

We are IntechOpen, the world's leading publisher of Open Access books Built by scientists, for scientists

4,800

Open access books available

122,000

International authors and editors

135M

Downloads

Our authors are among the

154

Countries delivered to

TOP 1%

most cited scientists

12.2%

Contributors from top 500 universities



WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index
in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com



Estimation of Electrical Power Quantities by Means of Kalman Filtering

Alberto Pigazo and Víctor M. Moreno
*University of Cantabria
Spain*

1. Introduction

The presence of non-linear loads and the increasing number of distributed generation power systems (DGPS) in electrical grids contribute to change the characteristics of voltage and current waveforms in power systems, which differ from pure sinusoidal constant amplitude signals. Under these conditions advanced signal processing techniques are required for accurate measurement of electrical power quantities. The impact of non-linear loads in electrical power systems has been increasing during the last decades. Such electrical loads, which introduce non-sinusoidal current consumption patterns (current harmonics), can be found in rectification front-ends in motor drives, electronic ballasts for discharge lamps, personal computers or electrical appliances. Current harmonics reduce the efficiency of low and medium voltage electrical grids (Dugan et al., 2003). It must be also considered that renewable energy sources in electrical grids can also deteriorate the electrical power quality. For instance, wind turbines can introduce flickering (Larson, 2000) and PV systems, due to solar radiance variations, generate variable output power. Moreover, such resources, especially in low-voltage systems, change their status (grid connection or disconnection) continuously, contributing to the electrical system instability.

Diverse approaches can be applied to characterize electrical signal waveforms in real-time: windowed or recursive Fourier transforms, wavelets, artificial neural networks (ANN) (Bollen & Gu, 2006). Kalman filtering can be applied to estimate electrical quantities in power systems, such as voltage and/or current magnitude, grid balance and/or frequency. The obtained signal measurements can be employed for revenue purposes, electrical grid characterization and/or active compensation of power system disturbances. This chapter is focused on Kalman filtering based approaches for estimation of electrical power quantities, such as voltage amplitude, current harmonics amplitude or grid frequency, under sinusoidal, non-sinusoidal, balanced or unbalanced conditions. Moreover, steady-state signals and transients in power systems are also analysed.

The second section in this chapter describes the characteristics of power quality disturbances in electrical grids, considering time and frequency domains. The following section reviews the applications of Kalman filters in electrical power systems. The fundamentals of Kalman and extended Kalman filtering techniques for estimation of power system signal waveforms are given in the fourth section. The implementations of Kalman filtering loops in MatLab/Simulink, as well as a new signal model for frequency estimation, are also given in this section. Section five will give the obtained simulation results under diverse conditions of the electrical grid. Finally, the conclusions of this chapter are shown.

Source: Kalman Filter: Recent Advances and Applications, Book edited by: Victor M. Moreno and Alberto Pigazo, ISBN 978-953-307-000-1, pp. 584, April 2009, I-Tech, Vienna, Austria

2. Power quality disturbances in electrical power systems

Electrical power networks integrate generation and distribution systems and electrical loads. Due to the environmental issues related to conventional generation systems, such as coal or nuclear plants, and the rising price of fossil fuels renewable energy sources, such as wind or photovoltaic generation systems, are becoming more and more interesting. In case of the European Union, the target is 20% of generation from renewable energy sources by 2020. Electrical loads are also being changed due to the impact of power electronics, which allow the efficiency, reliability and controllability to be increased at low cost. This is the case of electrical machines which are connected to the electrical grid through electronic power converters or switched power supplies in computers.

Due to this scenario, the waveforms of voltage and current signals in electrical grids present multiple disturbances which can reduce the efficiency and reliability of electrical systems. In order to manage the electrical grids such disturbances must be properly measured and their impact evaluated. Generally speaking, the electrical disturbances can arrive to a certain customer, maybe due to a fault (Fig. 1.a), or can be produced by a customer (Fig. 1.b). In the most general case, measurement equipments must consider both possibilities and their interaction (Fig. 1.c). Fig. 1.a shows a passive load connected to the electrical grid and a sudden variation of the voltage magnitude which, due to the passive load impedance, is translated to the current waveform. The effect of a distorting load is shown in Fig 1.b. As it can be seen, the electrical load contains a full-bridge diode rectifier with a capacitive dc side which produce current peaks at the grid side. Due to the impedance of distribution lines, such current pattern will distort the pure sinusoidal grid voltage. Finally, Fig. 1.c shows a more general case where a fault appears changing the current pattern of the non-linear load. According to (Bollen & Gu, 2006), power quality disturbances can be classified as variations and events. Variations are defined as *steady-state or quasi-steady-state disturbances that require continuous measurement* while events correspond to *sudden disturbances with a beginning and an ending* (time bounded disturbances). Frequency and voltage magnitude variations, unbalances, voltage fluctuations as well as waveform distortion (harmonics and interharmonics) are included in the first group while interruptions, voltage dips/swells and transients can be grouped as events.

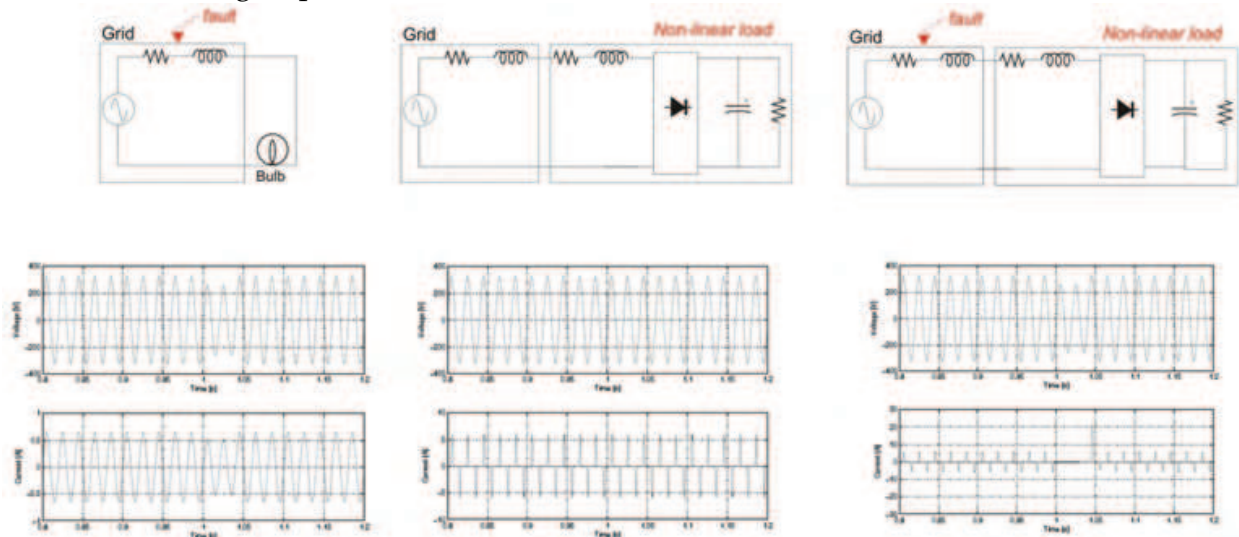


Fig. 1. Disturbances. a) From the electrical grid, b) from the load and c) both.

Frequency variations are due to active power mismatches between generators and electrical loads. A power-frequency control strategy is needed in order to maintain the fundamental frequency of the electrical grid. The frequency variations measured at the School of Nautical Studies, University of Cantabria, Santander, by means of Dranetz PowerPlatform1 are shown in Fig. 2.a. As it can be seen, the average value of the measured frequency is 50 Hz and the measured values variate between 49.93 Hz and 50.07 Hz continuously. According to IEC-61000-2-2 standard, the allowable frequency variations must be in range ± 1 Hz. Voltage magnitude variations cause problems to sensitive electrical loads, such as electronic devices. Fig 2.b shows magnitude variations in a three-phase power system. The average measured value of voltage in phase A is 232.40 Vrms. Maximum and minimum values are 243.15 Vrms and 222.39 Vrms respectively. Such magnitude variations are limited by IEC-61000-2-2 to a 3% of the nominal voltage. Voltage unbalances are also classified as variations and they are due to unbalanced loads, such as single-phase electrical loads connected to three-phase systems, or unbalanced system impedances. They can reduce the efficiency of rotating machines and produce erroneous firing angles in controlled rectifiers. Standard IEC-61000-2-2 allows 2% inverse sequences during unbalanced conditions.

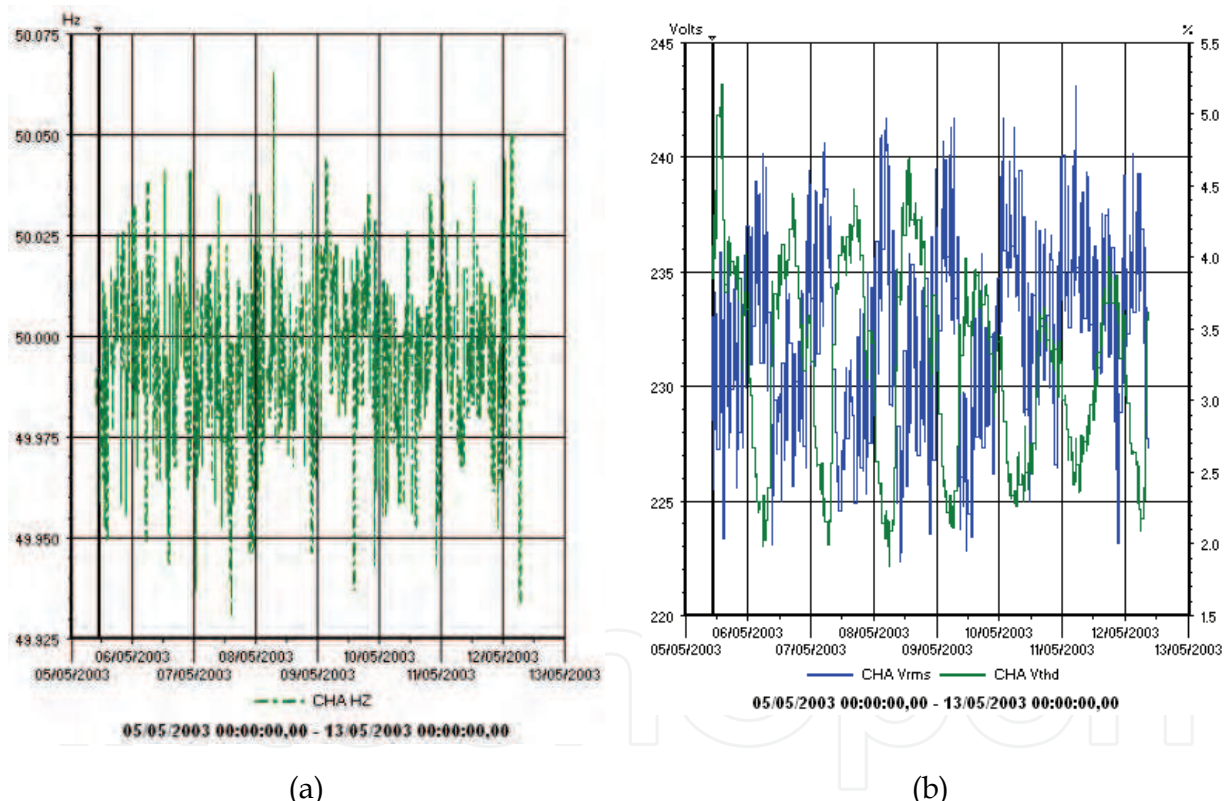


Fig. 2. a) Frequency and b) voltage magnitude variations measured at the School of Nautical Studies, Santander, Spain.

