude) and phase of synchronized harmonic components, also known as harmonic synchrophasors. Despite of PMUs represent an important technology advance, their measurements are subject to noise, transients, voltage sags/swells, outliers due to discrete events such as tap changer operation, cyber attacks and instrument transformers [2].

The problems and measurements errors for frequencies higher than 60Hz are much more significant. There are hardware-induced errors, such as A/D converters and non-linearity of potential and current transformers, as well as their calibration, which must be according to their frequency response. Other type of data acquisition problems are software-induced errors when using windowed FFTs to calculate the harmonic components, such as aliasing, leakage phenomena and picket-fence effect [4]. As a consequence of so many errors sources, processing PMU data before using it in different applications is extremely important [2].

This paper presents some filtering techniques in order to minimize systematic (outliers) and aleatory errors caused by data acquisition problems and power system dynamics, considering the time-varying aspects of the measured signals.

The moving average, the first order low-pass and the Kalman filters are used to estimate harmonic components, minimizing the effect of the measurement errors. Measurements acquired by the Alstom/GE commercial PMU are used for the application of the recursive filtering methods. The methodologies are compared considering the estimation of the sampled data and time-varying harmonic distortions during a sustained sag occurred at a substation monitored by the PMU.

II. Harmonic Data Acquisition

The commercial device manufactured by Alstom/GE company consists of two modules: one for the remote data acquisition (RA-331), and measurement of voltage/current waveforms and another one for the data processing (RPV-312), where the FFT is finally computed after being processed by a 16-bit A/D converter. The signal is then sent to a personal computer, where the oscillography record can be evaluated by any dedicated software.

A measured distorted signal is evaluated for each harmonic component separately using FFT, being possible to extract their amplitudes and phases which varies along the time as represented by Fig.1.

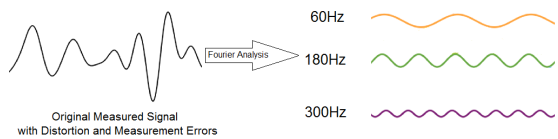


Figure 1: Fourier analysis.

A time-varying phasor measurement, $y(k)$ varying over time, k can be represented by the equation (1), in which Y_m^h is the magnitude of the signal for a given harmonic order h and θ^h is the phase angle of the synchrophasor in radians:

$$y(k) = \sum_{h=1}^{H_{max}} Y_m^h \, cos((2\pi h \ f_1)k + \theta^h) + \epsilon \qquad (1)$$

$$\epsilon \approx N(0, \sigma)$$

being H_{max} the maximum harmonic order considered for the study and ϵ is the measurement error with zero mean Gaussian Distribution with a correspondent covariance, σ,and f_1 is the fundamental frequency value in Hertz.

The sampling rate of the Alsom/GE equipment is 258 samples per cycle. It means that it is possible to evaluate until the 49^{th} harmonic order, according to IEC 61000-4-7:1991 standard. The equipment is also synchronized by GPS, considering the use of IRIG-B protocol and its PMU integrated function. If the device lose the IRIG-B synchronization, the measurements can be synchronized using NTP/SNTP protocol through Ethernet network. The equipment also has an internal clock in order to keep the synchronization and MODBUS and DNP3 interface for the integration with SCADA (Supervisory Control and Data acquisition) system.

III. Time-varying Harmonic Data Processing

For analysing time-varying harmonic synchrophasors, oscillography records can be evaluated by recursive digital filters for the real-time data processing, accompanying the dynamic changes of the monitored signals. The harmonic data processing is described by the flowchart in Fig. 2, according to the procedure described by [5].

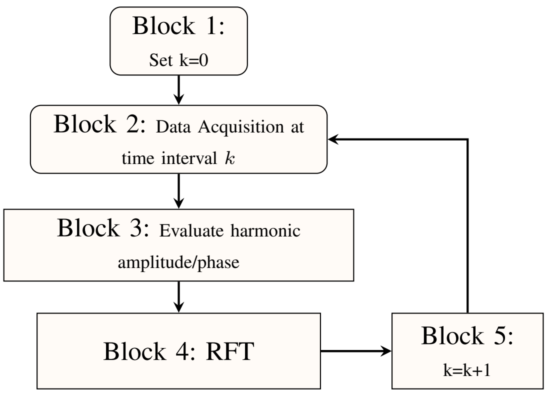


Figure 2: Data Acquisition System.

