Electric Power Generation, Transmission and Efficiency

Contributors

Gianfranco Chicco
Armando C. Oliveira
B. Chudnovsky
M. Perelman
Alexandre de Assis Mota
Saffa B. Riffat
Zhengwei Fan
R. Saveliev
G. P. Granelli
N. Spitz
E. Korytni
Yuehong Su
Y. H. Luo
Szabolcs Varga
Pierluigi Mancarella
Q. C. Wang
M. Montagna
Tao Lin Xialing Xu
Lia Toledo Moreira Mota
E. Bar-Ziv

Clément M. Lefebvre
Editor

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ELECTRIC POWER: GENERATION, TRANSMISSION AND EFFICIENCY

CLÉMENT M. LEFEBVRE
EDITOR

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PREFACE

This book presents new and important research on electric power and its generation, transmission and efficiency. The world is becoming increasingly electrified. For the foreseeable future, coal will continue to be the dominant fuel used for electric power production. The low cost and abundance of coal is one of the primary reasons for this. Electric power transmission, a process in the delivery of electricity to consumers, is the bulk transfer of electrical power. Typically, power transmission is between the power plant and a substation near a populated area. Electricity distribution is the delivery from the substation to the consumers. Due to the large amount of power involved, transmission normally takes place at high voltage (110 kV or above). Electricity is usually transmitted over long distance through overhead power transmission lines. Underground power transmission is used only in densely populated areas due to its high cost of installation and maintenance, and because the high reactive power gain produces large charging currents and difficulties in voltage management.

A power transmission system is sometimes referred to colloquially as a "grid"; however, for reasons of economy, the network is rarely a true grid. Redundant paths and lines are provided so that power can be routed from any power plant to any load center, through a variety of routes, based on the economics of the transmission path and the cost of power. Much analysis is done by transmission companies to determine the maximum reliable capacity of each line, which, due to system stability considerations, may be less than the physical or thermal limit of the line. Deregulation of electricity companies in many countries has led to renewed interest in reliable economic design of transmission networks.

Short Communication - In recent years, both utilities and the end-users of electric power are becoming increasingly concerned with power quality issues. In order to correctly evaluate the quality of power supply and accurately measure the levels of various power disturbances in current and/or voltage waveforms, additional two aspects of power quality studies have been proposed besides the detection of power disturbance, which are the classification or identification of the types of power disturbances and the measurement of the parameters of power disturbance waveforms. In this chapter, an advanced signal processing technique and artificial intelligence are introduced in this area to realize the functions mentioned above. In details, the Wavelet Transform is used to estimate the parameters of power disturbance and extract the pattern features for classification/identification; on the other hand, artificial neural network is used to classify/identify the types of power disturbances in voltage/current waveforms. Further, the performance of various wavelet functions and artificial neural networks are investigated. As a result, the combination use of the "Dmey" wavelet and the back propagation (BP) neural network is proposed for archiving desirable performance. A software package was developed by integrating the proposed techniques, and large amount of simulation results obtained using this software package proved the correctness and effectiveness of the applications of the advanced signal processing technique and artificial intelligence to power quality researches.

Chapter 1 - One of the major drivers of the electrical energy system evolution is the widespread adoption of emerging technologies for distributed generation, that are shifting the focus from the centralized production to the local production of electricity. Under the distributed generation paradigm, the present research scenario is more and more emphasising the role of solutions aimed at improving the energy generation efficiency and thus the sustainability of the overall energy sector. From this point of view, the development of multi-generation solutions for small-scale applications (below 1 MW), for instance producing at the same time electricity, heat and cooling power, represents a key asset for improving the performance of the future power system. In fact, the combined production of manifold energy vectors can bring several benefits in terms of energy saving and CO_2 emission reduction, as well as potential enhanced profitability of the plants exploiting the energy mix within the liberalised electricity market framework.

This chapter illustrates a comprehensive approach to multi-generation system characterization and planning. This approach is formulated in terms of the so-called *lambda analysis*, consisting of a unified framework to study multi-generation systems, that extends the classical models based on the analysis of the heat-to-power cogeneration ratio in cogeneration plants. In particular, the representation of the energy interactions within the multi-generation plant is summarized in terms of the transformation of a vector of original energy or cogeneration ratio values into an equivalent set of values, mathematically expressed by means of specifically defined *lambda transforms*. The conceptual scheme presented provides effective characterization and modelling of the production side, the demand side and their interactions in multi-generation systems.

