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Detection and Identification of Power Disturbance Signals Based on Nonlinear Time Series

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Abstract – **Power disturbances are increasing with the proliferation of non-linear devices. This paper introduces an novel idea for analyzing disturbance signals by treating them as nonlinear time series. Fractal number measurement and phase space reconstruction are two kinds of time series analytical tools widely used in nonlinear systems. Eight particular disturbance signals are selected and then analyzed using these two tools. Fractal number measurements are applied to detect transient disturbances and locate arising time, and phase space reconstruction, to identify and classify various types of disturbance signals. The results show that the methods proposed in this work are effective and intuitive.**

Index Terms – Power Disturbance; Nonlinear Time Series; Fractal Number Measurement; Phase Space Reconstruction.

I. INTRODUCTION

Power disturbance signals indicate power quality problems in user-side of power systems. Power quality is an increasingly important issue to electricity consumers at all levels of usage because of the high sensitivity of widely used equipments based on computers and microprocessors. But in modern power systems, the contamination of electromagnetic environment is getting worse along with the broader application of power electronics technology. To find disturbance source, and implement proper mitigation solution, one has to detect and identify different power disturbance signals first.

There are several patterns of power disturbance signals [2], with different characteristics of lasting time, variation amplitude, frequency spectrum, and so on for each. It is even more complex while more than one disturbance occurs simultaneously. The state-of-the-art analysis methods are typically base on mathematical deductions. Fast Fourier transform (FFT) has been widely applied to extract the harmonic contents of stationary signals where properties do not evolve over time. However, for those non-stationary signals, FFT is less efficient in tracking the signal dynamics [3,4]. Wavelet transform emerged to overcome the problems of FFT [5-7]. Benefited from the excellent temporal-frequency localization property, wavelet transform is suitable for weak signal and abrupt signal analysis. But the efficiency and accuracy of the transform strongly depend on the choice of mother wavelet. What's more, wavelet transform is sensitive to noise, and involves large computation cost since the transform carries on multi scales. In recent years, there are other methods such as S-transform [8,9], d-q transform [10] and Hilbert-Huang transform [11] applied in extracting characteristics of power disturbance signals. However, for all these analyzing tools based on domain transform, the calculation burden and accuracy are essentially in conflict. In addition, the time-frequency mapping is always followed by the phenomena of spectrum aliasing, frequency leakage and fence effect [12].

Fractal number measurement and phase space reconstruction are two kinds of widely used time series analyzing tools. A fractal dimension has served as index to quantify the complexity and roughness of signal. Fractal geometry has been suggested as an alternative for analyzing time-varying signals where other techniques have not achieved the desired results. The applications have extended from fractal image compression, fractal signal processing to biological modeling, geography, economic forecasting and even power engineering fields [13-15]. Phase space reconstruction was employed to reconstruct the motion on strange attractors in chaotic systems when first proposed. In recent years, several applications have proved it an effective tool in analyzing complex time series [16,17].

This paper introduces the above mentioned tools into power disturbance signals analysis. Simulation results show that, by fractal number measurement, occurrence of disturbance is well detected and arising time is pinpointed, and different disturbance patterns can be distinguished through constructing the trajectory of voltage signal by using phase space reconstruction idea.

II. TWO ANALYZING TOOLS FOR NONLINEAR TIME SERIES

A. *Theory of Fractal Number Measurement*

According to Barnsley, fractal dimension is the index to indicate how densely the fractals occupy the metric space where it lies [1]. A classical definition of fractal dimension is capacity dimension or called box dimension. Consider a n-dimension complete metric space R^n, F is a bounded subset in R^n which is nonempty. For each ε, let $N(\varepsilon)$ denotes the smallest number of closed balls of radius ε needed to cover the set of F, then the box dimension can be expressed by:

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$$D_B = \lim_{\varepsilon \to 0} \frac{\ln N(\varepsilon)}{\ln(1/\varepsilon)} \tag{1}$$

The box dimension takes into account the number of balls needed only, the number of set element in each ball is ignored. The information dimension is a generalization of box dimension having $N(\varepsilon)$ in (1) replaced with the average information function $I(\varepsilon)$:

$$D_I = \lim_{\varepsilon \to 0} \frac{\ln I(\varepsilon)}{\ln(1/\varepsilon)} \tag{2}$$

where $I(\varepsilon) = \sum_{i=1}^{N(\varepsilon)} -P(\varepsilon,i)\ln(P(\varepsilon,i))$ (3)

$P(\varepsilon,i)$ is the probability that a element of F is in the i^{th} box of size ε.

Another widely applied definition of fractal dimension is correlation dimension given as:

$$D_C = \lim_{\varepsilon \to 0} \frac{\ln C(\varepsilon)}{\ln \varepsilon} \tag{4}$$

where $C(\varepsilon)$ is the correlation integral defined as:

$$C(\varepsilon) = \lim_{N \to \infty} \frac{1}{N^2} \sum_{i,j=1}^{N} H(\varepsilon - \|x_i - x_j\|) \tag{5}$$

and H is Heaviside function.