The waveform is captured by the equipments and the process initializes with $k = 0$, representing the first time interval in which the harmonic components is going to be evaluated (Block-1). Then, new data are acquired at time interval k (Block-2). In Block-3, the waveform with distortions and noise measurement is processed by the Fourier transform to get all the amplitude and phase of harmonic components at time interval k. Then, a recursive algorithm is used to estimate harmonics (Block-4) reducing the measurement errors. In Block-5, the algorithm considers the process for the next time interval to be evaluated ($k = k + 1$). Again, the waveform data is collected and processed. The process is continuously repeated for estimating harmonic components with accuracy, reducing the measurement errors by recursive filtering technique (RFT), accompanying the signal variations over time.

IV. The Recursive Filtering Techniques

Recursive filtering techniques are closed-loops efficient methods. They reuse one of more of its outputs at a given time interval k as an input for another time interval ($k = k + 1$) to predict/estimate a current value [6], resulting in an endless estimation process of current values based on previous calculations [7]. The recursive filters are used for eliminating measurement errors and also for accompanying power system dynamics as discussed in [7]. In this paper, some of the techniques are briefly discussed in this section before demonstrating its effectiveness on time-varying harmonic synchrophasors estimation.

A. The Average Filter

A given data set comprises $k-1$ samples $(y_1, y_2, ..., y_{k-1})$, being a k^{th} measurement obtained at a given time k. The average of all the data is calculated based on the equation (2):

$$\bar{y}_{k-1} = \frac{y_1 + y_2 + ...y_{k-1}}{k-1} \tag{2}$$

Considering a new data y_k being added to that data set, the new average value, $\bar{y}_k$ can be obtained based on the previous average calculated result, $\bar{y}_{k-1}$. Thus, the average filter expression is defined by equation (3):

$$\bar{y}_k = \frac{k-1}{k}\bar{y}_{k-1} + \frac{1}{k}y_k \tag{3}$$

The recursive expression (3) reuses previous results to calculate current ones. Then, the new average value, $\bar{y}_k$ can be obtained only with the number of samples k and with the average calculated at previous step, $\bar{y}_{k-1}$.

B. The Moving Average Filter

The moving average filter calculates an average value of a given number of recent measurements. Thus, the filter computes the average value of a given quantity by adding a new measurement while discarding the oldest data, maintaining n number of samples [7]. This consideration allows the representation of dynamic changes in electrical waveforms [8].

The moving average of n number of samples is obtained using the equation (4), considering the average value, $\bar{y}_{k-1}$ of only n samples from $k - n^{th}$ to $k - 1^{th}$ data:

$$\bar{y}_{k-1} = \frac{y_{k-n} + y_{k-n+1} + ...y_{k-1}}{n} \tag{4}$$

By rearranging the equation (4), the recursive expression for moving average filter can be expressed by the equation (5), which is formally the recursive expression of the filtering method:

$$\bar{y}_k = y_k + \frac{y_k - y_{k-n}}{n} \tag{5}$$

C. The 1^{st} Order Low Pass Filter

The moving average filter weights equally all samples in the data set [7]. In the 1^{st} order low-pass filter, the most recent acquired measurement data is weighted heaviest and the oldest one weighted lightest, leading to the recursive expression presented by equation (6):

$$\bar{y}_k = \alpha\bar{y}_{k-1} + (1-\alpha)y_k \tag{6}$$

where $\bar{y}_{k-1}$ is the previous average calculated value and $\bar{y}_k$ is the current average value and y_k is the most recent acquired data, being the constant α in the range of $0 \leq \alpha \leq 1$.