The details of the approach presented are illustrated by reviewing the bulk of alternative schemes and equipment available on the market for setting up multi-generation plants. For each alternative, the suitable equipment models and the expressions of the relevant lambda transforms are presented.

Numerical applications are provided, referred to a multi-generation system for electrical, thermal, and cooling power production. The results highlight the potential of the lambda analysis framework and of the associated lambda transforms as an effective tool to assist the energy system planner.

The availability of such a synthetic and powerful tool is of utmost importance in order to effectively cope with the increasing complexity of the future electro-energetic systems, in which the efficiency enhancement will strongly depend on the integration of the equipment for local combined production of manifold energy vectors.

Chapter 2 - Genetic algorithms, proposed about 40 years ago, have been used as a general purpose optimization technique. In this work, the authors' experience with genetic algorithm based optimization is presented with reference to some electric power system analysis problems.

At first, the fundamentals of genetic algorithms are described: the basic genetic algorithm by John Holland is presented and the function of the three genetic operators of selection, crossover and mutation is discussed. Among the more recent theoretical developments, the micro-genetic approach by K. Krishnakumar and the algorithm of Chu and Beasley are considered. The former takes advantage from operating with small-sized populations and the latter proposes an effective technique to deal with functional constraints.

The second part of this work is concerned with the description of some applications of the above mentioned genetic algorithm based procedures to power system problems. The topics that are considered in detail are:

- allocation of compensating capacitors in high and medium voltage networks to improve voltage regulation;
- optimization of the topology of EHV networks with the aim of improving security and to overcome the problem of parallel or loop flows; control measures include switching of substation breakers as well as deployment and operation of phase shifting transformers;
- identification of multiple interacting bad data in state estimation, formulated as a combinatorial optimization problem.

The above mentioned items represent a clearly non-exhaustive list of the many application fields where genetic algorithms have been profitably employed, but the authors feel they demonstrate the main advantage of using genetic algorithms with respect to other search methods. Indeed no present day optimizer is so general, robust and flexible to deal with problems so different from each other as the ones considered here.

Chapter 3 - A three-step methodology was developed to provide reliable prediction of a coal's behavior in a utility boiler: (1) Extracting the combustion kinetic model parameters by combining experimental data from a pilot-scale test facility, Computational Fluid Dynamic (CFD) codes and an artificial neural network. While the combustion kinetic parameters used in the model code will not correspond to the combustion rate of a single particle of coal, these parameters do describe the combustion behavior of a "macroscopic" sample of tested coal. (2) Validation of the combustion kinetic model parameters by comparing diverse experimental data with simulation results calculated with the same set of model parameters. (3) The model parameters are then used for simulations of full-scale boilers using the same CFD code. For operational engineering information needed by the utility operator, the authors apply the predicted results to EXPERT SYSTEM, a boiler supervision system developed by Israel Electric Corporation (IEC). Four different bituminous and sub-bituminous coals with known behavior in IEC 550MW opposite-wall and 575MW tangential-fired boilers were used to show the adequacy of the methodology. The predictions are done with the CFD code, GLACIER, propriety of Reaction Engineering International (REI). Preconfigured GLACIER models of the test and full-scale furnaces were purchased from REI and validated by our group. This book chapter will include a detailed description of the methodology, test furnace facility and an example of the experimental and predictive combustion results from the four coals used to test the methodology. In addition, two previously unknown coals will be examined prior to their firing in the utility boilers and prediction of their behavior and operational parameters in the two boilers will be carried out.

Chapter 4 - Electrogasdynamic (EGD) power conversion is a process that converts thermal (internal/kinetic) energy into electric energy, without moving parts. Discrete particles are charged using a corona electrode and transported at high velocity against an electric field, to produce useful electric power. An important advantage of such a device is that it doesn't include moving parts and so requires very little maintenance.

