Signal Processing and Classification Tools for Intelligent Distributed Monitoring and Analysis of the Smart Grid

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Irene Y.H. Gu, Math H.J. Bollen and Cuong D. Le

Abstract – **This paper proposes a novel framework for an intelligent monitoring system that supervises the performance of the future power system. The increased complexity of the power system could endanger the reliability, voltage quality, operational security or resilience of the power system. A distributed structure for such a monitoring system is described and some of the advanced signal processing techniques or tools that could be used in such a monitoring system are given. Several examples for seeking the spatial locations and finding the underlying causes of disturbances are included.**

***Index Terms*— power transmission, power distribution, smart grids, signal processing techniques.**

I. Introduction

THE future power system is expected to differ from the existing power system in a number of ways. Electricity production will consist, to a much larger extent than before, of electricity from renewable sources like wind, solar or wave power. Production units will also be, to a much larger extent than before, small units distributed over the power system, many of which will be owned by small customers beyond the control of the system operators, instead of large units owned by a small number of large companies. Customers will, much more than in the past, be involved in the markets for electrical energy (spot market as well as balancing market) and in markets for ancillary services (such as operating reserve, reactive power, and many more). Communication and power-electronics control will become much more important parts of the system, including advanced protection systems, power-electronics based voltage control of the distribution system, but also FACTS devices and HVDC links. All this is often referred to as the "*smart grid*" or the "*intelligent power network*". The need for this advanced smart-grid technology is to a large extent driven by the integration of large amounts of renewable electricity production in the power system [1] but several other driving forces have also been identified.

Both the new sources of production and the new technology will make that the complexity and dynamics of the power system will increase significantly, while demands on reliability and operational security will remain the same or even become stricter as society's dependence on electricity increases. Reliability and operational security can partly be improved by the same type of new technologies used to allow the integration of large amounts of renewable electricity production. But new technology and the increased complexity of the system can also become a threat against the reliability and operational security.

Many new technologies require measurements (smart meters, power-electronic controllers, advanced protection devices), and these measurement data could be used to monitor the performance of the power system, including reliability, voltage quality and operational reserve. This information could next be used to provide feedback to the network operator to improve the performance and resilience when needed.

The resilience of the power system includes its ability to withstand intentional attacks, but also, and possibly more importantly, its resilience against unexpected and cascading technical errors. The power system protection and control play a very important role in keeping the system as a whole intact despite the failure of a part of the system. Incorrect operation of the protection or control could result in cascading failures, leading to large scale blackouts impacting whole countries or regions for several hours through days. By continuously monitoring the performance of the power system, including the protection and control, during minor disturbances, important information can be extracted about the ability of the protection and control to avoid cascading failures. Such information can be used to take appropriate measures, ranging from preventive maintenance and replacing faulty components to changing operational and design methods. Information can also be obtained from identifying trends towards deteriorating performance or resilience.

Analysis of disturbance recordings is performed regularly by transmission-system operators in many countries, and information about incorrect operations of protection and control is used to take appropriate measures. However, such analysis is currently done manually which is labor intensive and slow. Also this does limit the analysis to the highest voltage levels. The above-mentioned trends in the power system will increase the complexity of the power system also at lower voltage levels, where manual analysis is not practical. Manual analysis will further make it much harder to detect slow trends and information may easily be missed especially when the way of system operation is changing, as will likely

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be the case during the coming years. Unexpected cascading errors at lower voltage levels will not result in large-scale blackouts but will impact the reliability and voltage quality for the customers.

All these developments call for an effective intelligent monitoring system including automatic analysis of disturbances, diagnosis of their underlying causes, and detection of trends in performance. The main contributions of this paper are:

- ✓ Introducing the concept of an intelligent monitoring system that supervises the future electricity network. Such an independent system is needed to prevent deterioration of reliability, voltage quality, operational security and resilience of the future power system.
- ✓ Proposing a multi-layered distributed structure for such a monitoring system, along with a novel classification network based on connecting multiple multi-class AdaBoost sub-classifiers.
- ✓ Identifying the need for advanced signal-processing tools that will form the basis for such a monitoring system.
- ✓ Showing several novel examples and results based on our lately conducted work and findings.

Further, some thoughts about the developments needed towards such a monitoring system for a smart grid are given.

