SIGNAL PROCESSING TOOLS FOR VOLTAGE DIP ANALYSIS

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Abstract. This paper investigates the characterization of voltage dips with aim of selecting suitable feature extraction tools for the analysis of events. The symmetrical component method, ABC classification and the voltage dip segmentation method are discussed and a list of characteristics identified. Signal processing tools are reviewed and the Kalman filter and Ziarani algorithm selected as suitable feature extraction tools based on the analysis requirements of the dip segmentation method.

Key Words. Voltage dip, characterization, feature extraction, dip segmentation method

1. INTRODUCTION

Voltage dip characterization can be described as *"the description of voltage dip events through a limited number of parameters"* [1].

The requirements of characterization vary depending on application, and include [1]:

- Utility statistical dip performance reporting for its transmission and distribution systems,
- The description of dip performance at a particular site for use by utility customers.
- Contracting with end-customers,
- Definition of equipment dip immunity requirements,
- Definition of equipment dip immunity test requirements.

These characterisation applications are primarily driven by the response of end-user equipment to voltage dips and the ability of the utility to monitor and report voltage dip performance and analyse causes.

Additionally, characterisation can be conducted as an input to automated classification techniques, with the purpose of saving time spent by specialists manually analyzing data recorded by power quality monitors, protection relays and digital fault recorders [2].

In light of this requirement of characterisation, the aim then becomes "to find common features that are likely related to specific underlying causes in power systems" [3].

This paper investigates the characterization of voltage dips with aim of selecting suitable feature extraction tools for the analysis of events.

The structure of the paper is as follows: Section 2 reviews characterization of voltage dips, Section 3 discusses signal processing tools that are commonly applied in characterizing voltage dips. Section 4 discusses the selection of tools for feature extraction. Section 5 concludes.

2. CHARACTERISATION OF VOLTAGE DIPS

2.1 Residual Voltage and Longest Duration

Voltage dips are commonly characterised by the lowest voltage and longest duration measured across all channels [4].

IEC 61000-4-30 identifies this characterisation of voltage dips as a useful way of reducing data, interpreting and categorizing events [5]. Voltage dip duration is defined by IEC 61000-4-30 as the time from when the R.M.S. voltage on one phase drops below the dip threshold to the time when all three phases are above the dip threshold. This is illustrated in Figure 1.

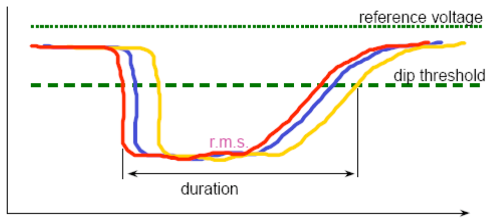


Figure 1: Dip Duration Characterisation [1]

Many utilities record only RMS voltage for statistical purposes and it is not possible to determine voltage characteristics without phasor information [6]. Bollen et al. [6] recognises that this limits the information on the voltage dip as seen at the end-user terminal. In practice a power quality monitor recording only RMS voltages may be the only information available to analyse voltage dips. This makes feature extraction from RMS data a key concern.

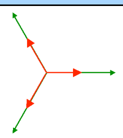
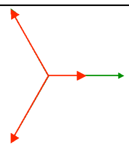
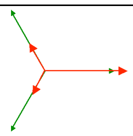
2.2 Symmetrical Component Method

The symmetrical component method [7, 8] classifies voltage dips in terms of changes in both the magnitude and phase angle. A dip is classified by a characteristic voltage and a PN factor and the method attempts to classify it into one of two main categories C (2-phase dips) and D (single phase dips). It is further identified by a subscript that indicates the symmetrical phase i.e. the least dipped phase for type C and most dipped for type D.

2.3 ABC Classification

The ABC classification [9] distinguishes between 7 different types of unbalanced three-phase voltage dips (A-G). Table 1 illustrates the dipped phases for each dip type according to the ABC classification and provides a comparison with the symmetrical component method.