D. Traditional Kalman Filter

The following brief description of Kalman Filter (KF) is according to the modeling summarized in [2]. This recursive filter is a predictor-corrector algorithm. It means that after each time and measurement update, the filtering process continues with the previous $a\ posteriori$ estimates which are used for the projection of a new $a\ priori$ estimate. KF recursively conditions the current estimate based on all the past measurements. This feature makes the KF suitable for real-time applications such as harmonic monitoring systems.

The KF equations are formally defined for a linear discrete time process, in the expressions (7).

$$\begin{aligned} y_k &= Ay_{k-1} + w_k \\ z_k &= Hy_k + v_k \end{aligned} \tag{7}$$

being y the state (variable to be estimated) and z the measurement value.

A is the transition function relating the state at a previous time step $k-1$ to the state at current step k while the function H relates the state y_k to the measurements z_k. The noise w_k is associated to the estimation process and v_k is the measurement noise. They are independent random variables with normal distributions according to equation (8), being Q the process noise covariance and R the covariance of the measurement noise:

$$\begin{aligned} p(w) &\approx N(0,Q) \\ p(v) &\approx N(0,R) \end{aligned} \tag{8}$$

The Kalman Filter is subdivided into two main steps:

1) Prediction Step: The time update equations projects forward in time the previous state $\hat{y}_{k-1}$ and the error covariance P_{k-1}, $a\ priori$(predicted) state estimates $\hat{y}_k^-$ and the $a\ priori$ error covariance P_k^- for the next time interval to be analysed k (equations (9)):

$$\begin{aligned} \hat{y}_k^- &= A\hat{y}_{k-1} \\ P_k^- &= AP_{k-1}A^T + Q \end{aligned} \tag{9}$$

2) Correction Step: A feedback is made by measurement update equations when incorporating a new measurement z_k into the $a\ priori$ estimate to compute an improved $a\ posteriori$ estimate, as in equations (10):

$$\begin{aligned} K_k &= P_k^- H^T(HP_k^- H^T + R)^{-1} \\ \hat{y}_k &= \hat{y}_k^- + K_t(z_k - H\hat{y}_k^-) \\ P_k &= (1 - K_k H)P_k^- \end{aligned} \tag{10}$$

where the variable K is the Kalman gain, z_k is the actual measurement at time k, $H\hat{y}_k^-$ is the predicted measurement, $\hat{y}_k$ is the $a\ posteriori$ estimate, determined by a linear combination of an $a\ priori$ estimate $\hat{y}_k^-$ and a difference between the actual measurement and the predicted one, weighted by the Kalman gain, K_k.

V. Case Studies and Results

For the case studies, a real oscillography record is used. Phasor measurements was obtained by a PMU signal measured at a substation when a sustained sag occurred in a 138 kV transmission line monitored by the Alsom/GE equipments (RPV-311 and RA-331) at a sampling frequency of 256 samples per second. The sustained temporary sag duration is approximately 130 milliseconds (8 cycles of 60Hz), according to Fig.3:

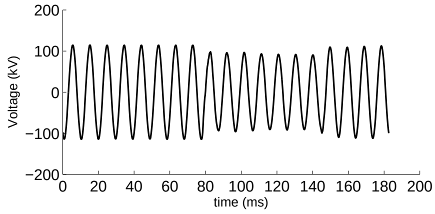


Figure 3: Measured voltage waveform

The resulting current values are also measured, and high current values are observed during the sag, represented in Fig.4. This oscillography record will be used as a reference for the following tests using the recursive filtering techniques. Before applying the filters into the current waveforms, each harmonic component (magnitude and phase) is evaluated individually by Fourier analysis, following the steps described in Fig.2 (flowchart of the general algorithm).