The basic equations for EGD power conversion are presented, as well as theoretical results for the process. The efficiency of EGD power conversion is calculated for different fluids. The existence of practical limits for conversion is discussed: electric breakdown strength and charge-to-mass ratio. Theoretical results for different working fluids are presented.

A Computational Fluid Dynamics model was developed as a tool to simulate the major characteristics of fluid flow in such a device and to identify the most important factors in the power conversion process. Model results are presented and discussed. The importance of the particle/electric field interaction is evaluated, taking into account turbulent effects. A parametric study to identify the best collector location is carried out.

Experimental results for an EGD apparatus and different operating fluids were also obtained in a test rig. An EGD nozzle was designed, built and experimentally tested. Tests of electric breakdown were carried out for different working fluids (refrigerants). Results are presented and compared to theoretical values. The use of electrospray is also investigated.

Chapter 5 - Load modeling has a significant impact on power systems operation, simulation and analysis. However, little attention has been paid to develop adequate load models and forecasting methods when compared to the effort spent with other power systems related problems. In this context, this chapter presents a review on load models and load forecasting techniques, and also discusses the new trends on these issues. These late tendencies include bottom-up and top-down approaches, gray box identification techniques and the use of fuzzy logic, among others. The discussion emphasizes the main concepts of each method. Especially in distribution networks, load modeling and forecasting may cause some inconvenient because, in order to monitor the residential consumption (in terms of total active power and the type of appliance), many measuring equipment must be installed, leading to undesired costs. This is also troublesome to the residents of the household. In order to minimize these inconvenient, non-intrusive load modeling and forecasting techniques must be applied. This new methodology is also presented and examined in this chapter, in a combination of a bottom-up approach with object-oriented programming techniques.

Chapter 6 - The objectives of this work are to study the primary chemical structure of soot aerosol derived from lump-coal pyrolysis in different experimental conditions in fixed bed. A laboratory-scale movable fixed bed, water-cooled soot aerosol collection system, and electric reactor have been designed and used in the process. Three kinds of coals, sized at 3-5 mm, have been heated in the experiments. Fourier Transform Infrared Spectroscopy has been employed to test functional groups of soot aerosol samples. Infrared spectra from 400 to 4000 cm^{-1} and semiquantitative analysis have been employed. The results of experiments show that contents of hydrogen-bonded are increased, contents of unsaturated hydrocarbons are decreased, and contents of aromatic hydrocarbons are increased with temperature increase; contents of hydrogen-bonded are increased, contents of unsaturated hydrocarbons are increased, and contents of aromatic hydrocarbons are increased early and decreased late with residence time extension; and the contents of unsaturated hydrocarbons derived from soot aerosol samples are higher than those from original coal samples, and contents of hydrogen bonded and aromatic hydrocarbons are different depending on chemical structure of original coals.

CONTENTS

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Short Communication

POWER QUALITY STUDIES BASED ON ADVANCED SIGNAL PROCESSING TECHNIQUE AND ARTIFICIAL INTELLIGENCE

Tao Lin Xialing Xu and Zhengwei Fan
School of Electrical Engineering, Wuhan University, China

ABSTRACT

In recent years, both utilities and the end-users of electric power are becoming increasingly concerned with power quality issues. In order to correctly evaluate the quality of power supply and accurately measure the levels of various power disturbances in current and/or voltage waveforms, additional two aspects of power quality studies have been proposed besides the detection of power disturbance, which are the classification or identification of the types of power disturbances and the measurement of the parameters of power disturbance waveforms. In this chapter, an advanced signal processing technique and artificial intelligence are introduced in this area to realize the functions mentioned above. In details, the Wavelet Transform is used to estimate the parameters of power disturbance and extract the pattern features for classification/identification; on the other hand, artificial neural network is used to classify/identify the types of power disturbances in voltage/current waveforms. Further, the performance of various wavelet functions and artificial neural networks are investigated. As a result, the combination use of the "Dmey" wavelet and the back propagation (BP) neural network is proposed for archiving desirable performance. A software package was developed by integrating the proposed techniques, and large amount of simulation results obtained using this software package proved the correctness and effectiveness of the applications of the advanced signal processing technique and artificial intelligence to power quality researches.

