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Self-tuning Kalman filter and machine learning algorithms for voltage dips upstream or downstream origin detection

H. Shadmehr, R. Chiumeo, and L. Tenti

Ricerca sul sistema energetico RSE SpA
Milano, 20134 (Italy)
Phone/Fax number:+0039 0239924748/+0039 0239925577, e-mail: riccardo.chiumeo@rse-web.it, houriyeh.shadmehr@rse-web.it, liliana.tenti@rse-web.it

Abstract. In this paper, self-tuning Kalman Filter (KF) is applied to a significant sample of full waveforms associated to the voltage dips monitored in the Italian distribution network by the QuEEN system, with the aim of events detection and waveforms segmentation. Segmentation is done in order to extract more features and information from the original voltage waveforms, to make easier voltage dips classification, based on the events source location (upstream/downstream from the point of measurement). The aforementioned classification is achieved by Machine Learning algorithms. The evaluation of the obtained results is based on the computation of a "confusion matrix".

Key words

Self-tuning Kalman Filter, Machine Learning, voltage dips, waveform segmentation.

1. Introduction

Nowadays, a significant amount of Power Quality (PQ) data is already available and, in the smart grid perspective, is probably going to grow due to the increased adoption of different type of monitoring devices [1]. In this context the investigation on methods and techniques for the automatic analysis of large amounts of data become an important issue for researchers and PQ engineers. In particular as far as voltage dips are concerned the aim of such methods should be that of discriminating the events due to faults from those with a different origin (induction motor starts, transformer energization etc.). Another issue of interest for PQ engineers, which concerns mainly events responsibility, is that of classifying and characterizing voltage dips on the base of their source location (upstream/downstream from the point of measurement).

In literature the last problem has been afforded by both advanced waveform analysis techniques [2, 3] and by an "experimental" method based on the comparison of the characteristics of events monitored at nearby primary substations [4].
In the former works mentioned, the authors have utilized an algorithm to segment the waveform into steady state and transient segments based on tensor theory [2] and on a "residual model" respectively [3]. The first method is not easily applicable to real monitoring system because of the cost of this solution which requires the monitoring of both voltage and current at each measurements point. The second method by now has been mainly applied to differentiate between events due to faults from those with a different origin. In any case, the proposed methods have been tested only on synthetic or semi-synthetic signals [5].

On the other hand the aforementioned "experimental" method [4], that has been applied by RSE since 2009 on the annual voltage dip statistic monitored by the QuEEN system (the Italian PQ system monitoring for survey purposes) [6], requires by now a wide monitoring system and time consuming procedure of data analysis (in fact some topological info from the TSO are needed to achieve a full automatic implementation).

In this paper, we apply self-tuning Kalman filter and machine learning algorithms to detect the upstream or downstream origin of the voltage dips monitored on field by the QuEEN system in the Italian MV distribution network. In order to achieve the full voltage waveforms some improvements have been recently introduced in the QuEEN monitoring system regarding the event acquisition.

The remainder of this paper is organized as follows: in section 2 a critical review of the segmentation methods proposed in literature, is presented by testing them on the available full voltage waveforms acquired on field. In section 3, the self-tuning Kalman filter and how the parameters are selected for its design are described, while the results of its application to a significant sample of voltage waveforms are shown in section 4. In the next section (section 5) the results obtained by the application of a machine learning algorithm to voltage dips upward/downward origin classification are presented. In the final section (section 5) some conclusions are drawn.

2. Critical review of segmentation methods

The first step afforded by any advanced waveform analysis technique is the event waveform segmentation that means to take apart the waveform to steady-state segments and transition segments (Fig.1). The segmentation techniques adopted by some of the works, such as [5, 7, 8], have been analysed hereafter by their application to real waveforms.
In fact, when these techniques (i.e. the "residual model by KF or by Butterworth filter", the "harmonic components method") are applied to voltage signals collected from PQ monitors located at the distribution networks, it is observed that each of them faces some obstacles in the segmentation procedure.