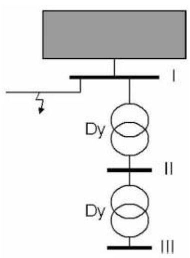
Table 1: Examples of Dip Vectors for ABC Classification

ABC Dip Classification	Vector Diagram	Symmetrical Component Classification
A		ANY
B		Da
C		Ca

The ABC classification is a special case of the symmetrical component method and has a number of benefits including [9]:

- It is a more intuitive classification that does not require the study of symmetrical component theory,
- It provides an easy to understand graphical interpretation of the propagation of unbalanced voltage dips through transformers. This is illustrated in Figure 2 for the translation through Dy transformers.

Figure 2: Dip Propagation [9]



FAULT TYPE	DIP LOCATION		
	I	II	III
3-Phase	A	A	A
3-Phase-to-ground	A	A	A
2-Phase-to-ground	E	F	F
2-Phase	C	D	C
1-Phase-to-ground	B	C	D

2.4 Dip Segmentation Method

Styvaktakis [10] introduces segmentation of power quality events as part of an automated classification method based on the underlying causes of voltage dips.

Djokić and Bollen [11] present the *dip segmentation method* as an approach for the analysis, description and characterisation of voltage dips in power systems and at end-user equipment terminals.

It is introduced to allow an improved assessment of factors and parameters possibly influencing the sensitivity of equipment at different voltage levels. The method is introduced with the intention of helping users and designers of electrical equipment to *"quantify, test and compare performance of their equipment in a simple, consistent, transparent and reproducible manner…."* [11].

The method aims to extend the description of dips beyond a single magnitude and duration as [11]:

- Differences between the 3 phase voltages are not considered,
- Voltage dips are not always rectangular ,
- Phase-shift and point-on-wave are not considered.

The method is based on the separation of recorded dip events into "dip segments" where a segment is described as a period of time during which the voltage magnitude and other properties of the voltage waveform remain more or less constant. The general description of a dip, regardless of type, based on the dip segmentation method consists of [11]:

- **One pre-event segment** – provides a description of the relevant voltage characteristics immediately before the dip occurs
- **Zero, one or more during-event segments** – provide a description of dip characteristics during which the voltage magnitude is constant
- **One or more transition segments** – provides a description of dip characteristics during the transition between two steady states.
- **One post-event or voltage recovery segment** – provides a description of voltage characteristics after the cause of the dip is cleared or eliminated

Figure 3 illustrates the segmentation of a multi-stage voltage dip.

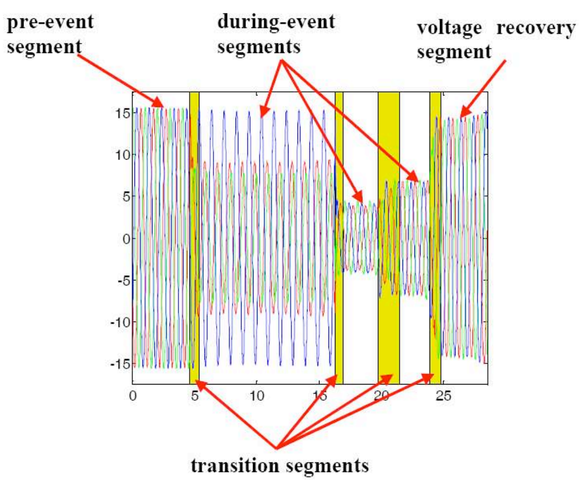


Figure 3: Segmentation of a multi-stage voltage dips [11]

The description of voltage dips in the dip segmentation method consists of [12]:

- Number of transition segments, duration of event segments
- Characteristics of the pre-event segment

- Characteristics of the event segments
- Characteristics of the transition segments
- Characteristics of the voltage recovery segments

A feature of the dip segmentation method is that it recognises includes the pre- and post-dip segments which fall outside of the time period of the actual voltage dip.

CIGRE/CIRED/UIE working group C4.110 introduces a table of voltage dip characteristics based on the dip segmentation method to *be "used as a "check-list" for a fast and transparent assessment of equipment and process sensitivity to voltage dips during all stages of equipment and process design"* [12].