Keywords: Power disturbance, Wavelet Transform, Artificial neural network.

1. INTRODUCTION

In recent years, microprocessor based control and electronic equipments are widely used in the world, which are sensitive to various power disturbances; on the other hand, the broad application of non-linear loads in power systems has also caused many negative impacts to electric power quality [1]. Therefore, both utilities and power users are becoming increasingly concerned with electric power quality issues. Once a power quality event occurs, besides the detection of power disturbances, the classification or identification of the types of power disturbances in a power quality event and the measurement of the parameters of power disturbance waveforms should also be performed, so as to correctly evaluate the quality of power supply and accurately measure the levels of various power disturbances in current and/or voltage waveforms, which are of significant helps to the mitigation of power quality issues.

Several signal processing and artificial intelligence methods have been used for classification/identification of the types of power disturbances, such as Expert System (ES) [2], Artificial Neural Networks (ANNs) [3], and the combination use of Wavelet Transform (WT) and ANNs. The disadvantage of the first method is that an ES becomes complicated and the searching efficiency decreases significantly while the types of power disturbances increase [4]; on the other hand, transplantation of this method from one case to another is not easy [5].The defect of the 2nd one is that it is relatively difficult to extract pattern features of various power disturbances directly.

The method based on the WT and ANN is studied in this chapter. Wavelet transform was used to locate the beginning and end of a power disturbance in the time domain, and extract pattern features of power disturbances for classification / identification using ANN. The parameters of various power disturbances were also estimated. A software package was developed by integrating the WT and ANN techniques, which was able to realize disturbance identification and parameter measurement.

2. BRIEF INTRODUCTIONS OF WAVELET TRANSFORM AND ARTIFICIAL NEURAL NETWORK

2.1. A Brief Introduction of Wavelet Transform

Wavelet transform is the inner product of the analyzed signal x(t) and a wavelet function $\psi_{a,\tau}(t)$, which is derived from mother wavelet function ψ(t) using dilation and shift operations [6]:

$$WT_x(a,\tau) = \langle x(t), \psi_{a,\tau}(t) \rangle = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\psi^*\left(\frac{t-\tau}{a}\right)dt \tag{1}$$

where

$$\psi_{a,\tau}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-\tau}{a}\right).$$

In practical applications, mother wavelet function $\psi(t)$ should meet the admissibility and normality conditions, and should have limited supporting areas in the time-frequency plane. The Wavelet transform is usually conducted as a multi-resolution analysis via the well known Mallat algorithm.

2.2. A Brief Introduction of Artificial Neural Network

Artificial neural network is a kind of new information processing system which can imitate the structure and function of brain cells and brain neurons on the basis of the study of the human brain mechanism. It is made up of a large number of neurons and can be classified into different types by combinations, for example, Back Propagation (BP) neural network, Self Organizing Map (SOM) network, Generalized Regression neural network, Probabilistic neural network , etc [7].

The BP neural network is widely used in many fields because it is simple and it is able to effectively extract useful information. In particular, it is very suitable for the applications with multiple inputs and multiple outputs relations [8].

3. Power Disturbance Classification/Identification Scheme Based on the Wavelet Transform and Artificial Neural Network

3.1. The Steps for the Classification/ Identification of Power Disturbance

The classification / identification of power disturbance is a procedure including pre-processing, feature extraction and pattern recognition. Pre-processing stage will de-noise and find/discard bad data, then the feature extraction stage forms the pattern features from power disturbance waveform, which are used in the pattern recognition stage to classify/identify the types of power disturbances. The procedure of power disturbance classification/identification is shown in figure 1.

Among the three stages, it is important to extract pattern features from a disturbance waveform rapidly and effectively. The sampled data from power disturbance waveform can be treated as a time sequence after pre-processing, and the WT, which is an advanced signal processing technique, can be of significant helps to feature extraction from the time sequence. The detailed scheme is introduced in the following.