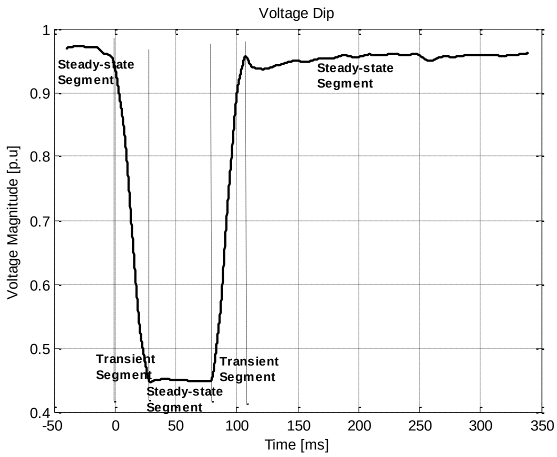

Fig. 1.Voltage waveform segmentation.

In the "residual model", for instance, the differences between Kalman filter estimation and voltage dip waveform (the residual) is used to identify the transition segments and a technique is introduced to set a threshold that helps to approximate both the beginning and ending points of the transient segment. In [5], two hypotheses (H_0 and H_1) have been considered for setting the residual threshold:

$$\boldsymbol{H_0} : \ \textit{\textbf{is not a transient segment}}$$
$$\textit{\textbf{residual}} < \textit{\textbf{Threshold}}$$

$$\boldsymbol{H_1} : \ \textit{\textbf{is a transient segment}}$$
$$\textit{\textbf{residual}} \geq \textit{\textbf{Threshold}}$$

To implement those hypothesis and set the proper threshold the probability density function of both transient and steady-state segments points are required. This implies the availability of a great amount of both types of segments. In practice, the lack of data often makes difficult the estimation of the probability density function for choosing proper threshold [9].

Another author adopts a threshold algorithm based on "cusum theory" [7]; this solution works well in those cases in which voltage dips have a rectangular shape. In other cases, as shown in Figure .2, the changes in voltage are small and the algorithm does not work very well (the red circle).

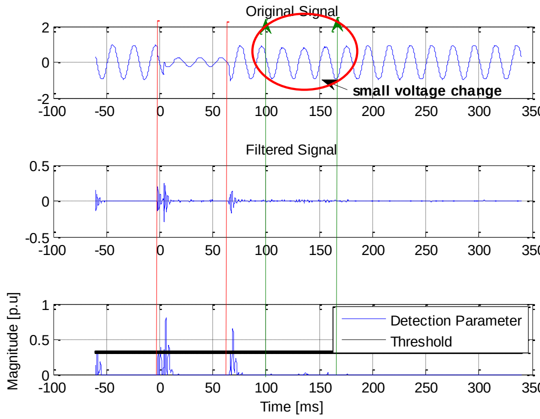

Fig. 2. An example of applied "cusum theory" on QuEEN voltage signal.

In other literature [8], an algorithm based on even harmonic components of the estimated voltage signal by KF is employed for the detection and segmentation of the voltage waveform. The voltage signal model adopted is shown in equation (1) and consists of the fundamental frequency component and a certain number of harmonics N:

$$\boldsymbol{z(t) = \sum_{n=1}^{N} A_n(t)\cos(n\omega_0 t + \theta_n(t))} \quad (1)$$

The result of the application of the KF algorithm is that the fundamental frequency component detects the voltage dips shape, while the second harmonic peaks identify the transient segment.
Even if this algorithm is not accurate as much as the previous mentioned algorithm, it is more applicable on real cases (as shown in next §).

In this study, an optimized kalman filter estimator is applied on significant amount of voltage dips waveforms obtained from QuEEN to extract more features for voltage dips classification purposes.