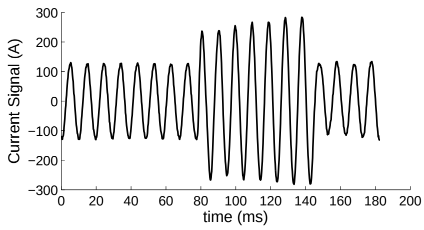


Figure 4: Measured current waveform

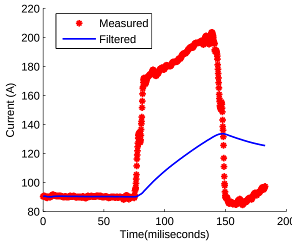
The results are discussed for each recursive filtering method, highlighting the advantages/disadvantages of using the digital filter under analysis for increasing the harmonic synchrophasor data accuracy. At each subsection, different parameters tuning are used for each computational test and filtering methodology.

A random noise of 5% of the measurement value is added to the measurements simulating a strong effect of aleatory errors as discussed in introduction section. The simulation of this aleatory errors has the purpose of validating the proposed recursive filtering methods considering strong external interference on the measurements acquired by the PMUs. In practical situations these errors can be generated by many sources either by software or hardware induced errors.

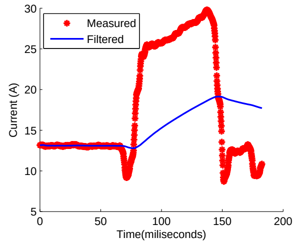
A. Results using Average Filter (AF)

Using the recursive expression in Equation (3), the average filter is computationally implemented as new current measurement is being acquired along the time and inserted into the data set. In Fig. 5, the amplitude of the signal for 60Hz, 180Hz and 300Hz ($1^{st}, 3^{rd}$ and 5^{th} harmonic orders, respectively) are estimated.

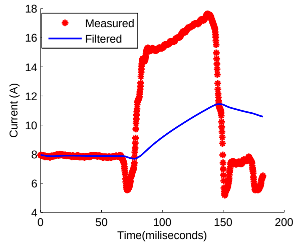
By the graphic results, it is already possible to conclude that the average filter is not a good option to filter the PMU measured signals, because the average filter is not capable of accompanying the dynamic of the signal. Thus, the time-varying aspect is not well estimated. In Table I, the



(a) 60Hz.



(b) 180Hz.



(c) 300Hz.

Figure 5: Harmonic Current Estimation by Average Filter.

normalized root means square error given in percentage values and associated to the difference between the filtered values and the actual ones are presented. The errors associated to the estimation/filtering process are all higher than 30%. As a conclusion, the average filter is not really an option for filtering PMU-measured data.

Table I: Errors for time k=180 ms using AF.

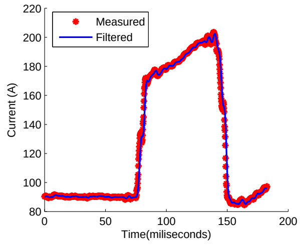
h	*Quantity*	*Actual*	*Filtered*	*Error (%)*
1	Y_m^1 *(A)*	97.0441	125.4150	29.2351
1	θ^1 $(^o)$	138.97	130.76	3.82
3	Y_m^3 *(A)*	10.7828	17.7172	64.3101
3	θ^3 $(^o)$	70.22	61.73	5.51
5	Y_m^5 *(A)*	6.4735	10.5801	63.4379
5	θ^5 $(^o)$	178.04	171.91	7.04

B. Results using Moving Average Filter

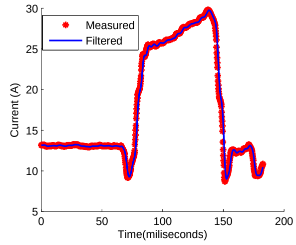
Using the equation (5), the filter is implemented. The tuning of the parameter n is very important for the effectiveness of the algorithm. This test considers $n = 10$ for using the recursive filter. For $n = 10$, harmonic currents amplitude are estimated as illustrated in Fig. 6 while in Fig. 7 results are presented for $n = 50$.

In Table II, the results are presented for the harmonic phasor measurements considering $n = 10$, and the difference between the actual values (amplitude/phase) is compared showing the percentage error between the actual and filtered results by the normalized root mean square error given in percentage value. In Table III, the results are presented for $n = 50$.