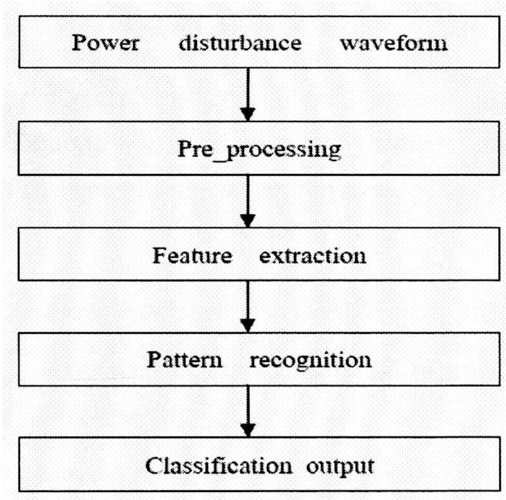

Figure 1. The procedure of power disturbance classification/identification.

3.2. Power Disturbance Feature Extraction Based on the WT

The Energy distributions of power disturbance waveforms in the frequency domain are different, therefore, the energy distributions obtained via the WT can be used as the pattern features for the distinction among various power disturbances [8].

After the M scales decomposition of a pre-processed power disturbance waveform using wavelet filter banks , the wavelet decomposition coefficients $d_k^{(j)}$ can be obtained, where j=1,2,...M, further, the energy distribution sequence can be built up as $E_j = \sum_k \left|d_k^{(j)}\right|^2$ .This procedure can also be applied to a normal voltage or current waveform to obtain sequences $d_k^{'(j)}$ and $E_j^{'} = \sum_k \left|d_k^{'(j)}\right|^2$. Then, the feature for pattern recognition can be described as $P = [p_1, p_2, \ldots, p_M]$, in which

$$p_j = \frac{E_j - E_j^{'}}{\sum_{j=1}^{M} \left|E_j - E_j^{'}\right|} \tag{2}$$

After large amount of experiments, the sampling frequency and decomposition scale M are chosen as 1200Hz and 6, respectively to balance recognition capability and computational burden. As an example, a normal voltage signal is a Sine waveform with 50.0Hz frequency and 50.0 Volt amplitude. Thus, the pattern features corresponding to different types of power disturbances, which are listed in the following, are obtained via (2) and are shown in figure 2 (a)-(f):

1. Voltage swell: amplitude is 70.0V during a 0.1 second disturbance.
2. Voltage sag: amplitude is 28.28V during a 0.1 second disturbance.
3. Voltage interrupts for a short time: amplitude is 0.0V during a 0.1 second disturbance.
4. Transient oscillation: amplitude is 53.55V during the disturbance and the primary frequency is 500.0Hz.
5. Harmonics: the third harmonic with an amplitude of 3.0V, the fifth harmonic with an amplitude of 5.0V, and the seventh harmonic with the amplitude of 7.0V.
6. Voltage fluctuation: Amplitude of the low frequency modulation signal is 0.5V, and the modulation frequency is 8.0Hz.

3.3. Power Disturbance Classification/Identification Based on the ANN

The ANN is used as a classifier in disturbance identification. Firstly, a certain number of pattern features corresponding to various known power disturbances are used to train an ANN, which will have the capability of disturbance identification in the end of this step. Then, whenever a power disturbance occurs, its pattern feature is extracted from the sampled time sequence via the WT. In the end, the obtained pattern feature is input into the trained ANN to get the type information of the power disturbance, which is the output of the ANN.