II. The Intelligent Monitoring System

A. Objective of the monitoring system

The main objective of the intelligent monitoring system is to detect deteriorating performance of the power system at an early stage. Deteriorating performance includes reliability and voltage quality in low and medium-voltage distribution networks but also operational security and resilience in sub-transmission and transmission networks.

Such a monitoring system should be able to determine:

- ✓ *When* events / disturbances happened in the power system;
- ✓ *Where* these events / disturbances occurred in the system;
- ✓ *Whether* the system, including protection and control, performed correctly;
- ✓ Any *trends in performance* that could point to deteriorating voltage quality or reliability or to deteriorating security or resilience.

B. Structure of the Monitoring System

A distributed configuration for such a monitoring system is shown in Fig. 1; different new functionalities will have to be investigated and developed corresponding to analysis and diagnosis in different layers. The distributed configuration consists of a number of layers: *the sensor layer*; one or more *distributed layers* and *the central layer*.

In the sensor layer, a range of measurement devices are used to obtain local information on voltage and current; for example: power quality monitors; protection relays; remotely-read electricity meters ("smart meters"); digital fault recorders; control systems for HVDC and other power-electronics devices; and phasor measurement units.

The individual processing units that make up the local layer receive measurement data from a number of neighboring devices, and perform coarse analysis, processing and diagnostic functions. An important task of the local layers is to ensure the independence of the monitoring system. The processing units should be independent from any protection and control system; they should also detect when a device in the sensor layer provides incorrect information. A high level of redundancy is therefore needed in the sensor layer. Redundancy in the distributed layer further increases the accuracy of the monitoring system.

The central layer receives all essential information from all units in the distributed layers, and performs various diagnosis and system performance analysis by integrating this information together with some additional information such as local weather (lightning, temperature, and wind speed), electricity flows and operational state of the power system.

The latter information should again be verified by using information obtained from the sensor layer through the distributed layers.

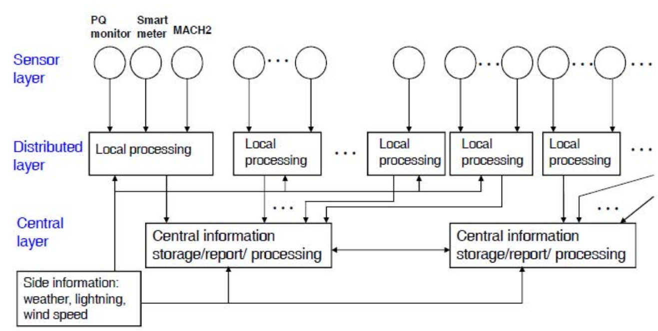

Fig. 1. A distributed configuration for an intelligent monitoring system.

C. Signal-processing techniques and tools

The intelligent monitoring system shown in Fig.1 requires a number of simple and advanced signal processing techniques and tools to extract information about the state of the power system. Some examples of advanced tools needed are described in the forthcoming section.

Depending on the processing layer, signal processing techniques/tools to be employed may concern:

a) Individual recordings at one location;
b) Multiple recordings obtained at the same time at different locations, or at different times at the same location;
c) Multiple recordings obtained in multiple locations over a long period of time.

III. Signal Processing Techniques and Tools

A. Time Allocation and Segmentation

Methods employed in this part are mainly within the local layer, but some may be embedded into devices in the sensor layer. Sensors play important roles in capturing power system disturbance data. Accurate triggering/detection helps to efficiently store only the disturbance data during continuous monitoring, and/or to allocate the exact time interval of disturbance-of-interest in the measured data. Processing in the local layer may include disturbance characterization, information extraction and coarse diagnosis.

The primary task of the local processing unit, in general, is to analyze disturbance waveforms, to find essential events (or disturbances) and collect their information related to the underlying causes (e.g. a failure of cable insulation causing over-current), and to discard minor events or variations (e.g. a normal switching of a feeder). Details of lower priority events may be discarded but their statistics kept. Robust signal processing techniques are required for accurate and reliable segmentation, characterization and pre-classification of underlying causes of disturbances. Side information may also be exploited, e.g. weather information (e.g. lightning, high wind, or extreme temperature at the time of event). Statistics of performance in nearby devices may be obtained by long-term trend analysis and modeling.