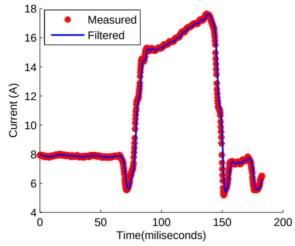
The more the number of samples n to get an average, the better the performance of the algorithm is. However, time delay is introduced when using $n = 50$ which makes variations of the data not being projected immediately [7]. On the other hand, with less number of samples, variations in the data is



(a) 60Hz.

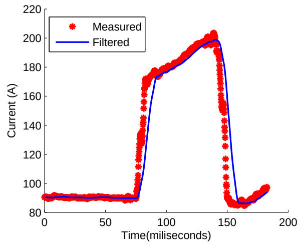


(b) 180Hz.

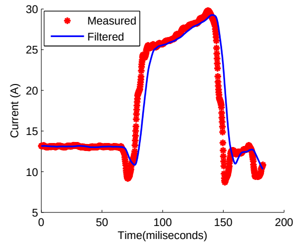


(c) 300Hz.

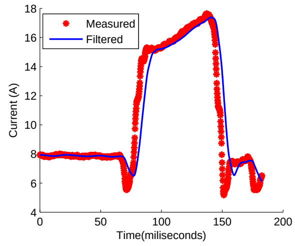
Figure 6: Harmonic Current Amplitude Estimation using $n = 10$.



(a) 60Hz.



(b) 180Hz.



(c) 300Hz.

Figure 7: Harmonic Current Amplitude Estimation using $n = 50$.

Table II: Errors for time k=180 ms for $n = 10$

h	*Quantity*	*Actual*	*Filtered*	*Error (%)*
1	Y_m^1 *(A)*	97.0441	93.7176	3.4230
1	θ^1 $(^o)$	138.97	137.76	0.89
3	Y_m^3 *(A)*	10.7828	10.3534	3.98
3	θ^3 $(^o)$	70.22	69.73	0.71
5	Y_m^5 *(A)*	6.4735	6.1413	5.1311
5	θ^5 $(^o)$	178.04	177.97	0.04

projected well but performance of noise reduction is poor, meaning that the percentage error is higher when $n = 10$.

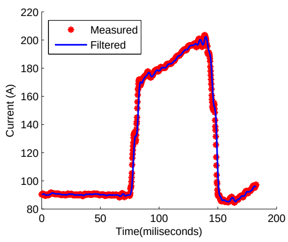
C. Results using Low-Pass Filter

The first order low pass filter is determined by applying equation (6) into the data acquisition for the current signals.

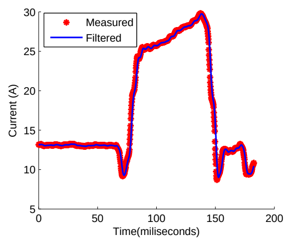
Table III: Errors for time k=180 ms for $n = 50$

h	*Quantity*	*Actual*	*Filtered*	*Error (%)*
1	Y_m^1 *(A)*	97.0441	96.0116	1.0640
1	θ^1 *(^{o})*	138.97	137.79	0.82
3	Y_m^3 *(A)*	10.7828	10.3534	3.9821
3	θ^3 *(^{o})*	70.22	69.70	0.69
5	Y_m^5 *(A)*	6.4735	6.2073	4.1113
5	θ^5 *(^{o})*	178.04	177.99	0.02

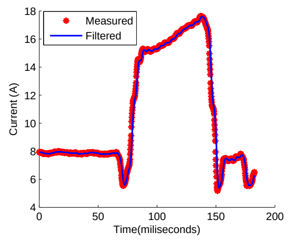
Results for the harmonic current amplitude for $\alpha = 0.7$ is illustrated by Figure 8.



(a) 60Hz.

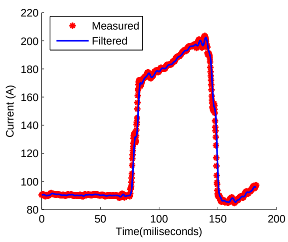


(b) 180Hz.