Voltage fluctuations, shown in fig. 3.a, denote fast changes in the voltage magnitude which can be produced by repetitive current changes, such as continuous starts and stops in air conditioning or heating systems, or fast current variations. They can generate braking or accelerating moments for electrical motors or light flickering. The short and long term allowable flickers are 1 and 0.8 respectively according to standard IEC-61000-2-2. Waveform distortions are due to non-linear elements in electrical power systems. This is the case of

grid-connected power converters or fluorescent lighting. Fig. 3.b shows the evolution of per-phase and neutral currents during the afternoon and night at the Economics Faculty, University of Cantabria, Santander, Spain. As it can be seen, depending on the daily power consumption, the current magnitude and its spectral distribution change. Fig. 3.c shows the spectral distribution of the phase-current, which presents a 47.32% Total Harmonic Distortion (THD). The voltage THD and the magnitude of individual voltage harmonics are limited in standard IEC-61000-2-2. Current harmonics can cause extra losses in transformers, neutral cable overheating in three-phase four-wire electrical systems and resonances in capacitor banks.

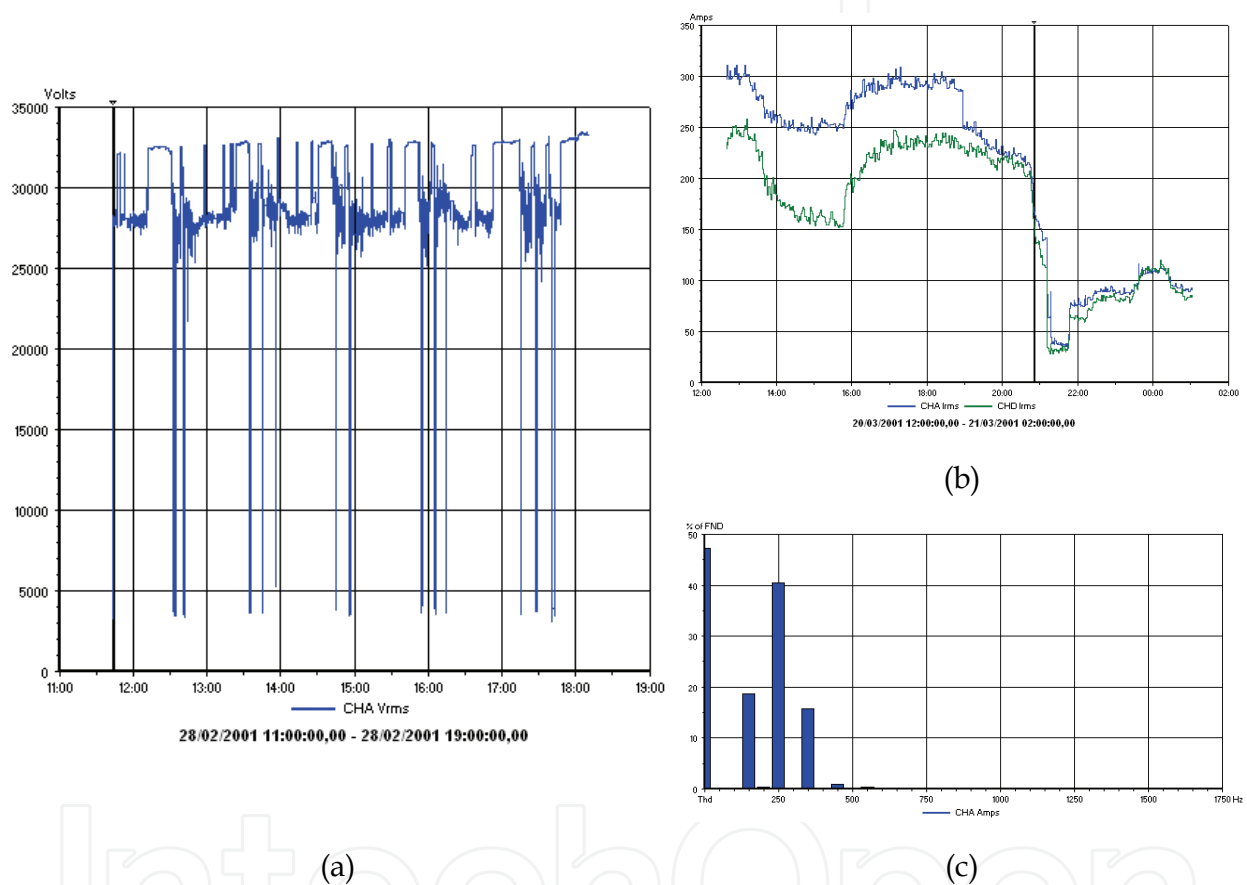


Fig. 3. a) Measured voltage fluctuations at the point of connection of an arc furnace. b) Per-phase and neutral current magnitudes (rms) and c) harmonic distribution of the phase current.

Short and long interruptions (fig. 4.a) occur when one or more customers are disconnected from the electrical grid and the voltage magnitude falls to zero or close to zero. They are produced by short circuits, earth faults, inadvertent operation of circuit breakers or intentional disconnection due to maintenance tasks. The consequences depend on the edge. Falling transients can cause electrical equipment malfunction while rising transients can cause transformers saturation or protections tripping in case of high start-up currents. Voltage transients (fig. 4.b) can be due to lightning or switching transients and can cause voltage dips or interruptions as well as voltage magnification, in case of switch on transients in capacitors, or restrikes during capacitors or inductances de-energizing.

Voltage magnitude reductions with short duration, typically less than one second, can be considered as voltage dips (fig. 5). They are produced by short circuits, earth faults, starting of induction motors or energizing of transformers and can cause undervoltages at the dc-bus of uncontrolled rectifiers.

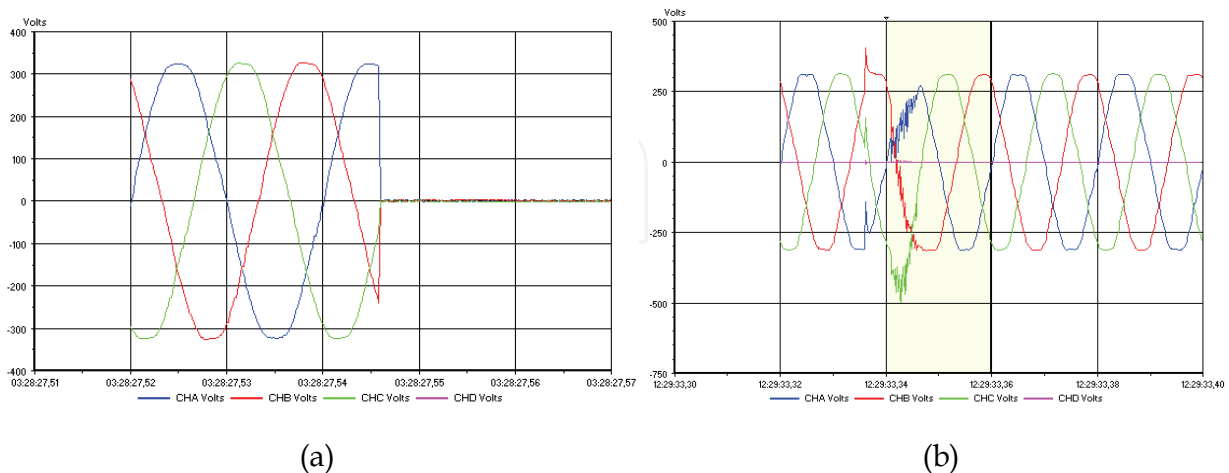


Fig. 4. a) Interruption, with a 1.018 s length, and b) voltage transient measured at the School of Nautical Studies, Santander, Spain.

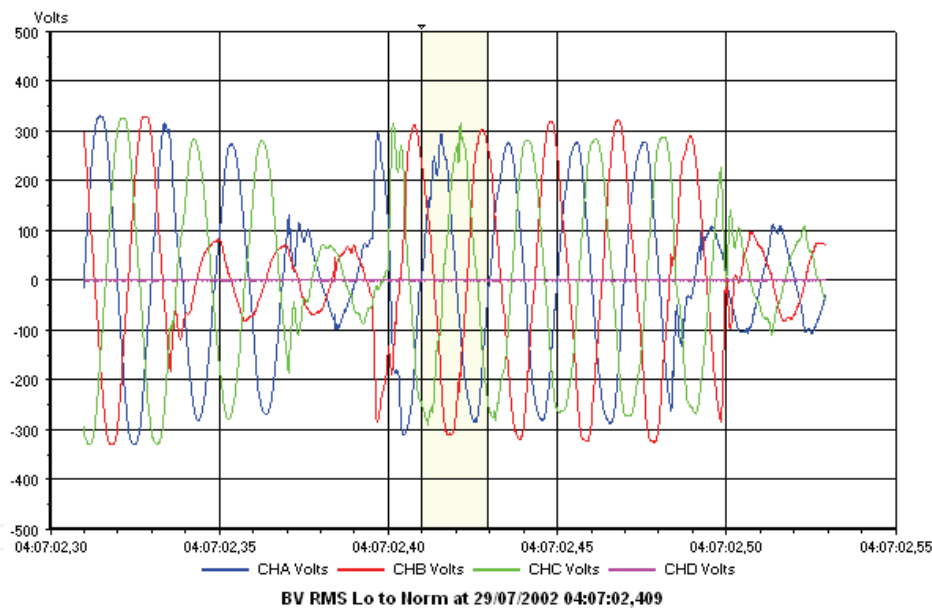


Fig. 5. Voltage dip measured at the School of Nautical Studies, Santander, Spain.