Table 2: Dip Segment Characteristics [12]

Dip Segment	Characteristics
Pre-Event Segment	Voltage magnitude Phase angle Harmonics Voltage unbalance Frequency
During Event Segment	Dip magnitude Dip Duration Dip Shape Dip Voltage Unbalance Dip phase angle unbalance Dip phase shift Distortion Transient
Transition Segment	Dip Initiation Point-on-wave of dip initiation Phase shift at the dip initiation Phase shift at the dip initiation Multistage dip initiation Dip ending Point-on-wave of dip ending Multistage dip ending Rate-of-change of voltage Damped oscillations
Post-Event Segment	Voltage recovery Post-fault dip (prolonged voltage recovery) Post-dip phase shift Multiple dip events (dip sequences) Multiple dip events Composite dip events Rate-of-change of voltage Voltage recovery time constant RMS voltage

The C4.110 checklist provides a structured list of characteristics for detailed analysis of voltage dips as a starting point for further characterisation and analysis of voltage dip events.

2.5 Summary and Conclusions of Characterisation

Four methods of characterisation of voltage dips have been presented and their key features discussed:

- The RMS voltages may be the only information available to analyse voltage dips. This makes feature extraction from RMS data a key concern.
- The ABC classification provides an intuitive insight into three phase unbalanced dips and their propagation through the network.
- The dip segmentation provides a methodology to conduct detailed analysis and characterisation of voltage dips and understand propagation through a network.
- A basic list of requirements to meet analysis in line with the dip segmentation method is outlined.

Any further analysis for feature extraction purposes will require that the tools used for feature extraction have the capacity to meet the analysis requirements of the individual dip segments, namely:

- High speed capability for transition segments
- Extraction of phase angle for point-in-wave analysis,
- Extraction of voltage magnitude and rate of change.

3. SIGNAL PROCESSING TOOLS FOR CHARACTERISATION

The methods for analysis and classification of power quality events consist of a number of steps each requiring specific tools [10]:

- Segmentation,
- Feature extraction,
- Additional processing,
- Classification.

The process and individual steps for analysis and classification are illustrated in Figure 4.

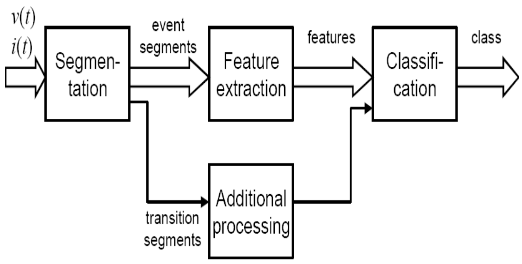


Figure 4: Analysis and Classification of Power Quality Events [10]

This discussion will focus on the tools required for segmentation and feature extraction of event data for input to classification.

Triggering (event detection) and segmentation are commonly treated as two separate topics in the literature [13] but both these processes require the detection of nonstationarity in a signal. A signal is stationary when it is statistically time invariant [13] i.e. its statistical properties do not change as a function of time. A non-stationary signal is therefore a signal for which the statistical properties change with time.

Event detection is commonly used in for online capturing of events and event segmentation takes place afterwards during event analysis [13]

3.1 Methods for Analysis

The following tools are commonly discussed in literature for analysis of power quality events [10, 13].

3.1.1 RMS Method

The general equation used to calculate RMS is:

$$V_{rms}(t_k) = \sqrt{\frac{1}{N}\sum_{t_k=t_k-N+1}^{t_k} v^2(t)} \ .$$

Event identification via RMS is done by comparing change in magnitude with a predetermined threshold. Application of RMS requires simple signal processing and is recognised as being very efficient. It is widely used in power quality instruments that monitor RMS.

Bollen et al [6] recognise the importance of phasor information and introduce a method to deduce phasors from RMS voltages for analysis purposes.

For analysis purposes a method of segmentation based of rate of change is introduced in [10] and finds application in a classification system based on RMS voltage only.

3.1.2 Short -Time Fourier Transform (STFT)

The short time Fourier transform of a signal *v[k]* is:

$$V_{STFT}(m,\omega) = \sum_k v[k]\cdot w[k-m]e^{-jwk} \ ,$$

Where $\omega=2\pi n/N$, N is the length of *v[k], n=1…..N,* and w[k-m] is a selected window that slides over the analysed signal

The STFT has limitations due to its fixed window length, which has to be chosen prior to the analysis. This drawback is reflected in the achievable frequency resolution when analysing non-stationary signals with both low and high-frequency components [14].

