Field Test of a System for Automated Classification of Power Quality Disturbances

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Abstract— **Power quality monitoring has advanced to an important tool for system evaluation and solving power-related problems. As a consequence the increased amount of recorded data requires more sophisticated analysis methods. The paper proposes a system for automated recording and classification of power quality disturbances. The system features statistical classification techniques applied to a frame-based event model. Results and experiences made by a test in a low-voltage power system are presented.**

Keywords— Classification system, field test, power quality, power quality monitoring.

I. INTRODUCTION

By the increased interest in Power Quality (PQ), monitoring PQ parameters has become an essential task for performance evaluation and troubleshooting in power systems. Two major fields of application for PQ monitoring can be quoted.

Permanent monitoring in order to characterize power system performance is a preventive task. By understanding the normal PQ performance, problems can quickly be identified. In addition it allows utilities to prove the system's compliance to standards like EN50160 [1] and EN61000 [2][3] in order to match requirements of customers. For competitive reasons the level of PQ performance may be a valuable information for utilities in the near future.

PQ troubleshooting is a reactive application of PQ monitoring. When facing power-related problems in facilities, the principle strategy is first to inspect the site and to gather system information. Then the system is monitored over a certain period of time, usually one or more weeks. After successful analysis of the recorded data corrective solutions can be applied to overcome the problem.

These two applications of PQ monitoring have a common aspect: the analysis deals with a huge amount of recorded data. Although steady-state measurements are analyzed automatically, the analysis of recorded events is still done manually by visual inspection, hence very time consuming and requiring a high expertise. Here a tool which is able to identify certain types of events automatically may reduce this analysis effort.

This paper proposes a method that classifies the type of PQ event automatically by its typical characteristics.

Some approaches have been studied applying artificial intelligence techniques before, one using artificial neural networks (ANN) [4], another applying a rule-based expert system [5]. These two approaches have achieved useful results, but offer low information about classification reliability.

The present approach uses statistical classification techniques on a frame-based event model. The basic methods have their origin in the field of speech recognition, where they have successfully been applied [6][7]. The key idea is, that in speech a single word consist of a sequence of distinct phones, that characterize the word. Hence identification of an unknown spoken word works by classification of phones and analyzing the phone sequence. Translating this method to the problem of PQ, it is assumed, that a PQ event can be split into a sequence of characteristic waveform frames. Similar to language, the set of possible PQ events defines an event vocabulary, a certain syntax of waveform frames determines a certain event.

A main objective of this classification system (CS) is robust and reliable type identification of PQ events. Robustness means, that for the benefit of abstraction capabilities and classification performance very special event types are not considered as targets. Reliable means, that a criterion has to be introduced, which assesses the quality of the classification result. As an open system, the CS should allow to improve its reference data in case of poor classification quality. Also a simple possibility for modifications and extensions of the event vocabulary should be realized.

First an overview of structure and main features of the PQ monitoring system prototype is given. In section III the individual modules of the monitoring system and their operation are discussed. Section IV describes a field test of the system and presents results and experiences, which have been achieved. Conclusions and future improvements are summarized in section V.

II. SYSTEM OVERVIEW

The PQ monitoring system prototype, which incorporates the CS for PQ events, consists of three major modules. The structure is given in figure 1.

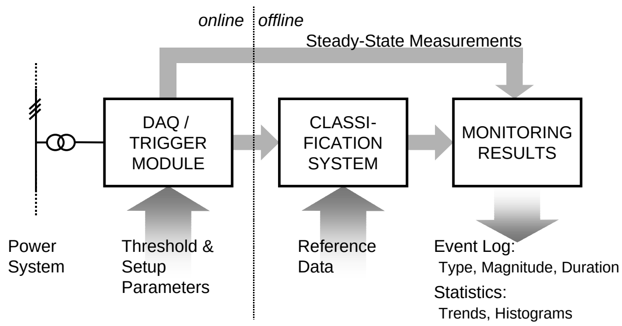

Fig. 1. Modules of the PQ monitoring and classification system

The data acquisition (DAQ) and trigger module establishes the interface of the CS to the power system. The CS is voltage oriented, hence the three phase-to-neutral voltages are connected to the monitor by isolating probes. In addition three current signals can be measured for more detailed PQ analysis. The DAQ and trigger module permanently calculates steady-state parameters, such as RMS values of fundamental and harmonic voltages and currents. Moving means of these parameters are stored for offline analysis. Monitoring voltage and current signals for exceeding predefined thresholds is the major task of the module. When a certain threshold is violated, all input signals are recorded for analysis of the CS module.