To accurately allocate the time of underlying events, methods for segmentation of voltage and current waveforms are required. The robustness of segmentation methods is determined by high accuracy of time location of the underlying transition (i.e., high time-resolution), high probability of correctly detecting a transition or a triggering (high detection), and low probability of incorrectly detecting a transition or a triggering (low "false alarm"). Some examples of classifier configuration, efficient segmentation and time allocation are described below.

B. Coarse-to-fine diagnosis of underlying causes

1) A robust coarse-to-fine classification network using multi-class AdaBoost

For a distributed configuration of an intelligent monitoring system in Fig.1, one of the key issues is to decide the structure or topology of the classifier. We propose to employ *a classification network* for such diagnosis purpose, where the network consists of a set of coarse classifiers and a fine classifier. Each coarse classifier is located in an individual unit of the local layer, while the fine classifier is located in the central layer. We propose to use the multi-class AdaBoost in [4,5] for classifying power disturbance data.

AdaBoost (Adaptive Boosting) is a game theory-based classification method that minimizes the generalization error on the test set through maximizing the minimum margins:

$$\max_{\boldsymbol{\alpha}} \min_{i} \frac{(\boldsymbol{\alpha}\cdot \mathbf{h}(x_i))y_i}{||\boldsymbol{\alpha}||_l \; ||\mathbf{h}(x_i)||_l}$$

where $\boldsymbol{h}(x_i) = [h_1(x_i) \quad \cdots \quad h_T(x_i)]^T$ is a vector containing a set of weak hypotheses (or, weak classifiers) and $\boldsymbol{\alpha} = [\alpha_1 \quad \cdots \quad \alpha_T]^T$ the weighted errors for the weak learners. The final hypothesis or classifier is formed by $H(x) = Sign(\sum_{t=1}^{T}\alpha_t h_t(x))$. The basic AdaBoost algorithm (for 2 classes) is summarized in Table 1: noting that there are two sets of weights, one $\{w_t^i\}$ is for training samples, another $\{\alpha_t\}$ is for weak learners. Further, the selection of weak learner algorithm is dependent on the designer, e.g. one may choose a simple weak learner such as 'decision stump' [13] or 'perceptron' [14].

Given: *n* supervised training samples (x_i, y_i) , i=1,…n, where the training samples $x_i \in X,$ and the class labels $y_i \in Y = \{-1, +1\}$

1. Initialize the weight distribution (for the training data) $w_1^i = \frac{1}{n}$;

For *t = 1* to *T (T is the total number of weaker learners)*:

2. Training the weak learner h_t using w_t^i;

3. Compute the error of the weak learner h_t: $X \to \{-1, +1\}$:

$$\epsilon_t = Pr_{i\sim w_t}[\, h_t(x_i) \neq y_i \,] = \textstyle\sum_{i:\, h_t(x_i) \neq y_i} w_t^i$$

4. Compute the weight for the weaker learner:

$$\alpha_t = \frac{1}{2} ln \frac{1-\epsilon_t}{\epsilon_t}$$

5. Update the weight distribution:

$$w_{t+1}^i = w_t^i \exp\ (-\alpha_t y_i h_t(x_i)) \,/ \sum_{i=1}^{N} w_t^i\ , \quad i = 1,2,\ldots,n$$

End {for}

6. Output the final classifier: $H(x) = sign(\sum_{t=1}^{T}\alpha_t h_t(x))$

Table.1 A pseudo algorithm of a binary-class AdaBoost from [12].

Two properties of AdaBoost that are particularly attractive to this application: (a) to perform sequential training (offline or online) by adding weak classifiers; (b) to provide the confidence level of classification (from the magnitude of weak classifier $|h_t(x)|$). The former one allows one to add new training data to online improve or adding new classes to the classifier, and the latter allows one to know how reliable the classification results are. It is worth noting that these two properties do not hold for a SVM (support vector machine) classifier that has become increasingly popular in the power system applications [6].

Key differences between AdaBoost and SVM classifiers: Comparing with using L_2 norm to both $\boldsymbol{\alpha}$ and H(x) in a SVM classifier that is realized by quadratic programming and using kernels in the high dimensional space, AdaBoost differs by using L_1 norm for $\boldsymbol{\alpha}$ and L_∞ norm for H(x), and is realized by linear programming and Greedy search.

