Wavelet-based identification and classification of voltage variations and capacitor switching transients

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Wavelet-Based Identification and Classification of Voltage Variations and Capacitor Switching Transients

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School of Electrical & Electronic Engineering

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List of Symbols

The following symbols are used throughout the thesis:

Signals

$f(t)$	Continuous time signal.
$f[n]$	Discrete signal.
$P_L(b,a)$	Energy density of low frequency component at time b and scale a .
$E_L(b,a)$	Energy of low frequency component at time b and scale a .
$P_W(b,a)$	Energy density of high frequency component at time b and scale a .
$E_W(b,a)$	Energy of high frequency component at time b and scale a .

Operators

$\langle f(t), g(t) \rangle$	Inner product.
$f * g(t)$	Continuous time convolution.
$f \otimes g[n]$	Circular convolution.

Transforms

$\mathcal{F}\{f(t)\}$	Fourier transform (3-1).
$\mathcal{F}\{f[k]\}$	Discrete Fourier transform (3-2).
$\mathcal{S}\{f(t, \xi)\}$	Windowed Fourier transform (3-3).
$\mathcal{W}\{f(b, a)\}$	Wavelet transform at time b and scale a (4-3).
$\mathcal{L}\{f(b, a)\}$	Wavelet transform for low-frequency approximation at time b and scale a (4-6).

Summary

In recent years, both the industrial and commercial electricity customers are increasingly concerned about the quality of electrical power. Sophisticated equipments, which are incorporating computer-controlled and microprocessor-based devices as well as power electronics-controlled motor drives, are sensitive to the supplied power quality. They require a constant supply voltage with a sinusoidal waveform at nominal frequency and magnitude. Disturbances such as voltage sags and swells, short duration interruptions and transients may disrupt the processes and lead to considerable economic loss. Therefore, the issue of power quality is receiving increasing attention from both the customers and the suppliers.

To find proper mitigation solutions and to improve power quality, power quality monitors are installed. As a result, large databases of samples are created and automatic processing of the data is required for fast and effective use of the available information. Various signal processing and decision making techniques are being used to process the disturbance data and to classify different types of power quality disturbances. With these techniques, the understanding of the nature of the disturbances can be obtained and the solution to mitigate their influence can be determined. Since the newly developed wavelet analysis has good performance when analyzing non steady-state phenomena, it is used in this thesis to classify short duration voltage variations and to identify capacitor switching transients.

A wavelet-based energy content method for classifying short duration voltage variations is proposed. The accurate time and magnitude information of the disturbances can be obtained using this method. Even the short duration voltage interruptions, which are difficult to be identified using the conventional RMS method, can be readily identified by this method.

To identify capacitor switching transients, a wavelet-based rank correlation method is proposed. This method can discriminate capacitor switching transients from other transients while tolerating some uncertainties with the system parameters. However, it

may misidentify several non capacitor switching transients whose transient frequencies are close to those of capacitor switching. Therefore, fuzzy technique is introduced to improve the accuracy of the identification. The results show that this wavelet-based fuzzy method can tolerate more uncertainties with the system and/or capacitor parameters, and discriminate non capacitor switching transients more accurately.

Chapter 1

Introduction

1.1 Motivation

The deterioration and wide-ranging impact of poor power quality has been gaining attention in recent years [1]-[3]. The electricity supply that was once considered acceptable by electricity companies and users is often considered a problem to the users of everyday equipment. This is because many of the modern loads such as computers and numerical control machines are highly susceptible to voltage disturbances. With today's highly interconnected power system networks, the impact of these disturbances can be extensive and damaging. Disturbances such as voltage sags, swells and short duration interruptions may disrupt the process and lead to considerable economic loss [4][5]. Transients may cause tripping, component failure, hardware reboot, software 'glitches' and poor product quality [6]. Harmonics influence transformer and neutral conductor heating. They also lead to reduce equipment lifespan, audio hum, video 'flutter', software glitches and power supply failure [7]. Utilities are therefore taking many prudent actions with the aim to either minimize the occurrence of such disturbances or to reduce their impacts on other parts of the network where sensitive loads may be connected. On the other hand, there is an increasing use of equipment that generate power quality problems, such as voltage sags caused by starting large induction motor. In addition, due to inherent nature of the power networks, these disturbances can never be completely prevented [8].

To solve these power quality problems and to improve the supply quality in a power network, extensive power quality monitors are being installed. Such extensive monitoring will result in a massive amount of data being processed [1][9][10]. Since individual inspection of all the waveforms is not a feasible option due to the large size of the databases, a suitable solution would be to extract automatically all relevant information from the recordings. This points towards the direction of intelligent power

quality monitoring and the development of automatic classification and analysis tools. Various techniques are required to extract the features of power quality disturbances and to categorize them. Several signal processing techniques, such as Fourier transform, filtering technique and wavelet transform, are being used to extract the features of disturbances [11]-[14]. Various decision making techniques, such as fuzzy technique, statistical method and neural network, are used to process these features and to classify them [15]-[17]. Through these approaches, an understanding of the nature of power quality disturbances can be acquired and suitable methods to mitigate these disturbances can be further developed.

The research work described in this thesis is to find methods for better classification of some particular power quality problems. It was carried out under the following two aspects:

A. Effective classification of short duration voltage variations

In some publications [18][19], typical voltage sag duration is defined to vary from 2 ms to several minutes. However, voltage sags that last less than half a cycle are categorized as transients in the IEEE standard 1159 [20] since they cannot be effectively classified by using the conventional RMS method. This categorizing method cannot truly reflect the changes of voltages and may influence the selection of mitigation solution. This research introduces a new technique that ensures a better description of these power quality disturbances and even short duration interruptions can be accurately classified.

B. Identification of capacitor switching transients

In the IEEE standard 1159 [20], power quality disturbances are categorized according to their frequencies, magnitudes and durations. If disturbances can be categorized according to their causes, the burden of power quality engineers can be further reduced [21]. They can quickly take action if they know the cause of a transient. In this thesis, a particular kind of transient, capacitor switching transient, is identified according to its cause. Switching capacitor bank(s) in power systems is often an integral part of the system design [22][23]. The solution to overcome capacitor switching transients is often different from those caused by equipment failures [24]-[26]. However, during

measurements, capacitor switching transients are always mingled among all kinds of other disturbances. Therefore, it would be beneficial if they can be identified and separated from other transients. This research studies the characteristics of capacitor switching transients and proposes methods to discriminate capacitor switching transients from other transients.

1.2 Major Contributions of the Thesis

As a result of the research work, the following original contributions have been made.

A) A wavelet-based energy content method is proposed to classify short duration voltage variations. In this method, the information of two different frequency bands is used. The time information of the disturbance, such as duration and occurrence instant of the disturbance, can be determined by analyzing the high frequency information. The energy content in the fundamental frequency band reflects the main energy change and can also be referred to a corresponding voltage RMS value [20]. Thus, the magnitude information of the disturbance can be obtained to determine the type of the disturbance.

B) A wavelet-based rank correlation method is proposed for identifying capacitor switching transients. This method can tolerate some uncertainties with the system and/or capacitor parameters. A signature for capacitor switching transients in a certain system is determined by a systematic analysis using an equivalent circuit. The identification is then carried out by evaluating the similarity between the signature and the transients. Continuous wavelet transform is used to extract the information of the specific frequency band and rank correlation is applied to process the information without being influenced by the different absolute magnitudes of the signals as they are being measured using different instruments. However, since only one signature is used, some non-capacitor switching transients, whose transient frequencies are close to that of the signature, may be misidentified as capacitor switching transients.

C) A wavelet-based fuzzy method is introduced to improve the accuracy of the identification of capacitor switching transients. In this method, multiple signatures and fuzzy technique are used. These signatures cover the range of possible changes in the characteristics of capacitor switching transients. Hence, the rank correlation results

using different signatures tend to complement each other. Fuzzy technique is used to aggregate these rank correlation results and identify whether the transient is caused by capacitor switching or not. Compared to the previous single signature method, this method can tolerate more uncertainties with the system and/or capacitor parameters, and can correctly identify some non-capacitor switching transients, even if their characteristics are close to some of the signatures.

1.3 Organization of the Thesis

The motivation and major contributions of the research have been outlined in this chapter. A review of power quality problems and some mitigation solutions are discussed in Chapter 2. The characteristics of power quality disturbances and some power quality solutions, including grounding techniques and power quality conditioning equipment, are briefly reviewed. Those familiar with power quality problems can skip this chapter, which is included for completeness sake.

Power quality measurement and assessment are introduced in Chapter 3. The general steps of measuring and analyzing power quality disturbances are given. Various signal processing and decision making techniques are briefly introduced with a substantial review on their applications in power quality measurement and assessment.

In Chapter 4, an introduction of wavelet analysis is given. Readers that are well versed in these information technologies can bypass most parts of Chapters 3 and 4, but the chapters contain significant amount of review on how the techniques are applied to power quality disturbance classification and characterization.

A wavelet-based energy content method for classifying short duration voltage variations is presented in Chapter 5.

In Chapter 6, a wavelet-based rank correlation method is developed to classify capacitor switching transients.

In Chapter 7, fuzzy technique is intended to enhance the tolerance of the uncertainties with the system parameters and improve the accuracy of identification of capacitor switching transients.

The main findings of the research and recommendation for future work are given in Chapter 8.

Chapter 2

Power Quality Problems

2.1 Introduction

The term “power quality” refers to a wide variety of electromagnetic phenomena that characterize the voltages and currents at a given time and at a given location in the power system. It is a concept for a multitude of individual types of power system disturbances. In this chapter, the characteristics of different power quality disturbances are briefly described. Then different ways to solve power quality problems are reviewed.

2.2 Characteristics of Power Quality Problems

The ability to define and understand the various types of power quality problems provides the necessary background needed to prevent and solve those problems. Each disturbance presents some characteristics that can be used as the reference to identify the type of power quality problems. The nature of variation in the basic components of the sinusoidal wave, i.e., magnitude, frequency and phase angle, identifies the type of power quality problems. A general description of typical power quality problems is given in Table 2-1 [20]. Their characteristics are briefly described in the following subsections.

Table 2-1 Categories and typical characteristics of power system electromagnetic phenomena defined in IEEE 1159:1995[20]

Categories	Typical spectral content	Typical duration	Typical voltage magnitude
1.0 Transients			
1.1 Impulsive			
1.1.1 Nanosecond	5 ns rise	< 50 ns	
1.1.2 Microsecond	1 μ s rise	50 ns-1 ms	
1.1.3 Millisecond	0.1 ms rise	> 1 ms	
1.2 Oscillatory			
1.2.1 Low frequency	< 5 kHz	0.3-50 ms	0-4 pu
1.2.2 Medium frequency	5-500 kHz	20 μ s	0-8 pu
1.2.3 High frequency	0.5-5 MHz	5 μ s	0-4 pu
2.0 Short duration variation			
2.1 Instantaneous			
2.1.1 Sag		0.5-30 cycles	0.1-0.9 pu
2.1.2 Swell		0.5-30 cycles	1.1-1.8 pu
2.2 Momentary			
2.2.1 Interruption		0.5 cycles-3 s	< 0.1 pu
2.2.2 Sag		30 cycles-3 s	0.1-0.9 pu
2.2.3 Swell		30 cycles-3 s	1.1-1.4 pu
2.3 Temporary			
2.3.1 Interruption		3 s-1 min	< 0.1 pu
2.3.2 Sag		3 s-1 min	0.1-0.9 pu
2.3.3 Swell		3 s-1 min	1.1-1.4 pu
3.0 Long duration variation			
3.1 Interruption, sustained		> 1 min	0.0 pu
3.2 Undervoltage		> 1 min	0.8-0.9 pu
3.3 Overvoltage		> 1 min	1.1-1.2 pu
4.0 Voltage Imbalance		steady state	0.5-2%
5.0 Waveform Distortion			
5.1 DC offset		steady state	0-0.1%
5.2 Harmonics	0-100 th H	steady state	0-20%
5.3 Interharmonics	0-6 kHz	steady state	0-2%
5.4 Notching		steady state	
5.5 Noise	broad-band	steady state	0-1%
6.0 Voltage fluctuations	<25Hz	Intermittent	0.1-7%
7.0 Power frequency variation		< 10 s	

2.2.1 Transients

Voltage transients are usually caused by lightning or switching operation [20]. They can result in degradation or immediate dielectric failure in all classes of equipments. Their high magnitudes and fast rise times contribute to insulation breakdown in electrical equipments like rotating machinery, transformers, capacitors, cables, and switchgear. Repeated application of lower-magnitude transients to these equipments causes slow degradation and eventual insulation failure, decreasing equipment mean time between failures (MTBF). In electronic equipment, power supply component failures can result from a single transient of relatively modest magnitude.

Broadly speaking, transients can be classified into two categories, impulsive and oscillatory. These terms reflect the wave shape of a voltage transient.

2.2.1.1 Impulsive

An impulsive transient is a sudden, non-power frequency change in the steady-state voltage that is unidirectional in polarity [20]. The time it takes for an impulsive transient to rise to its peak value and then decays to normal value determines its identity. Resistive components of the electrical transmission and distribution system help to damp (reduce) that transient current. The most frequent cause of impulsive transient is lightning stroke. Impulsive transient can excite power system resonance circuits and produce oscillatory transients.

2.2.1.2 Oscillatory

An oscillatory transient consists of a voltage whose instantaneous value changes polarity rapidly [20]. It can be interpreted with or without the dc component and/or the fundamental frequency component included. When characterizing the transient, it is important to indicate the magnitude with and without the dc component and/or the fundamental component. It is described by its spectral content (predominant frequency), duration and magnitude. The spectral content is subdivided into high, medium, and low frequency. The frequency ranges for these classifications are chosen to coincide with the common types of power system oscillatory transient phenomena. Oscillatory transients

generally do not decay quickly like impulsive transients. They tend to continue to oscillate for 0.5 to 3 cycles. Oscillatory transients with a primary frequency component greater than 500 kHz and a typical duration measured in microseconds (or several cycles of the principal frequency) are considered high-frequency oscillatory transients. These transients are usually due to some types of switching events. High frequency oscillatory transient is often the result of a local system response to an impulsive transient. A transient with a primary component between 5 and 500 kHz with duration measured in the tens of microseconds is termed as a medium-frequency transient. Medium frequency transient can also be the result of a system response to an impulsive transient. A transient with a primary frequency component less than 5 kHz, and a duration from 0.3 to 50 ms, is considered a low frequency transient. This category of phenomena is frequently encountered on sub-transmission and distribution systems and can be caused by many types of events, primarily capacitor bank energization.

2.2.2 Short duration voltage variation

Short duration voltage variations are usually caused by fault conditions, energization of large loads that require high starting currents, or intermittent loose connections in power wiring. Depending on the fault location and the system conditions, the fault can cause either temporary voltage rises (swells) or voltage drops (sags), or a complete loss of voltage (interruptions). The impact on the voltage during the actual fault condition is a short duration variation. Short duration is subdivided into three broad categories: instantaneous, momentary, and temporary. These durations are intended to correlate with typical protective device operation times.

2.2.2.1 Interruption

An interruption occurs when the supply voltage decreases to less than 0.1 pu for a period of time not exceeding 1 min. Interruptions can be the results of power system faults, equipment failures, and control malfunction. The interruptions are measured by their durations since the voltage magnitude is always less than 10% of their nominal values.

2.2.2.2 Sag

IEEE standard 1159 [20] defines voltage sag as a reduction in voltage for a short period of time. Typical sag duration defined in some publications ranges from 2 ms to a couple of minutes. Sag that lasts less than half a cycle cannot be characterized effectively as a change in the RMS value of the fundamental frequency value. Sag that lasts longer than 1 min can typically be controlled by voltage regulation equipment and may be associated with a wide variety of causes other than system faults. Therefore, these are classified as long duration variations (undervoltages).

Voltage sags are usually associated with system faults but can also be caused by switching of heavy loads or starting of large motors. A fault on a parallel feeder circuit will result in a voltage drop at the substation bus that affects all of the other feeders until the fault is cleared. Typical fault clearing times range from 3 to 30 cycles, depending on the fault current magnitude and the type of overcurrent detection and interruption. An induction motor will draw six to ten times its full load current during starting. This lagging current causes a voltage drop across the impedance of the system. If the current magnitude is large relative to the system available fault current, the resulting voltage sag can be significant.

2.2.2.3 Swell

A swell is defined as an increase in RMS voltage at the power frequency for durations from 0.5 cycles to 1 min. The typical magnitudes of swells are between 1.1 and 1.8 pu. Swell magnitude is also described by its remaining voltage, in this case, always greater than 1.0 pu. As with sags, swells are usually associated with system fault conditions, but they are much less common than voltage sags. A swell can occur due to a single line-to-ground fault on the system resulting in a temporary voltage rise on the unfaulted phases. Swells can also be caused by switching off a large load or switching on a large capacitor bank.

Swells are characterized by their magnitude value and duration. The severity of a voltage swell during a fault condition is a function of the fault location, system impedance, and grounding.

2.2.3 Long duration voltage variation

Long duration variations encompass RMS deviations at power frequency for longer than 1 min. Long duration variations are considered to be present when the ANSI limits are exceeded for greater than 1 min [20]. Long duration variations can be either overvoltage or undervoltage depending on the nature of the variation. Overvoltage and undervoltage generally are not the result of system faults. They are caused by load variations on the system and system switching operations. These variations are characterized by plots of RMS voltage versus time.

2.2.3.1 Sustained Interruption

The decrease to zero of the supply voltage for a period of time in excess of 1 min is considered a sustained interruption. Voltage interruptions longer than 1 min are often permanent in nature and require manual intervention for restoration.

2.2.3.2 Overvoltage

Overvoltages can be the result of load switching (switching off a large load), or variations in the reactive compensation on the system (switching on a capacitor bank). Poor system voltage regulation capabilities or controls result in overvoltages. Incorrect tap settings on transformers can also result in system overvoltages.

2.2.3.3 Undervoltage

Undervoltages are the result of events that are the reverse of events that cause overvoltages. A load switching on, or a capacitor bank switching off, can cause an undervoltage until voltage regulation equipment on the system can bring the voltage back to within tolerances.

2.2.4 Voltage imbalance

Voltage imbalance (or unbalance) is the deviation of one or two phase(s) from the average voltage of three phases. It can be estimated as the maximum deviation from the average of the three-phase voltages, divided by the average of the three-phase voltages, expressed in percent,

$$\text{Voltage imbalance} = 100 \times \frac{\text{max. deviation from average voltage}}{\text{average voltage}} \%$$

where average voltage =(sum of phase voltages)/3.

This expression considers only the magnitudes of the voltages. Another measure of voltage imbalance considers the ratio of the negative or zero sequence component to the positive sequence component. The negative or zero sequence voltages in a power system generally resulted from unbalanced loads cause negative or zero sequence currents to flow [20].

$$\text{Voltage imbalance} = 100 \times \frac{\text{negative(or zero) sequence component}}{\text{positive-sequence component}} \%$$

Potential causes of voltage unbalance include capacitor banks maloperation, lack of transposition, single phasing of equipments, and connecting more single-phase loads on one phase than another.

2.2.5 Waveform distortion

Waveform distortions are steady-state deviations from an ideal sinusoidal wave of power frequency primarily characterized by the spectral content of the deviation. There are five primary types of waveform distortion as follows: DC offset, harmonics, interharmonics, notching and noise.

2.2.5.1 DC offset

The presence of a DC voltage or current in an AC power system is termed DC offset. This phenomenon can occur as the result of a geomagnetic disturbance or due to the effect of half-wave rectification. Direct current in AC networks can be detrimental due to the increase in transformer saturation and additional stressing of insulation.

2.2.5.2 Harmonics

Harmonics are the major sources of waveform distortion. Harmonics becomes more common with the increasing uses of nonlinear equipments. Harmonic distortion levels

can be characterized by the complete harmonic spectrum with magnitude and phase angle of each individual harmonic component. It is also common to use a single quantity, the total harmonic distortion (THD), as a measure of the magnitude of harmonic distortion. Harmonic current results from the operation of nonlinear devices in the power system.

2.2.5.3 Interharmonics

Interharmonics can be found in networks of all voltage classes. They can be considered as discrete frequencies or as a wide-band spectrum. The main sources of interharmonic distortion are static frequency converters, cyclo-converters, induction motors, and arcing devices. Power-line carrier signals can also be considered as interharmonics.

The effects of interharmonics are not well known, but have been shown to affect power line carrier signaling, over-heating of induction motors and induce visual flicker in display devices such as CRTs , incandescent and fluorescent lamps.

2.2.5.4 Notching

Notching is a periodic voltage disturbance caused by the normal operation of power electronic devices when current is commutated from one phase to another. Voltage notching represents a special case that falls between transient and harmonic distortion. Since notching occurs continuously (steady-state), it can be characterized through the harmonic spectrum of the affected voltage. However, the frequency components associated with notching can be quite high and may not be readily characterized with measurement equipment normally used for harmonic analysis. Three-phase converters that produce continuous DC current are the major sources of voltage notching. The notches occur when the current commutates from one phase to another. During this period, there is a momentary short circuit between the two phases. The severity of the notch at any point in the system is determined by the source inductance and the isolating inductance between the converter and the point being monitored.

2.2.5.5 Noise

Noise is unwanted electrical signals with broadband spectral content lower than 200 kHz superimposed upon the power system voltage in phase conductors, or found on neutral conductors or signal lines. Noise in power systems can be caused by power electronic devices, control circuits, arcing equipments, loads with solid state rectifiers, and switching power supplies. Noise problems are often exacerbated by improper grounding. Noise consists of any unwanted distortion of the power signal that cannot be classified as harmonic distortion or transient. The frequency range and magnitude level of noise depend on the source that produces the noise and the system characteristics. A typical magnitude of noise is less than 1% of the voltage magnitude. Noise disturbs electronic devices such as microcomputer and programmable controllers. The problem can be mitigated by using filters, isolation transformers, or some line conditioners.

2.2.6 Voltage fluctuations

Voltage fluctuations are systematic variations of the voltage envelope or a series of random voltage changes, the magnitude of which does not normally exceed the voltage ranges of 0.95 to 1.05 of the nominal voltage. This type is characterized as a series of random or continuous voltage fluctuations. Any load that has significant current variations, especially in the reactive component, can cause voltage fluctuations. Voltage fluctuation is the response of the power system to the varying load. Arc furnaces are the most common causes of voltage fluctuations on the transmission and distribution system.

2.2.7 Power frequency variations

The power system frequency is directly related to the rotational speed of the generators in the system [20]. At any instant, the frequency depends on the balance between the load power and the dispatched generator power. When this dynamic balance changes, small changes in frequency occur. The size of the frequency shift and its duration depends on the load characteristics and the response of the generation system to load changes. Frequency variations that affect the operation of rotating machinery, or processes that derive their timing from the power frequency (clocks), are rare on modern interconnected power systems.