3.1.3 Park Vector - DQ Transform

Park's vector is based on the instantaneous vector sum of all of the three phase vectors (v1, v_2, v_3). The Park transform finds general application in the field oriented control of induction motors. The vector components (v_d, v_q) are given by [14]:

$$v_D = \sqrt{\frac{2}{3}}v_1 - \sqrt{\frac{1}{6}}v_2 - \sqrt{\frac{1}{6}}v_3 \ ,$$

$$v_Q = \sqrt{\frac{1}{2}}v_2 - \sqrt{\frac{1}{6}}v_3 \ .$$

3.1.4 Wavelet analysis

The wavelet transform is based on the decomposition of a signal into daughter wavelets derived from the translation and dilation of a fixed mother wavelet. The general formula is given by:

$$V_{WT} = \int_{-\infty}^{+\infty} v(t)\cdot \varphi^*_{a,b}(t)\cdot dt \ .$$

Wael et al. [15] point out that the application of wavelets to feature extraction is well researched and documented. The most popular applications of wavelets in power systems literature are [16]:

- Power system protection
- Power quality
- Power system transients
- Partial discharge
- Load forecasting
- Power system measurement

3.1.5 Multi-resolution S-Transform

The S-Transform is described as being either a phase-corrected version of the wavelet transform or a variable window Short Time Fourier transform that simultaneously localizes both real and imaginary spectra of the signal [17]. It is defined by convolving the analyzed signal, v[k], with a window function. The S-transform of a discrete signal *v[k]* can be calculated as:

$$V_{ST}[k,\frac{n}{N}] = \sum_{m=0}^{N-1} V[\frac{m+n}{N}]\cdot e^{\frac{-2\pi^2}{n^2}}\cdot e^{j\omega k} \ ,$$

where *k*,m and *n = 0,1…..N-1 and V[m+n/N]* is the fourier transform of the analyzed signal *v[k]* $\omega=2\pi n/N$, N is the length of *v[k]*[17] .

3.1.6 Extended Kalman filter

Kalman filtering is a parameter based modelling of an assumed process. If the process is non-linear then a linearization process is carried out and this leads to the extended Kalman filter.

Extended Kalman filtering provides good performance in both the detection of events and the estimation of event magnitude and duration [17]. Power system applications of Kalman filtering include [13]:

- Continuous real-time tracking of harmonics,
- Estimation of voltage and current harmonics for protection systems,
- Estimation of transient parameters.

Styvaktakis [10] discusses the application of Kalman filters to:

- Voltage magnitude estimation and the limitations in the presence of harmonics and short duration events,
- Segmentation of disturbance recordings and
- Voltage dip detection.

He concludes that the order of the model used by the Kalman filter significantly affects the magnitude estimate for the types of changes he identifies (fast, slow and fast repeating).

Further parameter-based methods for feature extraction discussed in the literature include multiple signal classification method (MUSIC), estimation of signal parameters via rotational invariances (ESPRIT), stochastic models e.g. auto regressive

(AR), auto-regressive moving-average (ARMA) and state space [13].

3.1.7 Method of Ziarani and Konrad

Ziarani and Konrad present a method of extracting nonstationary sinusoidal signals via a nonlinear adaptive filter and estimate the following parameters [18]: amplitude, phase and frequency.

The Ziarani algorithm demonstrates the following characteristics [18]:

- Simple structure,
- Low computational requirements, hence easily implemented in hardware and software,
- High degree of noise immunity and robustness,
- High speed,
- Effectiveness in tracking large variations in parameters.

Figure 5 illustrates a block diagram of the Ziarani Algorithm.

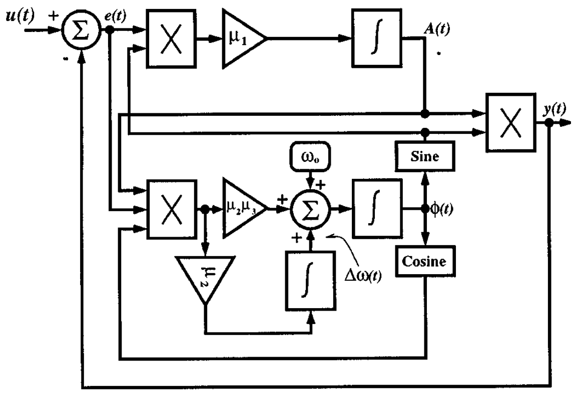


Figure 5: Block diagram of the Ziarani Algorithm [18]