3. Self-tuning Kalman Filter design

In order to design the KF estimator with a more accurate output, four essential parameters must be set: initial state estimate $\boldsymbol{x(0)}$, initial estimator error covariance $\boldsymbol{p(0)}$, system model error covariance $\boldsymbol{Q}$ and measurement error covariance $\boldsymbol{R}$ [8]. Table.1 reports the values chosen, in the study, for the parameters.

Table I- KF Setting

Model Order N	20
$\mathbf{x(0)}$	0
$\mathbf{p(0)}$	1 (e.g. the initial state vector at the beginning of the process is significantly different from observation.)
R	$\mathbf{10^{-5}}$ (e.g. the low value means low measurement error.)
Q	Self-tuning updating

In accordance with some literature [8], $\boldsymbol{Q}$ is supposed to be a diagonal matrix with the constant value ($\mathbf{0.05}\boldsymbol{pu}^2$) on the diagonal.
In this paper, on the contrary, in order to improve the fast adaptive capability of KF to the sudden changes of the input signal, $\boldsymbol{Q}$ is supposed to be updated during the KF processing in the following way [10]:

$$\widehat{\boldsymbol{Q}}(\mathbf{0}) = \mathbf{0.05}\, \boldsymbol{pu}^2 \quad (2)$$
$$\widehat{\boldsymbol{Q}}(\boldsymbol{n}) = \mathbf{0.5}\,(\widehat{\boldsymbol{w}}_\mathbf{1}(\boldsymbol{n}) + \widehat{\boldsymbol{w}}_\mathbf{1}(\boldsymbol{n}))\boldsymbol{I} \quad (3)$$
$$\widehat{\boldsymbol{w}}(\boldsymbol{n}) = \boldsymbol{k}(\boldsymbol{n})[\mathbf{v}(\boldsymbol{n}) - \boldsymbol{H}(\boldsymbol{n})\boldsymbol{x}(\boldsymbol{n})] \quad (4)$$

where, $\mathbf{k}, \mathbf{v}, \mathbf{H}$ are the Kalman gain, the measurement data, and the matrix that connects the measurement with the state-vector, respectively.

At the end of the process, the state-vector is estimated. The first four elements of the state-vector are employed to estimate the event (state 1 and 2) and to detect all the transients segments (state 3 and 4).

A. Threshold Setting

The detection of both the beginning and the ending points of a transient segment depend on the selected threshold. The threshold is computed from *Mean control chart* x-bar chart [11] as the following:

$$\boldsymbol{Threshold} = \bar{\bar{\boldsymbol{x}}} + \boldsymbol{L}\boldsymbol{\sigma}_{\bar{\boldsymbol{x}}} \quad (5)$$

where, $\bar{\bar{\boldsymbol{x}}}$ and $\boldsymbol{\sigma}_{\bar{\boldsymbol{x}}}$ are the average of sample means and standard deviation of the distribution of sample means. The value of $\boldsymbol{L}$ plays a crucial role in detecting the beginning and ending point of the transient segment. Thus, the L is chosen so that the "false alarm" takes the small value. Hence, the equation (5) is applied from right side and left side of the estimated second harmonic of full voltage waveform. And the selected value $\boldsymbol{L}$ for right side threshold is bigger than the selected value of $\boldsymbol{L}$ for left side threshold.

4. Results of Self-tuning KF application

Fig. 3 shows how KF estimates the magnitude of a full waveform voltage in case of event occurring three line to line voltages. Whereas, the result of waveform segmentation by right and left threshold setting for an event occurring in one line to line voltages, is presented in Fig. 4.

5. Machine learning algorithms for voltage dips classification

Among machine learning supervised classification algorithm, Support Vector Machine (SVM) has been chosen to classify the recorded voltage dips with respect to their source location (upstream or downstream from the measurement point) as this technique can be applied efficiently also to binary not linear classification problems [12]. In fact voltage dips of origin in the HV and MV networks plotted in the "duration/residual voltage plane" seem not to be linearly separable.