2) Extract useful features based on their underlying causes. Another important issue is to decide which features are used in the local layer and which in the central layer. Objective criteria should be employed to find the optimal classification network that minimizes the overall classification errors, taking into account several effects in the power system, e.g. different combinations appearing in local units, sensitivity/reliability of different devices, and weighting features according to their relevance to major events.

Extracting useful underlying cause-related features from a wide range of disturbance types in power systems with large amounts of renewable electricity production and other aspects of future power system is another key issue that requires specific knowledge of design and operations of power systems. Selection of such features may significantly impact the performance of the classifier.

In the following examples [11] we show how features are extracted from different local layers (in different levels of grids).

<u>Example-1:</u> Features for 3 underlying causes (faults, unit switching, capacitor energizing) from the disturbance waveforms in a zone of 20-kV grid

Three classes of underlying causes are considered from the disturbances in this example: fault, unit switching, and capacitor energizing. For each waveform data sequence (voltage and current) captured by a monitor, a segmentation algorithm [7,8] is first employed to the waveform data that results in a number of transition and event segments. A 3-component feature vector $\boldsymbol{f} = [f_1 \quad f_2 \quad f_3]^T$ is considered where:

f_1 = number of transition segments;

f_2 =high frequency components around the event in the voltage, when the voltage in event segment is within the normal operating limit;

f_3 = $|\Delta I|$, or the absolute value of changes in the current.

a) fault: if f_1>1, the underlying cause of the disturbance is due to "fault".

b) unit switching: If f_1=1, further examination is required of the data from the monitor connected to the terminal of the switched unit (i.e., a monitor most sensitive to the event). An event is classified as unit-switching if:

- Voltage in the event segment is within the normal operating limit, and not rich in high-frequency components around the switching instant (i.e. f_2 =low) , see the spectrogram in Fig. **2**.
- Absolute current change is high (i.e., f_3 =$|\Delta I|$ is high, e.g. $f_3 > T_3$ =0.9 (threshold)), where the current change is defined as $\Delta I = \frac{I_{event} - I_{pre-event}}{\max(I_{event}, I_{pre-event})}$ and I_{event} and $I_{pre\text{-}event}$ are the currents before and during the event segment, respectively. The sign of ΔI indicates a tripping or an energizing event.

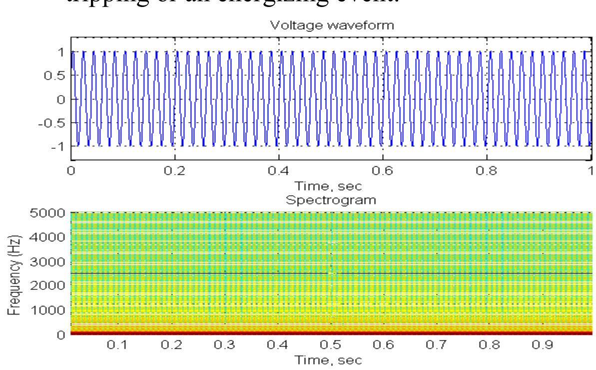

Fig. 2. Unit tripping event (at 0.5 sec) and its voltage spectrogram.

c) Capacitor energizing: If f_1=1, further examination is required of the data from the monitor closest to the capacitor (i.e. the monitor most sensitive to the event). An event is classified as capacitor energizing if:

- Voltage in the event segment is within the normal operating limit, but rich in high-frequency components around the energizing point (i.e., f_2= high, or $f_2 > T_2$ (threshold)), see the spectrogram in Fig. 3.

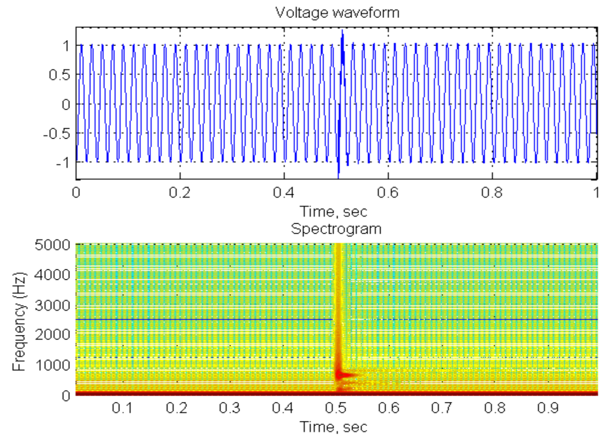

Fig. 3. Capacitor energizing event (at 0.5 sec) and its voltage spectrogram.