3. Application of Kalman filters to electrical power systems

An overview of the main power system disturbances has been given in the previous section. Once the importance of accurate measurements of the electrical power quantities has been established, this section is devoted to review previous works on Kalman filtering for estimation of frequency, amplitude and/or spectra of voltage and current signals in electrical power systems.

The fundamental frequency of the electrical power system can be accurately estimated for grid management purposes by means of Kalman filters. Firstly proposed in (Girgis & Hwang, 1984), an extended Kalman filter (EKF) is applied to a signal model composed by

three state variables which only considers the fundamental component (grid frequency, in-phase and in-quadrature components). (Dash et al., 1999) considers a three-phase configuration by means of a complex signal model; again, voltage harmonics are not modelled. In order to reduce the response time of the Kalman filter, (Dash et al., 2000) proposed to include a hysteresis method for resetting the covariance matrix after a signal transient. A new signal model, which considers three consecutive points of a pure sinusoidal signal, is applied to an EKF in (Routray et al., 2002). The effect of grid voltage harmonics is considered in (Aghazadeh et al., 2005) by including two state variables per modelled signal harmonic. In this case, a fixed axes signal model is proposed. The computational burden associated to EKFs can be reduced, as proposed in (Zhang et al., 2007), by means of an unscented Kalman filter (UKF) which avoids the computation of Jacobian matrices. A predictive frequency estimation algorithm, which models the frequency considering the slope and the previous estimation, is shown in (Adanir, 2007). In order to evaluate the frequency components of a certain power signal, an accurate measurement of the fundamental grid frequency is required. (Shaw & Laughman, 2007) proposed a signal model which considers zero crossings of the voltage signal and the number of samples between two zero crossings. Harmonics in voltage and current signals can be tracked by means of linear Kalman filters. The harmonics are modelled, considering stationary and rotating reference frames, in (Girgis et al., 1991). Two state variables are required per modelled harmonic (Beides & Heydt, 1991). A rotating reference frame model is employed in (Ma & Girgis, 1996), discussing the optimal location of the harmonic meters. The computational burden of the KF can be reduced by storing the pre-calculated filter gains (Moreno & Barros, 1997). (Al-Hamadi & Soliman, 2002) proposed a fuzzy signal model for linear Kalman filters in order to detect harmonic components. A complex linear model for harmonics estimation, which reduces the number of required state variables, is introduced in (Pradhan et al., 2004). Continuous and discrete approaches for harmonic identification are compared in (Alcaraz et al., 2006). Extended Kalman filters, as proposed in (Kumar et al., 2006), can be applied to a certain power system bus in order to measure active and reactive powers. (Yu et al., 2005) analyses the dynamical response of Kalman filters during power system transients and proposes an Adaptive Kalman filter in order to improve the performance of the estimation process. In case of (Macías & Exposito, 2006), such problem is solved by applying a self-tuning algorithm to the covariance matrix. As it is shown in (Moreno et al., 2007), the frequency resolution of Kalman filters for tracking of power system harmonics can be adjusted by a proper selection of the signal model frequencies. Power system unbalances can be also detected by applying Kalman filters. (Rosolowski & Michalik, 1994) proposed a stationary reference frame signal model in order to track Clarke transformation components. (Soliman & El-Hawary, 1996) extended this analysis by considering the effects of the frequency drift and the sampling frequency. (Pigazo & Moreno, 2008) proposed a rotating reference frame signal model for unbalances identification which allowed Park transformation components to be estimated directly. Previously paragraphs in this section were centred on variations. Voltage dips caused by power system faults can be classified as events. (Girgis & Brown, 1981) proposed a three-state signal model which allowed transient voltage variations to be tracked for computer relaying. First two states correspond to the fundamental grid frequency in a rotating reference frame while the third one, an exponentially decaying signal, is employed for fault detection purposes. This signal model was extended in (Girgis et al., 1990) by including two state variables per harmonic component to be tracked. An analysis of Kalman filters applied

to voltage phasors estimation is also given in (Woxd et al., 1985). A ground fault relaying schema based on Kalman filters is also proposed in (Murty & Smolinski, 1990). In this case only harmonic components are employed. An expert system for classification and analysis of power system events is proposed in (Styvaktakis et al., 2002). Three Kalman filters, one per phase, are applied in order to obtain frequency and harmonic measurements as well as a detection index. (Dash & Chilukuri, 2004) proposed to integrate wavelet transforms and Kalman filters in order to characterize short duration power quality disturbances. The phase-corrected wavelet transform, S-transform, allows the disturbances to be detected and time localized while the Kalman filter characterizes the disturbance. The impact of arc furnaces in electrical power systems can be also analysed by means of Kalman filters (Wang et al., 2005). In this case, the states-variables model considers the arc furnace characteristics and the electrical grid topology. Three Kalman filters are also considered in (Barros & Pérez, 2006) in order to detect voltage dips and swells. The voltage signals, which consist of fundamental component and harmonics, are modelled in a rotating reference frame. (González et al., 2006) proposed an equivalent approach without harmonic components in the signal model. (Ukil & Živanović, 2007) proposed several Kalman filters to be executed in parallel, each one using a different model, in order to reveal the power system disturbance. An extended Kalman filter, where the instantaneous phase at the fundamental grid frequency is also tracked, is proposed in (Pérez & Barros, 2008) for detection and analysis of voltage dips.

Due to the characteristics of discrete Kalman filters (accurate estimation of power signals and fast response time), they have been included in control algorithms in power converters. This is the case of (Lisserre et al., 2006), where Kalman filters are employed in grid-connected photovoltaic inverters in order to detect the islanding operation mode. Such inverters in distributed generation systems are also analysed in (Prodanovic et al., 2007), where Kalman filters are proposed in order to support the operation of the electrical grid. (Ahmed et al., 2008) discusses the compensation of the controller delays by applying Kalman filters. The synchronization, a key issue in distributed generation systems based on inverters, is discussed in (Cardoso et al., 2008). Special attention must be paid to applications where precision is a main issue, such as power converters for compensation of electrical grid disturbances. (Moreno et al., 2002) proposed a Kalman filter, using previously calculated Kalman gains and a stationary reference frame for current harmonic compensation in electrical grids by means of a shunt active power filter (SAPF). (Barros & Pérez, 2003) employed a synchronously rotating reference frame model in SAPF which requires an external phase locked loop (PLL) for synchronization. (Moreno et al., 2004) extended the stationary reference frame model in order to compensate the load reactive power. The employed model allowed the external synchronisation mechanism to be avoided. (Kwan et al., 2007), (Elnady & Salama, 2007) and (Griffo et al., 2007) proposed Kalman filters in order to control a Unified Power Quality Conditioner which allows both grid and load disturbances to be compensated.

Kalman filters have been also successfully applied to electrical grid management issues and electrical loads forecasting. First application of Kalman filters for electrical grid management is probably given in (Girgis, 1982), where faults are located by estimation of the apparent impedance to the fault. Kalman filters, modelling the fundamental grid frequency, are applied to voltage and current signals in order to estimate the impedance. (Heydt, 1989) proposed to analyse the optimal location of harmonic meters by means of Kalman filters.

Walsh transformations and Kalman filters cooperates in (Bhattacharya & Basu, 1993) in order to obtain medium range forecasts of power system load. Walsh transformations are substituted in (Zheng et al., 2000) by Wavelet transforms. Previously presented signal models are modified in (Soliman et al., 1995) by including time decaying amplitudes at each harmonic frequency in order to evaluate transient stability swings in large interconnected power systems. According to (Kim et al., 2001), Kalman filters can be also applied in order to determine the switching status of capacitive banks in electrical utilities. Load forecasting is analyzed again in (Trudnowski et al., 2001). In this case, Kalman filters allow very short load forecasting, typically less than two hours, to be carried out. The weather conditions are also considered in the signal model proposed in (Al-Hamadi & Soliman, 2004) in order to improve the load forecasting.

The characteristics of the electrical loads can be also estimated by applying Kalman filters. This is the case of (Soliman & Alammari, 2004), where a general passive electrical load (capacitive, inductive and resistive) is modelled in order to obtain its parameters under sinusoidal and non-sinusoidal conditions. The characterization of electrical loads becomes especially difficult in case of electrical machines, where mechanical forces must be also considered. This is the case of (Abu-Al-Feilat et al., 1999), where a two-state Kalman filter was proposed in order to estimate the synchronizing and damping torque coefficients of a synchronous electrical machine, or (Caruana et al., 2003), that estimates the flux position in cage induction machines by applying Kalman filters and high-frequency injection.

4. Linear and extended discrete Kalman filtering loops

This section reviews the principles of discrete Kalman filtering loops (Chui & Chen, 1999), both linear and extended, and gives their implementation in MatLab/Simulink. Commonly employed signal models in literature, and their implementation, are also given. Finally, a new three phase signal model for frequency estimation and harmonics tracking in three-phase three-wire power systems is proposed. Simulation results which have been obtained by applying this model are given in the following section.