2.3 Solutions to Power Quality Problems

There are many ways to solve or prevent power quality problems [8][27]. Their proposals address two fundamental areas: the power system and the equipment. Manufacturers of electrical equipment determine the electrical characteristics and the sensitivity of their products to power quality variations. When equipment is designed with particular attention to the power quality problems, the sensitivity of this equipment to power quality variations can be reduced and their influence on power quality can be weakened. On the other hand, optimizing the power system structures and using power conditioning equipments can mitigate against the cause or protect the sensitive equipments. Several approaches are given in the following subsections. However, when applying these methods, a good understanding of the power quality problems is needed. This is the essential target of power quality assessment, which is introduced in the next chapter.

2.3.1 Improving the sensitivity of equipment

Manufactures of sensitive equipment can reduce or eliminate the effects of power quality problems by designing their equipment to be less sensitive to voltage variations. For instance, they can simply adjust an undervoltage relay or add some devices, such as capacitors, to provide temporary energy storage when the voltage sags too low. They can alter their equipment to desensitize them to power quality problems. K-factor transformers [28]-[30] are the typical example of this aspect. They are designed to operate at lower flux densities even when supplying nonlinear loads. They can tolerate harmonics and still operate within their temperature limits.

2.3.2 Optimizing the power system structure

The transmission and distribution systems often act as a conduit for transmitting harmonics, transients, voltage sags, or voltage fluctuations from one end user to another. A more cost-effective solution to reduce transfer medium is proper wiring and grounding. It is reported that improper wiring and grounding practice causes 80 to 90 percent of power quality problems [8]. Morinec [31] introduced a grounding technique for computer numerical control machines to prevent operating problems related to power

quality. There is also an IEEE standard [32] on how to design, install, and maintain electrical power wiring and grounding (including both power-related and signal-related noise control) of sensitive electronic processing equipment used in commercial and industrial applications.

2.3.3 Using power conditioning equipment

Power conditioning equipment provides essential protection against power quality problems. Technically, power conditioning equipment are devices that reduce or eliminate the effects of power quality problems. The most common types of power conditioning equipment include uninterruptible power supplies, line conditioners and surge suppressors. Other types of power conditioning equipment include passive and active filters, dynamic voltage restorers, and various types of motor-generator sets.

Among these devices, the uninterruptible power supply (UPS) has been viewed as an effective mitigation method for many years. It provides a constant voltage and power source from a static or rotary source. UPS can be operated on-line or on stand by mode [5]. However, the rapid proliferation of load equipment with microprocessor-based controls and power electronic devices has resulted in the necessity to protect an entire plant, an entire feeder, or a block of customers or loads. In these cases, the use of large UPS systems usually becomes very expensive, not only because of the initial expense to purchase the system, but also the high energy loss due to the inefficiency of the power conversion process [33].

Dynamic Voltage Restorer (DVR) is one of the most promising series-connected devices to mitigate voltage sag/swell. DVR can rapidly inject series voltage to compensate for balanced or unbalanced sag/swell in the upstream supply voltage [34]. DVR can also be used as a series active filter [35].

Harmonic filters are the most widely used harmonic mitigation solution in the utilities. It includes passive filters and active filters [36]. Passive filters use fixed inductors and capacitors to bypass the harmonic components. Active filters use electronic means (inverters and rectifiers) to monitor and sense the harmonic currents and create counter-harmonic currents.

Surge suppressors are the most common devices that protect sensitive loads from overvoltage. They divert to ground or limit the transient voltage caused by lightning stroke or switching surges to a level that will not harm the protected equipment [37].

However, the purchase and installation of the power conditioning equipment can be expensive. The wiring, grounding and faulty equipment problems must be corrected before installing any power conditioning equipment.

2.4 Summary

The characteristics of different power quality problems are given according to the IEEE standard [20]. Their causes are briefly described. Some solutions of power quality problems have been reviewed.

Chapter 3

Power Quality Measurement and Assessment

3.1 Introduction

As solving power quality problems is becoming an important consideration for the power utility customers and industries, there have been some comprehensive analyses to accurately assess the power quality of distribution systems. To gain a better understanding of the nature of power quality problems, power quality measurement and assessment are needed. Generally, the power quality measurement and assessment can be divided into four steps: data acquisition, disturbance detection, classification and characterization.

Firstly, the data is sampled and digitized. The occurrence of a power quality disturbance must first be established before the samples are saved for further processing. Power quality assessment requires precise and continuous knowledge of the voltage waveform and perhaps current waveform over a wide bandwidth and with good resolution [1]. For harmonic analysis, the sampling frequency is determined by the frequency of the highest order harmonic that is of interest. To detect the very low magnitude high order harmonic, a large dynamic range of analogue-to-digital conversion is needed. In contrast, capturing transient wavefront requires a high sampling frequency but lower level analogue-to-digital conversion resolution is still acceptable. Many existing data acquisition systems are capable of meeting the requirements of power quality assessment [38][39].

The detection can be achieved using a simple threshold comparator or by looking for certain specific features related to disturbances. The detection of a power quality disturbance involves two things: detecting when the disturbance happens and its duration. Many newly developed signal processing techniques were introduced in order to realize more accurate triggering for the power quality monitors [40][41]. The details of these techniques are reviewed in the following sections.

After a power quality disturbance has been captured, it is necessary to determine its type and characteristics according to various international standards. As there are many different kinds of power quality disturbances, different processing methods may be required in order to extract specific features that are able to tell them apart from each other. This classification process also includes the identification and elimination of noise and/or bad data. After classifying the disturbance, the characteristics of the disturbance will be derived using techniques according to the specific features that are to be determined.

3.2 Techniques Used in Power Quality Measurement and Assessment

In power quality measurement and assessment, different techniques are used in order to find solutions for power quality problems. Generally, they can be divided into two main categories: signal processing techniques and decision making techniques [42]. Signal processing techniques, e.g. Fourier transform, are responsible for processing the large amount of recorded data. Decision making techniques, such as fuzzy technique, carry out the post-processing procedures, which identify and characterize the types of the power quality disturbances. These two categories are not mutually independent as they work together to explain or describe the power quality problems. In the following subsections, different techniques in these two categories are briefly discussed.

3.2.1 Signal processing techniques

Signal processing techniques are used throughout power quality measurement and assessment. They trigger power quality monitors, record/compress disturbance data and extract features of power quality disturbances. Fourier transform is the most popular signal processing technique as many existing power quality standards are based on the frequency domain. It assumes the analyzed signal to be stationary and periodic, and hence it is more suitable for steady-state phenomena. To analyze non-stationary and aperiodic signals, different time-frequency signal processing techniques are introduced, such as windowed Fourier transform and wavelet analysis. These signal processing techniques are applied to different situations and briefly depicted in the following subsections.

3.2.1.1 Fourier transform

Fourier transform (FT) is the most widely used signal processing technique. It analyzes a time-domain signal for its frequency content. The Fourier transform of a continuous periodic signal $f(t)$ is [43]

$$\mathcal{F}\{f(t)\} = \int_{-\infty}^{+\infty} f(t)e^{-j\omega \cdot t} dt \quad (3-1)$$

Through FT, signal $f(t)$ is broken into a series of continuous sine and/or cosine waves of various frequencies. As most signals are represented by a series of discrete samples, the Discrete Fourier Transform (DFT) is used to estimate their frequency spectrums. For a discrete signal $f[n]$ of N points, a direct calculation of its N discrete Fourier sums is

$$\mathcal{F}\{f[k]\} = \sum_{n=0}^{N-1} f[n]e^{\frac{-i2\pi k}{N}n}, \quad \text{for } 0 \leq k < N \quad (3-2)$$

where k is a non negative integer. It carries out an $N \times N$ arithmetic operation and requires a significant amount of computing time and resources. Therefore, the Fast Fourier Transform (FFT) is developed for the effective computation of the frequency spectrum. It uses sparse matrix techniques and only requires $N \times \log N$ arithmetic operations.

Fourier transform is a linear and symmetry transform. It provides a spectral density distribution, which identifies the amplitudes and phases at the various frequencies. However, when it does this, the time information of the signal is lost. For example, when Fourier transform is used to analyze power system transients or voltage sags, the starting and ending instants of the disturbance cannot be readily ascertained. Therefore, Fourier transform is not the suitable technique for the analysis of non-stationary power quality phenomena.

3.2.1.2 Filtering techniques

Sometimes only the information of a particular frequency band is needed in power quality assessment. In this situation, filtering techniques can be used. They are suitable for extracting signal in specific bandwidth, e.g. low-pass, band-pass and high-pass filters. “Filtering” is a linear process designed to alter the spectral content of an input signal (or

data sequence) in a specific manner [44]. It is implemented using filters that have specific magnitude and/or phase characteristics in the frequency domain. To obtain adjustable frequency bandwidth, a particular filtering technique, adaptive filtering, is developed. It estimates parameters in a window-based least squares (LS), recursive least squares (RLS) or least mean squares (LMS). Adaptive filters sense the properties of the environments in which they operate and adjust the filter parameters accordingly. Consequently, they are useful in a wide variety of applications in which the properties of the operating environments are not known, or in which they change with time in a previously unknown manner.

In power quality assessment, the filtering techniques are usually used for extracting the information of the particular frequency bands, such as in harmonic analysis [12][45].

3.2.1.3 Windowed Fourier transform

There is no time information given by the above techniques as they assume that the signal is periodic. Therefore, in order to track any time variation, windowed techniques, such as windowed Fourier transform (WFT), are used to provide the time information of signal. The WFT essentially divides the signal into sections with a finite energy symmetric window. The WFT of signal f by the window function g is defined by [44]

$$\mathcal{S}\{f(t, \xi)\} = \langle f, g_{t, \xi} \rangle = \int_{-\infty}^{+\infty} f(x) g(x-t) e^{-j\xi x} dx \quad (3-3)$$

where t and ξ are real numbers. t is the time position while ξ represents the frequency position.

The kernel of WFT is the window function g . The size of the window determines the precision of the WFT. Once the size of the window is decided, the window and the transform precision are the same for all frequencies. Briefly, the WFT has a constant time-frequency resolution. Since high-frequency oscillations require a narrow time window, while low-frequency oscillations require a wide time window, WFT has limited application for simultaneously detecting high and low frequency signals. In other words, it is not suitable for use in the detection of the power quality disturbances. It is mainly used for harmonics analysis [46]-[48].

3.2.1.4 Wavelet analysis

The Wavelet Transform (WT), originally derived to process seismic signals, provides a fast and effective way of analyzing non-stationary voltage and current waveforms. It carries out an optimized time-frequency analysis. It uses short time intervals for high-frequency components and long time intervals for low frequency components. Since it is the foundation of the following analysis in this thesis, only a brief overview is given here as it is thoroughly introduced in the following chapter.

In summary, the time-frequency characteristics of these four signal processing techniques can be depicted by Fig. 3-1. Through Fourier transform, as shown in Fig. 3-1(a), only the frequency information can be obtained. It is suitable for the steady-state phenomena in power systems. Fig. 3-1(b) shows the time-frequency plane for filtering techniques. Filtering techniques are based on Fourier analysis. They are used in disturbance analysis where only information at a particular frequency band is needed. Both the time and frequency information can be acquired from WFT although the resolutions are fixed in the entire time-frequency domain, as shown in Fig. 3-1(c). The most common applications of WFT in the power quality measurement and assessment are to analyze the harmonic and inter-harmonic phenomena. These phenomena may not be strictly periodic but any variation in their magnitudes and/or frequencies tends to be slow. Therefore, in these analyses, the lower time resolution is acceptable. Wavelet analysis, as shown in Fig. 3-1(d), is widely used in many aspects of power quality measurement and assessment because of its flexible time-frequency resolutions. More precise time but coarse frequency is set for the high frequency components and vice versa.

Fig. 3-1 Time-frequency planes of four signal processing techniques

(a) Fourier transform. (b) Filtering technique. (c) Windowed Fourier transform. (d) Wavelet analysis.

Generally, signal processing techniques play a very important role in the data acquisition, detection, classification and characterization of power quality disturbances. They analyze the disturbance data and extract their features for the further analysis.

3.2.2 Decision making techniques

After the data of power quality disturbances are obtained and processed by signal processing techniques, decision making techniques are used to process the extracted features. Different decision making techniques such as simple rule-based method, fuzzy technique, statistical technique and neural network approach, have been used in power quality assessment. They are often combined with signal processing techniques in order to achieve better performance when analyzing power quality problems.

3.2.2.1 Fuzzy technique

Fuzzy technique has rapidly become one of the most successful techniques for developing sophisticated control systems [49]. It is also widely used in the power systems such as in fault classification [50]. Fuzzy technique is based on natural language

and built on top of the experience of experts. It can tolerate the imprecise factors of the analysis. A fuzzy logic system generally relies on the experience of people who have already understood the system.

Fuzzy technique is primarily concerned with quantifying and reasoning about vague or fuzzy terms that appear in the natural language. Generally, the fuzzy logical process can be divided into five parts: fuzzification of the input variables, application of the fuzzy operator (AND or OR) in the antecedent, applying implication method from the antecedent to the consequent, aggregation of the consequents across the rules, and defuzzification [51]. A schematic of a fuzzy logic system is shown in Fig. 3-2.

Fig. 3-2 Schematic of a fuzzy logic system

The fuzzification of the inputs is carried out by different membership functions, which are chosen by the user, based on his/her experience. Through fuzzification, the degrees or antecedents of each input are obtained. Then fuzzy operator is used to process these antecedents by rules. One number that represents the result of the antecedents for each rule is obtained. Once proper weighting has been assigned to each rule, the implication method is implemented. It outputs one decision for all the inputs under one rule. In other words, implication is implemented for each rule. Since all the rules must be combined in some manner in order to make a decision, the outputs are aggregated. This aggregation combines the fuzzy sets, which represent the outputs of each rule, into a single fuzzy set. Finally, the defuzzification process is taken where a single output value is resolved from the fuzzy set.

In power quality assessment, fuzzy technique is widely used since there are many uncertain factors in power systems. Its applications in the power quality assessment are reviewed in the following subsection.

3.2.2.2 Probability and statistical approaches

Probability and statistical theory have been considered for many years as the only way to treat random variables [52][53]. Probability theory is a branch of mathematics, which develops models for “chance variations” or “random phenomena”. Statistics is the mathematical science of utilizing data about a population in order to describe it usefully, to draw conclusions and to make decisions. Statistical theory is used to process the available set of data or measurements in order to obtain parameters defining the occurrence properties of variables that are random in nature. Statisticians develop models based on probability theory. They determine which probability model is correct for a given type of problem and they decide what kinds of data should be collected and examined.

Probability and statistics are used in power quality assessment to characterize power quality problems and the sources that result in power quality problems [54][55].

3.2.2.3 Neural network approach

Neural networks are nonlinear computer algorithms that learn with feedback, and can model the behaviour of complicated nonlinear processes [56][57]. Because of this feature, they are well suited for modelling complex and non-linear processes. They are well founded in mathematics. Neural networks can have a variety of architectures that can be customized to solve a particular problem.

In neural networks, proper selection of parameters is often more important than the algorithm itself. Neural networks take this idea to the extreme by using very simple algorithms, but many highly optimized parameters. This is a revolutionary departure from the traditional mainstays of science and engineering: mathematical logic and theorizing followed by experimentation. Neural networks replace these problem-solving strategies with trial, error and pragmatic solutions.

Three commonly used decision making techniques are briefly illustrated above. Many newly developed decision making techniques are now being introduced in power quality

assessment, such as artificial intelligence and genetic algorithm. In the following section, the application of these techniques in power quality assessment is reviewed.

3.3 Review of Power Quality Measurement and Assessment

After having a rough overview of different techniques used in power quality measurement and assessment, their specific applications are reviewed in this section. Their applications are reviewed in sequence according to the steps in power quality measurement and assessment.

3.3.1 Data acquisition and disturbance detection

Signal processing techniques play a very important role in detecting and recording power quality disturbance. There are generally three different triggering methods for the power quality transient monitors: waveform detection, RMS detection and wavelet detection. Waveform detection is carried out by the voltage/current rise or voltage amplitude thresholds comparing voltage/current samples against those of the previous cycle. However, this detection approach is influenced by many factors, such as noise, harmonics and setting of the thresholds. In [1], an improved waveform detection method was introduced. The proposed method is able to mitigate the influence of high-order harmonic distortions. Each sampled point $A_v[n]$ is first squared and then subtracted from a corresponding point $A_{v-1}[n]$ on the previous half-cycle to obtain the variation in squared amplitude VSA_n of the time instant n .

$$VSA_n = A_v^2[n] - A_{v-1}^2[n] \quad (3-4)$$

The root mean square of this VSA_n over half-cycle interval gives the root mean absolute variation in squared amplitude $MAVSA_v$ in (3-5).

$$MAVSA_v = \sqrt{\frac{\sum_{n=1}^N |VSA_n|}{N}} = \sqrt{\frac{\sum_{n=1}^N |A_v^2[n] - A_{v-1}^2[n]|}{N}} \quad (3-5)$$

where N is the number of voltage samples in each half-cycle. The variable v indicates either a positive or negative half-cycle and $v-1$ is the corresponding previous half-cycle. In this manner, the influence of high order harmonics is weakened by a form of

averaging. However, this method still faces delay in detection and the problem of selecting the threshold. Similar or even longer delay can also be seen in the RMS detection.

Compared to other techniques, wavelet transform is deemed more suitable for the disturbance detection. It can detect the events more quickly because it is very sensitive to the irregular parts of a signal. When a disturbance occurs or ends, the signal would vary from its regular state, and hence its wavelet coefficients would change greatly. Therefore, choosing a threshold for wavelet-based detection methods would be much more straightforward. Yang [58] proposed a de-noising scheme to improve the wavelet-based detection. A statistical method, Kolmogoroff-Smirnov test method, was used to set adjustable thresholds for wavelet coefficients at different scales according to the background noise. In this manner, the influence of noise was mitigated. Angrisani [59] proposed another wavelet-based detection method that could work in a noisy environment. The noise level was estimated by evaluating the wavelet maximum modulus at different scales. Therefore, a threshold for detecting disturbances in noisy environments could be set according to this noise level. However, these two methods are rather complex to be implemented in practical systems. If the signal noise is white noise, using the squared coefficients of high frequency bands is enough to mitigate the influence of noise [60][61].

From the illustration in Chapter 2, it is known that power quality phenomena cover a broad frequency spectrum. For high frequency transients, high sampling frequencies are needed and this often results in a large amount of data being captured. Therefore, different data compression methods are being proposed to save storage requirement. Since wavelet analysis has good time-frequency characteristics, there are many wavelet-based data compression methods [62]-[64]. In [62], a minimum description length (MDL) criterion was used to select a suitable wavelet and to determine the number of wavelet coefficients which were kept for the subsequent analysis. This criterion was carried out by evaluating the nonzero wavelet coefficients at different scales and a data compression ratio of less than 11% could be obtained. However, in this method, different wavelets and different MDL values were used for different disturbances. Some simple wavelet-based data compression methods were given in [63] and [64]. In these methods, a single

threshold [63] or several thresholds for different wavelet frequency bands [64] were used. The wavelet coefficients below the threshold(s) were discarded. In this manner, the disturbance data were compressed to about one-sixth to one-third of the original data. Their data compression ratios were slightly higher than that proposed in [62], but they were easier to be implemented in practical systems.

3.3.2 Disturbance classification and characterization

Different characteristics, such as duration, frequency and magnitude, are used to classify and characterize power quality disturbances. Both signal processing and decision making techniques are widely used in the classification and characterization of power quality disturbances. The applications of these techniques are reviewed according to the type of signal processing technique used.

Fourier transform is the most widely used signal processing technique in the disturbance classification and characterization. The current power quality standard [20] is based on Fourier transform. It can directly analyze the steady-state phenomena, such as waveform distortion. For the non-steady state phenomena, the conventional method is to use the RMS curves, which is based on Fourier transform too [11][20]. Styvaktakis [65][66] classified different power quality events by analyzing the RMS values of different segments of the voltage waveform. A voltage disturbance was split into three segments: before, during and after the disturbances. These divisions between the segments corresponded to the types of disturbances. Therefore, they were used to classify the disturbances. An expert system was used to classify between different voltage variations. However, this method was significantly influenced by the window length of the RMS calculation.

Windowed Fourier transform is also used to classify power quality disturbances in [67][68]. Their classification procedures were similar to the conventional RMS method although the time information was more accurate than that of RMS method. However, their classification was heavily influenced by the selection of window functions.

Because of its good time-frequency characteristics, wavelet analysis is widely used in the classification and characterization of power quality disturbances. In [69]-[71],

disturbances signals were decomposed into different scales using discrete wavelet transform. Then, the wavelet coefficients of some particular frequency bands were used to classify some specific power quality disturbances, such as arc furnace and transformer fault transients. Since these specific transients have specific frequency characteristics, they could be directly identified by evaluating the wavelet coefficients of particular frequency bands. However, not all power quality disturbances could be classified in this manner. Different decision making techniques are also needed to process the extracted features and to help the classification of disturbances. Karimi [72] introduced an on-line voltage disturbance detection approach based on wavelet transform. Firstly, an error signal was obtained by filtering the fundamental component from the input signal. Then wavelet transform was used to decompose the transient part of the signal into several frequency bands and their corresponding energy contents were computed. Finally, a probability method, Maximum Likelihood criterion, was used to process these energy contents and discriminate the type of the disturbance. This method ensured a rapid detection and identification of the disturbances.

Gaouda [73] decomposed the whole signal into different bands and calculated the energy contents other than the transient parts of the signal. Using the entire energy content of the disturbance, the standard deviation multi-resolution analysis curve (std_MRA) of different disturbances could be obtained. Short duration voltage variations could be classified by referring to these std_MRA curves. However, this method was influenced by the disturbance magnitude as well as its duration. In [74], voltage sags and switching transients were classified using a wavelet-based fuzzy method. The energy contents in different wavelet frequency bands were used as signatures of different disturbances. Fuzzy technique was used to compare disturbances to these signatures and to make a decision whether the disturbance is of the same type as the signature. The accuracy of this method was not influenced by noise.

In [75], neural network was chosen to identify harmonics, voltage fluctuation and short duration voltage variations although the energy contents of different wavelet frequency bands were still used as the signatures of these disturbances. The neural network was used as it required less memory space and computing time. However, a large number of training examples were needed to achieve accurate identification. A more complicated

decision making process was presented in [76]. A neural-fuzzy classifier was used to process the information of different frequency bands and to identify all types of power quality disturbances listed in Table 2-1. The average correct recognition rate was higher than 93% but it was not readily to be implemented in practical system.