The CS is the core of the monitoring system. Out of the recorded voltage signals characteristic features are extracted. The type of the recorded event is determined by comparison of its extracted features with previous trained reference data. Afterwards the quality of the decision is tested. In case of sufficient quality the decision is accepted, otherwise the event is noted for manual classification.

The monitoring result module combines trends, histograms of processed steady-state measurements and an event log for a detailed PQ diagnosis. At that time those events with low classification quality can be classified manually by visual inspection. The result may be adopted by the reference data to enable a higher quality level in case of similar events.

III. SYSTEM OPERATION

The presented prototype of the PQ monitoring system is realized on a conventional PC platform with a DAQ board. The monitoring software runs under Windows NT in combination with Matlab. The mode of operations of the modules in figure 1 is described in detail in the following points.

A. DAQ and Trigger Module

As mentioned in section II the primary tasks of this module are:

- Interface between power system and CS.
- Detection and recording of PQ variations.
- Measuring steady-state values.
- Data processing for offline modules.

In low-voltage (LV) power systems voltage and current signals are directly measured by isolation probes and clamp-on current probes. In medium-voltage (MV) systems the voltage signals of local installed voltage transformers are connected to the isolation probes. The probe signals are the input of the DAQ board. The board features 8 differential inputs, 12 bit ADC resolution and 200 kS/s sampling rate.

Starting a PQ monitoring campaign first basic monitor parameters have to be set. The number and type of input signals are to be chosen. Next the sampling rate is set. For PQ event classification usually three line-to-neutral voltages are selected as input. A maximal sampling rate of 66 kS/s is possible for three channel acquisition, but 20 kS/s per channel proved to be sufficient. Other settings include averaging interval of steady-state measurements and pre- and post-trigger recording time. In order to detect PQ variations, the trigger module monitors four different signal parameters for threshold violations:

- Peak value of voltage and current,
- RMS value of voltage and current,
- relative waveform of voltage,
- harmonic voltages.

Peak and RMS values are verified every sample. The RMS value is calculated on the basis of a moving window of a half nominal cycle. The detection of relative waveform variations works by taking the sum of an actual voltage sample and its corresponding sample half cycle before. Under normal conditions the sum is about 0 V. When the sum exceeds a previous selected range, the number of violations is counted over a period of a half cycle. If this number is higher than a threshold, the system triggers. In addition it is possible to monitor harmonics of all channels by calculating a FFT over an interval of 200 ms. The system triggers, if an harmonic violates a predefined threshold.

In case of triggering, all signals are recorded. When the trigger is still active after recording time, new recordings follow, until the trigger gets inactive. Avoiding memory overflow, the system turns in a mode of sample recordings at regular intervals after an adjusted time. The system gets in normal monitoring mode if the trigger turns inactive.

The recorded events are stored on hard disk and can be analyzed by the CS.

B. Classification System

The appearance of PQ events of the same type can be very different. Variations in duration, magnitude and phase are self-evident. Even superpositions of different types PQ events may occur. To classify such events, a reduction to characteristic features is inevitable.

As mentioned in section I a methodology is applied similar to speech recognition [6][7]. The key idea of the present CS is that the complexity of PQ events can be sampled into a sequence of basic phenomena. For this purpose an event model has been developed. This model is shown in figure 2 by an example event [8].

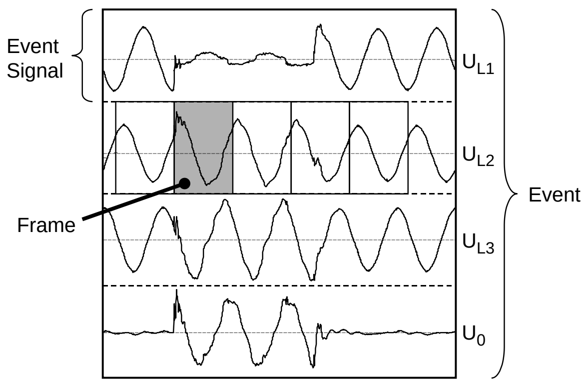

Fig. 2. Modules of a PQ monitoring and classification system

The event model consists of four "event signals", three recorded line voltage signals (U_{L1-3}) and the calculated zero-sequence voltage (U_0). Then each event signal is decomposed into small signal intervals, so-called "frames".