4.1 Linear Kalman filtering loop

Considering a discrete-time state-space representation of a linear system:

$$\begin{cases} \mathbf{x}_{k+1} = \mathbf{A}_k \mathbf{x}_k + \mathbf{B}_k \mathbf{u}_k + \Gamma \xi_k \\ \mathbf{s}_k = \mathbf{C}_k \mathbf{x}_k + \mathbf{D}_k \mathbf{u}_k + \eta_k \end{cases} \quad (1)$$

where ξ and η are uncorrelated noise sequences with normal probability distributions, \mathbf{u} is a deterministic input sequence, \mathbf{x} contains the system state variables, \mathbf{s} is a vector with the available measurements, \mathbf{A} is the state transition matrix, \mathbf{C} the measurement matrix and \mathbf{B} and \mathbf{D} matrices allow the deterministic input sequence to be considered. The recursive Kalman filtering loop for time instants $k=1,2,\dots$ can be written as:

$$\mathbf{P}_{k|k+1} = \mathbf{A}_{k-1} \mathbf{P}_{k-1|k-1} \mathbf{A}_{k-1}^T + \Gamma_{k-1} \mathbf{Q}_{k-1} \Gamma_{k-1}^T \quad (2.1)$$

$$\mathbf{G}_k = \mathbf{P}_{k|k-1} \mathbf{C}_k^T (\mathbf{C}_k \mathbf{P}_{k|k-1} \mathbf{C}_k^T + \mathbf{R}_k)^{-1} \quad (2.2)$$

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{G}_k \mathbf{C}_k) \mathbf{P}_{k|k-1} \quad (2.3)$$

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{A}_{k-1} \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_{k-1} \mathbf{u}_{k-1} \quad (2.4)$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{G}_k (\mathbf{s}_k - \mathbf{C}_k \hat{\mathbf{x}}_{k|k-1} - \mathbf{D}_k \mathbf{u}_k) \quad (2.5)$$

where \mathbf{P} is the covariance matrix and \mathbf{G} is a matrix containing the Kalman gains, which allows a least-squares sense optimal estimation of the state variables by adjusting the information which arrives from the process model and the measurements, $\hat{\mathbf{x}}_{k|k-1}$ is the estimation of the state variables at instant k from values at instant $k-1$. The filtering loop generates a prediction of the covariance matrix in (2.1), which is employed in (2.2) in order to obtain the Kalman gains, then, in (2.3) the covariance matrix is updated. Finally, the state variables are estimated in (2.4) according to the model and then, in (2.5), such estimation is updated by means of the obtained measurements. It must be considered that in most linear Kalman filters applied to the estimation of electrical power quantities the terms corresponding to \mathbf{u} can be avoided. Moreover, as initial values:

$$\mathbf{P}_{00} = \text{Var}(\mathbf{x}_0), \quad \hat{\mathbf{x}}_{00} = E(\mathbf{x}_0) \tag{3}$$

In case of correlated noise sequences, a complete description of the filtering loop can be found in (Chui & Chen, 1999). In certain cases where time independent A and C matrices are employed, as well as \mathbf{u} is neglected, the limiting Kalman filtering loop can be employed, where the time dependent \mathbf{G}_k can be substituted using its value at $\mathbf{G} = \lim_{k \rightarrow \infty} \mathbf{G}_k$ and, hence, the overall computational burden can be reduced.

Fig. 6 shows the implementation of the discrete Kalman filtering loop in MatLab/Simulink. As it can be seen, a triggered subsystem has been selected in order to apply an external synchronization signal. Moreover, the depicted structure can be repeated, independently of the employed model, and only A and C matrices must be changed in each case. Each Simulink block implements equations (2.1)-(2.5). In case the limiting approach is employed, and considering that the values of \mathbf{G} can be stored in the memory, the filtering loop can be simplified obtaining the block depicted in fig. 7. As it can be seen, in this case, \mathbf{G} must be supplied for each specific model.

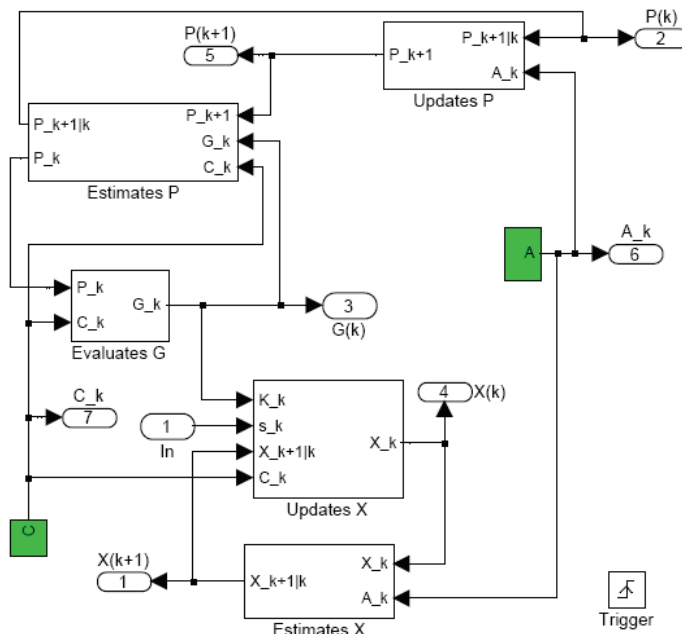


Fig. 6. Discrete Kalman filtering loop implementation in MatLab/Simulink.

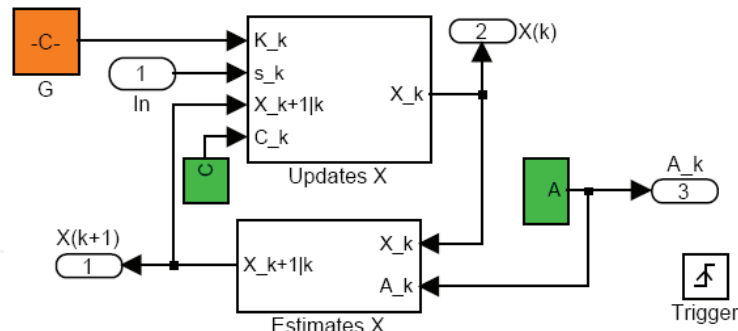


Fig. 7. Limiting approach of the discrete Kalman filtering loop implemented in MatLab/Simulink.

4.2 Extended Kalman filtering loop

In case the model is non-linear, the filtering loop in (2.1)-(2.5) can not be applied but the model can be linearized in order to estimate the state variables (Chui & Chen, 1999). Considering the system:

$$\begin{cases} \mathbf{x}_{k+1} = \mathbf{f}_k(\mathbf{x}_k) + \mathbf{H}_k(\mathbf{x}_k)\xi_k \\ \mathbf{s}_k = \mathbf{g}_k(\mathbf{x}_k) + \eta_k \end{cases} \quad (4)$$

$\mathbf{f}_k(\mathbf{x}_k)$ and $\mathbf{g}_k(\mathbf{x}_k)$ can be linearized around $\hat{\mathbf{x}}_k$ and $\hat{\mathbf{x}}_{k|k-1}$ respectively by means of a Taylor approximation and, hence, the filtering loop results on:

$$\mathbf{P}_{k|k-1} = \left[\frac{\partial \mathbf{f}_{k-1}}{\partial \mathbf{x}_{k-1}}(\hat{\mathbf{x}}_{k-1}) \right] \mathbf{P}_{k-1|k-1} \left[\frac{\partial \mathbf{f}_{k-1}}{\partial \mathbf{x}_{k-1}}(\hat{\mathbf{x}}_{k-1}) \right]^T + \mathbf{H}_{k-1}(\hat{\mathbf{x}}_{k-1}) \mathbf{Q}_{k-1} \mathbf{H}_{k-1}^T(\hat{\mathbf{x}}_{k-1}) \quad (5.1)$$

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{f}_{k-1}(\hat{\mathbf{x}}_{k-1}) \quad (5.2)$$

$$\mathbf{G}_k = \mathbf{P}_{k|k-1} \left[\frac{\partial \mathbf{g}_k}{\partial \mathbf{x}_k}(\hat{\mathbf{x}}_{k|k-1}) \right]^T \left(\left[\frac{\partial \mathbf{g}_k}{\partial \mathbf{x}_k}(\hat{\mathbf{x}}_{k|k-1}) \right] \mathbf{P}_{k|k-1} \left[\frac{\partial \mathbf{g}_k}{\partial \mathbf{x}_k}(\hat{\mathbf{x}}_{k|k-1}) \right]^T + \mathbf{R}_k \right)^{-1} \quad (5.3)$$

$$\mathbf{P}_{k|k} = \left(\mathbf{I} - \mathbf{G}_k \left[\frac{\partial \mathbf{g}_k}{\partial \mathbf{x}_k}(\hat{\mathbf{x}}_{k|k-1}) \right] \right) \mathbf{P}_{k|k-1} \quad (5.4)$$

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{G}_k (\mathbf{s}_k - \mathbf{g}_k(\hat{\mathbf{x}}_{k|k-1})) \quad (5.5)$$

Despite of the algorithm complexity, where partial derivatives must be computed, depending on the employed model the computational burden of this filtering loop can be quite low. The evaluation of the inverse matrix in (5.3) requires the most of the execution time.

The implementation of the extended Kalman filtering loop in MatLab/Simulink is shown in fig. 8. In this case, the simulink blocks require also partial derivatives evaluated from the state variables, as it is shown in the block labelled as *nonlinear H_O*, which is employed to evaluate \mathbf{A} , \mathbf{C} and their derivatives each time instant from the state variables values. It must be noted that one sample delay must be included before this block in order to avoid execution inconsistencies. Moreover, this is the block whose inner structure must be changed depending on the employed model.

4.3 Conventional signal models

Three signal model shown in literature are described in this section in order to show the principles of the method that will be proposed in the following subsection. Signals models

for harmonics tracking, considering both fixed and rotating axes approaches, and frequency estimation are explained and MatLab/Simulink implementations, which can be employed with the filtering loops described in 4.2 and 4.3, are given.

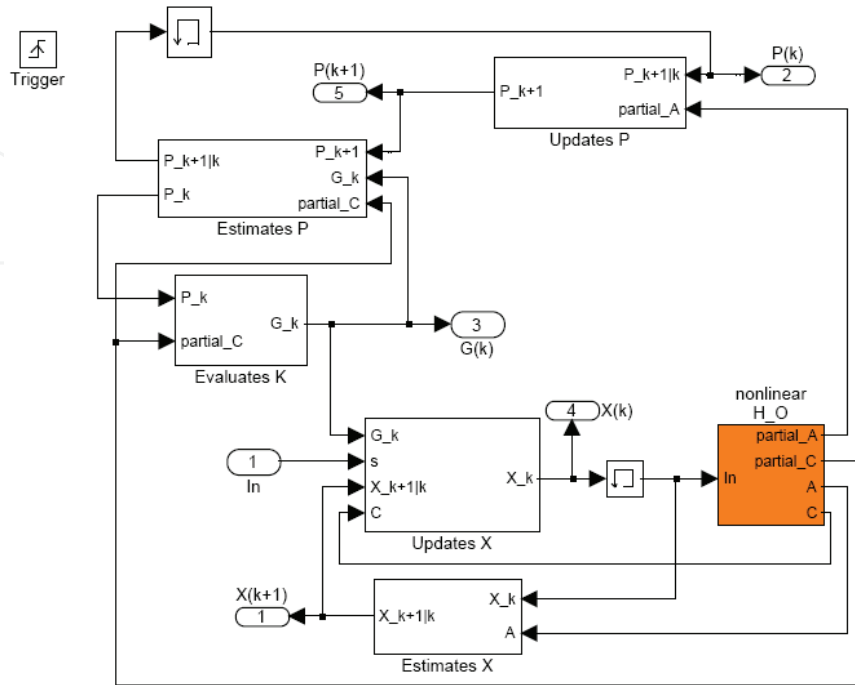


Fig. 8. Extended Kalman filtering loop implemented in MatLab/Simulink.