Naidoo and Pillay [19] review the application of this algorithm for power systems applications and identify the following advantages:

- Phase lock loop is not required
- Simple structure and easy to implement
- No windowing of data required
- Less processing power is required as compared to FFT and wavelets

It has the following disadvantages:

- Limited convergence speed posing problems for processing of short duration events
- The co-efficients have to be optimized for a particular application
- Errors associated with the algorithm are not known and require investigation

3.1.8 Forward Clarke Transform and Space Vector Definition

The Clarke transform is commonly used in real-time motor control applications. It transforms a 3-phase system to an equivalent two phase representation. Gargoom et al. [20] identify its advantages as being able to analyze all three phases of a power system simultaneously as well as its simplicity and speed. The Clarke transform is commonly used for the analysis of transient disturbances in three-phase systems. It relates the phase-to-neutral voltages and component voltages through a matrix expression [9]. Aller et al. [21] demonstrate the derivation of the space vector where the first two components $(x_\alpha(t), x_\beta(t))$ form the space vector and the third one $(x_0(t))$ representing the zero sequence voltage:

$$\begin{pmatrix} x_\alpha(t) \\ x_\beta(t) \\ x_0(t) \end{pmatrix} = \frac{2}{3} \begin{pmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{pmatrix} \begin{pmatrix} v_a(t) \\ v_b(t) \\ v_c(t) \end{pmatrix}$$

The space vector of the Forward Clarke Transform is then represented as:

$$S_v = x_\alpha(t) + jx_\beta(t) .$$

The magnitude and angle of the space vector is then:

$$|S_v(t)| = \sqrt{\left(v_\alpha(t)^2 + v_\beta(t)^2\right)},$$

$$angle\_S_v = \arctan\left(\frac{v_\beta}{v_\alpha}\right).$$

Gargoom et al. [20] utilise the mean and standard deviation of the space vector magnitude as features for event classification.

3.2 Comparative Analysis of Methods

Perez et al. [17] discuss the comparative performance of the most commonly used techniques for detection and analysis of voltage events in power systems, namely:

- RMS method,
- Discrete Fourier Transform and Short Time, Fourier Transform,
- Kalman Filtering,
- Wavelet Analysis.

Their conclusions [17] are that RMS and STFT show limited performance for short duration and low magnitude voltage events.

Wavelet analysis is deemed to provide the best performance in terms of detection and estimation of time-related parameters but has the drawback of requiring an additional method to discriminate between voltage events and other high frequency disturbances.

Gargoom et al. [14] conduct a comparative study on signal processing tools for feature extraction purposes and Table 3 summarizes the performance of some signal processing techniques [14].

	STFT	**Wavelet**	**S - Transform**	**Park's Vector**
Speed	Moderate	Moderate	Low	High
Sensitivity	Low	Moderate	High	High
Practical Implementation	Difficult	Difficult	Difficult	Easy
3-ph signals simultaneous	No	No	No	Yes

Table 3: Comparative analysis of Techniques [14]

4. SELECTION OF AN ANALYSIS METHOD

The characteristics of a suitable feature extraction method to meet the analysis requirements of the dip segmentation method were identified in 2.5.

The analysis of nonstationary signals is a requirement for detailed analysis of the transition segments and the associated segmentation of voltage dips.

Another factor to be taken into consideration is the application of the tool, in particular whether it will be an online or offline analysis application and the ease of implementation.

Based on the abovementioned criteria the tools identified for analysis and feature extraction are the Kalman filter and the method of Ziarani and Konrad. The Park's transform might also be suitable and some aspects of its use need to be examined further.

5. CONCLUSION

This paper has provided a review of voltage dip characterisation with the aim of selecting suitable signal processing tools for feature extraction

Requirements for selection of suitable signal processing tools for feature extraction are discussed and signal processing tools reviewed and comparative studies of performance are presented.

The Park's transform, Kalman filter and Ziarani and Konrad algorithm are selected as suitable feature extraction tools for further investigation and development, based on the characterisation requirements.

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