The classification procedure is divided into five steps, which are depicted in figure 3.

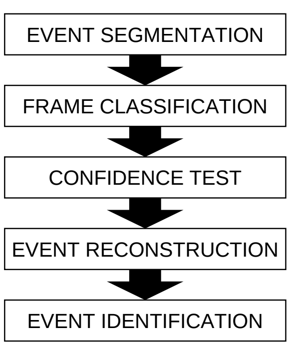

Fig. 3. Modules of a PQ monitoring and classification system

B.1 Event Segmentation

The events signals are decomposed into frames of fixed length of a nominal cycle. The trigger time determines the starting point of segmentation including one pre-trigger frame. Then the frames are serialized and passed to the frame classifier.

B.2 Frame Classification

The frame classifier decides the class of each frame. As classes basic PQ phenomena are chosen. A frame class consists of a "main characteristic" and may have a few "attributes", if existing. The RMS voltage of the frame determines its main characteristic. Attributes describe certain waveform phenomena. For instance the typical incepting voltage waveform of the faulted line can be expressed as "sag with oscillating transient and arcing character" for transient earth faults in MV power systems. This phenomenon is categorized by the frame class $\mathbf{U_{ota}}$. Table I shows the selected frame classes of the frame classifier.

TABLE I
Frame Classes

Main Characteristic	
N	RMS voltage in acceptable range
O	RMS voltage $> 1.1\,\text{pu}$
U	RMS voltage $< 0.9\,\text{pu}$

Attributes	
a	arcing characteristic
d	voltage distortion
it	impulsive transient
ot	oscillatory transient
r	repetitive disturbance

Classification starts with extracting relevant features from a single frame by signal processing. These features are peak and RMS value, THD and distortion index including inter-harmonics. In addition three features expressing the frame's time-frequency behavior are calculated by a modified discrete wavelet transform. These features are combined to a feature vector, which is the input of the classifier.

The present classification task requires a classifier with generalization and learning capabilities [9]. That is why rule-based classification is not suited for the present application. Statistical classifiers fulfil these requirements, thus selecting a parallel working Bayes and "k-nearest neighbor" (kNN) classifier. This structure proved efficiency in comparison to fuzzy and ANN classification techniques [10].

Each classifier of the parallel structure compares the input feature vector with its reference data, which originates from simulations and field recordings. That reference class, which fits best to the input vector determines the class membership of the present frame. When the two class votes of Bayes and kNN classifier coincide the decision is accepted, otherwise the classification failed.

B.3 Confidence Test

In order to allow only a reliable decision, its quality has to be tested. The strategy is to compare classification result and feature vector with previous successfully classified frames. Because the classifier techniques operate in a way of distance calculation, a confidence function can be calculated on the basis of histograms of previous classifier results [10]. If the actual result falls near a point of high accumulation, the confidence level is high. A decision has to reach a confidence level of at least 80%, otherwise the whole event is noted for manual classification

B.4 Event Reconstruction

After successful frame classification, the resulting frame types are arranged in form of the original signal. This sequence is denoted "waveform vector" and forms a row of the "waveform matrix". Figure 4 shows frame segmentation and classification of a sample event, an earth fault in a MV power system [8]. The results of