Firstly of all, it must be considered that in case of harmonics tracking, both in fixed and rotating axes approaches, two state variables are required per each considered frequency (fundamental, harmonics, interharmonics or subharmonics). Moreover, the dc component can be also included in both models by means of one state variable. The fixed axes approach considers that there is a stationary complex reference frame where all the considered harmonic components rotate. Due to this fact, and considering two consecutive samples of the m^{th} harmonic, its phasor can be tracked by means of two in-quadrature state variables

$$\begin{cases} x_{m,k}^\alpha = X_k \cos\left(m \frac{2\pi}{N} k\right) \\ x_{m,k}^\beta = X_k \sin\left(m \frac{2\pi}{N} k\right) \end{cases} \quad (6)$$

where $x_{m,k}^\alpha$ and $x_{m,k}^\beta$ are the orthogonal projections of its phasor at instant k , X_m is its amplitude and N is the number of considered samples at the fundamental grid frequency. At instant $k+1$, the phasor associated to this harmonic will rotate on these stationary axes at its frequency:

$$\begin{cases} x_{m,k+1}^\alpha = X_k \cos\left(m \frac{2\pi}{N} (k+1)\right) = x_{m,k}^\alpha \cos\left(m \frac{2\pi}{N}\right) - x_{m,k}^\beta \sin\left(m \frac{2\pi}{N}\right) \\ x_{m,k+1}^\beta = X_k \sin\left(m \frac{2\pi}{N} (k+1)\right) = x_{m,k}^\alpha \sin\left(m \frac{2\pi}{N}\right) + x_{m,k}^\beta \cos\left(m \frac{2\pi}{N}\right) \end{cases} \quad (7)$$

Selecting α and β components as state-variables, and considering k and $k+1$ instants, the harmonic m^{th} can be represented through a rotation matrix A_n which is time independent:

$$A_m = \begin{pmatrix} \cos\left(m\frac{2\pi}{N}\right) & -\sin\left(m\frac{2\pi}{N}\right) \\ \sin\left(m\frac{2\pi}{N}\right) & \cos\left(m\frac{2\pi}{N}\right) \end{pmatrix} \quad (8)$$

The complete signal, including all harmonics can be reconstructed by adding the real component, α , of each harmonic phasor. As a consequence, harmonics up to order n can be considered by employing $2n$ state variables:

$$A = \begin{pmatrix} A_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & A_n \end{pmatrix}, \quad C = (1 \ 0 \ \dots \ 1 \ 0) \quad (9)$$

Being time independent and constant matrices, they can be directly implemented in the schema depicted in fig. 6.

In case of the rotating axes approach, it is considered that each phasor is modelled in a certain complex frame which rotates at the frequency of the considered harmonic. Fig. 9 shows the principle for the fundamental component (in red) and the 5th harmonic (in blue). As it can be seen, each harmonic frequency is decomposed in its rotating reference frame resulting on two orthogonal components. As a consequence, A corresponds to the identity matrix while the measurement matrix becomes time dependent:

$$C = \left(\cos\left(\frac{2\pi}{N}k\right) \quad -\sin\left(\frac{2\pi}{N}k\right) \quad \dots \quad \cos\left(n\frac{2\pi}{N}k\right) \quad -\sin\left(n\frac{2\pi}{N}k\right) \right) \quad (10)$$

Due to the nature of C , the computational burden of the Kalman filter is increased in this case. In order to reduce the complexity, it is proposed in the literature to employ an external phase locked loop (PLL) which moves a pointer over the values stored in memory corresponding to the elements in (10).

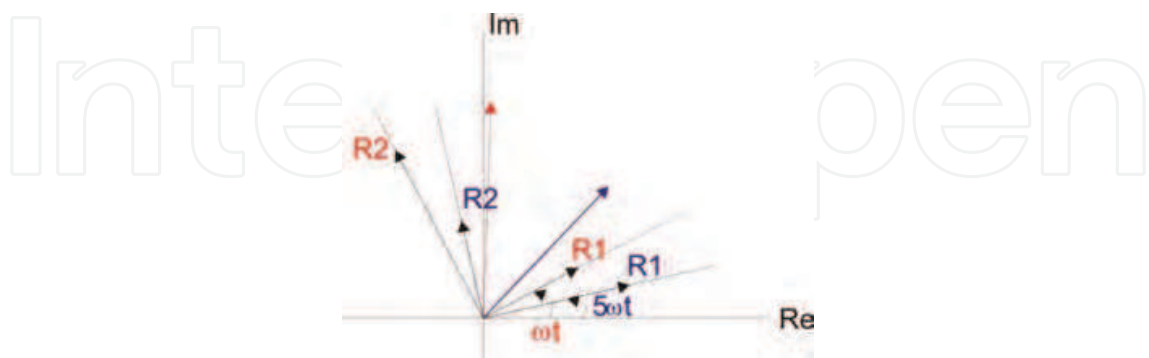


Fig. 9. Phasors for the fundamental component and the 5th harmonic in rotating reference frames.

In previous signal models, the fundamental grid frequency is considered constant, or in case of the rotating axes approach with PLL, the sampling frequency is dynamically changed in order to maintain constant the number of samples per cycle at the fundamental grid

frequency. If frequency measurements are required, the extended Kalman filtering loop depicted in fig. 8 must be employed. A first approach which can be applied to single phase power systems is:

$$A = \begin{pmatrix} A_1 & 0 & 0 & 0 \\ 0 & \ddots & 0 & \vdots \\ 0 & 0 & A_n & 0 \\ 0 & \dots & 0 & 1 \end{pmatrix}, \quad C = (1 \ 0 \ 1 \ 0 \ \dots \ 0) \tag{11}$$

where:

$$A_n = \begin{pmatrix} \cos(n2\pi T_s f) & -\sin(n2\pi T_s f) \\ \sin(n2\pi T_s f) & \cos(n2\pi T_s f) \end{pmatrix} \tag{12}$$

and T_s is the employed sampling frequency and f is the fundamental grid frequency to be estimated. As a consequence, the computational burden associated to the linearization process through the derivatives can be very high. In order to reduce it, (Routray et al., 2002) proposed a signal model considering three-consecutive points of a sinusoidal signal, as it is shown in fig. 10. From this figure, the relationship between these points is:

$$y_{k+1} = (2 \cos(2\pi f T_s))y_k - y_{k-1} \tag{13}$$

Considering y_k , y_{k-1} and $2\cos(2\pi f T_s)$ as state variables, the nonlinear signal model can be written as:

$$\begin{cases} x_{1,k+1} = x_{3,k}x_{1,k} - x_{2,k} \\ x_{2,k+1} = x_{1,k} \\ x_{3,k+1} = x_{3,k} \end{cases} \tag{14}$$

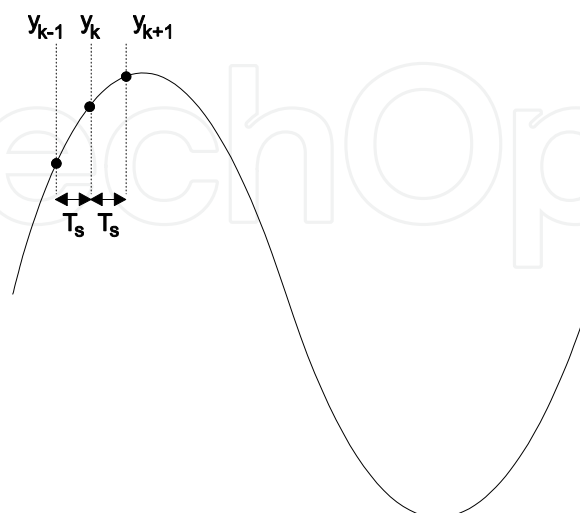


Fig. 10. Three consecutive sampling points of a sinusoidal signal in order to obtain a frequency measurement

As a consequence, the Simulink blocks to be employed in fig. 8 must implement the matrices:

$$\mathbf{x}_k = (x_{1,k} \quad x_{2,k} \quad x_{3,k}) \quad (15.1)$$

$$\mathbf{A}_k = \begin{pmatrix} x_{3,k} & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad (15.2)$$

$$\mathbf{C}_k = (x_{3,k} \quad -1 \quad 0) \quad (15.3)$$

$$\frac{\partial \mathbf{f}_k}{\partial \mathbf{x}_k} = \begin{pmatrix} x_{3,k} & -1 & x_{1,k} \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \quad (15.4)$$

$$\frac{\partial \mathbf{g}_k}{\partial \mathbf{x}_k} = (x_{3,k} \quad -1 \quad x_{1,k}) \quad (15.5)$$

Their implementation in MatLab/Simulink is shown in fig. 11.

4.4 Proposed signal model for frequency measurement

This section proposes a signal model for three-phase three-wire power systems which allows the fundamental grid frequency to be estimated accurately under unbalanced phase voltages. The signal model considers positive and negative sequences of the three voltage signals, as well as voltage harmonics, in order to estimate the fundamental grid frequency:

$$\mathbf{s}_k = (v_{A,k} \quad v_{B,k} \quad v_{C,k}) \quad (16.1)$$

$$\mathbf{x}_k = (x_{1_p^+} \quad x_{1_q^+} \quad \dots \quad x_{n_p^{\text{sign}}} \quad x_{n_q^{\text{sign}}} \quad f)^T \quad (16.2)$$

where n is the harmonic order, sign denotes the sequence of the modelled harmonic and subindexes p and q correspond to in-phase and in-quadrature components of the considered harmonic. As a consequence, the measurement equation can be designed by applying the Clarke's transformation to the phase voltages:

$$\mathbf{C} = \begin{pmatrix} 1 & 0 \\ -\frac{1}{2} & \frac{\sqrt{3}}{2} \\ -\frac{1}{2} & -\frac{\sqrt{3}}{2} \end{pmatrix} \begin{pmatrix} \mathbf{I} & \mathbf{I} & \dots & \mathbf{I} & 0 \\ & & & & 0 \end{pmatrix} \quad (17)$$