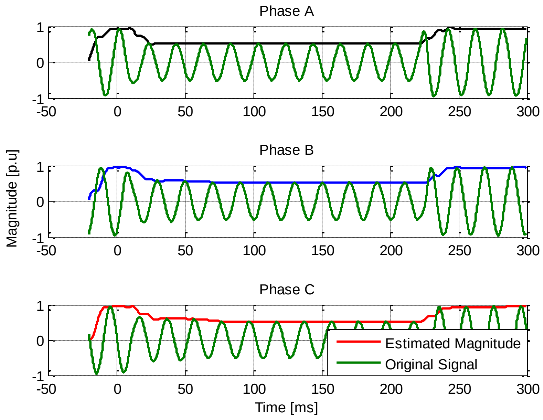

Fig. 3. Estimated magnitude by KF for three line to line voltage event.

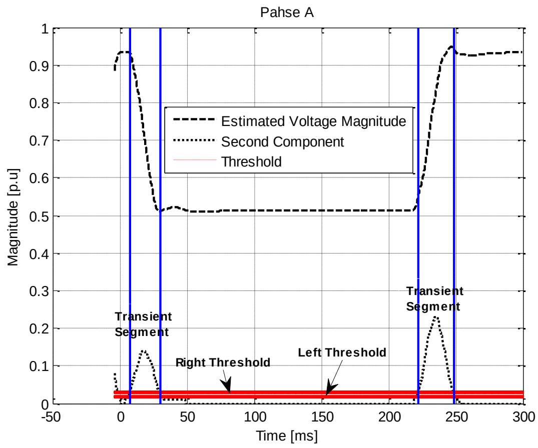

Fig. 4. Detection of transition segments for one line to line event by the second harmonic and set right and left threshold.

However, SVM succeeds in separating the data in two classes with as big a margin as possible.
By considering at first only two features, voltage dip duration and depth, we get a model that does not fit the "training set" (data used to train the algorithm) very well, probably due to lack of features.

A. More features are needed

For this reason the aforementioned waveform analysis method (§3) has been applied to the set of waveforms at disposal to extract other features. These features include:

(i) the number of line to line voltages involved in the event ("*phase feature*");

(ii) two-dimensional geometric shape of voltage dips as shaped by the transient and steady-state segments identified by KF ("*shape feature*"). For instance, Fig. 5 shows a typical rectangular "three voltages" event characterized by two transient segments with one steady-state segment; whereas, Fig. 6 shows a triangular "one voltage" event characterized by two transient segments and the lack of any "steady-state segment".

Analysis has been done on 410 full voltage waveforms acquired from the Italian MV distribution network by the QuEEN system. Table II reports the obtained statistical results.

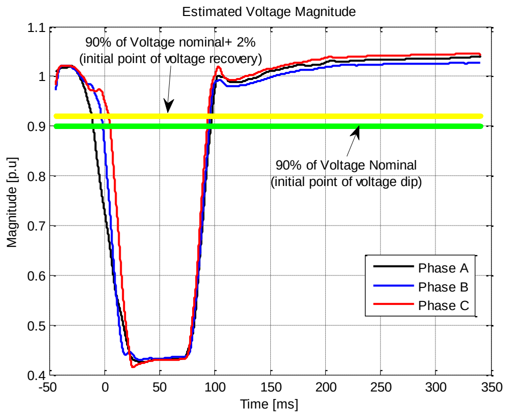

Fig. 5. A rectangular and "three voltages" event KF estimation.