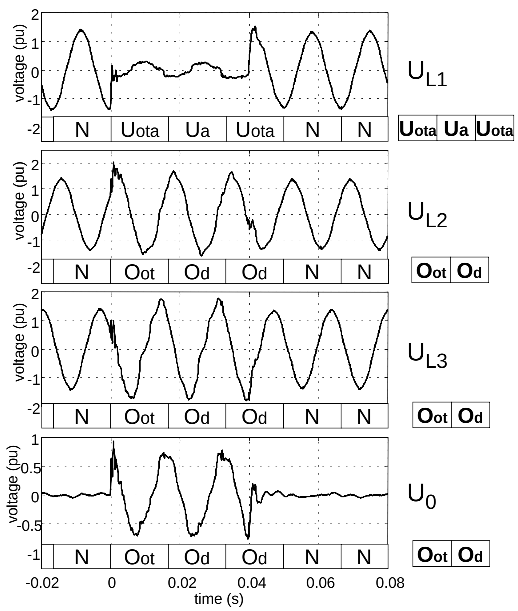

Fig. 4. Classification of frames and resulting waveform vectors of a sample PQ event

frame classification are drawn under the plot for each signal voltage. Afterwards the waveform vectors are condensed. This means that same consecutive frame types are reduced to a single instance (in case of event type "$\mathbf{O_d}$" for signals U_{L2}, U_{L3}, U_0). Frames of type "**N**" are removed. The condensed waveform vectors are shown on the right side of the plot.

B.5 Event Identification

The procedure for type identification of the sample event is illustrated in figure 5. First the signal types are identified. The waveform vectors a compared to signal patterns in a look-up table. For example the waveform vector of line 1 matches with the pattern "Fault, arcing" by the use of wildcards ("*"). The waveform vectors of line 2 and 3 can be identified as "Swell, transient". The waveform vector of the zero sequence voltage is only tested for voltage unbalance. The results of signal identification form the "signal vector" and are compared to entries in the event pattern table. The present sample event would be identified as shown in the figure. When no matches can be found

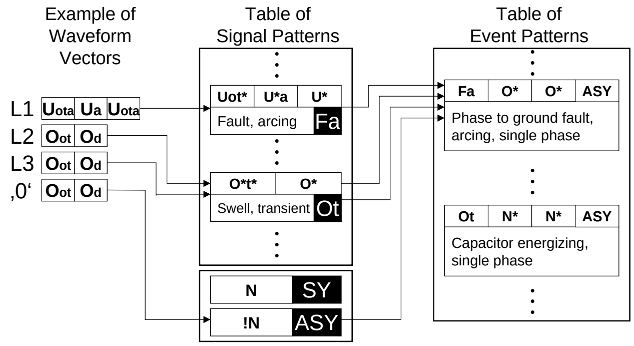

Fig. 5. Modules of a PQ monitoring and classification system

in signal or event pattern table, the event is noted for manual classification.

The advantage of these look-up tables is their simple expandability. Like a construction kit, existent patterns can be modified, new signal and event pattern can be added.

C. Results Module

As mentioned in section II the results of steady-state measurements and of the event classification system are brought together to enable an assessment of the monitoring campaign. Trend and histogram plots of RMS voltages, harmonics, THD and voltage unbalance can be generated. But most important is the event log, where trigger time, magnitude, duration and of course the type together with its confidence level is listed. In case of unknown event types, it is possible to plot the recorded event and classify it manually. Depending where the classification failed, in frame classification or event identification, unknown waveforms can improve the reference data or new signal and event patterns can be added to the look-up tables, respectively. A summary of occurred event types concludes the PQ analysis module.

IV. FIELD TEST

A. Monitoring Location

A field test was carried out at two different low-voltage power systems of the university campus. Figure 6 shows the diagram of the campus power system. An internal 6 kV-power system distributes the electric energy to several low-voltage systems.

At two different service entrances of low-voltage systems – locations A and B – the PQ monitoring system was installed. The two investigated power systems supply different loads. The system at location A supplies two office buildings and a laboratory. Hence location A is mainly characterized by lighting and computer loads and in addition by a 150 kW induction motor with power factor correction, which is installed at the laboratory. The power system at location B supplies experimental set-ups for adjustable speed drives (ASD).

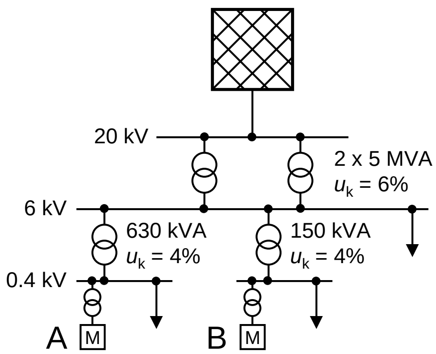

Fig. 6. One-line diagram of monitored power system

The three phase-to-neutral voltages were monitored at the two service entrances over a week period, respectively. Monitoring could not performed simultaneously, because only one PQ monitoring system was available.