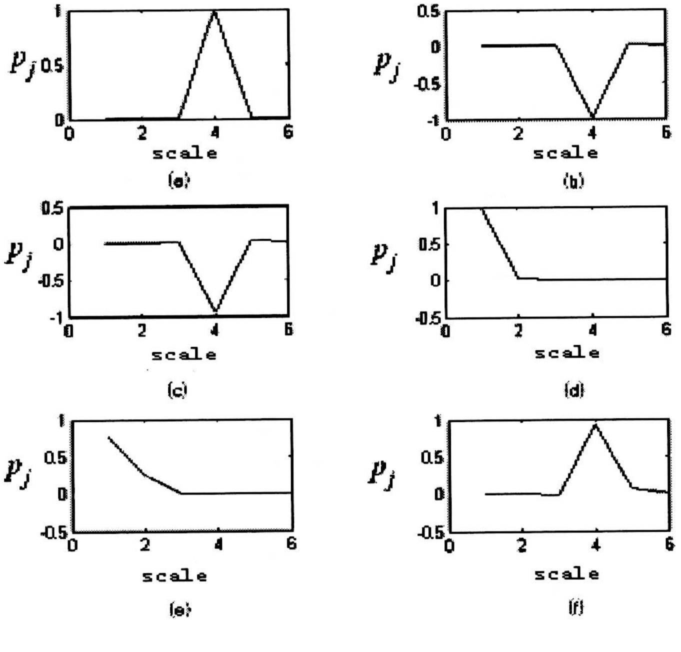

Figure 2. The Energy distributions of different power disturbances.

4. Power Disturbance Parameters Estimation Based on Wavelet Transform

The types of power disturbances studied in this paper include voltage swell, voltage sag, short time voltage interruption, transient oscillation, harmonics and voltage fluctuations. The parameters of these power disturbances and their meanings are shown in tables 1 and 2, respectively.

As the maximum module values in $d_k^{(j)}$ for all decomposition scales indicate the location of singular point in a disturbed waveform [8], the occurrence and end of a power disturbance can be easily detected through the maximum wavelet decomposition coefficients and, in consequence, the duration of the disturbance can be obtained. Further, the RMS values and amplitudes of the normal period and the duration of a disturbance can also be obtained. Because the WT can de-composite the signal components in a disturbance waveform into different frequency bands, thus the fundamental and harmonic components can be separated in the frequency domain through proper selection of the wavelet decomposition scale. In consequence, the RMS values / amplitudes of the fundamental and harmonic components can be measured in respective frequency bands. The principles of RMS value / amplitude and frequency measurement are introduced in the following sections.

Table 1. Power disturbance parameters

The types of power disturbances	Parameters
Voltage swell	T_s、T_e、V_{rms}^0、V_{rms}^1
Voltage sage	T_s、T_e、V_{rms}^0、V_{rms}^1
Short time voltage interruption	T_s、T_e、V_m^0、V_m^1
Transient oscillation	T_s、T_e、V_m^0、V_m^1、f_1
Harmonics	T_s、T_e、V_{rms}^n
Voltage fluctuation	T_s、T_e、V_m^0、V_m^2、f_2

Table 2. The meanings of the parameters in table 1

Parameters	Meanings
T_s	The beginning of a power disturbance
T_e	The end of a power disturbance
V_{rms}^0	The RMS value in normal condition

Table 2. (Continued).

Parameters	Meanings
V_{rms}^1	The RMS value during a power disturbance
V_m^0	The amplitude in normal condition
V_m^1	The amplitude during a power disturbance
V_m^2	The amplitude of the low frequency AM signal during voltage fluctuation
V_{rms}^n	The RMS value of the fundamental and harmonic components during harmonics
f_1	The primary frequency during transient oscillation
f_2	The modulation frequency of the low-frequency AM signal during voltage fluctuation

4.1. RMS Value and Amplitude Measurement

The RMS value is defined in the following:

$$U = \sqrt{\frac{1}{N}\sum_{i=1}^{N} v^2(i)} \tag{3}$$

where N is the number of samples in a cycle of the fundamental component. If the sampling frequency is 1200.0 Hz and the fundamental frequency is 50.0Hz, then N in (3) is 24.

Provided the observation window is 0.5 second, there are 601 samples in total, which forms a sample sequence $V = \{v(i)|1 \le i \le 601\}$. The first 24 samples in the sequence, i.e. $V_{p1} = \{v(i)|1 \le i \le 24\}$, are used to estimate the RMS value at the beginning via (3); similarly, $V_{p2} = \{v(i)|2 \le i \le 25\}$, which is obtained from the sample sequence using a moving window, is used to estimate the instantaneous RMS value at the next sampling time. This procedure repeats until V_{p578} is used to estimate the last RMS value in the original sample sequence. This method can also be applied to the fundamental component and harmonics instead of the sampled disturbance waveform, which are obtained after the WT based de-composition and re-construction procedure.