Generally, the selection of which technique to use depends on the users. Their knowledge and experiences would influence the selection. With newly developed techniques being introduced into power quality assessment, there are many choices that may make the identification and characterization easier.

3.4 Summary

To solve power quality problems, a good understanding of their characteristics and causes is very important. This is the ultimate aim of power quality measurement and assessment. Many techniques have been used in power quality measurement and assessment. In this chapter, some techniques commonly used in power quality measurement and assessment are briefly introduced and some of their applications are reviewed. As wavelet analysis forms the foundation of the disturbance identification methods described in Chapters 5, 6 and 7, it is further explained in the following chapter.

Chapter 4

Introduction of Wavelet Analysis

4.1 Introduction

Wavelet analysis is a tool for carving up functions and data into components of different frequency bands, and allows one to study each component separately. It can be also used in the study of operators linked to partial differential equations. The main idea of wavelet analysis has existed since the early 1800's. At that time, Joseph Fourier discovered that signals could be represented with superposed sine and cosine waves, which comprise the basis of Fourier analysis. The basis of wavelet analysis is wavelike function, which plays the same role as the sine and cosine waves in Fourier analysis. However, wavelet algorithms process data at different scales or resolutions. In the 1980s, the basis of wavelet analysis, these wavelike functions (wavelets), was defined in the context of quantum physics [77][78]. From the beginning of the 1990s, wavelet analysis began to be implemented in science and engineering. It has been found that wavelet analysis is particularly useful for analyzing signals that can be described as aperiodic, noisy, intermittent or transient [79]. Other wavelet applications include data compression, earthquake-prediction and pure mathematical applications [78]. In recent years, there are more and more applications in power systems, especially in power quality assessment [80].

Wavelet analysis has the ability to examine the signal simultaneously in time and frequency domains. It is a distinctly different method from the other time-frequency techniques. Wavelet analysis uses little wavelike functions, known as wavelets. Wavelets are used to transform the investigated signal into another representation and represent the signal information in a useful form. During the transform, a basic function or a mother wavelet is dilated or compressed to obtain the appropriate wavelet functions or wavelets for the analysis in the different frequency bands. A contracted, high

frequency version of the mother wavelet is used in temporal analysis, while a dilated, low-frequency version of the same mother wavelet is used in frequency analysis.

Wavelet transform is carried out by convolving the wavelet with the signal or function. The wavelet can be manipulated in two ways: it can be moved to various locations on the signal and it can be stretched or squeezed i.e. scaled. If the wavelet matches the shape of the signal well at a specific scale and location, then a large transform value is obtained. If, however, the wavelet and the signal do not correlate well, a low value of the transform is obtained. The transform is usually computed at various locations of the signal by using various scales of the mother wavelet. It is done in a smooth continuous fashion for the continuous wavelet transform or in discrete steps for the discrete wavelet transform. The basic theories of these two types of wavelet transforms are briefly introduced in the following sections. The efficiencies of the two transforms are discussed and the properties of mother wavelets are studied. The general consideration of selecting mother wavelet is also given.

4.2 Continuous Wavelet Transform

Compared to other time-frequency analysis, continuous wavelet analysis decomposes signals with less resolution limitation. Continuous wavelet transform (CWT) can operate at successive scales, from that of the original signal up to the highest scale that is only limited by the Nyquist sampling theorem [81]. CWT is also continuous in terms of time shifting. During computation, the scaled mother wavelet is shifted smoothly over the full domain of the analyzed signal. Accordingly, a one-dimensional signal is translated into a two-dimensional time-frequency joint representation by the coefficients of CWT. This smooth transition of the scaled mother wavelet implies many overlaps in subsequent transforms and results in highly redundant coefficients.

4.2.1 Wavelet function

A wavelet function ψ is a function of zero average

$$\int_{-\infty}^{+\infty} \psi(t) dt = 0 \quad (4-1)$$

It can be dilated with a scale parameter a , and translated by time b [81]:

$$\psi_{b,a}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \quad (4-2)$$

where a is a positive real number and b is a real number. This function is typically normalized as $\|\psi\|=1$ and centered in the neighborhood of $t=0$. The continuous wavelet transform of a signal $f(t)$ at a scale a and time b is computed by convolving the signal $f(t)$ with an appropriate wavelet function $\psi_{b,a}$ [81]:

$$\mathcal{W}\{f(b,a)\} = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{a}} \psi^*\left(\frac{t-b}{a}\right) dt = \langle f, \psi_{b,a} \rangle = f * \bar{\psi}_a(b) \quad (4-3)$$

where $\bar{\psi}_a(t) = \frac{1}{\sqrt{a}} \psi^*\left(\frac{-t}{a}\right)$. In (4-3), the symbol $*$ denotes convolution between the two functions. ψ^* is the complex conjugate of the function ψ .

In CWT calculation, the values of scale a are associated with the length or support¹ of signal $f(t)$. For simplicity, the support of signal $f(t)$ is typically normalized to between $[0,1]$. As a result, the scale factor a is normalized to $0 < a < 1$ as well. The Fourier transforms of $\bar{\psi}_a(t)$ are the same as the typical frequency responses of band-pass filters. From (4-3), it is obvious that the expansion in the time b involves the lengthening of the time periods and a corresponding lowering of associated frequencies. The value of the scale a is inversely proportional to all characteristic frequencies of ψ , including the passband center frequency. The frequency responses of db2 mother wavelet, as shown in Fig. 4-1, are used to show the typical frequency responses of mother wavelets at different scales. Fig. 4-1(a) shows the waveform of db2 mother wavelet. It has an irregular waveform. Its frequency responses at several scales are shown in Fig. 4-1(b). From this figure, it can be seen that when the scale value a increases and approaches 1, the characteristic frequencies of scale a reduce.

¹ The word “support” is a mathematical term. For a function $f(t)$ and t is the set of arguments of the function f , the support of function f is defined as the closure of t if f is nonzero over this closure.

Fig. 4-1 db2 mother wavelet and its frequency responses at normalized scales
(a) db2 mother wavelet. (b) Frequency responses at normalized scales.

CWT is carried out by the dilated wavelets with such band-limit frequency responses. During the calculation of CWT, the values of the scale a can be successively changed to obtain the information of a particular frequency band. The wavelet coefficients of $\mathcal{W}f(b,a)$ correspond to band-limited high frequency bands of signal f when scale $a < 1$.

4.2.2 Scaling function

With wavelet functions, however, only the information of the normalized scale $a < 1$, corresponding high frequency bands, can be obtained. In order to obtain the low frequency information of the signal and to truly represent and reconstruct the original signal $f(t)$, it is necessary to complete the information corresponding to wavelet coefficients $\mathcal{W}f(b,a)$ for the normalized scale $a > 1$. This can be achieved by introducing a scaling function ϕ that is an aggregation of the mother wavelets ψ at scales greater than 1. The frequency response of the scaling function ϕ can be interpreted as the impulse response of a low-pass filter. The modulus of its Fourier transform is defined by [81],

$$|\hat{\phi}(\omega)|^2 = \int_1^{+\infty} |\hat{\phi}(a\omega)|^2 \frac{da}{a} \quad (4-4)$$

where $\hat{\phi}(\omega)$ denotes the Fourier transform of scaling function $\phi(t)$. It is verified in [81] that the scaling function $\phi(t)$ can be normalized as $\|\phi\|=1$ and has finite energy

$$\lim_{x \rightarrow \infty} |\hat{\phi}(\omega)|^2 = \int_1^{+\infty} \frac{|\hat{\psi}(\omega)|^2}{\omega} d\omega < +\infty \quad (4-5)$$

Denoting $\phi_a(t) = \frac{1}{\sqrt{a}} \phi(\frac{t}{a})$ and $\bar{\phi}_a(t) = \phi_a^*(-t)$, the low-frequency approximation of $f(t)$ at the scale a is [81]

$$\mathcal{L}\{f(b, a)\} = \langle f, \phi_{b,a} \rangle = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{a}} \phi^*\left(\frac{t-b}{a}\right) dt = f * \bar{\phi}_a(b) \quad (4-6)$$

For illustration, Fig. 4-2 again uses db2 mother wavelet to explain the characteristics of the scaling function. Fig. 4-2(a) shows the scaling function of db2 mother wavelet while Fig. 4-2(b) depicts its frequency responses at normalized scales. As mentioned above, all the scales in the convolution between the scaling function and the signal are greater than 1. When the scale a increases and approaches infinite, the characteristic frequencies of scale a decrease to zero.

Fig. 4-2 Scaling function of db2 mother wavelet and its frequency responses at normalized scales

(a) Scaling function of db2 mother wavelet. (b) Frequency responses at normalized scales.

As shown in Fig. 4-2 (b), with the scaling function, the approximate information of the signal (low frequency information) can be obtained. However, not all mother wavelets have corresponding scaling functions. According to their orthogonality, mother wavelets can be divided into two main types: redundant mother wavelet and orthogonal mother wavelet. It is proved in [81] and [82] that all orthogonal mother wavelets have their

corresponding scaling functions. Furthermore, if two orthogonal mother wavelets are used in wavelet analysis, one for decomposition and the other for perfect reconstruction, these two mother wavelets form a pair of biorthogonal mother wavelets.

4.2.3 CWT integral transform

The CWT coefficients contain the complete position/time information in various scales as they carry out integral analysis of signals in specific frequency bands. Fig. 4-3 shows an example of CWT decomposition. The original signal is displayed in Fig. 4-3(a) and it is part of a power system transient waveform. Fig. 4-3 (b), (c) and (d) depict the continuous wavelet coefficients of several scales. These scales are discontinuous scales and their scale values increase from Fig. 4-3 (b) to (d). The aim of using these discontinuous CWT scales is for comparing them to discrete wavelet transform (DWT) decomposition in the later discussion. From these figures, it can be seen that the numbers of the coefficients at different scales are the same as the number of sample points of the original signal. It implies that the complete time information is kept during the CWT decomposition. The time resolutions of the different scales do not degrade. Furthermore, it can also be deduced that if the scales are successive, CWT results in highly redundant coefficients. Hence, the integral information of the signal, including the time and frequency information, is kept after CWT decomposition at the cost of high redundancy and large storage space.

In the above discussion, the term “scale” is used. The value of a normalized scale a represents the frequency resolution and frequency band of that scale.

Fig. 4-3 Integral decomposition of continuous wavelet transform (CWT)

(a) The analyzed signal. (b) CWT coefficients at low scale. (c) CWT coefficients at middle scale. (d) CWT coefficients at high scale.

4.3 Discrete Wavelet Transform

CWT is a highly redundant transform. To carry out an effective calculation and reduce storage space, discrete wavelet transform (DWT) can be chosen. In DWT calculation, signals are decomposed into discontinuous scales and the wavelet function is only scaled and translated in discrete steps. DWT process can be best illustrated through the process of discretizing the CWT. The computation of DWT is carried out with discrete version of the wavelet function and the scaling function.

4.3.1 Discrete wavelet function

Suppose signal $f(t)$ is a continuous-time signal that is uniformly sampled at intervals N^{-1} over $[0,1]$. N is the total number of samples representing the signal with the “normalization over time”. Wavelet transform of $f(t)$ can only be calculated for scales within the range of $N^{-1} < \lambda^j < 1$, where λ is a positive real number and j is a negative integer. The normalized signal can be considered as $f(t) = f(N^{-1}t)$. If $\psi(t)$ is a mother

wavelet function whose support is included in $[-K/2, K/2]$ (K is the support length of the mother wavelet function), its discrete expression scaled by λ^j is defined by

$$\psi_j[n] = \frac{1}{\sqrt{\lambda^j}} \psi\left(\frac{n}{\lambda^j}\right) \quad \text{for } 2K N^{-1} \leq \lambda^j \leq 1 \quad (4-7)$$

Thus, in DWT, the information in the high frequency bands can be carried by D_j as follows [81],

$$D_j[n] = \mathcal{W}\{f[n, \lambda^j]\} = \sum_{m=0}^{N-1} f[m] \psi_j^*[m-n] = f \otimes \bar{\psi}_j[n] \quad (4-8)$$

where $\bar{\psi}_j[n] = \psi_j^*[-n]$. The symbol $\otimes$ denotes the circular convolution² of two discrete functions.

If $\lambda=2$, the DWT, including the convolution with the discrete scaling function which will be discussed in the following section, is known as the discrete dyadic wavelet transform. It is the most widely used transform in the discrete wavelet analysis.

4.3.2 Discrete scaling function

Similar to the discretization of the wavelet function, if the mother wavelet has a corresponding scaling function $\phi(t)$, the discrete expression of $\phi(t)$ scaled by λ^j ($j>0$) is defined by $\phi_j[n] = \frac{1}{\sqrt{\lambda^j}} \phi\left(\frac{n}{\lambda^j}\right)$ for $n \in [-N/2, N/2]$. The information of the low frequency

band is then carried by $\hat{A}_j$, which are coefficients of scaling function respectively [81]:

$$\hat{A}_j[n] = \mathcal{L}\{f[n, \lambda^j]\} = \sum_{m=0}^{N-1} f[m] \phi_j^*[m-n] = f \otimes \bar{\phi}_j[n] \quad (4-9)$$

where $\bar{\phi}_j[n] = \phi_j^*[-n]$.

² If $f[n]$ and $h[n]$ have period N along their rows and columns, then the circular convolution is defined as

$$f \otimes h[n] = \sum_{p=1}^{N-1} f[p] h[n-p] \quad [80].$$

4.3.3 Fast discrete wavelet transform

In the dyadic DWT calculation, a fast DWT can be used to compute the orthogonal wavelet coefficients of a signal measured at a finite resolution. In order to carry out a fast cascade computation, two particular filters are constructed. One is a high-pass filter. The other is a low-pass filter. The high-pass filter is determined from both the wavelet function and the scaling function. It produces the details (high frequency) of wavelet decomposition. The low-pass quadrature filter is determined by the scaling function only. It is associated with the approximations (low frequency) of the wavelet decomposition. These two filters can be defined as [81]:

$$\text{High-pass filter } h[n] = \frac{1}{\sqrt{2}} \left\langle \psi\left(\frac{t}{2}\right), \phi(t-n) \right\rangle \quad (4-10)$$

$$\text{Low-pass filter } g[n] = \left\langle \frac{1}{\sqrt{2}} \phi\left(\frac{t}{2}\right), \phi(t-n) \right\rangle \quad (4-11)$$

For any scale 2^j (j is a non-negative integer), the detail and approximate coefficients can be calculated by (4-12) and (4-13).

$$D_{j+1}[n] = \langle f, \psi_{j,n} \rangle = \langle \hat{A}_j, h_{j,n} \rangle = \hat{A}_j \otimes \bar{h}_j[n] \quad (4-12)$$

$$\hat{A}_{j+1}[n] = \langle f, \phi_{j,n} \rangle = \langle \hat{A}_j, g_{j,n} \rangle = \hat{A}_j \otimes \bar{g}_j[n] \quad (4-13)$$

where $\bar{h}_j[n] = h_j^*[-n]$ and $\bar{g}_j[n] = g_j^*[-n]$.

In the following discussion of DWT, the term “level” is also used. The relationship between scale a and level j is shown by the formula $a=2^j$ (j is a positive integer). When the signal is analyzed by DWT, it is more convenient to use the level or a scale value that is not normalized. If the level or its corresponding scale value is used, it directly shows how deep the signal is decomposed into the lower frequency bands when it is processed during the DWT calculation. Through this expression, the resolution of the scale $a=2^j$ or level j does not change for the approximate coefficients. For the detail coefficients, the resolution of the scale $a=2^j$ (level j) is 2^{j-N} . N is the maximum level and 2^N is the highest scale that the signal can be decomposed into. Furthermore, the relationship between this scale and frequency can be described by the following equation:

$$F_a = \frac{f_s \cdot F_c}{a} \quad (4-14)$$

where $a=2^j$ is the scale, f_s is the sampling frequency and F_c is the center-frequency of a selected mother wavelet. F_a is the pseudo-frequency corresponding to the scale a . The center-frequency of a mother wavelet is obtained by choosing the maximum frequency component of the Fourier spectrum of its wavelet function. This frequency component approximately captures the main wavelet oscillations [83]. It is a convenient and simple characterization of the dominant frequency of a mother wavelet. When a mother wavelet is dilated by a factor a , its center-frequency becomes $\frac{F_c}{a}$. Therefore, if the sampling frequency of the signal is f_s , the pseudo-frequency of the scale a is obtained by (4-14), which can be used to pre-estimate the frequency ranges of various scales.

Based on the above discussion, the decomposition process of fast DWT is depicted by Fig. 4-4.

Fig. 4-4 Diagram of fast DWT decomposition

The original signal is passed through the two filters producing the detail and approximate coefficients of the scale 2 (level 1) accordingly. The approximate coefficients of each scale can then be passed through these two filters multiple times to continue further decomposition. By this method, the decomposition can be carried out until reaching the highest scale. In this computation process, the shifting of the wavelet in the time domain is realized through convolving the signal with the two filters while

the dilation of the wavelets is implemented by downsampling the results of the convolutions. The downsampling process keeps the even indexed elements discarding the odd indexed elements. Although the lengths of the filters do not change, the coefficient lengths of the different scales/levels change because of this downsampling. In this manner, the effect of dilating both the wavelet function and the scaling function can be achieved. The signal is fast decomposed into scales that are required for the analysis since less data or less computation is needed in this decomposition. The total number of coefficients, including the detail coefficients and approximate coefficients, is determined by the length of the signal and the mother wavelet used. If the length of the signal is N and the length of the mother wavelet is n , the total number of coefficients m can be estimated by

$$m = \text{floor}\left(\frac{N-1}{2}\right) + n \quad (4-15)$$

The function ' $\text{floor}(X)$ ' rounds down the element X to the nearest integer. Therefore, the total number of DWT coefficients is slightly higher than that of the original signal. Compared to CWT coefficients at each frequency band, which are as long as the original samples, a large amount of storage space is saved by using DWT. But the resolution of DWT in both time and frequency domains are degraded.

4.3.4 Multi-resolution analysis

In the DWT, a wavelet function and its corresponding scaling function of a selected scale and at a time position, constitute an orthonormal basis. Due to this orthonormal property, there is no information redundancy in DWT computation. In addition, with this choice of scale and time, there exists the multi-resolution analysis (MRA) algorithm [81][83], which decomposes a signal into scales with different time and frequency resolutions. MRA is designed to give good time resolution and poor frequency resolution at high frequency bands while good frequency resolution and poor time resolution at low frequency bands. The fundamental concept involved in MRA is to find the average features as well as the intricate details of the signal by scalar products with scaling signals and wavelets. Fig. 4-5 shows an example of MRA. For ease of comparison with the CWT integral analysis, the same signal, as in Fig. 4-3, is used. Fig.

4-5(b), (c) and (d) depict its wavelet coefficients at the particular scales, which are the coefficients of same scales as shown in Fig. 4-3.

Fig. 4-5 Multi-resolution analysis of discrete wavelet transform (DWT)

(a) The analyzed signal. (b) DWT coefficients at low scale. (c) DWT coefficients at middle scale. (d) DWT coefficients at high scale.

Compared to Fig. 4-3, it can be seen from Fig. 4-5 that the number of coefficients in MRA is much less than that of continuous wavelet analysis even they have the same scales. In the CWT integral analysis, the decomposition produces the same number of the coefficients at all scales. Thus, the time information of these scales is kept completely. The total number of CWT coefficients can be excessively, depending on the number of decomposition levels. If more detail frequency information is needed, successive CWT decomposition would be carried out. This results in more coefficients. On the contrary, as mentioned above, the total number of coefficients in entire DWT is fixed. It depends on the length of the signal and the type of mother wavelet. This characteristic is very useful in data compression because a large amount of data space is saved by keeping only the coefficients of particular scales. However, the MRA method degrades the time and frequency resolutions.

4.4 Properties of Mother Wavelets

The effectiveness of CWT and DWT is influenced by the choice of mother wavelet and its scaling function, if it exists. Different types of mother wavelets have different properties. Applying wavelet analysis requires careful consideration of the type of mother wavelet. A suitable mother wavelet can make the analysis more effective. There are many mother wavelets and they can be divided into three types according to their orthogonality: redundant wavelets, orthogonal wavelets and biorthogonal wavelets. Orthogonal and biorthogonal wavelet analysis lead to no redundancy in their analysis. In addition, the biorthogonal mother wavelets have an advantage over the orthogonal mother wavelets because their filters are symmetric and can be used to exactly reconstruct the original signal. A more comprehensive summary of some mother wavelets and their properties is tabulated in Table 4-1 [83].

Table 4-1 Summary of wavelet families and associated properties (to be continued)

Properties	Morlet (morl)	Mexican-hat (mexh)	Meyer (meyr)	Haar (Haar)	Daubechies (dbN)
Regularity	Infinitely	Infinitely	Infinitely	No	Arbitrary
Compactly supported orthogonal	No	No	No	2	2N-1
Symmetry	Yes	Yes	Yes	Yes	Asymmetry
Number of vanishing moments				1	N
Existence of scaling function	No	No	Yes	Yes	Yes
Orthogonal analysis	No	No	Yes	Yes	Yes
Biorthogonal analysis	No	No	Yes	Yes	Yes
FIR filters (length)	No	No	No	2	2N
Fast algorithm	No	No	No	Yes	Yes
Continuous transform	Yes	Yes	Yes	Yes	Yes
Discrete transform	No	No	Yes	Yes	Yes
Explicit expression	Yes	Yes	No	Yes	No

Table 4-1 (Continued)

Properties	Gaussian (gaus)	Symlet (symN)	Coiflet (coifN)	Biorthogonal wavelet Pairs (biorNr.Nd)
Regularity	Infinitely	Arbitrary	Arbitrary	Arbitrary
Compactly supported orthogonal	No	2N-1	6N-1	2Nd+1
Symmetry	Yes	Near symmetry	Near symmetry	Yes
Number of vanishing moments		N	2N	Nr-1
Existence of scaling function	No	Yes	Yes	Yes
Orthogonal analysis	No	Yes	Yes	No
Biorthogonal analysis	No	Yes	Yes	Yes
FIR filters (length)	No	2N	6N	Yes
Fast algorithm	No	Yes	Yes	Yes
Continuous transform	Yes	Yes	Yes	Yes
Discrete transform	No	Yes	Yes	Yes
Explicit expression	Yes	No	No	For splines

From Table 4-1, it can be seen that there are many types of mother wavelets. Even the wavelets in the same wavelet family may have different characteristics. The performance of a wavelet-based application strongly depends on the choice of the mother wavelet. Hence, in order to make a wavelet-based method more effective and efficient, it is necessary to consider the properties of the selected mother wavelet. Several important properties of mother wavelets are summarized in the following sections.