B. Results

B.1 Steady-State Measurements

Figure 7 shows the trend of the steady-state-measurements recorded at location A. The extrema

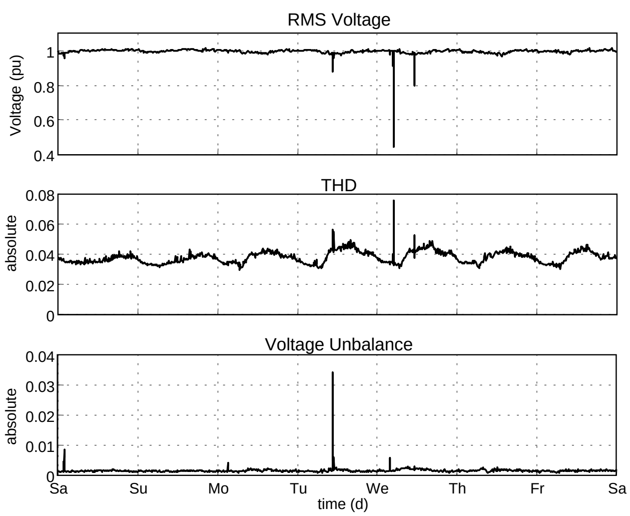

Fig. 7. Trends at location A, 09/09/2000 - 09/16/2000

of RMS voltage and THD can be seen. The lower plot shows the trend of voltage unbalance. During a week with thunderstorms, events in form of voltage sags are obvious in the RMS voltage trend. Effects of theses events are visible in THD and voltage unbalance plot. According to standard EN50160 [1], 95% of the steady-state measurement are to be in acceptable range of RMS voltage $(0.9 - 1.1\,\text{pu})$, THD $(< 8\%)$ and voltage unbalance $(< 2\%)$. Even with those voltage sags compliance to EN50160 is kept.

In comparison to location A the trends measured at location B, depicted in figure 8, show no significant events. The RMS voltage shows a lower level,

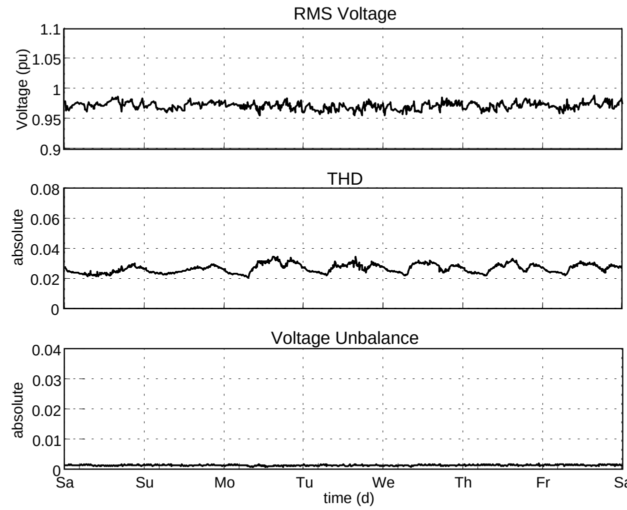

Fig. 8. Trends at location B, 11/04/2000 - 11/11/2000

because of the transformers tap changer remained on $U_n = 380\,\text{V}$. Also THD has a lower level, which can be mainly traced back to missing computer loads and fluorescent lights. In addition with a low voltage unbalance trend the compliance of the trend to EN50160 is proved.

B.2 Event Analysis

Table II shows the summary of the classification of the events recorded at location A.

TABLE II
EVENTS AT LOCATION A

Event type	**#**
Voltage sag, balanced	3
Voltage sag, unbalanced	1
Capacitor energizing	47
unknown	9
total:	60

Totally 60 events were recorded. The majority was classified as capacitor energizing, that can be most probably traced back to the power factor correction of the induction motor. Four voltage sags are identified. Knowing the transformer type, interpretations of the events can be drawn. Three were balanced sags, in spite of unequal phase-to-neutral voltages. Thus they can be assumed as result of remote faults in transmission systems. The unbalanced sag was an internal event. Nine events kept unknown, because of unsufficient confidence level after frame classification. Visual inspection of those unknown events identified them as slight waveform distortions.