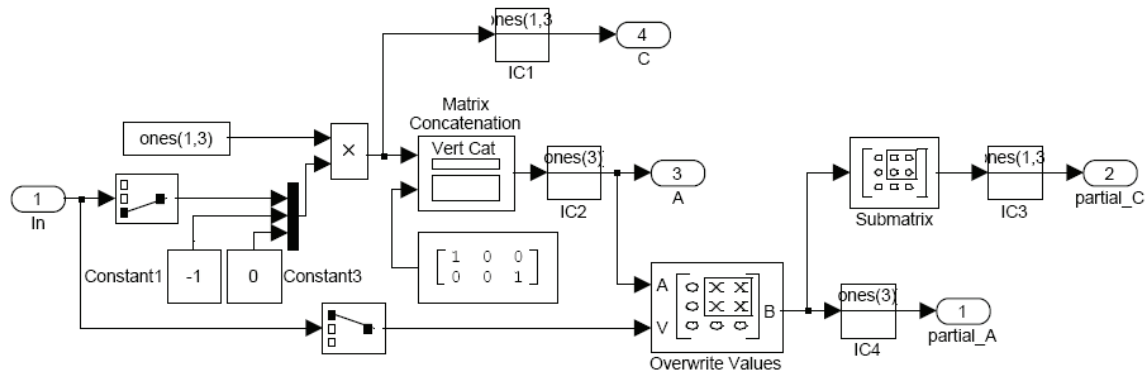


Fig. 11. Implementation of equations (15.1)-(15.5) in MatLab/Simulink

The second matrix in (17), where I is a 2x2 identity matrix, allows $\alpha\beta$ components of the grid voltage to be decomposed on the considered harmonics and sequences. The non-linearity appears inside the transition matrix:

$$A_k = \begin{pmatrix} A_1^+ & 0 & \dots & \dots & 0 \\ 0 & A_1^- & \ddots & & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & & & A_n^{sign} & 0 \\ 0 & \dots & \dots & 0 & 1 \end{pmatrix} \tag{18}$$

where, considering T_s as the sampling time:

$$A_n^{sign} = \begin{pmatrix} sign \cdot \sin(n2\pi T_s f) & \cos(n2\pi T_s f) \\ \cos(n2\pi T_s f) & -sign \cdot \sin(n2\pi T_s f) \end{pmatrix} \tag{19}$$

The MatLab/Simulink implementation of (18) and its derivative is shown in fig. 12. As it can be seen, the implementation allows the positive and negative sequences of the fundamental component, as well as 5th and 7th harmonics with negative and positive sequences respectively, are modelled.

5. Simulation results

The results shown in this section have been obtained by means of MatLab/Simulink and considering a three-phase three-wire balanced non-linear load, a full bridge diode rectifier with highly inductive dc side, which has been fed by diverse test source voltages. Both the proposed signal model and the model in (Routray et al., 2002) has been applied in order to evaluate the performance of the proposed method. The Simulink model considers the A/D subsystem ($T_s=156.25 \mu s$ and time delays due to the signal acquisition) and includes anti-aliasing filters (Butterworth, 4th order and 3.2 kHz cut-off frequency).

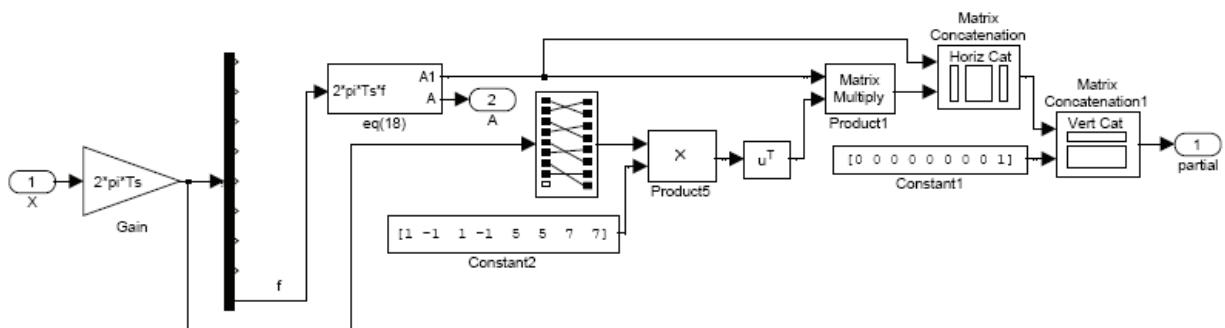


Fig. 12. Simulink implementation of (18) and its partial derivative.

5.1 Balanced grid voltages

The grid voltages are balanced and pure sinusoidal at 50 Hz. In order to test the tracking capability of each method, a frequency variation is applied from 0.4 s to 0.5 s by means of a frequency ramp where the final frequency reaches 48Hz. The obtained results are shown in fig. 13. As it can be seen in fig. 13.a, the proposed method tracks the frequency variation with a 2.97 ms delay, which corresponds to 19 samples, while the signal model described in

(Routray et al., 2002) oscillates around the applied grid frequency and generates spikes during the frequency variation (fig. 13.b). The proposed method generates a smoother and slower response due to the selected state variables.

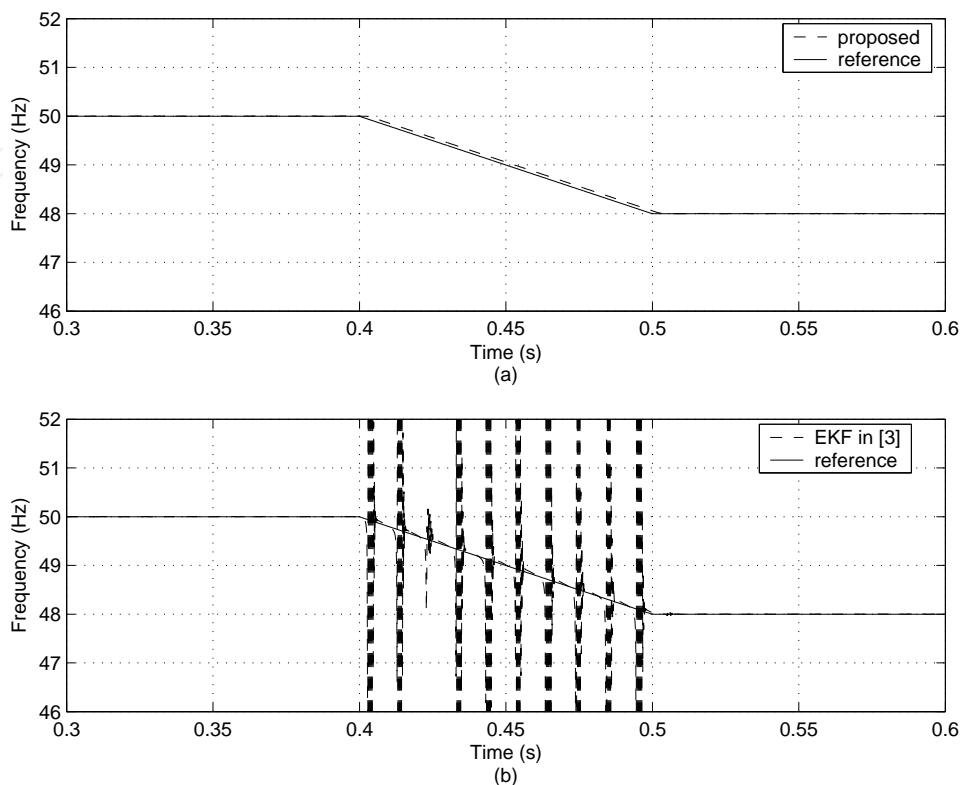


Fig. 13. Simulation results under a ramp frequency variation. Measured frequency applying a) the proposed signal model and b) the EKF in (Routray et al., 2002).

5.2 Unbalanced grid voltages

The initially balanced and pure sinusoidal grid voltages at 50 Hz become unbalanced at 0.4 s while both EKF are being applied to the measured voltages. The applied voltage unbalance is shown in fig. 14.a. From fig. 14.b and 14.c, both methods results on frequency transients during the unbalance transients. The maximum deviation of the proposed signal model is 2.43 Hz while the signal model described in (Routray et al., 2002) reaches 464.22 Hz. The measured response times are 12.8 ms and 15.3 ms, with the proposed method being the faster one due to simultaneous measurement of the three phase voltages.

5.3 Harmonically distorted grid voltages with a voltage dip

This last simulation test applies balanced grid voltages with harmonic distortion between IEEE Std. 519-1992 limits (1st is 100%, 5th is 2% and 7th is 4% with VTHD<5%). A 40% voltage dip occurs at 0.4 s and finishes at 0.6 s. Fig. 15.a shows the applied test conditions. The proposed signal model, due to the modelled harmonic components, track the fundamental grid frequency properly (fig. 15.b) while the signal model described in (Routray et al., 2002) generates spikes in the frequency estimation (fig. 15.c). Moreover, the proposed signal model allows the voltage dip to be detected due to the measured frequency transients.

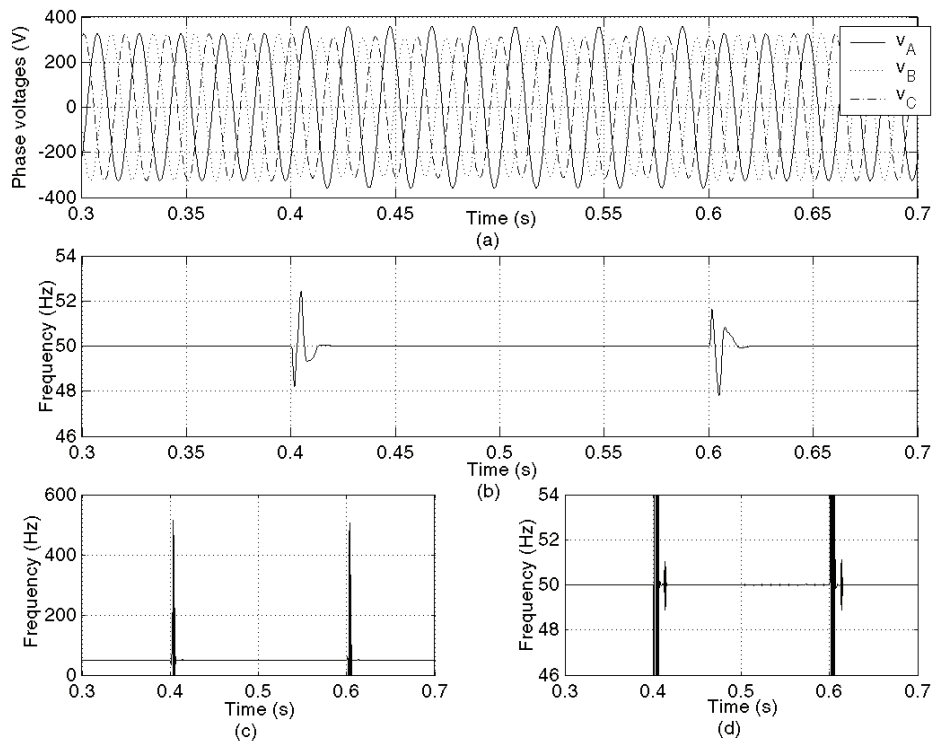


Fig. 14. a) Applied test grid voltages and the obtained frequency measurements by applying the b) proposed signal model and c) the EKF in (Routray et al., 2002), which is detailed in d).