4.4.1 Number of vanishing moments

A wavelet ψ is defined to have p vanishing moments if

$$\int_{-\infty}^{+\infty} t^k \psi(t) dt = 0 \quad \text{for } 0 \leq k < p \quad (4-16)$$

where p and k are integers. This means that ψ is orthogonal to any $p-1$ degree polynomial. The regular parts of the signal, whose degrees are not greater than $p-1$, can

then be readily compressed during wavelet transform. Suppose signal $f(t)$ is continuously differentiable at point zero, it can be expanded into the following Taylor expansion series,

$$f(t) = [f(0) + tf'(0) + t^2 f^{(2)}(0) + \dots + t^{p-1} f^{(p-1)}(0)] + g(t) \quad (4-17)$$

where $g(t)$ is the irregular part of the signal $f(t)$. Both $g(t)$ and $f(t)$ have the same wavelet detail coefficients. With sufficient number of vanishing moments, the wavelet transform process would systematically suppress the regular parts of the signal and focus on the irregular parts [81][84][85]. Therefore, the detail coefficients at the regular parts would be much smaller than those at the irregular parts. This helps to reveal the irregular parts and this property is very useful when processing irregular signals.

4.4.2 Support of mother wavelet

Suppose signal $f(t)$ has an isolated singularity at point t_0 (i.e. $f(t)$ is only not differentiable at t_0) and t_0 is inside the support of the wavelet function at scale a_0

$\psi_{b,a_0}(t) = \frac{1}{\sqrt{a_0}} \psi\left(\frac{t-b}{a_0}\right)$, the wavelet detail coefficients at this scale may have large

values. If the mother wavelet ψ has a compact support of size K , there will be K wavelets ψ_{b,a_0} whose support includes t_0 . Hence, to minimize the number of high amplitude coefficients, the support size of ψ must be kept small. It is proved in [81] and [82] that the constraints imposed on orthogonal wavelet imply that if ψ has p vanishing moments then its support size is at least $2p-1$. However, a larger number of vanishing moments is needed to compress the regular parts of a signal, especially if the signal has few isolated singularities and is very regular between singularities. If there are more singularities, it may be better to decrease the size of its support size at the cost of reducing the number of vanishing moments. In other words, a trade-off between the number of vanishing moments and the support size must be made when one chooses a particular mother wavelet. This is because the wavelets used are orthogonal wavelet, whose support size always increases/decreases in tandem with the number of vanishing moments. Hence, a trade-off between the number of vanishing moments and the support size must be made when choosing a particular wavelet.

4.4.3 Regularity of mother wavelet

The regularity of mother wavelets has mostly a cosmetic influence on the error introduced by thresholding or quantizing of the wavelet coefficients. If the mother wavelet ψ is r -time continuously differentiable at time/position b and r is a non-negative integer, then its regularity is r . The greater r is, the more regular the mother wavelet is. Take Daubechies wavelets family as an example. Their regularities are shown in Table 4-2 [83].

Table 4-2 Regularity of Daubechies wavelets

ψ	db1=Haar	db2	db3	db4	db5	db7	db10
Regularity (r)	discontinuous	0.5	0.91	1.27	1.59	2.15	2.90

It is seen from Table 4-2 that there is an asymptotic relation linking the size of the support of the Daubechies wavelets dbN and their regularity: when N increases to infinity, the regularity r becomes about one fifth of N . The longer support a Daubechies wavelet has, the more regular the wavelet is.

Regularity is useful in estimating the local properties of a function or signal. With a regular mother wavelet, the reconstructed signal will be smoother.

4.4.4 Symmetry of mother wavelet

Symmetric wavelets show no preferred direction or emphasis in “time,” while asymmetric wavelets give unequal weighting to different directions. If a wavelet function ψ is symmetric, it is easier to deal with the boundaries of the signal, because the phase shift caused by this wavelet function is linear. Compared to nonlinear phase shift, the linear phase shift is generally more acceptable, especially in image processing. If the mother wavelet is not symmetric, then the wavelet transform of the mirror of an image is not the mirror of the image’s wavelet transform. In power quality assessment, the influence of the signal border distortion of the signal can be mitigated by using symmetric mother wavelets [86].

4.4.5 General criteria for choosing mother wavelet

To choose a suitable mother wavelet as the basis for a certain wavelet analysis, the properties of wavelet families mentioned above must be considered carefully. Generally, the aim of the wavelet analysis and the characteristic of the analyzed object determine the type of mother wavelet. If a signal has a few isolated singularities and is very regular between singularities, a wavelet with many vanishing moments can be chosen to produce a large number of small wavelet coefficients. If the density of singularities increases, it might be better to decrease the size of its support at the cost of reducing the number of vanishing moments. Wavelet analysis that overlaps the singularities of a signal would create high coefficient values. Furthermore, if signal reconstruction is needed, a more regular wavelet is preferred in order to obtain a smoother reconstructed signal. Finally, if the analysis is to be carried out on only some specific frequencies, the center-frequency of the wavelet, the sampling frequency of the signal and the length of the signal must be taken into consideration simultaneously.

How to choose a mother wavelet can proceed according to the following two steps [83]:

- 1) Step 1. ***Determine the wavelet type.*** This is the most important step. If a fast algorithm is needed, the wavelet must have FIR filters (see Section 4.3.3). If the approximation part of the analysis is needed, the scaling function of the wavelet is required. Comparing to orthogonal wavelets, biorthogonal wavelets have some advantages during the reconstructive process. The symmetry and the exact reconstruction are possible at the same time. In term of wavelet selection, mother wavelets can be divided into four categories:
 - *Orthogonal wavelets with FIR filters.* These wavelets can be defined through a scaling filter. Predefined families of such wavelets include Haar, Daubechies, Coiflet, and Symlet.
 - *Biorthogonal wavelets with FIR filters.* These wavelets can be defined through two scaling filters for reconstruction and decomposition respectively. The BiorSplines wavelet family is a predefined family of this category.

- *Orthogonal wavelets without FIR filter, but with scaling function.* These wavelets can be defined through the definition of a wavelet function and a scaling function. The Meyer wavelet family is a predefined family of this category.
 - *Wavelets without FIR filter and without scaling function.* These wavelets can be defined through the definition of a wavelet function only. Predefined families of such wavelets include Morlet and Mexican_hat.
- 2) Step 2. ***Define the orders of wavelets within the given family.*** There are some wavelet families, which have a single wavelet, such as Haar, Meyer and Morlet, or many wavelets such as Daubechies, Coiflet, etc. If a family contains many wavelets, this ordering must be decided. This involves several issues regarding their properties including the number of vanishing moments, the regularity and the compact support size. According to the above discussion, some compromises have to be made between the number of vanishing moments and the support size of the filters.

4.5 Summary

Wavelet analysis is a useful tool in the time-frequency analysis. The two types of wavelet transforms, CWT and DWT, have their respective advantages. They can be applied in different areas. For the subtle frequency/time analysis, CWT can be applied. CWT processes the signals without losing any time resolution and is especially true for very subtle information. CWT can be easily interpreted since its redundancy tends to reinforce the trait more visibly. Furthermore, all the information at different frequency bands can be obtained by changing the scale. Thus, the CWT gains in “readability” and in ease of interpretation at the expense of a large storage space. DWT ensures space-saving coding and is sufficient for exact reconstruction. DWT processes signals with a multi-resolution approach. As discussed in Section 4.3.4, the time resolution in the higher scales (lower frequency bands) is low because of downsampling in DWT calculation. With the decrease of the data length, some parts of the time information are lost. On the other hand, according to equation (4-14), the lower frequency bands become narrower giving a better frequency resolution. In the high frequency bands, the situation is reversed where a relatively lower frequency resolution but a higher time resolution

can be achieved. However, it provides the most compact representation of the signal. This discrete transform is fast and suitable for data compression and filtering large arrays of data. In the subsequent chapters, these two types of wavelet transforms are used for the analysis of different power quality disturbances. In the Chapter 5, DWT is used to analyze the short duration voltage variations. With MRA of DWT, the computation time and storage spaces can be reduced. In Chapters 6 and 7, CWT in turn is applied to analyze the information of a particular frequency band. The integral analysis of CWT ensures that complete information of this frequency band can be fully obtained.

Chapter 5

Wavelet-Based Energy Content Method for Classifying Short Duration Voltage Variations

Having briefly introduced power quality assessment and wavelet analysis in the previous chapters, a wavelet-based energy content method is proposed to classify and characterize short duration voltage variations in this chapter. This method is based on the notion that disturbance signals (voltages) are comprised of two parts: the fundamental frequency part and the transient part. Accurate time information of disturbances can be extracted from the transient part while the magnitude information can be obtained by evaluating energy changes in the fundamental frequency band. Therefore, short duration voltage variations can be identified. The details of this method and its application are discussed in the following sections.

5.1 Introduction

As reviewed in Chapter 2, short duration voltage variations is the most common power quality problem. In power systems, short duration voltage variations are classified according to their durations and voltage magnitudes [20]. An interruption is deemed to have occurred when the supply voltage decreases to less than 0.1 pu for a period of time not exceeding 1 min [20]. Voltage sag is a voltage drop reaching 10-90 percent of the rated system voltage and lasting from 0.5 cycle to 1 min. A swell is an increase in RMS voltage at the power frequency for duration from 0.5 cycle to 1 min. The typical magnitude of swell is between 1.1 and 1.8 pu. These definitions are based on the conventional RMS measurement method. However, the information during the transient process is not fully used by this conventional method. Fig. 5-1 shows a typical voltage sag waveform. Obviously, at the beginning and ending of the disturbance, many oscillatory transient components appear. They tend to be under-damped and decay away within a cycle. It is because there are energy redistributions at the beginning and the ending of the disturbances. Since the power system comprises of a multitude of energy

components, such as capacitors and inductors, the transient behaviour during the redistribution cannot be avoided.

Fig. 5-1 Typical waveform of a voltage sag

Generally, the voltage before disturbance can be expressed by

$$V_1(t) = A_0 \sin(\omega_0 t + \varphi_0) \quad (5-1)$$

where A_0 , ω_0 and φ_0 are the amplitude, frequency and initial phase angle of the fundamentals frequency component. Other steady-state phenomena are ignored.

When a disturbance occurs, many oscillatory transients would appear. The disturbance voltage is

$$V_2(t) = A_1 \sin(\omega_0 t + \varphi_1) + A_2 e^{-\alpha_2 t} \sin(\omega_2 t + \varphi_2) + \dots \quad (5-2)$$

where A_x , ω_x and φ_x are the amplitude, frequency and initial phase angle of different frequency components. The exponential damping coefficient α_x denotes the rate at which each transient component decays away.

5.2 Duration Detection Using Wavelet Transform

In Section 3.3.1, different detection methods are reviewed and it was revealed that conventional detection techniques have some pitfalls, such as delay in detection and the difficulty in deciding threshold settings. Using Wavelet analysis can overcome these shortcomings because wavelet analysis performs well in the analysis of irregular signals. Wavelet analysis can systematically compress the regular parts of a signal. This is very useful in the detection of disturbances. From (5-1) and (5-2), the voltage is sinusoidal before the disturbance and contains many transient components during the disturbance. The voltage waveform is singular at the instant when the disturbance occurs. Taking regular voltage waveform $V(t)$, the derivation below shows that the wavelet coefficient of $V(t)$ at the time instant of t_0 and scale a_0 using a mother wavelet ψ with p vanishing moments (p is a positive integer) can be written as

$$\mathcal{W}\{V(t_0, a_0)\} = \sum_{n=p}^{\infty} \frac{V^{(n)}(t_0)}{n!} \int_{-\infty}^{+\infty} t^n \cdot \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{t}{a_0}\right) dt \quad (5-3)$$

where n is a positive integer and $V^{(n)}(t_0)$ is the n th derivative of $V(t)$ at time instant t_0 .

Derivation:

The wavelet coefficient at time t_0 and scale s_0 can be computed by applying (4-3) on $V(t)$,

$$\mathcal{W}\{V(t_0, a_0)\} = \int_{-\infty}^{+\infty} V(t) \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{t-t_0}{a_0}\right) dt \quad (5-4)$$

This voltage $V(t)$ at time instant t_0 can be expanded into a Taylor series as follows,

$$V(t) = V(t_0) + \sum_{n=1}^{\infty} \frac{1}{n!} V^{(n)}(t_0) \cdot (t-t_0)^n \quad (5-5)$$

Substituting (5-5) into (5-4),

$$\begin{aligned}
 & \mathcal{W}\{V(t_0, a_0)\} \\
 &= \int_{-\infty}^{+\infty} \left\{ V(t_0) + \sum_{n=1}^{\infty} \frac{1}{n!} V^{(n)}(t_0) \cdot (t-t_0)^n \right\} \cdot \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{t-t_0}{a_0}\right) dt \\
 &= \int_{-\infty}^{+\infty} V(t_0) \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{t-t_0}{a_0}\right) dt + \sum_{n=1}^{\infty} \int_{-\infty}^{+\infty} \frac{1}{n!} V^{(n)}(t_0) \cdot (t-t_0)^n \cdot \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{t-t_0}{a_0}\right) dt
 \end{aligned}$$

Defining $\Delta = t - t_0$, the above equation can be simplified to

$$\begin{aligned}
 & \mathcal{W}\{V(t_0, a_0)\} \\
 &= \int_{-\infty}^{+\infty} V(t_0) \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{\Delta}{a_0}\right) d\Delta + \sum_{n=1}^{\infty} \int_{-\infty}^{+\infty} \frac{1}{n!} V^{(n)}(t_0) \cdot \Delta^n \cdot \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{\Delta}{a_0}\right) d\Delta \\
 &= V(t_0) \int_{-\infty}^{+\infty} \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{\Delta}{a_0}\right) d\Delta + \sum_{n=1}^{p-1} \frac{1}{n!} V^{(n)}(t_0) \int_{-\infty}^{+\infty} \Delta^n \cdot \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{\Delta}{a_0}\right) d\Delta \\
 &\quad + \sum_{n=p}^{\infty} \frac{1}{n!} V^{(n)}(t_0) \cdot \int_{-\infty}^{+\infty} \Delta^n \cdot \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{\Delta}{a_0}\right) d\Delta
 \end{aligned}$$

Using (4-1) and (4-16),

$$\begin{aligned}
 & \int_{-\infty}^{+\infty} \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{\Delta}{a_0}\right) d\Delta = 0 \\
 & \int_{-\infty}^{+\infty} \Delta^n \cdot \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{\Delta}{a_0}\right) d\Delta = 0 \quad \text{for } 0 \leq n \leq p-1
 \end{aligned}$$

Hence, the first and second terms of $\mathcal{W}\{V(t_0, a_0)\}$ are zero and only the third term is left.

Replacing the symbol Δ with the symbol t , $\mathcal{W}\{V(t_0, a_0)\}$ can therefore be rewritten as

$$\mathcal{W}\{V(t_0, a_0)\} = \sum_{n=p}^{\infty} \frac{V^{(n)}(t_0)}{n!} \int_{-\infty}^{+\infty} t^n \cdot \frac{1}{\sqrt{a_0}} \psi^*\left(\frac{t}{a_0}\right) dt$$

Q.E.D.

□

If the signal $V(t)$ is regular, (5-3) is limited and converges to zero [81]. For small scale a_0 , the wavelet coefficient $\mathcal{W}\{V(t_0, a_0)\}$ is small compared to its initial voltage magnitude [85]. Typically, it is less than 0.1% at these small scales [87].

On the contrary, if $V(t)$ is singular and not differentiable at the time instant t_f , (5-3) would be invalid for computing the wavelet coefficient. The wavelet coefficient $\mathcal{W}\{V(t_f, a_0)\}$ then can only be represented by the full expression (5-4). The wavelet coefficient at this time point would be significantly larger at these small scales [81][82][85][88]. Typically, this value is less than 40% of its original voltage magnitude [87].

Based on the above analysis, it can be concluded that the wavelet coefficients would change significantly at the points when the disturbance occurs and ends. The wavelet coefficients before those points are usually much smaller. This characteristic can be used to identify the occurrence and ending instants. Therefore, the duration of the disturbance can be obtained from these instants.

In the above analysis, the scale a_0 is not fixed to a particular scale. This means that this deduction is applicable for all the small scales. Several researchers have shown that most transient components in short duration voltage variations have characteristic frequencies about 1 kHz [89]. Similarly, in this thesis, the 1 kHz transient component is used to determine the time information of short duration voltage variations.

5.3 Magnitude Computation Using Wavelet Transform

Besides the time information that can be extracted from the 1 kHz frequency band, the magnitude or energy information is also needed to classify these voltage variations. During short duration voltage variations, the energy changes mainly in the fundamental frequency band. This energy information of the fundamental frequency band can be obtained by using wavelet transform. As the fundamental frequency in power systems is low (i.e. 50 Hz or 60 Hz), the wavelet approximate coefficients of the fundamental frequency band can be used to calculate the energy of the fundamental frequency. From

(4-6), the energy density of any voltage signal $V_3(t)$ at the fundamental scale a_N and time instant t_0 is [81]

$$P_L(t_0, a_N) = \left| \mathcal{L}\{V_3(t_0, a_N)\} \right|^2 \quad (5-6)$$

where $\mathcal{L}\{V_3(t_0, a_N)\}$ is the fundamental frequency approximation of $V_3(t)$ obtained through the wavelet transform, P_L is the energy density obtained by the wavelet transform with a scaling function.

Therefore, the energy of half a cycle in the fundamental frequency band can be computed from

$$E_L(a_N) = \int_{t_0}^{t_0 + \frac{T_0}{2}} P_L(t, a_N) dt = \int_{t_0}^{t_0 + \frac{T_0}{2}} \left| \mathcal{L}\{V_3(t_0, a_N)\} \right|^2 dt \quad (5-7)$$

where T_0 is the fundamental period, E_L is the energy obtained by the wavelet transform with a scaling function. $E_L(a_N)$ represents the half cycle energy of the voltage signal V_3 at the time instant t_0 and scale a_N .

This energy definition is in fact similar to that of RMS. This energy content can be referred to a corresponding voltage RMS value. Hence, the type of disturbance can be determined according to the IEEE standard [20] as shown in Fig. 5-2. During an interruption, the energy content will be lower than 10% of the nominal value. The energy changes caused by sags are between 10% and 90% of the nominal level while those caused by swell are from 110% to 180%. Combining with the time information obtained earlier, the voltage variation can then be classified to one of the categories listed in Table 2-1.

Fig. 5-2 Energy content changes of fundamental frequency band for different disturbances

5.4 Implementation of Wavelet Transform

5.4.1 CWT vs. DWT

As introduced in Chapter 4, there are two types of wavelet transforms: CWT and DWT. From the above illustration, it can be concluded that only the information of two different frequency bands is needed. Namely, one high frequency band is for finding the detail time information and the other fundamental frequency information is for determining the changes in the voltage magnitude. This can be achieved by either wavelet transforms. However, as DWT can optimize its resolution with good time resolution in the high frequency bands and good frequency resolution in the low frequency band, its calculation is not redundant, saving a large amount of storage space. Moreover, a much faster algorithm can be achieved with DWT giving a lower computation time. Therefore, it is unnecessary to use CWT for high precision time information in both scales at the cost of longer computational time and larger storage space. Hence, DWT is selected for this analysis.

5.4.2 Choice of mother wavelet

Choosing a suitable mother wavelet is the first and most important step in any wavelet applications. Different mother wavelets are designed for different purposes. In power

quality assessment, many different types of mother wavelets have been used. Santoso [90][91] chose db4 mother wavelet to carry out an orthogonal or non-redundant analysis. Huang selected Morlet mother wavelet because it has good symmetry [86] and chose Coiflet mother wavelet to compress well the regular parts of signals [92]. In these applications, mother wavelets were used to decompose and reconstruct signals in order to obtain the partially reconstructed signals at particular scales. As discussed above, the mother wavelet in the wavelet-based energy content method has two functions: one is to extract the time information of the disturbances; the other is to compute the energy content in the fundamental frequency band. To extract the precise time information of the disturbance, large wavelet coefficient values are needed when the disturbance occurs and ends. The mother wavelet should have more than one vanishing moment to suppress sufficiently the regular part of the voltage waveform. Furthermore, the wavelet that has short support size is suitable in this situation for the calculation in the high DWT scales (low frequency). At the same time, fast algorithm is needed to ensure fast computation. Hence, the wavelet transform must be implemented by FIR filtering. Wavelet symmetry does not play an important role in power quality assessment and hence, the mother wavelet does not need to be symmetric. With these arguments, only several wavelet families can be considered and they are the Daubechies, Coiflet, Symlet and biorthogonal wavelet families. Haar mother wavelet is also considered for comparison as it has the shortest compact support size.

5.4.2.1 Support sizes of different mother wavelets

After the general consideration of selecting mother wavelets, the performances of different mother wavelets in this application are studied. As illustrated above, the suitable mother wavelet should have short support size. Therefore, the mother wavelets that have shortest support size in their individual wavelet families are considered. Since Symlet wavelets are obtained by modifying Daubechies wavelets in order to acquire better symmetry, the low order Symlet wavelets are actually the same as the corresponding Daubechies wavelets. Therefore, Symlet wavelets are not considered in the following study. Hence, the performances of Haar mother wavelet and three other mother wavelets, which have the shortest support size in their individual wavelet family, are compared. The wave shapes of these four mother wavelets are shown in Fig. 5-3 and their properties are summarized in Table 5-1.

Fig. 5-3 Wave shapes of different mother wavelets

(a) Haar mother wavelet. (b) db2 mother wavelet. (c) coif1 mother wavelet. (d) bior2.2 mother wavelet.

Table 5-1 Summary of the four type wavelets and their properties

Properties	Haar (Haar)	db2 (Daubechies)	coif1 (Coiflet)	bior2.2 (Biorthogonal)
Regularity	No	Arbitrary	Arbitrary	Arbitrary
Compactly supported orthogonal	2	3	5	5
Symmetry	Yes	Asymmetry	Near symmetry	Yes
Number of vanishing moments	1	2	2	1
Existence of scaling function	Yes	Yes	Yes	Yes
FIR filters length	2	4	6	6
Explicit expression	Yes	No	No	No

Fig. 5-4 depicts the wavelet coefficient values of these four mother wavelets in the high frequency band for a voltage interruption waveform as shown in Fig. 5-4 (a). Fig. 5-4 (b), (c), (d) and (e) are the results of Haar, db2, coif1 and bior2.2 wavelet transforms respectively. As discussed in Section 5.2, the wavelet coefficients change significantly at

the two singular points, the beginning and ending instants of the disturbance. From (b), Haar mother wavelet is not a good choice compared to other mother wavelets as it cannot suppress the regular part of the voltage well. This is because although it has shortest support size, it is discontinuous and has only one vanishing moment. (c), (d) and (e) look very similar. But the db2 result has a sharper peak at the beginning of the disturbance than the other twos. Moreover, db2 has the shortest filter length among them. The calculation of DWT is typically carried out through filtering process using integral filters derived from the mother wavelets. If the filters are short, there would be less convolution computation needed in the filtering process and hence faster computation. Therefore, db2 is considered as the best choice of mother wavelet for extracting the time features of power quality variation.