Example-2: *Features for 3 underlying causes (fault, capacitor energizing, transformer energizing) from the disturbance waveforms in* the zones of 130-kV and 400-kV grids

For each waveform data sequence captured by a monitor, a segmentation algorithm [7,8] is first employed to the voltage waveform data that results in a number of transition and event segments. A 2-component feature vector $\boldsymbol{f} = [f_1 \quad f_2]^T$ is considered where:

f_1 = number of transition segments;

f_2 =high frequency components at around the event in the voltage.

a) fault: similar to example-1, if the number of transition segments, $f_1 > 1$;

b) capacitor switching and transformer energizing: both have one transition segment $f_1 = 1$. Further, both have harmonic contents at low frequencies. However, comparing with their voltage spectrograms, a capacitor switching event has high energy at the relatively high frequency range (>500Hz), whereas a transformer energizing event has high energy at relatively low frequency range. See the spectrograms in Fig. 4.

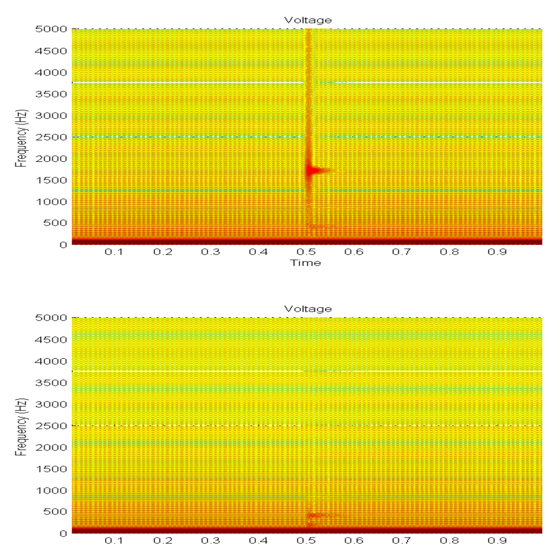

Fig. 4. Voltage spectrograms. Top: capacitor switching; bottom: transformer energizing.

C. Space Allocation of Underlying Events

The spatial location of an underlying event that resulted in the disturbance can be estimated by using gathered measurements from multiple locations synchronized over the same time interval. This is mainly performed in the units of local layer but some can also be in the central layer. A systematic step-by-step approach should be applied by exploiting the following information:

- Extract information about the direction pointing towards the underlying event from the measurement location.
- Estimate the closest location of monitoring point to which the underlying event occurred, by using the information about the deviations of major features in voltage and current from their pre-event values at multiple locations, and the severity of such deviations in different locations.

An example is given below for determining the spatial location of two specific types of disturbances: upstream/ downstream faults, and capacitor energizing.

a) Distinguish between upstream and downstream faults:

The relative location of fault is determined by comparing the phase angles of pre-fault and during-fault currents. Considering a simple system in Fig. 5 with a pure inductive fault current and active power flow from A to B. Upstream and downstream are defined according to the direction of active power flow, i.e. a fault at F1 (or F2) is an upstream (downstream).

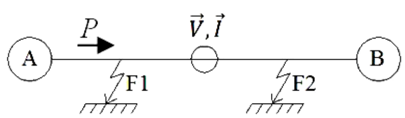

Fig.5. A simple system.

Consider the time instant immediately after the fault inception and assume that $\boldsymbol{I}_{during} = \boldsymbol{I}_{pre} + \boldsymbol{I}_f$, where $\boldsymbol{I}_{during}$ is the during-fault current, $\boldsymbol{I}_{pre}$ the pre-fault or load current, $\boldsymbol{I}_f$ is the fault current. The pre-fault current may be either inductive or capacitive, and the fault may occur either at F1 (upstream) or F2 (downstream). This leads to four possible combinations, as shown in Fig. 6.

a) By observing Fig.6(a) (inductive pre-fault current, downstream fault) and Fig.6(b) (capacitive pre-fault current, downstream fault), and assuming the active power flow from A to B, one may conclude that $\boldsymbol{I}_{pre}$ lies somewhere in the positive plane of the real axis, and the actual during-fault current lies somewhere between $\boldsymbol{I}_f$ and $\boldsymbol{I}_{during}$ (the dashed region). Thus, in both cases of inductive or capacitive pre-fault current, $\boldsymbol{I}_{during}$ always lags behind $\boldsymbol{I}_{pre}$ if it is a downstream fault.