For a single frequency signal component, its amplitude $U_{\max}$ and RMS value U_{rms} satisfies the following relation: $U_{\max} = \sqrt{2}U_{rms}$. Thus, the amplitudes of the fundamental component and harmonics can be obtained easily from their respective RMS values.

4.2. Frequency Measurement

The zero crossing detection method is used to estimate the instantaneous frequencies of the fundamental component and harmonics. In the Sine waveform shown in figure 3, the zero crossing points are 1 and 2, their X-coordinates are “a” and “b”, respectively. In consequence, the cycle T and frequency f of the single frequency signal component are as follows:

$$T = 2 \times (b - a),\ f = \frac{1}{T} \tag{4}$$

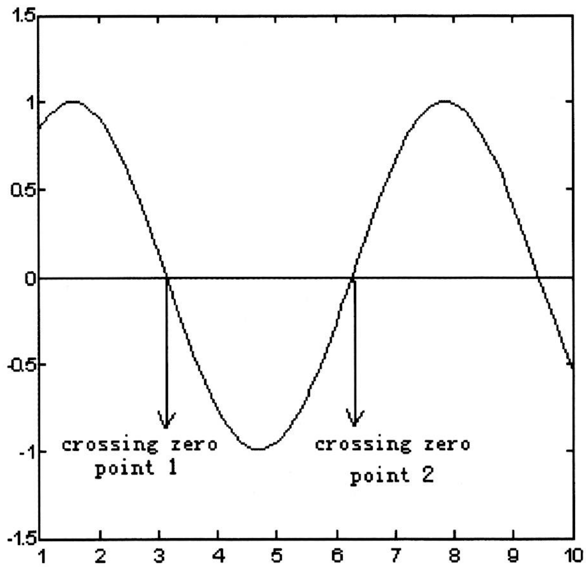

Figure 3. The zero crossing method.

In practical applications, the samples may not contain a zero point due to the sampling interval. In the following situations, namely $v(i) > 0$ and $v(i+1) < 0$, or $v(i) < 0$ and $v(i+1) > 0$, the location of the zero crossing point P can be determined:

$$p = (i + \frac{|v_i|}{|v_i| + |v_{i+1}|}) \times T_s \tag{5}$$

where T_s is the sampling interval.

Apparently, it is easy to form the sequence of zero crossing point $Z = \{z(i) \mid 1 \le i \le M\}$ from the original sample sequence, where M is the number of zero crossing points in the sequence. Further, the frequency during any half cycle can be determined based on the locations of two consecutive zero crossing points in sequence Z using (4) and (5). In the end, a frequency sequence $F = \{f(i) \mid 1 \le i \le M-1\}$ can be obtained.

5. The Selection of Wavelet Function for Power Disturbance Identification and Parameter Estimation

In the cases of both disturbance pattern feature extraction and parameter estimation, the WT is used to de-compose various signal components in the disturbance waveform into different frequency bands. Thus, the magnitude frequency properties of the wavelet filter bank should be ideal low pass and band pass. However, this requirement cannot be well satisfied in practical applications and, if the wavelet function used in the WT is not properly selected or constructed, spectrum leakage appears in the scale domain during the WT. Consequently, the energy distribution of a normal or disturbance waveform along the scale axis is different to its actual situation, which leads to the mal-extraction of disturbance pattern features and further affects the correctness of disturbance identification as well as the accuracy of disturbance parameter estimation. Therefore, the first criterion for the selection of wavelet function in this chapter can be concluded that the magnitude frequency property of the filter bank corresponding to the selected wavelet function should be as close as possible to ideal low pass and band pass to avoid or minimize spectrum leakage.

In order to accurately detect the occurrence and end of a power disturbance, the WT based on the selected wavelet function should have good singularity detection capability, which is able to capture even slight distorts or abnormal changes in the signal waveform corresponding to the occurrence and end of a power disturbance. This is the second criterion for the selection of wavelet function in this paper.

Based on the two selection criteria, a “Dmey” wavelet [9] is selected for the WT based disturbance feature extraction and parameter estimation.

6. A Software Package Developed for Power Disturbance Identification and Parameter Estimation

A software package integrating the above mentioned signal processing and artificial intelligence techniques was developed for power disturbance classification/identification. The user interface of this software package is shown in figure 4.