Fig. 5-4 Comparison of four mother wavelets in the high frequency band

(a) The original signal. (b) High frequency information extracted by Haar mother wavelet. (c) High frequency information extracted by db2 mother wavelet. (d) High frequency information extracted by coif1 mother wavelet. (e) High frequency information extracted by bior2.2 mother wavelet.

5.4.2.2 Number of vanishing moments

Next the influence of the number of the vanishing moments on the performance of this wavelet-based method is studied. The mother wavelets chosen for comparison are db2 and db8. Their main differences are shown in Table 5-2. Here, not only the performance

on extracting high frequency information is studied, but that of computing the fundamental frequency energy content is also compared. The results are shown in Fig. 5-5. Fig. 5-5 (a) shows an interruption waveform. (b) and (c) show the coefficients of db2 and db8 in the high frequency band respectively. On the other hand, (d) and (e) depict their performances of computing the energy content in the fundamental frequency band.

From Fig. 5-5 (b) and (c), it can be concluded that both db2 and db8 mother wavelets can be used to extract the time information of the disturbance although db8 mother wavelet has more vanishing moments. However, their performances in the fundamental frequency band are slightly different, as shown in Fig. 5-5 (d) and (e). The energy content obtained by db2 drops lower than 0.1 while that obtained by db8 only reaches about 0.3. This is because the energy sensitivity of the wavelet coefficient is influenced by the iterative convolution and downsampling process during DWT calculation (see Section 4.3.3). A mother wavelet with more vanishing moments, or longer support size, would degrade this sensitivity. Hence, the drop of the energy content obtained by db8 is smaller than that obtained by db2 since the support size of db8 is much longer. Therefore, a mother wavelet with short support size, such as db2, is deemed more suitable and chosen for this wavelet-based energy content method. It is used in the subsequent verification analyses.

Table 5-2 Difference between db2 and db8 mother wavelets

Properties	db2	db8
Compactly supported orthogonal	3	15
Number of vanishing moments	2	8
FIR filters length	4	16

Fig. 5-5 Comparison between db2 and db8 mother wavelet

(a) Original signal. (b) High frequency information extracted by db2 mother wavelet. (c) High frequency information extracted by db8 mother wavelet. (d) Fundamental energy contents calculated by db2 mother wavelet. (e) Fundamental energy contents calculated by db8 mother wavelet.

5.5 Verification

After selecting a suitable mother wavelet, verification of this wavelet-based energy content method is carried out. The Western System Coordinating Council (WSCC) 3-machines 9-bus system [93] is chosen as the test case in these verification simulations. Its layout is shown in Fig. 5-6 and its detailed parameters are given in Appendix A. This test system was set up in the Matlab/Simulink environment. Its version is 6.1.0.450 Release 12.1. The Power System Blockset is used to simulate faults and switching operations. In this manner, the necessary disturbance data can be obtained to verify this wavelet-based energy content method.

Fig. 5-6 Diagram of WSCC 9-bus system

The voltage waveform is sampled at 256 samples per fundamental cycle (50Hz), corresponding to 12.8kHz of sampling frequency. Because of the downsampling during the DWT decomposition, the number of coefficients at high scale (low frequency) is significantly reduced. Therefore, to ensure that the calculation of the energy in the fundamental frequency band is accurate, the signal is only decomposed to scale 32 (2^5 for level 5) by DWT. The approximate coefficients at scale 32 contain the information about the fundamental frequency component. In this scale, eight approximation coefficients correspond to a full fundamental cycle. The energy content can then be calculated using (5-7) over these coefficients. In actual fact, only four coefficients corresponding to half a cycle are needed and this would keep the computational burden low without losing any accuracy. On the other hand, the detail coefficients of scale 8 (2^3 for level 3) are used to extract the time formation of the disturbance. The pseudo-frequency of this scale is obtained using (4-14) to be 1.067kHz. Even though these waveforms are obtained from simulations and hence practically noise-free, but for completeness sake, the detail coefficients of scale 8 are still squared, which is a commonly used technique to mitigate the influence of noise. At this scale, one

coefficient corresponds to 8 original sample points in the time domain. This causes a small error in detecting the precise time when the disturbance occurs and ends. The maximum error is found to be 0.625 ms.

The effectiveness of this method is compared against the conventional RMS method. The half-fundamental cycle RMS calculation is used to deduce the starting and ending points of the disturbance and the voltage magnitude. The results are compared to those of the wavelet-based energy content method.

5.5.1 Momentary interruption

Fig. 5-7 shows how to classify voltage interruption using this wavelet-based energy content method. Fig. 5-7(a) depicts that an interruption occurs at the instant of 41.48 ms (531th sample point) and it lasts for 32.81ms, 420 sample points. The high frequency band (around 1 kHz) information extracted by the discrete wavelet transform is shown in Fig. 5-7(c). The large squared coefficient values represent the occurrence of the disturbance. The coefficients change sharply at the beginning and the end of the disturbance, which are found to be at 41.87 ms (67th coefficient number) and 75 ms (120th coefficient number) respectively. The duration is found to be about 33.13ms or 53 coefficient values. Fig. 5-7(d) shows the energy in the fundamental frequency band. The energy reduces to below 0.1 pu indicating that it is a voltage interruption. The disturbance therefore is identified as a voltage interruption lasting 33.13 ms and the error in the time duration determination is about 0.39 ms only.

With the conventional RMS method shown in Fig. 5-7(b), the disturbance is also correctly identified as a voltage interruption, but it is said to occur at 43.13 ms (552th sample point) and last for 40.16 ms, 514 sample points. This duration calculation is about 7.35 ms more than the actual duration and this error is much larger than that in the wavelet-based energy content method. Hence, it can be concluded that the wavelet-based energy content method shows a better performance in the identification of momentary interruptions.

Fig. 5-7 Classification of a momentary interruption

(a) Original momentary interruption waveform. (b) Result of the conventional RMS method. (c) Information of 1 kHz frequency band. (d) Energy content in the fundamental frequency band.

5.5.2 Voltage sag

Fig. 5-8(a) depicts a voltage sag, which occurs at the instant of 43.05 ms (551th sample point) and lasts for 38.20 ms or a total of 489 sample points. The high frequency band information extracted by DWT is shown in Fig. 5-8(c). The beginning and ending instants of the disturbance can be determined according to the significant changes of the squared coefficients, which are found to be at 43.13 ms (69th coefficient number) and 81.88 ms (131th coefficient number) respectively. Hence, the duration is determined to be about 38.75 ms, corresponding to 69 coefficient numbers. Fig. 5-8(d) shows the energy content in the fundamental frequency band. This energy content reduces to 0.5 pu and as it stays above 0.1pu, it is deemed a voltage sag and not an interruption.

The result of the conventional RMS method is shown in Fig. 5-8(b). The disturbance is determined as a voltage sag but it is determined to occur at 43.98 ms (563th sample point) and to last for 40.63 ms, 520 sample points.

The errors in the time information for these two methods are 0.55 ms and 2.43 ms respectively. Therefore, a higher accuracy is achieved by the wavelet-based energy content method than the RMS method in the identification of voltage sag.

Fig. 5-8 Classification of a voltage sag

(a) Original voltage sag waveform. (b) Result of the conventional RMS method. (c) Information of 1 kHz frequency band. (d) Energy content in the fundamental frequency band.

5.5.3 Voltage swell

Fig. 5-9 (a) shows the waveform of a voltage swell, which begins at 39.14 ms (501th sample point) and lasts for 38.98 ms or 499 sample points. Fig. 5-9 (c) shows the squared coefficients of the high frequency band while Fig. 5-9 (d) shows the energy content of the fundamental frequency band. An increase in energy indicates that it is a voltage swell. It occurs at the instant of 39.38 ms (63th coefficient number) and the duration is determined to be 39.38 ms corresponding to 63 coefficient numbers. The error in detecting the begin point is 0.24 ms while the error in the duration is 0.4 ms.

In comparison, the result of the RMS method shown in Fig. 5-9 (b) also pinpoints accurately that the voltage variation is a swell but the determined duration is 37.5 ms or

480 sample points. Due to the “delaying” effect introduced when computing RMS values, the beginning time of the swell is found to be 46.95 ms or 601th sample point with a much greater error of more than 7 ms.

It is obvious that in the classification of voltage swell, the time information obtained by the wavelet-based energy content method is much more accurate.

Fig. 5-9 Classification of a voltage swell

(a) Original voltage swell waveform. (b) Result of the conventional RMS method. (c) Information of 1 kHz frequency band. (d) Energy content in the fundamental frequency band.

5.5.4 Short interruption

This wavelet-based energy content method can effectively characterize very short duration voltage variations. Those interruptions with durations shorter than half a fundamental cycle are worthy to be mentioned, as it is difficult for the RMS method to detect these short interruptions.

Fig. 5-10 Characterization of a short interruption

(a) Original short interruption waveform. (b) Result of the conventional RMS method. (c) Information of 1 kHz frequency band. (d) Energy content in the fundamental frequency band.

Fig. 5-10 (a) shows a short interruption lasting for about 8.91 ms, 114 sample points. The time information of the disturbance can be acquired through the analysis of the high frequency squared coefficients as shown in Fig. 5-10 (c) while the change of the energy content at the fundamental frequency is shown in Fig. 5-10 (d). As the energy reaches below 10%, it is accordingly deemed to be a voltage interruption. Its duration obtained from Fig. 5-10 (c) is about 15 coefficient numbers or 9.38 ms. On the contrary, if using the RMS method as shown in Fig. 5-10 (b), the RMS magnitude does not drop below 0.1 pu and the disturbance would be identified as a voltage sag instead. This obviously does not reflect the actual type of this voltage disturbance. In contrast, the wavelet-based energy content method has proven that even the shortest voltage variation can be correctly identified. It is to be noted that the shortest duration mentioned here is half of a fundamental cycle as any disturbance shorter than that is no longer considered as voltage variations but as voltage transients.

5.5.5 Triangular voltage dip

The wavelet-based energy content method can also be used to classify some particular sags, such as triangular-shaped voltage sags caused by motor starting. In these cases, the time information of the fundamental frequency band is needed to judge when the voltage recovers to the nominal range. Fig. 5-11 shows an example.

Fig. 5-11 Characterization of a triangular voltage dip

(a) Original triangular voltage dip waveform. (b) Result of the conventional RMS method. (c) Information of 1 kHz frequency band. (d) Energy content in the fundamental frequency band.

Fig. 5-11 (a) shows a voltage sag caused by motor starting. Its magnitude dips abruptly at the time instant of 169.3 ms (2167th sample point) and recovers gradually over several cycles to about 456.88 ms (5448th sample point). From the high squared coefficients in the 1 kHz frequency band shown in Fig. 5-11 (c), the starting instant of the motor can be easily determined. The motor is determined to start at the time at 169.38 ms (271th coefficient number), 0.08 ms from the actual starting at 169.3 ms. However, since the voltage recovers smoothly, the wavelet coefficients in this high frequency band cannot reflect when the voltage reaches its nominal value. Nevertheless, the energy content of the fundamental frequency band can be used to determine when the voltage has

recovered fully. This is similar to the conventional RMS method and the voltage is deemed to recover fully at the time instant of 457.5 ms (183th coefficient number). Using the RMS method, this disturbance is identified as a sag that occurs at 171.33 ms (2193th sample point) and lasts for 289.7 ms. The time errors in the RMS method are about 2.03 ms for the occurrence instant and 2.12 ms for the duration while those for wavelet-base energy content method are 0.08 ms and 0.54 ms. Therefore, the proposed method can provide more precise time information.

5.6 Summary

In this chapter, a new wavelet-based energy content method for classifying short duration voltage variations is proposed. The information in the high frequency band (about 1 kHz) is used to extract the time information of the disturbances, namely the beginning and ending instants. The energy of the fundamental frequency band is computed to determine the type of the variations. With the need to evaluate these two frequency components using DWT, a selection of a suitable mother wavelet was being undertaken. The intended mother wavelet should have short support size, large number of vanishing moments and can be implemented by a fast algorithm. With these requirements, db2 mother wavelet is chosen for use in this technique.

It is shown that this wavelet-based energy content method can classify and characterize the voltage variations with an obvious advantage in pinpointing the time information of the disturbance. Comparing to the RMS method, it can give more precise time information and better description of disturbance waveforms. Compared to other methods that use wavelet analysis, this method does not require the signal to be reconstructed resulting in much faster calculation and less memory storage.

Furthermore, it is obvious that this wavelet-based energy content method can be extended to classify and characterize long duration voltage variations since the main difference between the two categories is merely the time duration. When this type of disturbance occurs or ends, significant changes in the wavelet coefficients at 1 kHz frequency band would still exist. These sharp changes form the basis for extracting the time information of the disturbance.

Chapter 6

Classification of Capacitor Switching Transients

After applying wavelet analysis for classifying short duration voltage variations, another wavelet-based application in power systems, a wavelet-based rank correlation method for identifying capacitor switching transients, is introduced in this chapter. Firstly, a systematic analysis of the characteristics of this type of switching transients is carried out. The study focuses on the uncertainties brought about by not having thorough knowledge of the system and/or capacitors. Then, the wavelet-based rank correlation method for identifying capacitor switching transients is illustrated. This method is adapted according to the special characteristics obtained from the above mentioned systematic analysis. Several illustrations using dynamic simulations are included to demonstrate the suitability and capability of this method.

6.1 Characteristics of Capacitor Switching Transients

Among many power quality disturbances captured by monitoring equipment, the majority is the result of switching actions in the power networks with the bulk of these caused by the day-to-day switching of power system equipment such as capacitors [22][94]. Capacitor switching transients would then be mingled among the captured disturbances. Hence, they need to be isolated so that they can be handled in a separate manner. As they are part and parcel of the system design, the solution to overcome them is often different from those caused by equipment failures. Therefore, it would be beneficial if they can be identified and separated from other transients. In addition, they typically do not pose any significant threat to the system operation or other loads and hence, separating them would allow greater attention to be spent on analyzing other unexplained transients.

Power network can be regarded as comprised of multitudes of RLC elements. They also tend to be under-damped and when capacitor switching occurs, oscillatory transients occur at frequencies that are much higher than the fundamental frequency. These

transients, being oscillatory with certain dominant frequencies, imply that the system may have several natural resonance frequencies in its response. For a brief period following switching, the transient part of the voltage waveform $V_4(t)$ can be expressed in the following general form,

$$V_4(t) = e^{-\alpha_1 t} \cdot A_1 \cdot \sin(2\pi f_1 t + \varphi_1) + e^{-\alpha_2 t} \cdot A_2 \cdot \sin(2\pi f_2 t + \varphi_2) + \dots \quad (6-1)$$

where A_x , f_x and φ_x are the amplitudes, frequencies and initial phase angles of the respective oscillatory transient components. The exponential damping coefficient α_x denotes the rate at which each transient component decays away. The initial magnitude A_x and phase angle φ_x of each component depend on the instant (point on wave) when the switching occurs. For each switching, there may be several oscillatory transient components depending on the power network's structure and its contents.

6.1.1 General model for analyzing capacitor switching transients

The analysis of capacitor switching operation in power systems can be generalized using an equivalent circuit model as shown in Fig. 6-1 [95][96]. R_s and L_s form the system impedance arising from transformer leakage reactance, line resistance and reactance, and generators' sub-transient, transient or synchronous reactance, depending on the time-scale of interest. For analysis of capacitor switching transients, the generator's sub-transient reactance should be considered. C_s denotes the amount of capacitance already

Fig. 6-1 General model for capacitor switching analysis

exists in the system, and this can comprise of stray capacitances at the bus bar or reactive-compensation capacitors that are already connected to the system.

To model the switching of a capacitor bank [94][95], $CB1$ is operated or closed. C_c would be the capacitance of the capacitor bank that is switched while L_c and R_c are the external inductance and the inherent resistance of the capacitor bank. In general, capacitor switching can be categorized into two types, namely isolated capacitor switching and back-to-back capacitor switching. The main difference between them is the value of the system capacitance C_s . In the isolated capacitor switching, the system capacitance comprises of the stray capacitances, which are usually very small (hundreds of pico-farads) [97]. On the contrary, in the back-to-back capacitor switching, there are already some capacitors connected to the system thereby contributing to the system capacitance. Thus, the system capacitance is much larger, typically about several microfarads or even larger [97].

In addition, when a capacitor bank is switched on, there are always two major transient components. One is customarily known as the inrush transient while the other is called the system response or energizing transient. The inrush transient is caused by connecting an uncharged capacitance to a charged system capacitance. This causes an initial downward surge of the system voltage at the instant when the uncharged capacitance is connected to the system. The voltage drops sharply as the system capacitance, which is already charged, tries to charge up the uncharged capacitance. This transient can be significant when turning on large capacitor banks. On the other hand, when switching inductive load, the inrush transient will be small and of short duration with inconsequential impact and thus can be readily ignored. Some loads however are fitted with power factor correction capacitors, and their switching may lead to significant inrush too. Nevertheless, this inrush transient is not used in the identification process as it is of high frequencies in tens of kilohertz [94], making it difficult to measure. In addition, capacitors are often fitted with external inductance of about 1 mH to limit the inrush current and this affects the measurement [98].

After the initial inrush, the system would eventually reach another state of equilibrium and as it charges up all the capacitance in the entire network. This charging may result in another voltage and current surge, which can cumulate into another transient. Typically,

due to the presence of both inductances and capacitances in the system, this transient would be oscillatory and would be damped out eventually by the system resistance. This transient is usually called the system response or energizing transient. Unlike the inrush transient, the characteristics of this transient are different as the system source has a more substantial influence.

The severity (magnitude and duration) of the above transients also depends on the location of the measurement instrument with respect to that of the capacitor. In isolated capacitor switching, the initial inrush current flows through the supply system and would result in an initial drop in voltage followed by overvoltage due to the system response. Eventually, a higher steady-state voltage can be obtained. On the other hand, in back-to-back switching, portion of the inrush current originates from the already connected capacitor, which is usually near to the switched capacitor. Hence, the overvoltage experienced in the supply side would be lower than that during isolated capacitor switching. However, the opposite happens at the capacitor bank terminal. The close proximity and the lack of inductance and resistance between the charged capacitor and the switched capacitor during back-to-back energization result in high overvoltage to occur there. In addition, the larger combined capacitance (from both capacitors) would cause transients with longer duration.

6.1.2 Numerical analysis for capacitor switching transients

When a capacitor is switched on, as modelled by closing circuit breaker *CB1* in Fig. 6-1, the transient response can be derived from the corresponding equivalent circuit and expressed as a set of integral-differential equations as follows,

$$\begin{aligned}
 E(t) &= R_s \cdot i(t) + L_s \cdot \frac{di(t)}{dt} + V(t) \\
 V(t) &= \frac{1}{C_s} \int_0^t [i(t) - i_L(t)] dt \\
 V(t) &= R_C \cdot i_L(t) + L_C \cdot \frac{di_L(t)}{dt} + \frac{1}{C_C} \int_0^t i_L(t) dt
 \end{aligned} \tag{6-2}$$

where $E(t)$ is the source voltage and $V(t)$ is the measured voltage. Transforming the above equations to the Laplace or s domain, the following characteristic equation is obtained.

$$\begin{aligned} C_s C_C L_s L_C \cdot s^4 + (R_s C_C C_s L_C + R_C C_C C_s L_s) \cdot s^3 \\ + (C_s L_s + C_C L_s + L_C C_C + R_s R_C C_s C_C) \cdot s^2 = 0 \\ + (R_s C_s + R_s C_C + R_C C_C) \cdot s + 1 \end{aligned} \quad (6-3)$$

According to [95] and the analysis in Section 6.1.1, the roots of this equation (6-3) would be two different pairs of complex roots, representing the two transient components. They can be written as,

$$\begin{aligned} s_{1,2} &= -\alpha_1 \pm j\omega_1 \\ s_{3,4} &= -\alpha_2 \pm j\omega_2 \end{aligned} \quad (6-4)$$

Therefore, the frequencies of these two transient components are

$$\begin{aligned} f_1 &= \omega_1 / 2\pi \\ f_2 &= \omega_2 / 2\pi \end{aligned} \quad (6-5)$$

Their corresponding damping time constants are

$$\begin{aligned} T_{C1} &= \frac{1}{\alpha_1} \\ T_{C2} &= \frac{1}{\alpha_2} \end{aligned} \quad (6-6)$$

In this manner, the characteristics of capacitor switching transient can be obtained. However, with many variables in (6-2), symbolic representations of these four parameters are rather complicated. Therefore, a numerical approach is adopted to study the characteristics of these two transient components. In essence, the variables in (6-3) are replaced by numerical values, and the corresponding transient resonant frequencies and damping time constants are computed from (6-4), (6-5) and (6-6). Since the frequency of the inrush transient is much higher than that of the system response transient, it is easy to identify which one is the inrush component and which one is the system response component. In the following discussion, only the system response transient is analyzed in preparation for the identification of capacitor switching

transients. With the use of the above numerical approach, the values of R , L and C are also varied to investigate how they affect the transients' characteristics.

A 138kV 60Hz test system is used to illustrate this numerical method, as shown in Fig. 6-2 [97]. Two 40 MVar capacitor banks at the 138kV busbars are used to simulate the two types of capacitor switching transients. The three-phase fault current at the capacitor bus terminal is approximately 13.7 kA, giving a system short circuit capacity of about 1890.6 MVA. From this test system, the general model of switching transient, as shown in Fig. 6-1, is approximated as follows,

- System resistance R_s of 0.58 Ω .
- System inductance L_s of 15.39mH giving X_s of 5.8 Ω and system X/R ratio of 10.
- System stray capacitance of 1200 nF for the analysis of isolated capacitor switching.
- In the back-to-back capacitor switching, one of the two 40 MVar capacitor banks is assumed to be connected to the system when the other one is switched.

Fig. 6-2 Diagram of a 138 kV 60Hz system

The characteristics of the system response transient are then investigated for the different possible values of the system parameters and switched capacitor as follows,

- The capacitor power rating is varied from 20 MVar to 100 MVar, a relatively large range.
- External inductance of capacitor bank for limiting in-rush current is varied between 0.5 and 1.5mH, according to [98].
- The system stray capacitance is assumed to be varying from 800 nF to 2000 nF [97].
- The uncertainty in the system inductance and resistance is assumed to be $\pm 40\%$. For the test system shown in Fig. 6-2, this effectively varies the system X/R ratio from 6 to 14.
- The capacitor resistance R_c is assumed to 10 times of the system resistance, 5.8Ω . It includes the pre-insertion resistor and/or the resistance of the connections. This resistance is assumed to have an uncertainty of $\pm 40\%$.