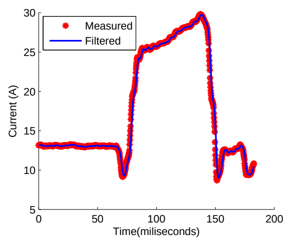


(c) 300Hz.

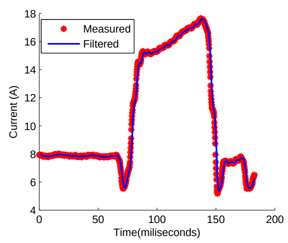
Figure 8: Harmonic Current Amplitude Estimation using $\alpha = 0.7$.



(a) 60Hz.



(b) 180Hz.



(c) 300Hz.

Figure 9: Harmonic Current Amplitude Estimation using $\alpha = 0.9$.

In order to contrast and compare the effectiveness for these two situations $\alpha = 0.7$ and $\alpha = 0.9$, Tables IV and V present results for the harmonic phasor measurements and the error between the actual and filtered (estimated) value at $k = 180$.

Table IV: Errors for time k=180 ms and $\alpha = 0.7$

h	*Quantity*	*Actual*	*Filtered*	*Error (%)*
1	Y_m^1 *(A)*	97.0441	95.5818	1.5069
1	θ^1 *(^{o})*	138.97	137.77	0.90
3	Y_m^3 *(A)*	10.7828	10.1774	5.6148
3	θ^3 *(^{o})*	70.22	69.79	0.70
5	Y_m^5 *(A)*	6.4735	6.0846	6.0075
5	θ^5 *(^{o})*	178.04	177.98	0.04

Table V: Errors for time k=180 ms and $\alpha = 0.9$

h	*Quantity*	*Actual*	*Filtered*	*Error (%)*
1	Y_m^1 *(A)*	97.0441	96.3485	0.7168
1	θ^1 *(^{o})*	138.97	137.76	0.89
3	Y_m^3 *(A)*	10.7828	10.5801	1.8795
3	θ^3 *(^{o})*	70.22	69.73	0.71
5	Y_m^5 *(A)*	6.4735	6.3493	1.9181
5	θ^5 *(^{o})*	178.04	177.97	0.04

The filter is more sensitive to the variation of measured data than moving average filter. Therefore, weighting for measurement increases in computation of the estimate. for $\alpha = 0.7$, the low-pass filter becomes more sensitive to the variation of measurement rather than noise filtering. This is the reason why there was more error in the estimate for this case. In contrast, when α is equal to 0.9, the error is reduced but variation tracking becomes slower.

D. Results using Kalman Filter

It is considered a simple case of traditional Kalman Filter. Considering the expressions in equation (7), the following statements are considered:

1) The state to be estimated is the quantity value to be filtered (amplitude/phase of each harmonic order) as considered for the other types of recursive filters;
2) The function H which relates state to measurement is set equal to 1, because the quantity to be estimated is the same type of measured quantity;
3) Considering the steady-state of the power systems, the value for A is set equal to 1 (there are no significant variation between the previous estimate value and the current ones).

Summing up, the following parameters A, H, Q, R which represent the system model are considered as:

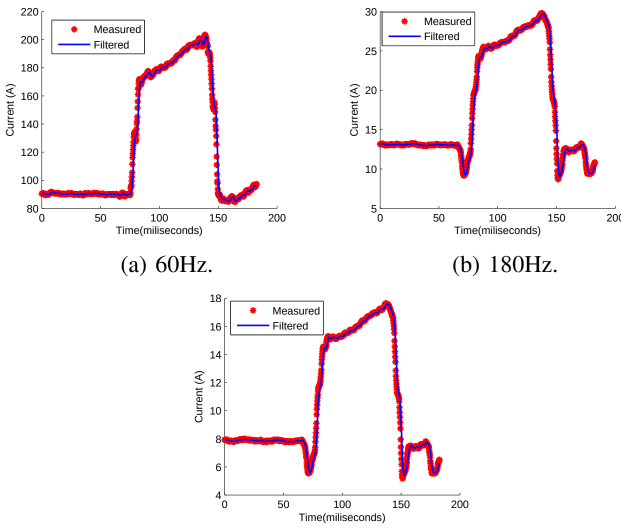
$$\begin{aligned} A &= 1 \\ H &= 1 \\ Q &= 0.001 \\ R &= 0.05 \end{aligned} \tag{11}$$