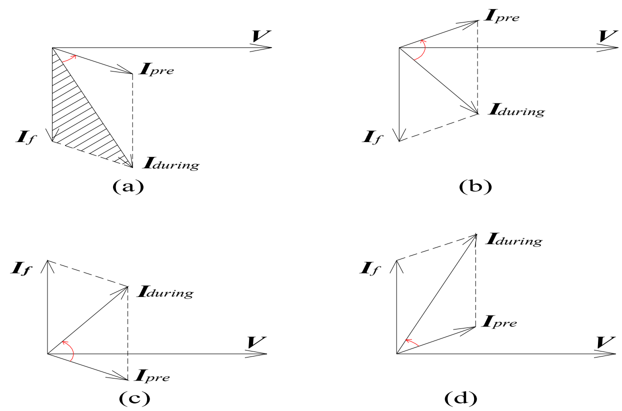

Fig.6. Phasor diagrams.

b) Similarly, for upstream faults, $\boldsymbol{I}_{during}$ always leads ahead $\boldsymbol{I}_{pre}$. Fig.6(c)(d) show the phasor diagrams of an upstream fault with inductive and capacitive pre-fault current, respectively. From this analysis, the relative fault location is determined by comparing the phase angles of pre-fault and during fault currents. Many algorithms have been developed to track the phase angles based on the zero crossings, e.g. FFT, and Phase Lock Loop. An example of a downstream fault by both zero crossings and FFT phase angle tracking (from EMTDC) is shown in Fig.7, which confirms the proposed method. The upper plot in Fig.7 shows three zero-crossing points associated with a downstream fault.

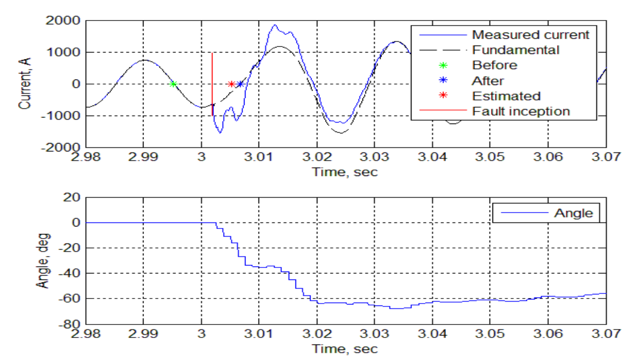

Fig.7. Phase angle tracking by zero crossing and FFT. In the figure, "Before/After" denote the closest zero-crossings of fundamental current before/after the fault inception instant, and "Estimated" denotes the estimated zero-crossing without the presence of fault.

The estimated time is $t_{estimated} = t_{before} + 0.5T$, where T is the fundamental cycle. In this case, $t_{after} > t_{estimated}$ implying that the during-fault current lags the pre-fault current. This confirms a downstream fault case. The lower plot in Fig. 7 shows the difference between the pre-fault and during-fault current angles computed by FFT in EMTDC. The negative value implies that the during-fault phase angle is smaller than the pre-fault phase angle, or during-fault current lags behind the pre-fault current.

b) Tracking the location of events

Although many studies have been reported on tracking the location of faults, only a few results are reported on tracking the locations of other events, e.g., relative source location of shunt capacitor switching transients [9, 10]. Reference [11] shows the tracking of locations of capacitive switching event family (capacitor switching or cable energizing), where the relative location of disturbance source is determined by looking at the initial direction of fundamental and harmonic currents. This is based on the fact that immediately after energizing instant, harmonic currents rush into the switched device. Hence, one may compare the initial phase angles of the fundamental and harmonic currents to determine the relative switching location. The procedure can be summarized as:

- Extract the fundamental current (I_1) from the measured current (I);
- Calculate the total harmonic current $I_h = I\text{-}I_1$;
- Find the first peak in the harmonic current, denoted by the point: t_p on the time axis;
- Compare the direction of I_1 and I_h at the time instant t_p: If $I_1(t_p)*I_h(t_p) > 0$, the initial harmonic and fundamental currents are in the same direction, indicating a downstream energizing event, and the vice versa.