Therefore, the corresponding parameter values of the simplified equivalent circuit and their variable ranges are shown in Table 6-1,

Table 6-1 Parameter values of the simplified equivalent

Parameter	Value
$R_s(\Omega)$	$0.58 \times (60 \sim 140)\%$
$L_s(\text{mH})$	$15.39 \times (60 \sim 140)\%$
$C_{s1}(\text{nF})$	$1200 \times (66.7 \sim 166.7)\%$
$C_{s2}(\mu\text{F})$	$5.571 \times (50 \sim 250)\%$
$R_c(\Omega)$	$5.8 \times (60 \sim 140)\%$
$L_c(\text{mH})$	$1 \times (50 \sim 150)\%$
$C_c(\mu\text{F})$	$5.571 \times (50 \sim 250)\%$

where C_{s1} and C_{s2} represent the system capacitance in isolated and back-to-back switching respectively.

Using the numerical method and solving (6-3), the characteristic changes of these two frequency components can be obtained. One of them is higher than 3 kHz and the other is lower than 650 Hz. It is obvious that the latter is the system response transient according to the above analysis. As mentioned above, only the system response transient is analyzed and used for identifying capacitor switching. Therefore, the characteristic changes of the system response in different capacitor switching are obtained and shown in Fig. 6-3 and Fig. 6-4.

Fig. 6-3 Characteristic changes of the system response transient in isolated capacitor switching

Fig. 6-3 shows the characteristic changes of the system response in isolated capacitor switching. The abscissa represents the damping time constant, while the ordinate shows the characteristic frequency. A mid point with frequency of 480 Hz and damping time constant of 7 ms is the expected characteristic as derived from Fig. 6-2. However, as each of the parameters is varied, the characteristic frequency and/or the time constant would vary accordingly. Nonetheless, this analysis reveals that the system inductance (line B) and the switched capacitance (line E) have the most significant influence on the

response. This indirectly stipulates that knowing these two parameters is adequate at determining the system response frequency and time constant. Overall, the frequency varies by $\pm 150\text{Hz}$ while the time constant varies over $\pm 3\text{ ms}$.

Fig. 6-4 Characteristic changes of the system response transient in back-to-back capacitor switching

Fig. 6-4 shows the corresponding changes in back-to-back capacitor switching. It can be seen that not only the system inductance and the load capacitance, but the system capacitance also exerts significant influence on the frequency and time constant. This is because in the back-to-back capacitor switching, the system capacitance is of equivalent ratings as the switched capacitance. With larger capacitance, the characteristic frequency is lower and varies over a smaller range of $\pm 100\text{ Hz}$. However, the damping time constant varies over a wider range from about 8 ms to 30 ms.

Generally, the characteristics of the system response in capacitor switching fall within certain range when the system and/or the capacitor vary. This observation is very useful for the identification and classification of these switching transients. In practical power systems, the exact values of the system parameters and switched capacitor are generally

not known. However, approximations can be made to estimate the possible range of frequencies and damping time constants that the system response is likely to fall within. The transient magnitude varies widely depending on the system, capacitor size and point on wave when the switch is closed. This variation invalidates the use of absolute correlation on the magnitudes of the transient, unless they are normalized first. Armed with the above information, the identification technique can be made robust or adaptable to these changing characteristics.

There have been many efforts in the analysis of capacitor switching transients, which tried to use these observed characteristics. The dominant oscillating frequency and the magnitude variation of the transient are typically used to identify the size and location of the shunt capacitor [99]. In [60], Santoso used the typical frequency and the variation of step voltages after switching instant to characterize capacitor switching transients. Despite all these efforts, differentiating capacitor switching transients from other transients remains a challenge. This is because the transient behaviour depends considerably on the system and the connected devices.

6.2 Wavelet-Based Rank Correlation Method

A wavelet-based rank correlation method is proposed for the identification of capacitor switching transients with the consideration of the uncertainty of the system and capacitor(s). This method is based on the above systematic analysis of capacitor switching transients in the measured system. The waveform information in the particular frequency band can then be used to judge whether the transient is caused by capacitor switching or not.

To carry out analysis in the particular frequency band, wavelet analysis is applied. As discussed in Chapters 3 and 4, there are many types of signal processing techniques. Fourier transform and related techniques that are derived from it such as WFT can only extract information of frequencies that are multiples of the fundamental frequency. These signal processing techniques are not suitable for this application because the possible frequency range of capacitor switching transients in power systems may not be equal to a whole multiple of the fundamental frequency. Although some other filtering techniques can extract the information of the particular frequency band, they are not as

sensitive to the transient components as wavelet analysis is when properly set up. Wavelet analysis can focus on the irregular part of the disturbance signal and extract the information of the particular frequency band.

However, there are two types of wavelet transforms, CWT and DWT. In the dyadic calculation of DWT, the scales or the frequency bands are discrete as the scale value must be 2^n , $n=1, 2, \dots$. Therefore, the frequency ranges of various frequency bands are fixed when the sampling frequency is fixed as explained in Section 4.3.3. Since the characteristics of the system response to capacitor switching operation vary in a certain range, it is hard to find a DWT scale that contains the integral information of the system response. This would complicate the subsequent rank correlation analysis since the identification has to be carried out on several DWT scales simultaneously. On the other hand, CWT has a relatively more flexible frequency characteristic. In CWT calculation, the scale value is continuous and can be any positive real number. Thus, the pseudo-frequency of a CWT frequency band can be easily adjusted to obtain a particular frequency band. Moreover, because of downsampling in the DWT decomposition, its time resolution deteriorates at higher scales (low frequency bands). Since the system response frequency of capacitor switching transient is usually lower than 1 kHz [20][100], which is relatively low considering that the sampling frequency can be as high as up to 10 kHz, the time resolution in this low frequency band obtained by DWT would be low. On the contrary, CWT is a kind of redundant calculation. The time resolution at different frequency bands remains the same as that of the original signal, as illustrated in Section 4.2. Hence, CWT is chosen instead of DWT in this application, as its frequency band can be easily tuned to contain the system response to capacitor switching. In addition, there is no degradation of the time resolution as encountered in the DWT. For readers who are interested in the different performance from using DWT and CWT, several trials of using DWT in identifying capacitor switching transients were carried out and the results are presented in Appendix B.

Then, rank correlation method is chosen to process the information of this particular frequency band. It is a kind of nonparametric statistical method. It is used to evaluate the similarity between transients and the signature (capacitor switching transient) despite

their different magnitudes. More details of the rank correlation technique are given in the following subsections.

6.2.1 Rank correlation method

From the wavelet processing described in the preceding chapter, the extracted characteristics need to be analyzed in order to deduce if a particular event corresponds to capacitor switching. One simple way of implementing this identification is to look for similarity between the wavelet coefficients of the captured disturbance against those of a signature waveform for capacitor switching. This can be done by correlating the two sets of data with each other. However, this method is significantly influenced by their magnitudes. If the absolute magnitudes of both data differ, this correlation would fail to match them. Another option is rank correlation, which is not influenced by the actual magnitudes of both the signature and the disturbance. Instead of comparing the absolute magnitudes, rank correlation evaluates whether the shape of a signal fits that of another signal. This method is immune to the measurement methods as it only concerns with the shape or magnitude variation and not on the actual value. It is easy to implement and appears to be a good choice for comparing the magnitude variation of capacitor switching transients. There are two main types of rank correlation methods [101]. One is the Spearman rank correlation method. The other is the Kendall rank correlation method. They are briefly introduced in the following paragraphs.

6.2.1.1 Spearman rank correlation method

Spearman rank correlation is a distribution-free analogy of correlation analysis. It compares two independent random variables, each at several levels (which may be discrete or continuous). It judges whether the two variables co-vary, i.e. vary in similar direction; or if as one variable increases, the other variable tends to increase or decrease. Spearman rank correlation works on ranked (relative) data, rather than directly on the data itself. In particular, the smallest data value is replaced with a 1, the next smallest with a 2, and so on. It measures the non-linear relationship or the similarity between two variables despite their different magnitudes. It is suitable for use with skewed data or

data with extremely large or small values. When there are “ties³” in both sets of data, the Spearman rank-order correlation coefficient can be calculated as [101]:

$$\rho_s = \frac{1 - \frac{6}{N^3 - N} \left[\sum_{i=1}^N (R_i - S_i)^2 + \frac{1}{12} \sum_k (f_k^3 - f_k) + \frac{1}{12} \sum_m (g_m^3 - g_m) \right]}{\left[1 - \frac{\sum_k (f_k^3 - f_k)}{N^3 - N} \right]^{1/2} \left[1 - \frac{\sum_m (g_m^3 - g_m)}{N^3 - N} \right]^{1/2}} \quad (6-7)$$

where N is the length of the two variables; R_i is the rank of one variable; S_i is the rank of the other variable. f_k is the number of ties in the k^{th} group of the ties among the R_i 's. g_m is the number of ties in the m^{th} group of the ties among the S_i 's. Ties are assigned if some variables have identical values, and the average of their adjacent ranks is used in the computation. This Spearman's ρ_s coefficient indicates agreement. A value near 1 indicates good agreement while a value near zero, poor agreement.

6.2.1.2 Kendall rank correlation method

Kendall's τ correlation is also a non-parametric measure of the agreement between two rankings. The different amplitude information caused by different measurements is also ignored. In the Kendall rank correlation of two variables (x_i, y_i) , a pair is called concordant if the relative ordering of the ranks of two x 's is the same as the relative ordering of the ranks of the two y 's. A pair is called discordant if the relative ordering of the ranks of two x 's is the opposite from the relative ordering of the ranks of the two y 's. If there is a tie in the y 's, an “extra x pair” is called. If the tie is in both the x 's and the y 's, a pair is ignored. Kendall's τ is defined by the following simple combination of these various counts [101]:

$$\tau = \frac{\text{concordant} - \text{discordant}}{\sqrt{\text{concordant} + \text{discordant} + \text{extra-y}} \sqrt{\text{concordant} + \text{discordant} + \text{extra-x}}} \quad (6-8)$$

³ If some elements of an array have identical values, they are considered as ‘ties’ in the ranking of the array. These elements will be assigned the same rank.

Therefore, Kendall's τ must lie between 1 and -1. A value of τ close 1 indicates good agreement.

6.2.1.3 Comparison between two methods

The rank correlation coefficients, Spearman's ρ_s and Kendall's τ , are all computed by processing the rank orders of the two variables. From the above introduction, it can be concluded that Spearman's ρ_s pays more attention to comparing the change tendencies of the two variables while Kendall's τ is concentrated on the minute changes of these two variables. For this application, even with the same system and capacitor parameters but at different operating instants, the transient waveform may not be the same as the signature waveform at a certain frequency band. Therefore, only their magnitude variations in particular frequency band are useful for identification and the Spearman's ρ_s is selected for this application.

6.2.2 Illustration of the wavelet-based rank correlation method

As illustrated above, the dominating transient can be generally expressed as $e^{-\alpha_1 t} \cdot A_1 \sin(2\pi f_1 t + \varphi_1)$. The exact value of its oscillating frequency is unknown unless all the system parameters are known. However, the probable frequency range can be estimated prior to classification through judicious numerical studies as described in Section 6.1.2. Accordingly, the CWT computation can then be tuned to the specific frequency band in order to acquire the integral information of this frequency band. Furthermore, the magnitude variation $e^{-\alpha_1 t} \cdot A_1$ can be reflected by the energy change of this particular frequency band. The detailed information of the voltage $V_c(t)$ at a particular scale a_c and time instant t_0 can be obtained by (4-3) (repeated here for ease of reference)

$$\mathcal{W}\{V_c(t_0, a_c)\} = \int_{-\infty}^{+\infty} V_c(t) \frac{1}{\sqrt{a_c}} \psi^*\left(\frac{t-t_0}{a_c}\right) dt = \langle V_c, \psi_{t_0, a_c} \rangle = V_c * \bar{\psi}_{a_c}(t_0)$$

Therefore, its energy density at this scale and at this time instant can be calculated as

$$P_w(t_0, a_c) = |\mathcal{W}\{V_c(t_0, a_c)\}|^2 \quad (6-9)$$

With this energy density definition, the energy of half a cycle, which indirectly reflects the magnitude of this frequency band, is

$$E_w(a_c, t_0) = \int_{t_0}^{t_0 + \frac{T_l}{2}} P_w(t, a_c) dt = \int_{t_0}^{t_0 + \frac{T_l}{2}} |\mathcal{W}\{V_c(t, a_c)\}|^2 dt \quad (6-10)$$

where T_l is the period of the signature system response. By sliding the computation window over time, the change in the energy would reflect the magnitude variation $e^{-\alpha_l t} \cdot A_l$ as follows,

$$e^{-\alpha_l t} \cdot A_l = E_w(a_c, t) \quad (6-11)$$

Then the rank correlation is used to evaluate the similarity between the magnitude variation of the disturbance and that of a predefined signature waveform in particular frequency band a_c . The Spearman's ρ_s gives a value close to 1 if the disturbance data matches the signature. This would verify that the disturbance is caused by capacitor switching, and hence can be set aside. Otherwise, the cause of the disturbance is unknown and further analysis is warranted.

In this method, there are two factors that influence the results of rank correlation or the identification results. One is the selection in a particular frequency band. CWT calculation is actually equivalent to band-pass filtering with a limited bandwidth. Therefore, it is necessary for the frequencies of actual capacitor switching transients to be as close as possible to that of the signature. Otherwise, the subsequent correlation of their magnitude variations would not be appropriate. Therefore, estimating the possible frequency range for capacitor switching transients is the first and most important step in this method.

The other factor is the selection of the calculation window for the rank correlation. The comparison between the signature and transient must be carried out within certain time duration. If the two waveforms have similar magnitude variations, their rank correlation

results are not influenced by the length of window or the beginning instant. However, this correlation is only valid within the duration when the transient exists. In a practical system, it is impossible to predict when the transient will actually occur and end. Nevertheless, since the transients are usually obvious just after the disturbance, the information just after the occurrence of the transient can be used in the rank correlation. In addition, as the duration of the pre-defined signature is known, the length of the rank correlation window can be chosen as the duration of the signature.

6.3 Verification of the Wavelet-Based Rank Correlation Method

In this section, an example is used to illustrate the steps involved in the identification of capacitor switching transient. The results also serve to verify the applicability of this wavelet-based rank correlation method. The test system shown in Fig. 6-2 is used in this illustration and verification.

6.3.1 Selection of the signature

Firstly, preparing the identification method involves the selection of an appropriate signature as a general representation of the capacitor switching transient. The test system is first simplified into a single-phase equivalent circuit similar to the one shown in Fig. 6-1. The characteristic frequency and time constant of the system response are then deduced from numerical analysis of the simplified equivalent circuit (see Section 6.1.1). With an assumed capacitor of 40 MVar, the response characteristics are as shown in Fig. 6-3 for isolated capacitor switching transient and Fig. 6-4 for back-to-back capacitor switching transient. Aggregating both results, as shown in Fig. 6-5, gives an average characteristic frequency of about 450 Hz and a damping time constant of 10.6 ms. Therefore, the comparison window for rank correlation calculation is determined to be about 22 ms after the occurrence of the transient. In this time period, the voltage magnitude decreases to 13% (twice the damping time constant) and main voltage variations at this particular frequency band can be captured.

Fig. 6-5 Characteristic parameter change range for capacitor switching transients

6.3.2 Selection of the mother wavelet

Wavelet processing is responsible for sifting out the needed frequency component determined from the aforementioned numerical analysis. It therefore has to be tuned to the expected characteristic frequency and to possess sufficient bandwidth to allow certain degree of frequency deviation. These factors are determined by the sampling frequency, the value of the CWT scale and the choice of mother wavelet.

There are many different types of mother wavelets, each having unique characteristics that make them suitable for analyzing certain type of signal. Generally, the most suitable mother wavelet is one with shape resembling that of the analyzed signal. As capacitor-switching transient is oscillatory, the shape of the mother wavelet should be close to a sinusoid. The center-frequency of mother wavelet needs to be considered when deciding the wavelet scale setting. The pseudo-frequency at a scale a_c can be estimated from (4-14). To simplify the CWT computation, the simpler db2 mother wavelet is selected ahead of others. Its center-frequency F_c is 0.6667. For this illustration, the sampling

frequency f_s is set at 15.36 kHz, and a wavelet scale of 22.8 is used. Therefore, the corresponding frequency of this scale can be obtained according to (4-14):

$$F_a = \frac{f_s \cdot F_c}{a_c} = \frac{15.36 \times 10^3 \times 0.6667}{22.8} = 449.12 \text{ Hz}$$

Hence, the pseudo-frequency of scale 22.8 is 449.12 Hz, which is close to 450 Hz, the dominant system response frequency of the signature. The corresponding bandwidth of the wavelet filter at this scale is narrow, about 300 Hz, as shown in Fig. 6-6.

Fig. 6-6 Frequency response of db2 mother wavelet at CWT scale 22.8

6.3.3 Identification process

After the above preparations, the identification of capacitor switching transients can be carried out. Firstly, CWT at scale 22.8 is carried out. As analyzed above, this particular scale or frequency band covers the possible characteristic frequencies of capacitor switching transients in this test system. Using (6-10) and sliding over time, the magnitude variations $e^{-a_1 t} \cdot A_1$ in this particular frequency band can be obtained.

The Spearman ρ_s rank correlation is calculated to compare these magnitude variations against the signature and to decide if the transients are caused by capacitor switching. As

illustrated in Section 6.3.1, the comparison is carried out within this 22 ms period after the occurrence of the transients.

6.3.4 Dynamic simulation verifications

Dynamic simulation of this test system is carried out using Matlab/Simulink (Version 6.1.0.450 Release 12.1). The results of the transient simulations are processed with CWT and rank correlation to identify if they are caused by capacitor switching. Several scenarios are considered in the simulations to demonstrate the robustness of the method. These includes,

- Different switching instants as shown in Fig. 6-7
- Different capacitor ratings/sizes
- Isolated versus back-to-back switching
- Different system parameters
- Non capacitor switching transients

Switching in a three-phase system can produce transients in each of the phases. The magnitudes of these transients can be significantly different but generally, one phase is much smaller compared to the other two. This is because at the switching instant, the instantaneous magnitude of that phase voltage is small, close to zero while those of the other two phases are much larger. Hence, to maintain identification precision, only the two more significant phases are considered in the process.

Fig. 6-7 Operation instants of phase A

Fig. 6-8 shows three-phase voltage waveforms of an isolated capacitor switching transient. In this case, a 40 MVar capacitor bank (C40AL in Fig. 6-2) is switched on and the operation instant of Phase A is Instant 1 as shown in Fig. 6-7. For the signature, the waveform is mathematically derived as described in Section 6.3.1. It is assumed that the capacitor bank is switched on at the peak of the fundamental waveform in order to have the biggest transient waveform for constructing the signature. The corresponding magnitude variations of the signature and the transient at scale 22.8 can be calculated by (6-11) and their shapes are shown in Fig. 6-9.

Fig. 6-8 Original three-phase voltage waveforms of a capacitor switching transient

Fig. 6-9 Magnitude variations of the signature and the transient at CWT scale 22.8

As mentioned above, the sampling frequency is 15.36 kHz. Therefore, the magnitude variations of the signature and the three phases in Fig. 6-9 contain 339 data points each. The rank of the largest data point is thus 339 and the rank of the smallest data point is 1. In this manner, the magnitude variations of different data set are reorganized such that only the ranks of each set are used. In this way, the waveform magnitudes as shown in Fig. 6-9 are transformed into their ranks as shown in Fig. 6-10. In the following analysis, only the similarity between the ranks of the signature waveform and the tested waveform is used.

Fig. 6-10 Ranks of the signature and the transient

The rank correlation results of three phases are obtained by comparing each phase to the signature individually. These show their respective similarities with the signature. As discussed above, the instantaneous transient magnitudes of the three phases are different, which can also be seen in Fig. 6-8 and Fig. 6-9. In this case, the transient magnitude of Phase C is the smallest among these three phases. This is also reflected in its ranks. Its rank orders have the most amounts of fluctuations compared to that of the signature, as shown in Fig. 6-10. Therefore, its rank correlation result is the smallest among the three phases. As the rank correlation results of Phase A and B can depict the transient better, their average value is taken and used as the final result for these entire three phases. Comparing this average value to some threshold, such as 0.9, the deduction on whether the transient is caused by capacitor switching can then be made. In the following subsections, several simulation cases are carried out to validate this wavelet-based rank correlation method.

6.3.4.1 Effect of different switching instants

In this section, the influence of the different capacitor switching instants on the identification is studied. Tables 6-2 and 6-3 show a summary of the simulations for

different capacitor sizes and different switching instants. For each of the cases, it is obvious that one phase shows a poorer correlation compared to the other two, which has been discussed above. Hence, the average results, as shown in the last column, are taken from the two more significant phases only. A result close to 1 denotes close resemblance to the signature, pinpointing that the disturbance is a capacitor switching transient.

Table 6-2 Results of isolated capacitor switching transients

Capacitor size	Switching Instant	Phase A	Phase B	Phase C	Average of two max. phases
40 MVar	1	0.977	0.976	0.859	0.976
	2	0.977	0.954	0.877	0.966
	3	0.967	0.674	0.981	0.974
	4	0.969	0.975	0.911	0.972
	5	0.925	0.955	0.975	0.965
80 MVar	1	0.922	0.933	0.732	0.928
	2	0.931	0.903	0.765	0.917
	3	0.924	0.626	0.934	0.929
	4	0.902	0.935	0.783	0.918
	5	0.828	0.879	0.935	0.907

Table 6-3 Results of back-to-back capacitor switching transients

Capacitor size	Switching Instant	Phase A	Phase B	Phase C	Average of two max. phases
40 MVar	1	0.923	0.869	0.646	0.896
	2	0.869	0.923	0.694	0.896
	3	0.892	0.924	0.578	0.908
	4	0.911	0.409	0.927	0.919
	5	0.751	0.845	0.922	0.883
80 MVar	1	0.716	0.845	0.466	0.780
	2	0.570	0.672	0.837	0.754
	3	0.753	0.838	0.334	0.796
	4	0.827	0.737	0.405	0.782
	5	0.716	0.845	0.466	0.780

Different switching instants mean that different instantaneous voltage magnitudes are impressed on the uncharged capacitor when it is switched. A large instantaneous magnitude would result in substantial transient and vice versa. As the three phases are phase-shifted by 120° , it is expected that the corresponding instantaneous voltage

magnitudes are different. As a result, the rank correlation results vary across the phases from one instant to another as shown in Tables 6-2 and 6-3. Nonetheless, two of the phases always show significant transients and that allows the rank correlation method to produce noticeable result. It can therefore be concluded that this method, based on the two phases with the most significant rank correlation results, can minimize the influence of instantaneous voltage magnitude on the identification of capacitor switching transient.