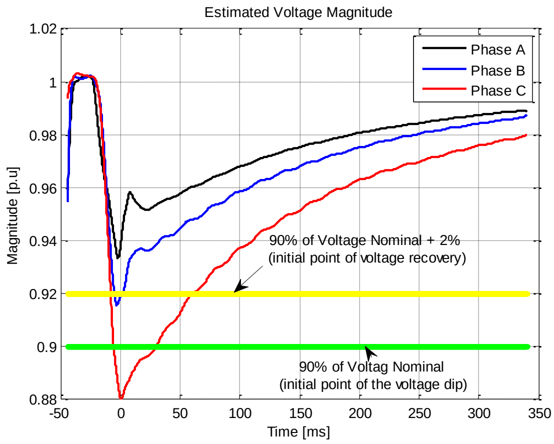

Fig. 6. A triangular and "one voltage" event KF estimation.

Table II- The statistical result.

Total Number of Full Waveforms	Total Success Cases		Total Failure Cases	
410	346	84%	64	16%

Success cases are those which self-tuning KF has estimated the event voltage and extracted the phase and shape features correctly; while failure cases associated with those which have been estimated correctly even if their features have not been extracted properly.

B. The Support Vector Machine algorithm

At the end of these analysis a matrix $X_{N \times M}$ is obtained, where N is the number of the success cases (346) and M is the number of features (4: Duration, Residual Voltage, Number of line to line voltages involved, and Shape).

Support Vector Machine as a supervised machine learning classification technique is employed to classify voltage dips with respect to their source location.
For this purpose, the matrix $X_{N \times M}$ is divided into two sub-matrixes: a) 70 percent of the $X_{N \times M}$ has been taken as a training set matrix (242 out of 346); b) 30 percent of the $X_{N \times M}$ as a test set matrix (104 out of 346) [13]. The events in the two sub-matrixes are chosen randomly, by a suitable Matlab algorithm, to better verify the SVM algorithm performance.
The training set matrix is used to train the model and then the model performance is evaluated with the test set matrix.

Basically, SVM maps the training set into kernel space by a kernel function (Gaussian Radial Basis Function Kernel 'rbf') and then, it applies another function in order to find the separating hyperplane so that minimises the margin between the two classes [14]. In this work, Sequential Minimal Optimization (SMO) has been utilized.

6. Evaluating the Performance of the Model

Confusion matrix gives possibility to evaluate and validate the model. Confusion matrix is a matrix $C \times C$, where C is the number of classes (here, upstream, downstream from measurement point - $C = 2$).

The Confusion matrix has been applied to both the "training set" and "test set" matrix. Accuracy says, the total number of the test set cases which have been correctly identified by the model, is 83% and 91% respectively. It worth noting that, the higher accuracy for the "training-set" does not guarantee the high performance of the model.

Table III represents the confusion matrix which has been calculated on the 104 data set. True positive rate (sensitivity) and true negative rate (specificity) indicate the rate of positive cases (HV origin) and negative cases (MV origin) which are classified correctly. They are 87% and 94%; respectively.

Table III. Confusion Matrix calculated on the 104 data set.

		Predicted Labels (Model)		
		False (MT)	True (AT)	
True Labels	False (MT)	43	6	Specificity= 43/(43+6)=0.87
	True (AT)	3	51	Sensitivity= 51/(3+51)=0.94
		Negative Predictive Value= 43/(43+2) =0.95	Positive Predictive Value= 51/(51+7)= 0.87	Accuracy= (43+51)/ (43+6+3+51)= 0.91

7. Conclusion

In this paper, self-tuning KF is used and applied to a significant sample of voltage dips full waveforms acquired in the Italian distribution network, in order, at first, to detect voltage dips and then estimate their voltage magnitude. Additional features are then identified such as: "phase feature" and "shape features" by segmentation and the estimated voltage magnitude. These features, together with the event duration and event residual, are utilized to classify voltage dips on the base of their source location (HV and MV).

The aforementioned classification is done by a Support Vector Machine algorithm: the performance of the algorithm has been evaluated by confusion matrix applied to both a "training set" and "test set" event matrix, obtaining an accuracy of 83% and 91% respectively.

The analysed events refer to 410 full real voltage waveforms acquired from the Italian MV distribution network by the QuEEN system.

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