At location B totally 23 events were recorded. After automated classification all events remained unknown after frame classification. By visual inspection the unknown events were identified as typical events of ASD

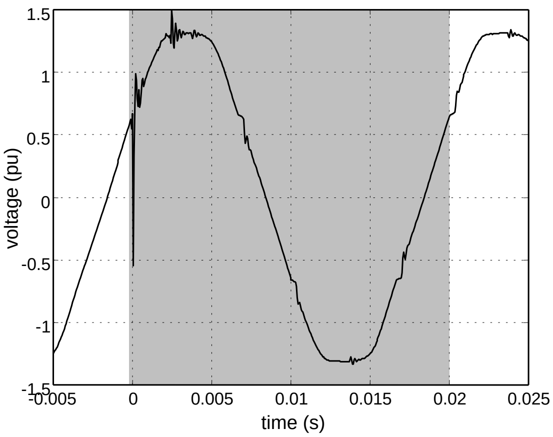

Fig. 9. Added frame class "$\mathbf{N_{asd}}$"

starting. A sample frame is depicted in figure 9. The solution was to introduce a new frame class "$\mathbf{N_{asd}}$" by adopting an event frame to the reference data. Table III shows the results after reclassification the events.

TABLE III
EVENTS AT LOCATION B

Event type	#
ASD starting	22
unknown	1
total:	23

The single unknown event showed a slight waveform distortion.

V. CONCLUSIONS

This paper presented a power quality monitoring system, which features an automated event classification. Main goal of the system is robust and reliable classification of power quality events.

The system allows modifications and extensions of its knowledge data by a type of construction kit for power quality events. After description of structure and operation of the system prototype, results of a field test were presented.

The field test proved efficency of the system and made the advantage of the open classification system obvious. By introducing a new frame type nearly all events could be classified successfully. So it is possible to build a reference data of a specific power system. This allows a simple identification of new unknown event types in a set of recorded events.

Future work will include the extension of the event reference data and the signal and event pattern tables. It is also intended to gain experience by system tests in medium-voltage power systems.

REFERENCES

[1] EN 50160, "Voltage characteristics of electricity supplied by public distribution systems", *European Standard CENELEC*, November, 1994.
[2] EN 61000-2-2, "Electromagnetic Compatibility, Section 2: Compatibility levels for low frequency conducted disturbances and signaling in low-voltage power supply systems", (IEC 1000-2-2: 1990), *German Version EN 61000-2-2*, 1993.
[3] EN 61000-2-4, "Electromagnetic Compatibility, Section 4: Compatibility levels in industrial plants for low frequency conducted disturbances", (IEC 1000-2-2: 1994), *German Version EN 61000-2-4*, 1994.
[4] A. Gosh, D. Lubkeman, "The classification of power system disturbance waveforms using a neural network approach", *IEEE Transactions on Power Delivery*, Vol. 10, No. 1, January, 1995, pp. 109-115.
[5] S. Santoso, J. Lamoree, M. Grady, E. Powers, S. Bhatt, "A scalable PQ Event Identification System", *IEEE Transactions on Power Delivery*, PE-109PRD (09-99), 1999.
[6] R. Hoffmann, *Signalanalyse und -erkennung*, Springer, Berlin-Heidelberg, 1998.
[7] L. R. Rabiner, B.-H. Juang, *Fundamentals of speech recognition*, Prentice Hall, Englewood Cliffs, 1993.
[8] IEEE Working Group, power quality event characterization (1159.2), test waveform "wave7.xls", *http://grouper.ieee.org/groups/1159/2/testwave.html*.
[9] H. Englert, J. Stenzel, "Design of a classification system for power quality disturbances", *12th International Conference on Power System Protection*, Bled, Slovenia, 2000.
[10] H. Englert, J. Stenzel, "A parallel classifier structure for identification of power quality disturbances", *accepted paper for 2000 National Power System Conference*, December 20-22, Bangalore, India.