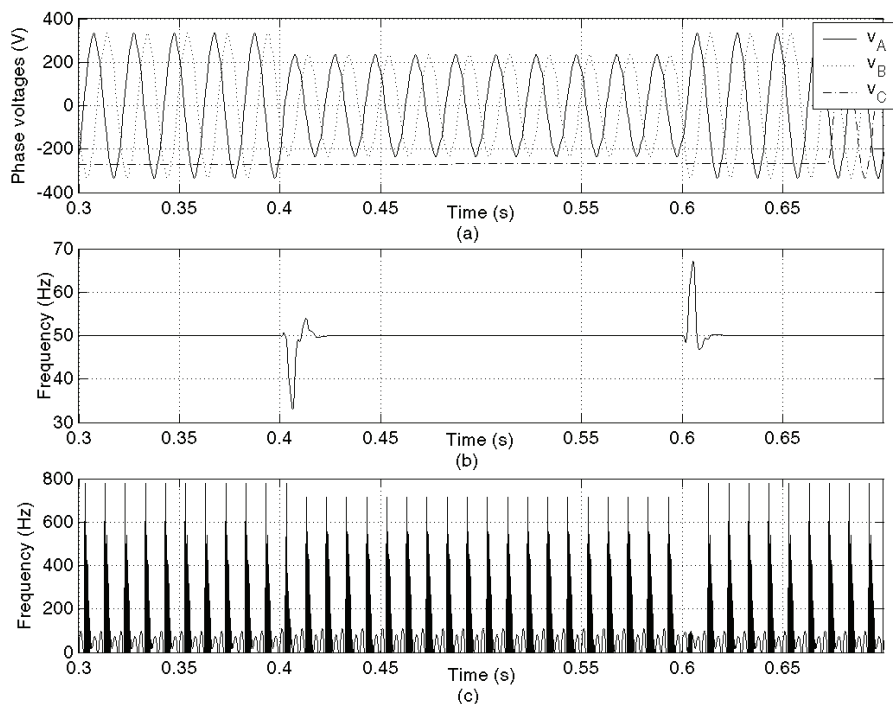


Fig. 15. a) Test grid voltages and the obtained frequency measurements applying b) the proposed signal model and c) the EKF in (Routray et al., 2002).

6. Conclusion

This chapter gives an introduction to the applications of Kalman filtering in electrical power systems. Power quality disturbances are introduced, considering their sources and impact, and monitoring examples are given. The literature on this researching area is reviewed, given a detailed analysis of the most applied signal models as well as their implementation in MatLab/Simulink. Moreover, a new signal model which considers a three-phase three-wires power system with voltage unbalances and harmonically distorted grid voltages is given. The proposed signal model is compared to a previously proposed signal model in single phase power systems by means of simulation tests carried out using MatLab/Simulink.

7. References

- Abu-Al-Feilat, E. A.; Younan, N. & Grzybowski, S. (1999). Estimating the synchronizing and damping torque coefficients using Kalman filtering. *Electric Power Systems Research*, Vol. 52, No. 2, (November 1999) 145-149, ISSN: 0378-7796.
- Aghazadeh, R.; Lesani, H.; Sanaye-Pasand, M. & Ganji, B. (2005). New technique for frequency and amplitude estimation of power system signals. *IEE Proceedings - Generation, Transmission and Distribution*, Vol. 152, No. 3, (May 2005) 435-440, ISSN: 1350-2360.
- Ahmed, K. H.; Massoud, A. M.; Finney, S. J. & Williams, B. W. (2008). Autonomous control of a PWM inverter in islanded distributed generation with different feedback signals, *Proceedings of 4th IET Conference on Power Electronics, Machines and Drives 2008 (PEMD 2008)*, pp. 573-577, ISBN: 978-0-86341-900-3, York, UK, April 2008, Institution of Engineering and Technology (IET), London.
- Alcaraz, R; Bueno, E. J.; Cóbreces, S.; Rodríguez, F. J., Espinosa, F. & Muyulema, S. (2006). Power System Voltage Harmonic Identification Using Kalman Filter, *Proceedings of 12th International Power Electronics and Motion Control Conference (EPE-PEMC 2006)*, pp. 1283-1288, ISBN: 1-4244-0120-8, Portoroz, August 2006.
- Adanir, T. (2007). Extremely short term frequency estimation (ESTFE) algorithm for underfrequency protection. *International Journal of Electrical Power & Energy Systems*, Vol. 29, No. 4, (May 2007), 329-337, ISSN: 0142-0615.
- Al-Hamadi, H. M. & Soliman, S. A. (2002). Kalman filter for identification of power system fuzzy harmonic components. *Electric Power Systems Research*, Vol. 62, No. 3, (July 2002) 241-248, ISSN: 0378-7796.
- Al-Hamadi, H. M. & Soliman, S. A. (2004). Short-term electric load forecasting based on Kalman filtering algorithm with moving window weather and load model. *Electric Power Systems Research*, Vol. 68, No. 1, (January 2004) 47-59, ISSN: 0378-7796.
- Barros, J. & Pérez, E. (2003). An adaptive method for determining the reference compensating current in single-phase shunt active power filters. *IEEE Transactions on Power Delivery*, Vol. 18, No. 4, (October 2003) 1578-1580, ISSN: 0885-8977.
- Barros, J. & Pérez, E. (2006). Automatic Detection and Analysis of Voltage Events in Power Systems. *IEEE Transactions on Instrumentation and Measurement*, Vol. 55, No. 5, (October 2006) 1487-1493, ISSN: 0018-9456.

- Beides, H. M. & Heydt, G. T. (1991). Dynamic state estimation of power system harmonics using Kalman filter methodology. *IEEE Transactions on Power Delivery*, Vol. 6, No. 4, (October 1991) 1663-1670, ISSN: 0885-8977.
- Bhattacharya, T. K. & Basu, T. K. (1993). Medium range forecasting of power system load using modified Kalman filter and Walsh transform. *International Journal of Electrical Power & Energy Systems*, Vol. 15, No. 2, (April 1993) 109-115, ISSN: 0142-0615.
- Bollen, M. H. J. & Gu, I. (2006). *Signal Processing of Power Quality Disturbances*, Wiley-IEEE Press, 978-0-471-73168-9, USA.
- Brown, R. G. (1983). *Introduction to Random Signal Analysis and Kalman Filtering*, Wiley, 0-471-08732-7, USA.
- Cardoso, R.; de Camargo, R. F.; Pinheiro, H. & Gründling, H. A. (2008). Kalman filter based synchronisation methods. *IET Generation, Transmission & Distribution*, Vol. 2, No. 4, (July 2008) 542-555, ISSN: 1751-8687.
- Caruana, C.; Asher, G. M.; Bradley, K. J. & Woolfson, M. (2003). Flux position estimation in cage induction machines using synchronous HF injection and Kalman filtering. *IEEE Transactions on Industry Applications*, Vol. 39, No. 5, (September 2003) 1372-1378, ISSN: 0093-9994.
- Chui, C. K. & Chen, G. (1999). *Kalman filtering with real-time applications*. 3rd Edition, Springer-Verlag, 3-540-64611-6, Germany.
- Dash, P. K.; Pradhan, A. K. & Panda, G. (1999). Frequency estimation of distorted power system signals using extended complex Kalman filter. *IEEE Transactions on Power Delivery*, Vol. 14, No. 3, (July 1999) 761-766, ISSN: 0885-8977.
- Dash, P. K.; Jena, R. K.; Panda, G. & Routray, A. (2000). An extended complex Kalman filter for frequency measurement of distorted signals. *IEEE Transactions on Instrumentation and Measurement*, Vol. 49, No. 4, (August 2000) 746-753, ISSN: 0018-9456.
- Dash, P. K. & Chilukuri, M. V. (2004). Hybrid S-transform and Kalman filtering approach for detection and measurement of short duration disturbances in power networks. *IEEE Transactions on Instrumentation and Measurement*, Vol. 53, No. 2, (April 2004) 588-596, ISSN: 0018-9456.
- Dugan, R. C.; McGranaghan, M. F.; Santoso, S. & Beaty, H. W. (2003). *Electrical Power Systems Quality, 2nd Edition*, McGraw-Hill, 0-07-138622-X, USA.
- Elnady, A. & Salama, M. M. A. (2007). Mitigation of the voltage fluctuations using an efficient disturbance extraction technique. *Electric Power Systems Research*, Vol. 77, No. 3-4, (March 2007) 266-275. ISSN: 0378-7796.
- Girgis, A. A. & Brown, R. G. (1981). Application of Kalman Filtering in Computer Relaying. *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-100, No. 7, (July 1981) 3387-3397, ISSN: 0018-9510.
- Girgis, A. A. (1982). A New Kalman Filtering Based Digital Distance Relay. *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-101, No. 9, (September 1982) 3471 - 3480, ISSN: 0018-9510.
- Girgis, A. A. & Hwang, T. L. D. (1984). Optimal Estimation Of Voltage Phasors And Frequency Deviation Using Linear And Non-Linear Kalman Filtering: Theory And Limitations. *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-103, No. 10, (October 1984) 2943-2951, ISSN: 0018-9510.