Fig.8 shows an example of one upstream and one downstream capacitor switching event.

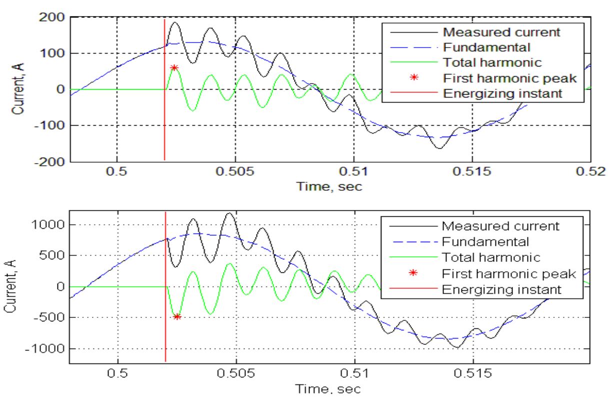

Fig. 8.Capacitive switching events. (top: Downstream, bottom: Upstream).

D. Extract information from events, and estimate the risk of cascading failure (or event)

Extracting information from individual events is an essential step in the monitoring system. Especially information on the performance of the protection and control system during events should be extracted. Such information is essential in determining the vulnerability of the system, e.g. the risk of a cascading event. The information extracted from individual events not only will be used for coarse diagnosis and analysis in the local layer, but also will be transferred to the central layer for final classification and other additional analysis and statistics, e.g. long-term statistics on system reliability, availability, quality and vulnerability, which may help network operators on planning and expanding the power system. The information may also be used for exchanging with other systems (within or outside the country in large-scale interconnected power systems). In particularly, the information extraction should focus on:

1) Characterize underlying event and the system performance during the event.

For each individual event, information on time and spatial location, together with an appropriate set of features, will be used to characterize the underlying event as well as the performance of the power system during the event. For example, information about the duration of voltage dips or interruptions can be used to evaluate the performance of protection relays and switching devices. A circuit breaker should be taken out for maintaining if the difference in closing/opening time instants of three phases suddenly increases. Of special importance is the information about the correct or incorrect performance of protection and control, especially those related to renewable energy sources. This information from multiple disturbances over a longer period of time will be used to obtain trends that could point to vulnerabilities of the power system.

2) Analyze long-term trends for assessing the performance of power systems with large amounts of renewable electricity production.

Long-term trend analysis of both events and variations, e.g. in frequency, voltage magnitude, flicker, and harmonic distortion, is useful for following up the operation conditions of individual devices as well as the system as a whole. Long-term trend analysis is also important in its own right in terms of early predicting possible cascade failures and assessing the health of the system. A sudden change in the trend likely implies something is happening with the supervised device. The trend of partial discharge, for example, is an index for the health of insulation. A sudden increase in partial discharge frequency and level gives an alarm for network operators to apply appropriate solutions to prevent possible insulation breakdown which may lead to supply interruption. Long-term-trends and statistics of measured voltage and current waveforms at multiple locations over a longer period of time are especially useful in a power system with large amounts of renewable electricity production. This type of trend analysis can be applied to improve system reliability by early detecting, locating, and repairing incipient failures before catastrophic failure. Long-term trend analysis may also be employed to assess the quality of power. Processing data in a long term to obtain statistics of power quality indices, e.g., total harmonic distortion, waveform distortion, and symmetrical component deviation can help network operators to plan the system to meet the requirement on power quality. Statistics on the number of events/variations per year can be used to quantify the system availability.

IV. Conclusions

The introduction of new technology in the power systems (the smart grid) will offer new opportunities but it will also lead to new challenges and threats. One such threat is a potential reduction of the resilience of the system component failures because of the unknown behavior of new technology, new design and operation rules and an overall increase in complexity. At the same time the availability of vast amounts of measurements data offers the opportunity for an intelligent monitoring system. Such a system will enable the early detection of threats like an increased risk that a single component failure will result in a cascading failure. Such a system will enable an overall increase in continuity of supply and voltage quality.

Such an intelligent system requires the development of appropriate signal-processing tools, some of which are described in this paper.

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