Note that the covariance $Q = 0.001$ means that there is w_k (process noise) being considered as 0.1%. In various case studies, it is common to set $Q \approx 0$ for steady-state estimation and $Q \approx 1$ considering the estimation of transients [10].

A random noise of 5% of the measurement is considered for the measured values: $R = 0.05$.

The next step is to set the initial estimate. If any information about the initial condition is considered it is important to set a large *a priori* covariance associated to the initial value. For the simulations for the harmonic components parameters, it is considered the initial values are: $\hat{x}_0^-$=0 for current amplitudes and $\hat{x}_0^- = 0^o$ for current phase angles once there are no information about the initial values. The covariances are set equal to 10%: $P_0^- = 0.1$ for both current amplitudes and phase angles.

In Figure 10, the estimation results for current amplitude can be observed when using KF.



(a) 60Hz. (b) 180Hz. (c) 300Hz.

Figure 10: Harmonic Current Amplitude Estimation using KF.

It is clear that the initial values can be set according to the knowledge of the measurements or by previous measured data. However, even considering an extreme initial condition, setting all the parameters equal to zero the Kalman filter is capable of filtering the measurement errors. It shows efficiency for providing harmonic phasor measurements with high accuracy.

Results for KF with $Q = 0.001$ are shown in Table VI:

Table VI: Errors for time k=180 ms with Q=0.001

h	*Quantity*	*Actual*	*Filtered*	*Error (%)*
1	Y_m^1 (A)	97.0441	95.5814	1.5058
1	θ^1 (^{o})	138.97	137.70	0.8000
3	Y_m^3 (A)	10.7828	10.1770	5.6141
3	θ^3 (^{o})	70.22	69.71	0.7000
5	Y_m^5 (A)	6.4735	6.0842	6.0071
5	θ^5 (^{o})	178.04	177.97	0.0400

Considering parameter $Q = 0.1$ for the process noise, Table VII present some results. The Q covariance value associated to the process noise can influence the results as cited by literature [10]. Once the voltage sag is a power quality disturbance much more transient than steady-state, the more Q approaches 1, the better the performance of KF is.

Table VII: Errors for time k=180 ms with Q=0.1

h	*Quantity*	*Actual*	*Filtered*	*Error (%)*
1	Y_m^1 (A)	97.0441	97.0438	0.0001
1	θ^1 (^{o})	138.97	138.94	0.020
3	Y_m^3 (A)	10.7828	10.7830	0.020
3	θ^3 (^{o})	70.22	70.27	0.710
5	Y_m^5 (A)	6.4735	6.4633	0.018
5	θ^5 (^{o})	178.04	178.14	0.040

VI. Conclusions

In this paper, different recursive algorithms were considered for a comparative analysis. The average filter does not accompany the dynamic changes of the monitored signals, not being a viable solution for time-varying harmonic components estimation.

The moving average and the low-pass filters are able to filter measurement noise and estimating the harmonic components. However, their parameters tuning influences in the filtering process which can be more or less noisy according to the number of samples used to compute the estimated value and the α parameter, respectively. The difference between the measured and the filtered values are also very sensitive to their parameters tuning.

Kalman Filter is the most robust algorithm to be implemented computationally. However, their results are superior to the other recursive filters once this algorithm is capable of minimizing the covariance value associated to the filtered values, besides increasing the accuracy of the estimation results and tracking harmonic currents.

Once the phasor measurements cannot be directly fed to an application without adequate data processing, the considered filtering techniques represents a viable solution for minimizing harmonic measurement errors in real time.

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