- Girgis, A. A., Chang, W. & Makram, E. B. (1990). Analysis of high-impedance fault generated signals using a Kalman filtering approach. *IEEE Transactions on Power Delivery*, Vol. 5, No. 4, (October 1990) 1714-1724, ISSN: 0885-8977.
- Girgis, A. A.; Chang, W. B. & Makram, E. B. (1991). A digital recursive measurement scheme for online tracking of power system harmonics. *IEEE Transactions on Power Delivery*, Vol. 6, No. 3, (July 1991) 1153-1160, ISSN: 0885-8977.
- González, M.; Cárdenas, V. & Álvarez, V. (2006). Detection of sags, swells, and interruptions using the digital RMS method and Kalman filter with fast response. *Proceedings of IEEE 32nd Annual Conference on Industrial Electronics (IECON 2006)*, pp. 2249-2254, ISSN: 1553-572X, Paris, France, November 2006, Institute of Electrical and Electronics Engineers.
- Griffo, A.; Carpinelli, G.; Lauria, D. & Russo, A. (2007). An optimal control strategy for power quality enhancement in a competitive environment. *International Journal of Electrical Power & Energy Systems*, Vol. 29, No. 7, (September 2007) 514-525, ISSN: 0142-0615.
- Heydt, G. T. (1989). Identification of harmonic sources by a state estimation technique. *IEEE Transactions on Power Delivery*, Vol. 4, No. 1, (Jan. 1989) 569 - 576, ISSN: 0885-8977.
- Kim, J.; Grady, W. M.; Arapostathis, A.; Soward, J. & Bhatt, S. C. (2001). A time-domain procedure for locating switched capacitors in power distribution systems. *IEEE Transactions on Power Delivery*, Vol. 17, No. 4, (October 2002) 1044-1049, ISSN: 0885-8977.
- Kumar, A.; Das, B. & Sharma, J. (2006). Robust dynamic state estimation of power system harmonics. *International Journal of Electrical Power & Energy Systems*, Vol. 28, No. 1, (January 2006) 65-74, ISSN: 0142-0615.
- Kwan, K. H., So, P. L. & Chu, Y. C. (2007). A harmonic selective unified power quality conditioner using MVR with Kalman filters. *Proceedings of the International Power Engineering Conference 2007 (IPEC 2007)*, pp. 332-337, ISBN: 978-981-05-9423-7, Singapore, December 2007.
- Larson, A. (2000). *The power quality of wind turbines*. Ph.D. thesis, Chalmers University of Technology, 0346-718X, Göteborg, Sweden.
- Liserre, M.; Pigazo, A.; Dell'Aquila, A. & Moreno, V. M. (2006). An Anti-Islanding Method for Single-Phase Inverters Based on a Grid Voltage Sensorless Control. *IEEE Transactions on Industrial Electronics*, Vol. 53, No. 5, (October 2006) 1418-1426, ISSN: 0278-0046.
- Ma, H. & Girgis, A. A. (1996). Identification and tracking of harmonic sources in a power system using a Kalman filter. *IEEE Transactions on Power Delivery*, Vol. 11, No. 3, (July 1996) 1659-1665, ISSN: 0885-8977.
- Macías, J. A. R. & Exposito, A. G. (2006). Self-tuning of Kalman filters for harmonic computation. *IEEE Transactions on Power Delivery*, Vol. 21, No. 1, (January 2006) 501-503, ISSN: 0885-8977.
- Moreno, V. M. & Barros, J. (1997). Application of Kalman filtering for continuous real-time tracking of power system harmonics. *IEE Proceedings - Generation, Transmission and Distribution*, Vol. 144, No. 1, (January 1997) 13-20, ISSN: 1350-2360.
- Moreno, V. M.; Pigazo, A. & Diego, R. I. (2002). Reference estimation technique for active power filters using a digital Kalman algorithm, *Proceedings of 10th International*

- Conference on Harmonics and Quality of Power (ICHQP'02)*, pp. 490-494, ISBN: 0-7803-7671-4, Brazil, 2002.
- Moreno, V. M.; Pigazo, A. & Diego, R. I. (2004). Reference current estimation under distorted line voltage for control of shunt active power filters, *IEEE Transactions on Power Electronics*, Vol. 19, No. 4, (July 2004) 988-994, ISSN: 0885-8993.
- Moreno, V. M.; Liserre, M.; Pigazo, A. & Dell'Aquila, A. (2007). A comparative analysis of real-time algorithms for power signal decomposition in multiple synchronous reference frames. *IEEE Transactions on Power Electronics*, Vol. 22, No. 4, (July 2007) 1280-1289, ISSN: 0885-8993.
- Murty, Y. V. S. & Smolinski, W. J. (1990). A Kalman filter based digital percentage differential and ground fault relay for a 3-phase power transformer. *IEEE Transactions on Power Delivery*, Vol. 5, No. 3, (July 1990) 1299-1308, ISSN: 0885-8977.
- Pecen, R.; Ula, S. & Timmerman, M. (2004). Modeling and simulation of a Kalman filter based control scheme for an AC/DC power system. *International Journal of Electrical Power & Energy Systems*, Vol. 26, No. 3, (March 2004) 173-189, ISSN: 0142-0615.
- Pérez, E. & Barros, J (2008). An extended Kalman filtering approach for detection and analysis of voltage dips in power systems. *Electric Power Systems Research*, Vol. 78, No. 4, (April 2008) 618-625, ISSN: 0378-7796.
- Pigazo, A. & Moreno, V. M. (2008). 3 Φ -3w Signal Model for Power System Harmonics and Unbalance Identification Using Kalman Filtering. *IEEE Transactions on Power Delivery*, Vol. 23, No. 2, (April 2008) 1260-1261, ISSN: 0885-8977.
- Pradhan, A. K.; Routray, A. & Sethi, D. (2004). Voltage phasor estimation using complex linear Kalman filter, *Proceedings of 8th IEE International Conference on Developments in Power System Protection*, pp. 24-27, ISBN: 0-86341-385-4, Amsterdam, Netherlands, April 2004.
- Prodanovic, M.; De Brabandere, K.; Van den Keybus, J.; Green, T. & Driesen, J. (2007). Harmonic and reactive power compensation as ancillary services in inverter-based distributed generation. *IET Generation, Transmission & Distribution*, Vol. 1, No. 3, (May 2007) 432-438, ISSN: 1751-8687.
- Rosolowski, E. & Michalik, M. (1994). Fast identification of symmetrical components by use of a state observer. *IEE Proceedings - Generation, Transmission and Distribution*, Vol. 141, No. 6, (November 1994) 617-622, ISSN: 1350-2360.
- Routray, A.; Pradhan, A. K. & Rao, K. P. (2002). A novel Kalman filter for frequency estimation of distorted signals in power systems. *IEEE Transactions on Instrumentation and Measurement*, Vol. 51, No. 3, (June 2002) 469-479, ISSN: 0018-9456.
- Shaw, S. R. & Laughman, C. R. (2007). A Kalman-filter spectral envelope preprocessor. *IEEE Transactions on Instrumentation and Measurement*, Vol. 56, No. 5, (October 2007) 2010-2017, ISSN: 0018-9456.
- Soliman, S. A.; Al-Kandari, A. M. & El-Hawary, M. E. (1995). Linear Kalman filter algorithm for analysis of transient stability swings in large interconnected power systems. *Electric Power Systems Research*, Vol. 34, No. 3, (Sept. 1995) 173-178, ISSN: 0378-7796.
- Soliman, S. A. & El-Hawary, M. E. (1996). Application of Kalman filtering for online estimation of symmetrical components for power system protection. *Electric Power Systems Research*, Vol. 38, No. 2, (August 1996) Pages 113-123, ISSN: 0378-7796.

- Soliman, S. A. & Alammari, R. A. (2004). Harmonic modeling of linear and nonlinear loads based on Kalman filtering algorithm. *Electric Power Systems Research*, Vol. 72, No. 2, (December 2004) 147-155, ISSN: 0378-7796.
- Styvaktakis, E.; Bollen, M. H. J. & Gu, I. Y. H. (2002). Expert system for classification and analysis of power system events. *IEEE Transactions on Power Delivery*, Vol. 17, No. 2, (April 2002) 423-428, ISSN: 0885-8977.
- Trudnowski, D. J.; McReynolds, W. L. & Johnson, J. M. (2001). Real-time very short-term load prediction for power-system automatic generation control. *IEEE Transactions on Control Systems Technology*, Vol. 9, No. 2, (March 2001) 254-260, ISSN: 1558-0865.
- Ukil, A. & Živanović, R. (2007). The detection of abrupt changes using recursive identification for power system fault analysis. *Electric Power Systems Research*, Vol. 77, No. 3-4, (March 2007) 259-265, ISSN: 0378-7796.
- Wang, F.; Jin, Z.; Zhu, Z. & Wang, X. (2005). Application of Extended Kalman Filter to the Modeling of Electric Arc Furnace for Power Quality Issues, *Proceedings of International Conference on neural Networks and Brain (ICNN&B'05)*, pp. 991-996, ISBN: 0-7803-9422-4, Beijing, China, October 2005.
- Woxd, H. C.; Johnson, N. G. & Sachdev, M.S. (1985). Kalman Filtering Applied to Power System Measurements Relaying. *IEEE Transactions on Power Apparatus and Systems*, Vol. PAS-104, No. 12, (December 1985) 3565 - 3573. ISSN: 0018-9510.
- Yu, K. K. C.; Watson, N. R. & Arrillaga, J. (2005). An adaptive Kalman filter for dynamic harmonic state estimation and harmonic injection tracking. *IEEE Transactions on Power Delivery*, Vol. 20, No. 2, Part 2, (April 2005) 1577-1584, ISSN: 0885-8977.
- Zhang, J.; Swain, A.; Nair, N.-K. C. & Liu, J. J. (2007). Estimation of power quality using an unscented Kalman filter. *Proceedings of 2007 IEEE Region 10 Conference (TENCON 2007)*, pp. 1-4, ISBN: 978-1-4244-1272-3, Taipei, October 2007.
- Zheng, T.; Girgis, A. A. & Makram, E. B. (2000). A hybrid wavelet-Kalman filter method for load forecasting. *Electric Power Systems Research*, Vol. 54, No. 1, (April 2000) 11-17, ISSN: 0378-7796.

IntechOpen



Kalman Filter Recent Advances and Applications

Edited by Victor M. Moreno and Alberto Pigazo

ISBN 978-953-307-000-1

Hard cover, 584 pages

Publisher InTech

Published online 01, April, 2009

Published in print edition April, 2009

The aim of this book is to provide an overview of recent developments in Kalman filter theory and their applications in engineering and scientific fields. The book is divided into 24 chapters and organized in five blocks corresponding to recent advances in Kalman filtering theory, applications in medical and biological sciences, tracking and positioning systems, electrical engineering and, finally, industrial processes and communication networks.

How to reference

In order to correctly reference this scholarly work, feel free to copy and paste the following:

Alberto Pigazo and Víctor M. Moreno (2009). Estimation of Electrical Power Quantities by Means of Kalman Filtering, Kalman Filter Recent Advances and Applications, Victor M. Moreno and Alberto Pigazo (Ed.), ISBN: 978-953-307-000-1, InTech, Available from:

http://www.intechopen.com/books/kalman_filter_recent_advances_and_applications/estimation_of_electrical_power_quantities_by_means_of_kalman_filtering

INTECH

open science | open minds

InTech Europe

University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

© 2009 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the [Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License](#), which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.

IntechOpen

IntechOpen