6.3.4.2 Effect of different capacitor size or ratings

Capacitor switching transients for capacitors of different sizes are discussed in this section. The lower halves of Tables 6-2 and 6-3 show the results for switching a 80 MVAR capacitor. As shown in Fig. 6-5, the characteristic of the signature is close to the characteristic range of isolated capacitor switching transients with 40 MVAR capacitor. Therefore, the rank correlation results for switching 40 MVAR capacitor are better than those for switching 80 MVAR capacitor. This can be observed by comparing the upper halves to the lower halves of Tables 6-2 and 6-3. However, all of the correlation results are larger than 0.75 and they are still reasonably good for the identification of capacitor switching transients, especially for isolated switching. This is because although different capacitor sizes would result in different characteristic frequencies, the relative frequency variations are small. In these cases, the frequency variations are found to be smaller than ± 50 Hz in isolated switching and -100 Hz in back-to-back switching. They can still be covered by the frequency range of CWT filtering at scale 22.8 (± 150 Hz). Therefore, the rank correlation results of these identifications are still satisfactory.

6.3.4.3 Isolated versus back-to-back switching

By comparing the results in Table 6-2 to those in Table 6-3, the influence of different system capacitances is analyzed. Table 6-2 shows the results for isolated switching while those of back-to-back switching are depicted in Table 6-3. Generally, the two different conditions are expected to produce different responses. However, their characteristics overlap each other in both frequency and time domains as shown in Fig. 6-5. Therefore, the selected signature, which is close to isolated capacitor switching transients, can also be used for the identification of back-to-back capacitor switching transients. As a result, a better matching can be observed for isolated capacitor switching transients, as shown

in Table 6-2. However, the rank correlation results of back-to-back capacitor switching transients are still larger than 0.750 in the lower half of Table 6-3. Therefore, this signature can work with the certain changes of the system capacitance and capacitor value.

6.3.4.4 Effect of different system inductances

It is difficult or near impossible to be completely certain about AC system parameters. This uncertainty may affect the identification accuracy. Table 6-4 shows the correlation results for various switching instants with the AC system inductance varied by $\pm 30\%$ from that used to derive the signature without changing any of the capacitor parameters. As expected, the rank correlation results are very good, greater than 0.950. This is because the influence of the system inductance on the isolated capacitor switching transient is relatively small, especially on the damping time constants. In Fig. 6-3, the damping time constant varies from 6 ms to 9 ms while the system inductance is varied by $\pm 40\%$. Therefore, the magnitude variations of these capacitor switching transients can be fully covered by the rank correlation calculation window (22 ms). Thus, the rank correlation results with varied system inductance are found to be better than those with changed system capacitance and/or the switched capacitor.

Table 6-4 Results of capacitor switching transients with the changes of the system inductance

System inductance	Switching Instant	Phase A	Phase B	Phase C	Average of two max. phases
70%	1	0.974	0.964	0.85	0.969
	2	0.985	0.958	0.902	0.971
	3	0.961	0.692	0.983	0.972
	4	0.968	0.968	0.902	0.968
	5	0.917	0.963	0.970	0.966
130%	1	0.962	0.958	0.848	0.960
	2	0.972	0.942	0.868	0.957
	3	0.95	0.697	0.971	0.960
	4	0.954	0.961	0.889	0.958
	5	0.908	0.945	0.964	0.954

6.3.4.5 Non capacitor switching transients

To verify the validity of this method, some other types of transients, such as inductive load switching and faults, are used to test the rejection capability of this method. The inductive switching cases are obtained by switching a 40MVA inductive load to the 138 kV bus bar while the fault cases are assumed to occur along the transmission line, Line 1. The results are shown in Table 6-5.

Table 6-5 Results of non capacitor switching transients

Causes of transients	Cases	Phase A	Phase B	Phase C	Average of two max. phases
Inductive switching	1	0.0802	0.530	0.639	0.585
	2	0.624	0.218	0.423	0.523
	3	0.650	0.515	0.486	0.582
	4	0.243	-0.122	0.188	0.216
	5	0.385	0.177	-0.0736	0.281
Fault	1	0.673	0.570	0.421	0.622
	2	0.531	0.539	0.215	0.535
	3	0.596	0.598	0.206	0.597
	4	0.856	0.534	0.546	0.701
	5	0.140	-0.228	0.527	0.334

Generally, the characteristic frequencies of these transients are not close to that of the signature, which is for capacitor switching transients. Rank correlation would therefore produce low or even negative results. However, for some non capacitor switching transients, their rank correlation results are still relatively large and close to the threshold for the identification of capacitor switching transient. Cases 1 and 4 of fault transients in Table 6-5 are such examples. Fig. 6-11 shows the waveforms of the Case 4 fault transient. It is caused by a single-phase-to-ground fault, and the transient components at the beginning of the disturbance last for less than 20 ms. Fig. 6-12 and Fig. 6-13 show the magnitude variations of the transient component and their corresponding ranks at the CWT scale 22.8 respectively.

Fig. 6-11 Waveforms of Case 4 fault transient

Fig. 6-12 Magnitude variation of Case 4 fault transient at CWT scale 22.8

Fig. 6-13 Ranks for Case 4 fault transient

From Fig. 6-12, it can be seen that at the CWT scale of 22.8, the transient magnitudes of the three-phases do not vary much, especially that of Phases A. The rank of Phase A fluctuates with that of the signature as shown in Fig. 6-13, resulting in high rank correlation result, as shown in Table 6-5. Certainly, a threshold can be pre-set in order to avoid this misclassification. However, implementing a threshold also brings about other concerns. If the threshold is high, some capacitor switching transients may be bypassed. If the threshold is low, there may not be sufficient margin between those of capacitor switching and other switching. To overcome this issue and to avoid using a fixed threshold, a further consideration of this wavelet-based rank correlation method is taken. In this method, only one signature is used for identification of all types of capacitor switching transients. Therefore, it can only accommodate small deviations in the transient frequency or time constant around those of the signature. As a result, it sometimes misclassifies certain disturbances. However, if multiple signatures are used, multiple scales and multiple calculation windows can be used to provide more rank correlation results. This then requires a suitable approach to combine the multiple rank

correlation results. This improved method using multiple signatures is discussed in the following chapter.

6.4 Summary

Oscillatory transient often occurs whenever a capacitor is turned ON in a power systems. As these capacitor switching transients may cause disruption to the operation of other electrical devices, they need to be identified so that appropriate approaches can be devised to minimize their impact. However, these transients would be mingled among all the other disturbances captured by the power quality monitors. Hence, they need to be isolated so that they can be handled in a separate manner. Existing identification technique concentrates on detecting the dominant frequency of the oscillation, but this can be erroneous as many power system disturbances are wideband with many frequency components and they can be wrongly detected as such a transient. This chapter presents a technique that considers the transient's damping time constant in addition to its dominant frequency.

The monitored AC system is first simplified to a single-phase equivalent. The characteristic of its response to capacitor switching is systemically analyzed. The influence of different system parameters and capacitor ratings was also evaluated. The results are then used to develop a signature as the reference for identifying capacitor switching transients. Continuous Wavelet Transform is used to confine the analysis to a specific frequency band that is known to include the system response transients. Rank correlation is then used to compare the typical decaying pattern of the transient magnitude to the signature. A close correlation result indicates that it is due to capacitor switching. This method works well for pointing out capacitor switching transients even when there are discrepancies in the system actual parameters and those used in the equivalent circuit. However, this method faces some difficulties when separating some non-capacitor switching transients. In order to overcome this misidentification, an improved method, which is based on the approach mentioned before, is proposed in the following chapter.

Chapter 7

Wavelet-Based Fuzzy Method for Classifying Capacitor Switching Transients

7.1 Introduction

In the previous chapter, the wavelet-based rank correlation method for identifying capacitor switching transient was discussed. Its pitfall is also discussed. In that method, only one signature is used to estimate both isolated and back-to-back capacitor switching transients. However, there is a tradeoff. To achieve reasonable outcome for both capacitor switching transients, the characteristic frequency of the signature is set in the center of the possible frequency range of both capacitor switching transients. However, this impairs the rejection of other transients as the method uses a fixed frequency band and a fixed calculation window. It may make a mistake if other transients have frequency components near the characteristic frequency of the signature transient. Furthermore, the results of this method are compared to a threshold. A suitable threshold setting needs to be set. Therefore, a fuzzy classification is developed for the previous wavelet-based rank correlation method to improve its identification of capacitor switching transients as well as rejection of other transients. It is found that this approach can tolerate more uncertainties in the system parameters during classification while maintaining good rejection to other disturbances.

The approach to combine fuzzy logic with wavelet analysis is widely used in power systems such as in fault classification [50]. In [50], wavelet transform is used to denoise the measured current signal and to remove high frequency transients and harmonics. This is done to extract the fundamental frequency component for use in classifying between different types of unbalanced faults. The classification is based on the values of the zero sequence current and the phase angles of the phase currents. Fuzzy logic is introduced to overcome the uncertainties in the system parameters or caused by the use of different measurement systems. In the proposed wavelet-based fuzzy method, wavelet

transform is used differently as CWT is applied to extract a particular transient component, while rejecting other frequency components including the fundamental frequency component. The extracted transient component is then matched with signatures representing capacitor switching transients. However, similar fuzzy logic approach is employed to overcome uncertainties in the system and component parameters.

In the proposed wavelet-based fuzzy method, multiple signatures are used. They contain both isolated and back-to-back capacitor switching transients for identifying capacitor switching transient. Each disturbance waveform is compared to these signatures respectively using the previous wavelet-based rank correlation method. The fuzzy technique is then used to process these multiple rank correlation results and to make a decision whether the transient is caused by capacitor switching or not. There are many decision making techniques, as introduced in Chapter 3. However, fuzzy technique is the only one that can handle imprecise, vague or ‘fuzzy’ information [49][102]. This is what is needed in this identification of capacitor switching transients. Therefore, fuzzy technique is chosen for this application, taking into consideration the many uncertainties encountered in the analysis.

There are two aspects in the wavelet-based fuzzy method. One is the selection of the multiple signatures and the other is the application of the fuzzy technique. They are described in details in the following section.

7.2 Selection of Multiple Signatures

The selection of signatures is an important step in the wavelet-based fuzzy method. The pitfalls of a single signature have been illustrated in Chapter 6. Therefore, two or more signatures can be used to enhance the accuracy of the identification of capacitor switching transients. These signatures are distributed in the possible range of capacitor switching transients. It is possible for a capacitor switching transient to find a signature with similar characteristics. Therefore, a very satisfied rank correlation result can be obtained. In other words, these signatures complement each other to improve the acceptability of identification as well as enhance the rejection capability of this method. To be consistent, the test system used in previous chapter (Fig. 6-2) is also used in this

chapter. Based on the former numerical analysis, the whole range of the system response characteristics in capacitor switching is shown in Fig. 7-1.

Fig. 7-1 Characteristic changes of capacitor switching transients

For simplicity, only two representative signatures, Signature A and Signature B, are used to explain how the wavelet-based fuzzy method uses the fuzzy technique to improve the identification of capacitor switching transients as well as the rejection of other transients. These two signatures are chosen to be located at the two typical points among the possible range of values, as shown in Fig. 7-1. Signature A and Signature B are representative signatures for isolated capacitor switching and back-to-back capacitor switching, respectively. The characteristic of Signature A is close to the range of isolated capacitor switching transients. Its characteristic frequency is 500 Hz and its damping time constant is less than 8 ms. Therefore, the corresponding scale in the continuous wavelet transform is 20.5 and the calculation window length for rank correlation is set to less than one fundamental cycle, 16 ms. Signature B is chosen to be close to the range of back-to-back capacitor switching transients. Its characteristic frequency is slightly lower at 360 Hz. Its damping time constant is much higher, about 17 ms. Accordingly, the CWT scale is 28.4 and the calculation window length is about 35 ms. With these two

significantly different signatures and two different rank correlation windows, the characteristics of these two different types of the capacitor switching transients can be fully represented and ensure that the possible range of both types of capacitor switching transients is covered.

7.3 Application of Fuzzy Technique

As shown in Fig. 7-1, the characteristics of capacitor switching transients vary over 300Hz in frequency range and higher than 30 ms in the damping time constant. This variation is due to many uncertain parameters, either the system parameters or the capacitor parameters. Therefore, fuzzy technique can be used to improve the identification, as it possesses the unique ability at handling imprecise information. This section explains how fuzzy technique is used in the identification process. It is divided into 3 steps, as follows,

- Fuzzifying multiple rank correlation results
- Fuzzy operator, implication and aggregation for defuzzification
- Defuzzifying and outputting the final result

7.3.1 Fuzzifying the rank correlation results

Firstly, multiple rank correlation results are fuzzified. These rank correlation results indicate the level of similarity between the signatures and the transient waveform. According to the fuzzy rule, these results can be approximately divided into five parts:

- Very low (VL). In this range, the values of the rank correlation results are very small or negative, which means that the transient is definitely not similar to the capacitor switching signature.
- Low (L). In this range, the values of the rank correlation results are small. The transient may not be similar to the capacitor-switching signature.
- Middle (M). In this range, it is hard to tell whether the transient is similar to the signature or not. The transient can not be clearly identified if it is caused by capacitor switching otherwise.

- High (H). In this range, the transient waveform is similar to the signature. The transient is likely to be caused by capacitor switching.
- Very high (VH). In this range, the transient waveform is very similar to the signature. It is a definitely capacitor switching transient.

Based on the above divisions, five fuzzy membership functions are defined, as shown in Fig. 7-2. They cover the common demarcations of the rank correlation values.

Fig. 7-2 Five fuzzy membership functions

7.3.2 Fuzzy operator, implication and aggregation for defuzzification

After fuzzifying the rank correlation results of the two signatures, two sets of membership degrees are obtained. Each set contains five separate membership degrees. They are outputs of the five fuzzy membership functions, VL, L, M, H and VH. The two signatures play equally important roles in the identification. Hence, the weights of the two sets of membership functions are the same in the following analysis. There are many types of fuzzy operators or fuzzy rules, such as AND and OR fuzzy operators. In this application, the most similar of the analyzed transient with either signatures is the optimal result and hence, the fuzzy operator OR is used. It selects the maximum membership degrees from the two sets for the subsequent defuzzification. In other words,

if the membership degree of H in one set is larger than that in the other set, the former membership degree is selected for the following defuzzification. In this manner, a new set of membership degrees, a fuzzy set, is obtained.

7.3.3 Defuzzification

The input for the defuzzification process is the fuzzy set, which is obtained in the previous process. Its output is the probability whether the transient is caused by capacitor switching or vice versa. The probability can also be divided into five ranges.

- Definitely Not. In this range, it can be judged that the transient is definitely not caused by capacitor switching.
- Not. In this range, the transient is unlikely a capacitor switching transient. To enhance the rejection of this membership function, the peak of this membership function inclines slightly toward the range of “Definitely Not”.
- Possible. When the value of the probability is in this range, it is difficult to tell if the transient is caused by capacitor switching or not.
- Yes. In this range, the transient is possibly a capacitor switching transient. To increase the acceptance of this membership function, the peak of this membership function leans slightly toward the range of “Definitely Yes”.
- Definitely Yes. In this range, the transient is definitely a capacitor switching transient.

Therefore, five defuzzy membership functions are obtained, as shown in Fig. 7-3.

Fig. 7-3 Five defuzzy membership functions

The aim of this defuzzification is to ascertain the authenticity of the transient. There are many types of defuzzification methods, such as centroid method, bisector method and composite maximum method [51][103]. The centroid method determines the center of gravity of the final fuzzy space and uses this value as its output. This defuzzification method is sensitive to the preceding fuzzy operators. The bisector method computes the bisector of the final fuzzy space and uses this value as the output of the fuzzy system. The composite maximum method makes use of the maximum values of the fuzzy set. According to the different process of these maximum values, it can be divided into three types, mean of maximum method (MOM), smallest of maximum method (SOM) and largest of maximum method (LOM). Fig. 7-4 shows an example to explain the relationships between these three maximum defuzzification methods.

Fig. 7-4 Three types of maximum defuzzification methods

Among these defuzzification methods, the centroid method is widely used in process control while its results are highly influenced by the rules executed. The composite maximum method produces a result that is sensitive to the truth produced by the single rule that has the highest predicate truth. Therefore, this method is often applied in risk evaluation. Similarly, it can be also used in this application to defuzzify the aggregate fuzzy output set and evaluate the certainty of capacitor switching. Furthermore, SOM method is selected to enhance this method's ability to reject other types of transients.

7.3.4 A complete fuzzy inference diagram

Finally, an inference is drawn from the fuzzy set to ascertain if the transient is caused by capacitor switching. To help explaining the fuzzy process, an example as shown in Fig. 7-5 is used to illustrate it. Input 1 and input 2 are the rank correlation results of the Signature A and B respectively. They are obtained using the wavelet-based rank correlation method. Then these two inputs are fuzzified by the five fuzzy membership functions (Fig. 7-2). The fuzzifications of these two inputs are shown in the columns 1 and 2 of Fig. 7-5 respectively. The maximum membership degrees of the two sets are selected to be the inputs to the defuzzification membership functions, as shown in the blocks of column 3. The five upper rows of column 4 show the outputs of the defuzzy membership functions. The outputs of "Definitely Not" and "Not" defuzzy membership functions are zeros. The output of "Possible" is also almost zero while the "Yes" and "Definitely Yes" membership functions show larger outputs. Then, these five outputs are combined to obtain the final fuzzy space, shown in the lower right-hand corner of Fig.

7-5. Finally, SOM defuzzification method is applied. The final result is the level of certainty that the transient is caused by capacitor switching as shown on the red line. It is 79.5% in this example.

Fig. 7-5 A complete fuzzy inference diagram

7.4 Verification of the Wavelet-Based Fuzzy Method

The identification of the capacitor switching transients are carried out phase by phase. For single-phase transients, the results of the wavelet-based fuzzy method have given the certainty that the transient is capacitor switching transient. As discussed above, in the wavelet-based rank correlation method, the average value of the two more significant phases is used for a three-phase system in order to maintain identification precision. However, with the application of multiple signatures, the accuracy of identification is improved. For a capacitor switching transient, a signature whose characteristics are very close to those of the transient can be found. Therefore, this transient is tuned to the particular frequency band of this signature and a large rank correlation results can be

obtained despite the small magnitude of the transient. The influence of transient magnitudes is further mitigated. Hence, the certainties of the three phases have the same weights for the final output of three-phase transients. The final result can be obtained by averaging the certainties of three phases.

7.4.1 Capacitor switching transients with the changes of either system capacitance or capacitor capacitance

Firstly, capacitor switching transients for either different system capacitance or different capacitor ratings are studied. The results are shown in Tables 7-1 and 7-2. In the following tables, the “Certainty” value is the result of the wavelet-based fuzzy method for each of the phases. The “Final result” is the average certainty of the three phases.

In Table 7-1, the capacitor rating is varied over a relatively large range for the case of isolated capacitor switching. The switching instant is also varied. The characteristic of Signature A is close to that of isolated capacitor switching transient. Therefore, the rank correlation results of Signature A are larger than those of Signature B. The final results show that this method works well even with significant difference in the capacitor size between the signature and the analyzed transient. The certainties of identifying these transients are all higher than 80%. Table 7-2 shows the results for similar variations in capacitor size as in Table 7-1 but for the case of back-to-back capacitor switching. The switching instant is also varied. As characteristic of Signature B is close to that of back-to-back capacitor switching transient, the rank correlation results of Signature B in these identifications are larger than those of Signature A. Combining the identification results of three phases, the final results are all higher than 60%, confirming that this method is also applicable for identifying back-to-back capacitor switching transients.

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Table 7-1 Results of isolated capacitor switching transients

Capacitor ratings	Switching instant		Phase A	Phase B	Phase C	Final result
20 MVar	1	Signature A	0.923	0.966	0.975	99.6%
		Signature B	0.823	0.89	0.921	
		Certainty	98.7%	100%	100%	
	2	Signature A	0.975	0.955	0.952	100%
		Signature B	0.916	0.865	0.835	
		Certainty	100%	100%	100%	
40 MVar	1	Signature A	0.974	0.979	0.886	90.7%
		Signature B	0.905	0.921	0.738	
		Certainty	100%	100%	72.2%	
	2	Signature A	0.978	0.969	0.900	98.7%
		Signature B	0.915	0.875	0.755	
		Certainty	100%	100%	96.0%	
80 MVar	1	Signature A	0.958	0.951	0.734	93.3%
		Signature B	0.806	0.861	0.674	
		Certainty	100%	100%	79.9%	
	2	Signature A	0.966	0.906	0.733	91.6%
		Signature B	0.846	0.848	0.651	
		Certainty	100%	96.8%	77.8%	
100 MVar	1	Signature A	0.617	0.781	0.869	80.8%
		Signature B	0.596	0.678	0.828	
		Certainty	71.1%	80.0%	91.2%	
	2	Signature A	0.902	0.677	0.710	84.6%
		Signature B	0.820	0.721	0.575	
		Certainty	96.2%	80.0%	77.7%	

Table 7-2 Results of back-to-back capacitor switching transients

Capacitor ratings	Switching instant		Phase A	Phase B	Phase C	Final result
20 MVar	1	Signature A	0.331	0.536	0.795	64.2%
		Signature B	0.427	0.629	0.75	
		Certainty	49.5%	73.8%	69.4%	
	2	Signature A	0.809	0.576	0.368	73.8%
		Signature B	0.759	0.692	0.633	
		Certainty	67.3%	79.6%	74.6%	
40 MVar	1	Signature A	0.904	0.815	0.542	83.3%
		Signature B	0.896	0.846	0.596	
		Certainty	96.5%	87.6%	65.8%	
	2	Signature A	0.821	0.908	0.604	86.3%
		Signature B	0.823	0.889	0.647	
		Certainty	84.7%	97.1%	77.2%	
80 MVar	1	Signature A	0.673	0.743	0.367	66.8%
		Signature B	0.653	0.783	0.422	
		Certainty	79.9%	71.2%	49.3%	
	2	Signature A	0.393	0.604	0.741	66.3%
		Signature B	0.619	0.683	0.873	
		Certainty	47.5%	80.0%	71.5%	
100 MVar	1	Signature A	0.609	0.645	0.811	68.1%
		Signature B	0.472	0.643	0.709	
		Certainty	49.6%	77.0%	77.8%	
	2	Signature A	0.815	0.742	0.54	63.4%
		Signature B	0.731	0.525	0.547	
		Certainty	73.9%	71.3%	44.9%	

7.4.2 Capacitor switching transients with the system inductance changes

In the following cases, the system inductance is varied by $\pm 40\%$ and evaluated for both types of capacitor switching transients. The analysis in Section 6.1.2 (Fig. 6-3 and Fig. 6-4) shows that the system inductance has more influence on the damping time constants than on the characteristic frequency. Hence, in these cases, the durations of the capacitor switching transients are more affected than their oscillatory frequencies. Since the rank correlation calculation window of Signature B is longer than that of Signature A, the

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rank correlation results of Signature B show higher values because its window matches the duration of the transient when evaluated any CWT at scale 28.4. The results are shown in Table 7-3 and they are all higher than 70%. It shows that this method can still work even when the system inductance has varied from that used to generate the signatures.

Table 7-3 Results of different system inductances

System Inductance (Types)	Load capacity		Phase A	Phase B	Phase C	Final Result
60% (Isolated capacitor switching)	40 MVar	Signature A	0.954	0.957	0.866	98.2%
		Signature B	0.988	0.991	0.89	
		Certainty	100%	100%	94.5%	
	80 MVar	Signature A	0.950	0.961	0.755	97.5%
		Signature B	0.967	0.973	0.878	
		Certainty	100%	100%	92.6%	
60% (Back-to-back capacitor switching)	40 MVar	Signature A	0.852	0.926	0.494	92.1%
		Signature B	0.927	0.948	0.646	
		Certainty	99.1%	100%	77.1%	
	80 MVar	Signature A	0.611	0.718	0.53	72.3%
		Signature B	0.886	0.802	0.382	
		Certainty	93.9%	76.4%	46.6%	
140% (Isolated capacitor switching)	40 MVar	Signature A	0.827	0.927	0.582	91.8%
		Signature B	0.901	0.929	0.677	
		Certainty	96.1%	99.2%	80.0%	
	80 MVar	Signature A	0.908	0.950	0.726	91.3%
		Signature B	0.930	0.946	0.803	
		Certainty	99.3%	100%	74.7%	
140% (Back-to-back capacitor switching)	40 MVar	Signature A	0.869	0.876	0.451	78.1%
		Signature B	0.821	0.881	0.567	
		Certainty	91.2%	93.0%	50.0%	
	80 MVar	Signature A	0.788	0.838	0.406	75.1%
		Signature B	0.843	0.860	0.610	
		Certainty	87.1%	89.7%	48.4%	

7.4.3 Non-capacitor switching transients

Some non-capacitor switching transients are used to test the rejection capability of this method.

Firstly, transients caused by faults are used (results shown in Table 7-4). These transients are caused by different faults along Line 1 of the system shown in Fig. 6-2. From these results, it can be seen that all the certainty values are smaller than 35%. It can then be directly identified that they are not capacitor switching transients. Here, Case 1 of single-phase-to-ground fault is emphasized as it is also the Case 4 in Table 6-5 in Chapter 6. The transient is wrongly identified as capacitor switching transients by the wavelet-based rank correlation method when a single signature is used in Section 6.3.4.5. Once again, the rank correlation with Signature A also shows rather high output but with the aid of Signature B, the transient is rightly reflected as a non-capacitor switching transient.

Table 7-4 Results of the transients caused by faults

Fault type	Case		Phase A	Phase B	Phase C	Final Result
Single-phase to-ground fault	1	Signature A	0.942	0.689	0.815	33.3%
		Signature B	0.329	0	-0.0026	
		Certainty	99.9%	0	0	
	2	Signature A	0.878	0.496	0.57	2.49%
		Signature B	-0.0409	-0.0942	0.151	
		Certainty	0	0	7.47%	
Two-phase to-ground fault	1	Signature A	-0.591	-0.0745	0.783	14.9%
		Signature B	0.17	0.582	0.358	
		Certainty	0	0	44.7%	
	2	Signature A	0.819	-0.0271	0.562	3.29%
		Signature B	-0.0083	-0.116	0.189	
		Certainty	0	0	9.86%	
Three-phase to-ground fault	1	Signature A	0.809	0.639	0.716	28.9%
		Signature B	0.0353	0.204	0.151	
		Certainty	0	9.98%	76.7%	
	2	Signature A	0.789	0.839	0.616	26.8%
		Signature B	0.0853	0.184	0.101	
		Certainty	0	9.68%	70.9%	
Phase-to-phase fault	1	Signature A	0.910	0.841	-0.0007	34.8%
		Signature B	0.0831	0.239	0.145	
		Certainty	96.1%	8.35%	0	
	2	Signature A	0.832	-0.287	0.808	1.35%
		Signature B	-0.111	-0.0721	0.287	
		Certainty	0	0	4.04%	
Three-phase fault	1	Signature A	0.778	0.639	0.616	27.7%
		Signature B	0.0353	0.284	0.151	
		Certainty	0	75.7%	7.47%	
	2	Signature A	0.889	0.739	0.716	25.6%
		Signature B	0.0353	0.0034	0.111	
		Certainty	0	0	76.7%	

In addition, Table 7-5 shows the results of the transients caused by other switching operations, including inductive load switching and transformer energization at 138 kV bus bar in Fig. 6-2. The capacity of the inductive load is 40MVA and that of the transformer is 200MVA. Since the characteristic frequencies and durations of these non-

Wavelet-Based Fuzzy Method for Classifying Capacitor Switching Transients

capacitor switching transients are different from those of capacitor switching transients, the rejection capability of this method can be verified. This method rejects them accordingly. All of the certainties are lower than 40%, clearly indicating that they are not capacitor switching transients.

Table 7-5 Results of other switching transients

Type	Case		Phase A	Phase B	Phase C	Final Result
Inductive switching	1	Signature A	0.126	0.662	0.927	36.3%
		Signature B	0.0317	0.208	0.0591	
		Certainty	0	9.92%	99.1%	
	2	Signature A	0.916	0.614	0.503	35.8%
		Signature B	0.0953	0.0222	0.174	
		Certainty	98.0%	0	9.24%	
	3	Signature A	0.871	0.829	0.553	19.2%
		Signature B	0.201	0.292	0.294	
		Certainty	0.1	3.58%	43.9%	
	4	Signature A	0.713	0.251	0.128	0
		Signature B	-0.0599	-0.1471	0.089	
		Certainty	0	0	0	
	5	Signature A	0.492	0.699	-0.0788	3.21%
		Signature B	0.183	-0.0333	-0.0354	
		Certainty	9.64%	0	0	
Transformer energization	1	Signature A	0.46	0.459	-0.249	16.6%
		Signature B	0.157	-0.062	0.0335	
		Certainty	49.9%	0	0	
	2	Signature A	0.504	-0.153	0.424	3.16%
		Signature B	-0.0374	-0.0112	0.179	
		Certainty	0	0	9.48%	
	3	Signature A	0.376	0.0883	0.503	15.9%
		Signature B	-0.0749	0.130	0.0697	
		Certainty	0	0	47.8%	
	4	Signature A	0.485	0.410	-0.170	16.3%
		Signature B	0.109	-0.0737	0.0811	
		Certainty	49.0%	0	0	
	5	Signature A	0.412	-0.128	0.491	16.2%
		Signature B	-0.0765	0.0962	0.0948	
		Certainty	0	0	48.6%	

Finally, transmission line/cable energization is considered. A 100 km transmission line is switched ON to the 138 kV bus bar in Fig. 6-2 to generate the transmission line/cable energization transients. Under this no-load switching condition, the inherent capacitance of transmission line/cable would affect the transient process [95]. Therefore, the resulting transient has characteristics that are similar to those of capacitor switching transients. This can also be seen from the identification results shown in Table 7-6. Some of them are close to 50% certainty value. Since the lowest certainty of capacitor switching transients is 63.4% from Table 7-2, these transients can be still distinguished by setting an acceptance/rejection certainty value around 60%.

Table 7-6 Results of transmission line/cable energization transients

Type	Case		Phase A	Phase B	Phase C	Final Result
Switching transmission line/cable	1	Signature A	0.439	0.496	0.37	32.7%
		Signature B	0.699	0.785	0.0778	
		Certainty	49.9%	48.3%	0	
	2	Signature A	0.472	0.234	0.394	35.3%
		Signature B	0.547	0.618	0.119	
		Certainty	49.6%	8.70%	47.5%	
	3	Signature A	0.212	0.338	0.267	29.4%
		Signature B	0.586	0.705	0.0616	
		Certainty	9.82%	78.3%	0	
	4	Signature A	0.325	0.694	0.846	47.1%
		Signature B	0.577	0.846	0.102	
		Certainty	61.7%	79.4%	0	
	5	Signature A	0.0832	0.508	0.603	32.4%
		Signature B	0.43	0.533	0.0589	
		Certainty	49.7%	47.4%	0	

From Tables 7-4 and 7-5, which are non-capacitor switching transient, excluding transmission line/cable energization transient, the rank correlation results of Signature B are usually smaller than those of Signature A. It is because a lower frequency band and a longer calculation window are used for the rank correlation with Signature B. Furthermore, its magnitude variation is also gentler than that of Signature A. Hence, smaller rank correlation results of Signature B are obtained.

For transmission line/cable energization transients the rank correlation results are shown in Table 7-6, this is slightly different. The rank correlation results with Signature A are much smaller than those with Signature B. Since the frequency range of these transients is close to that of capacitor switching transients, different damping time constant or different duration is the key point for identification, as shown in Fig. 7-6. Hence, smaller rank correlation results of Signature A are obtained.

Fig. 7-6 Magnitude variations of the signatures and the transmission line/cable switching transient

(a) Magnitude variations of Signature A and the transient at CWT scale 20.5.

(b) Magnitude variations of Signature B and the transient at CWT scale 28.4.

From the above illustration, the advantage of using multiple signatures is demonstrated. Different signatures have different identification range and rejection capability. They can complement each other. Some can improve the acceptability of this method, such as Signature A in identifying back-to-back capacitor switching transient. Some can complement the rejection capability of this method, such as Signature B in rejecting the transients caused by inductive load switching and transformer energization.

7.5 Summary

Multiple signatures and the fuzzy technique are used to improve the wavelet-based rank correlation method. In this wavelet-based fuzzy method for identifying capacitor switching transients, multiple signatures are used to achieve a better evaluation of the transient waveforms. Then, fuzzy technique is used to overcome the uncertainty problem during the identification. It aggregates the rank correlation results of different signatures

and outputs a simple and clear result. More representative signatures would result in better identification of the capacitor switching transients. However, better classification does not mean that a higher numerical value will always be obtained. In the fuzzification and defuzzification process, those rank correlation results that are larger than 0.8 are given higher priorities and hence they contribute more to the final results than the smaller correlation results. Therefore, there is a higher chance of getting a larger final value if more signatures are used since one of the rank correlation results will be very close to 1. Dynamic simulations have verified the effectiveness and adaptability of this method in various circumstances where the switching instants, system parameters or capacitor ratings are different from those used to generate the signature. Some non-capacitor switching transients are also used to verify the rejection capability of this method. Compared to the wavelet-based rank correlation method, the acceptance and rejection capability of this wavelet-based fuzzy method is better.

Chapter 8

Conclusions and Recommendations

In this chapter, the main results from the earlier chapters are summarized. Some general conclusions are also made and several potential extensions of this work are proposed.

8.1 Conclusions

Instead of Fourier analysis, wavelet analysis is used in this thesis to process disturbance data and to extract the features of power quality disturbances since it has good time-frequency characteristics and is suitable for analyzing non-periodic signals. Several wavelet-based methods for classifying power quality disturbances are presented in this project.

A wavelet-based energy content method is proposed to effectively identify short duration voltage variations. In this method, the information of two different frequency bands, the 1 kHz frequency band and fundamental frequency band, is used. The information of the 1 kHz frequency band is used to accurately extract the time information of the disturbance, i.e. beginning instant and duration of the disturbance. The information of the fundamental frequency band is used to estimate the fundamental energy change in a power system and determines the voltage magnitude change. In this manner, short duration voltage variations can be classified into various subcategories according to the standard [20]. DWT can optimize its resolution with good time resolution in the high frequency bands and good frequency resolution in the low frequency band saving a large amount of storage space. Moreover, a much faster algorithm can be achieved with DWT giving a lower computation time. Therefore, DWT is selected for this application. The selection of suitable mother wavelet was also considered. In this application, the mother wavelet should have short support size but sufficient number of vanishing moments and can be implemented efficiently through FIR filters. Therefore, db2 mother wavelet is chosen and several disturbances are used to verify this method. Compared to the conventional RMS method, this method can give

better description of the short duration voltage variations with more accurate time and magnitude information. Even the short duration interruption, which is often misidentified by the conventional RMS method, is correctly identified. Compared to other wavelet-based methods, this method does not require reconstruction of the signal resulting in much simpler implementation.

A wavelet-based rank correlation method was developed to identify capacitor switching transients. These transients often occur when capacitor bank(s) are switched on. To systematically analyze these transients, the monitored system is simplified to a single-phase equivalent circuit. Using a numerical method, the influences of different system and capacitor bank parameters on the transient characteristics are evaluated. It can be concluded that the system response characteristics to capacitor switching transient vary in a relative small range besides the changes of the system and capacitor bank parameters. Based on this conclusion, a wavelet-based rank correlation method is proposed to identify them. A signature for representing capacitor switching transients in the system is first derived through the aforementioned numerical analysis. The transients are then identified by comparing to this signature. Continuous wavelet transform is used to extract the information of a particular frequency band, which coincides with the characteristic frequency of the signature. Rank correlation is used to evaluate the similarity between the signature and the transient. It was found out that this wavelet-based rank correlation method can tolerate some uncertainties with the system and/or capacitor bank parameters. However, it may misclassify some non-capacitor switching transients, especially those with characteristic frequencies close to that of the signature.

An improved method, the wavelet-based fuzzy method, is developed to enhance the accuracy of the above identification of capacitor switching transients. This method is based on the wavelet-based rank correlation method but multiple signatures are used instead of a single signature. Using similar wavelet-based rank correlation method, multiple rank correlation results are obtained to complement each other since the signatures cover all the possible characteristics of capacitor switching transients. Fuzzy technique is then used to aggregate these rank correlation results and to arrive at a decision on whether the transient is caused by capacitor switching. Compared to the previous single-signature method, this method can tolerate more uncertainties in the

system and capacitor parameters. At the same time, the rejection of non-capacitor switching transients is also improved. It has been proven to correctly identify those non capacitor switching transients, whose characteristics are similar to some of the signatures.

8.2 Recommendations

Notwithstanding the progress described in this thesis, the following areas are suggested as possible areas for further investigation.

In Chapter 5, the wavelet-based energy content method is applied to classify short duration voltage variations. This method can be extended to identify long duration voltage variations since the main difference between them is just the duration.

Moreover, the wavelet-based energy method can be “re-designed” for other types of disturbances. In Chapter 5, only the energy content of the fundamental frequency band is used. In future studies, the energy contents of other frequency bands can also be used to classify other types of power quality disturbances. On the other hand, in current application, a simple threshold method is able to meet the requirement of classification. However, some more complicated decision making techniques may be required to help in the classification of other disturbances. In this way, the wavelet-based energy content method can be extended to classify other types of disturbances.

In Chapter 6, the systematic analysis of the capacitor switching is based on the conventional Laplace analysis. The main limitation of this analysis is that only local representation of transient signals in either time or frequency domain can be obtained. In the same chapter, wavelet analysis is only used to extract the information of a specific frequency band. Hence, the advantages of wavelet analysis are not fully utilized. Wavelet technique, which incorporates characteristics in time and frequency domains, presents a possible solution for accurate frequency response representation while retaining the time information. Hence, applying wavelet-based models of power system components in time-frequency domain simulation can be explored. With the time-frequency domain simulation, the analysis results of capacitor switching transient do not need to be transferred between time and frequency domains. They can be directly used to design the wavelet-based identification methods. Therefore, the wavelet-based

analysis for capacitor switching transients is more straightforward and can readily be used to develop wavelet-based approaches.

On the other aspect, effective application of wavelet analysis requires thorough knowledge of wavelet basis function. A searching or matching algorithm can be developed to choose a suitable mother wavelet according to its applications. Further details also need to be considered such as the necessary sampling rate and wavelet scale in order to achieve the necessary time-frequency resolution. In addition, the existing mother wavelets are not designed for power quality assessment. In Chapter 5, the mother wavelet is chosen by evaluating the performances of different mother wavelets. In Chapter 6, the mother wavelet is selected by its shape which resembles the sine waveform. Therefore, there are compromises when choosing suitable mother wavelets. If new mother wavelets can be specially designed by combining the characteristics of power quality disturbances with the essence of wavelet analysis, these wavelet-based methods for power quality assessment may become more effective. The shapes of these new mother wavelets can be made more suitable to detect the irregular parts of the sine or cosine signals. They may have explicit expression, which can then be used to establish power system models in the time-frequency domain.

Finally, in this thesis, only a few types of power quality disturbances are identified. Short duration voltage variations are classified according to the IEEE standard [20]. Capacitor switching transients are specifically identified according to their causes. However, not all the power quality disturbances have been classified according to their causes. If the disturbances caused by some other day-by-day operations, such as load operation, can be automatically classified, the burden on the power quality engineers can be further reduced. Their attentions can be concentrated on more severe transients, such as those caused by abnormal operations or faults. Some common operations, such as transformer switching and motor starting, can be included to make this power quality disturbance classification and characterization more complete.

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Appendices

Appendix A

Parameters of WSCC System

Table A-1 Machine data of WSCC system [93]

Parameter	Bus 1	Bus 2	Bus 3
T'_{d0}	8.96	8.5	3.27
T'_{q0}	0.31	1.24	0.31
T''_{d0}	0.05	0.037	0.032
T''_{q0}	0.05	0.074	0.079
H	22.64	6.47	5.047
T_{FW}	0	0	0
X_d	0.146	1.75	2.201
X_q	0.0969	1.72	2.112
X'_d	0.0608	0.427	0.556
X'_q	0.0608	0.65	0.773
$X''_d = X''_q$	0.05	0.275	0.327
X_l	0.026	0.22	0.246
S_{GA}	0.898	0.911	0.825
S_{GB}	9.610	8.248	2.847

Table A-2 Exciter data of WSCC system [93]

Parameter	T_R	K_A	T_A	K_E	T_E	K_F	T_F	S_{EA}	S_{EB}
Bus1,2,3	0	20	0.2	1.0	0.314	0.063	0.35	2.5484	0.5884

Table A-3 Load data of WSCC system [93]

Parameter	Bus 1	Bus 2	Bus 5	Bus 6	Bus 8
P_L	1.80	0.50	0.25	0.25	1.0
Q_L	0.265	0	0.075	0.075	0.35

Appendix B

DWT Application in Identifying Capacitor Switching Transients

In Section 6.2.2, the choice of using CWT or DWT for identifying capacitor switching is discussed. To give more in depth comparison, several trials of using DWT in the identification of capacitor switching transients are presented in this appendix. The DWT is used in the wavelet-based rank correlation method and the identification results are compared to those obtained using CWT in Chapter 6.

To maintain consistency, the DWT also uses db2 as the mother wavelet. Since the sampling frequency of the test system is 15.36 kHz, the frequency range of DWT scale 32 (level 5) is determined to be from 240 Hz to 480 Hz. This range encloses the system response frequency of the single signature (450 Hz). The coefficients at DWT scale 32 and CWT scale 22.8 are shown in Fig. B-1.

Fig. B-1 The wavelet decomposition of the single signature

(a) The original waveform of the single signature. (b) DWT coefficients at scale 32 (level 5). (c) CWT coefficients at scale 22.8.

In the following identification, the coefficients of DWT scale 32 are used. The magnitude variations are computed in similar manner to those in CWT calculations of

(6-10) and (6-11). Using DWT, the rank correlation method identifies several capacitor switching transients as shown in Table B-1. For comparison, the identification results of using CWT are also given.

Table B-1 Results of capacitor switching transients

	Scale	Phase A	Phase B	Phase C	Average of two max. phases
DWT	32	0.704	0.701	0.716	0.71
CWT	22.8	0.977	0.976	0.859	0.976

The capacitor switching transients are caused by switching a 40 MVar capacitor bank (C40AL) in the test system (see Fig. 6-2 in Section 6.1.2). The rank correlation results of DWT scale 32 are acceptable for indicating that they are capacitor switching transients although much better results are obtained by using CWT.

However, some non-capacitor switching transients may be wrongly identified if using DWT. Table B-2 shows an example. This non-capacitor switching transients are produced by switching a 40 MVA inductive load at the 138 kV busbar (see Fig. 6-2 in Section 6.1.2). The highest rank correlation result from DWT scale 32 is larger than 0.6. Compared to the rank correlation results of capacitor switching transients shown in Table B-1, it would be difficult to tell them apart, i.e. that this transient is not caused by capacitor switching. On the contrary, the rank correlation results from using CWT are low, indicating clearly that they are not capacitor switching transients.

Table B-2 Results of inductive switching transients

	Scale	Phase A	Phase B	Phase C	Average of two max. phases
DWT	32	0.651	0.661	0.609	0.656
CWT	22.8	0.243	-0.122	0.188	0.216

To explain these identification results, Fig. B-2 and B-3 are used. The magnitude variation of DWT scale 32 coefficients for inductive switching transients is shown in Fig. B-2 while that of CWT scale 22.8 is shown in Fig. B-3.

Fig. B-2 Magnitude variation of DWT scale 32 coefficients for inductive switching transients

Fig. B-3 Magnitude variation of CWT scale 22.8 coefficients for inductive switching transients

Comparing these two figures, it can be seen that the magnitude variation of DWT coefficients is quite rough because the time resolution degrades with higher DWT scales. The extracted information of the system response transients at high DWT scales is not sufficient for a good description of the capacitor switching transient and this may lead to erroneous identification. This poor time resolution at high DWT scales cannot be overcome because of the downsampling in the DWT calculation (see Section 4.3.3). This inflexibility is caused by DWT aiming to achieve zero redundancy in its wavelet domain representations.

Based on the above discussion, it can be concluded that CWT is more suitable and convenient to use in the identification of capacitor switching transients because it provides a flexible frequency characteristic and good time resolution in all scales.

Vita

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Research related to this thesis has result in the following publications:

[1] H. Y. Zhu and S. Chen, "Identification of capacitor switching transients with consideration of uncertain system and component parameters," submitted, *IEEE Trans. Power Delivery*.

[2] H. Y. Zhu and S. Chen, "Wavelet-based energy content method for classifying and characterizing short-duration voltage variations". *The 6th International Power Engineering Conference*, Singapore, 27-29 Nov. 2003, vol. 1, pp. 423-428.

[3] H. Y. Zhu and S. Chen, "Advance signal processing techniques for power quality analysis," *International Power Quality Conference 2002*, Singapore, 21-25 Oct. 2002.