Each fractal dimension definition has its suitable application. Correlation dimension is easy to calculate by personal computer, so for in our studies we quantify the voltage signal in terms of fractal number, which is a generalized correlation dimension in nature:

$$F_m = \frac{\sqrt{\sum_{i=1}^{N-l} \|x_{i+k} - x_i\|^2}}{\sqrt{\sum_{i=1}^{N-l} \|x_{i+l} - x_i\|^2}} \tag{6}$$

where $\|\,\boldsymbol{.}\,\|$ denotes Euclidean norm. F_m is the fractal number of $m-th$ data subset containing N data points. k and l are the small sampling steps which specifies the time interval between close data points, such that l is greater than k. The computation turned out to be more efficient in the case if the ratio l to k is not an integer, and the number of subnets to the number of signal periods is not an integer either.

B. *Theory of Phase Space Reconstruction*

The basic idea of phase space reconstruction is to treat the value of specific variable at a certain moment and those values after $\tau, 2\tau..., (\mathrm{m}-1)\tau$ time intervals as coordinates of a special point in m-dimension phase space. One can get the graphic representation of nonlinear system by describing a sequence of points in the above phase space. For example, for a single variable time series $x_1, x_2, \ldots x_N$, we can construct a m-dimension phase space by introducing embedding dimension parameter m and delay time τ:

$$X_i = [x_i, x_{i+\tau}, \ldots x_{i+(m-1)\tau}]^T \tag{7}$$

where $i = 1, 2, \ldots L, L = N - (m-1)\tau$.

Then we obtain the space matrix which represents the point coordinates in the signal trajectory:

$$\begin{aligned} X_1 &= [x_1, x_{1+\tau}, \ldots, x_{1+(m-1)\tau}]^T \\ X_2 &= [x_2, x_{2+\tau}, \ldots x_{2+(m-1)\tau}]^T \\ &\vdots \\ X_L &= [x_L, x_{L+\tau}, \ldots x_{L+(m-1)\tau}]^T \end{aligned} \tag{8}$$

For chaotic time series, such as electroencephalogram, short-time power load, stock exchange, meteorological information and so on, phase space reconstruction trajectory is essentially the strange attractor of the chaotic system. The signals discussed in this paper are disturbance component carried by periodical voltage signals, so we construct counterfeit phase plot in $x(t)-x(t+\tau)$ phase plane to describe the signal trajectory. By comparing the trajectory of disturbance signal with stable limit cycle of pure sine wave, disturbance pattern is identified from graphic perspective in time domain. This method overcomes discrimination problem caused by spectrum aliasing through time-frequency transforming.

III. Disturbance Pattern Concerned

According to recommended practices for monitoring electric power quality sponsored by IEEE standards coordinating committee 22 on power quality [2], there are ten common voltage disturbances, which are voltage sags, voltage swells, voltage interruptions, voltage spikes, voltage notches, harmonics, interharmonics, voltage fluctuations, undervoltage and overvoltage. Undervoltage and overvoltage are in nature voltage sags and voltage swells whose duration is more than one minute. So we take into account the above eight patterns only.

IV. Detection Of Power Disturbance Signals Using Fractal Measurement

The simulation results are shown in Fig.1 to Fig.6, including disturbance waveforms and corresponding fractal numbers of sags, swells, interruptions, spikes, notches and harmonics.

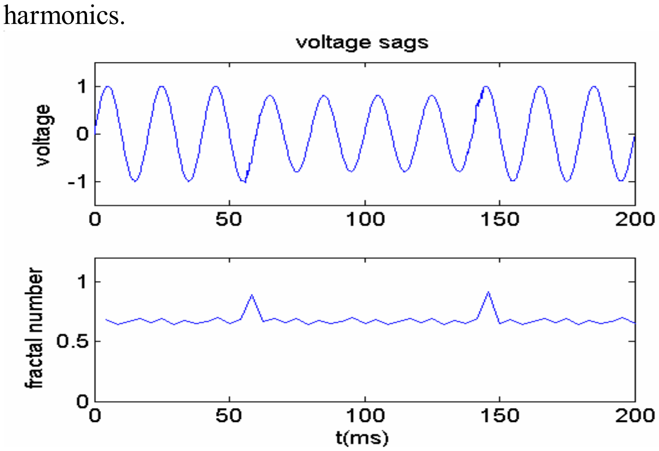

Fig.1 Waveform and fractal number of voltage sags

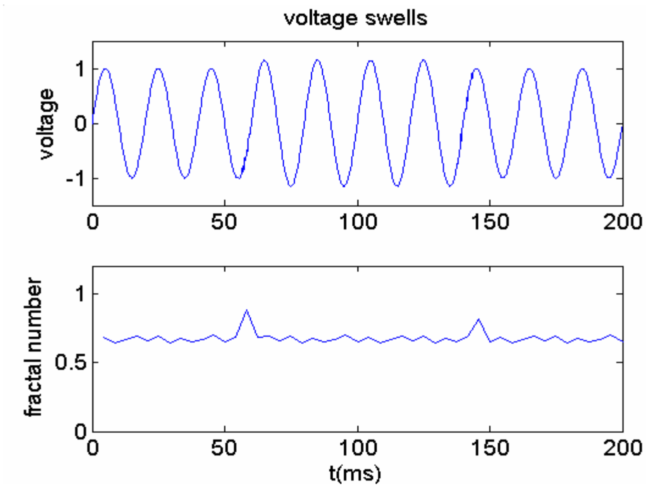

Fig.2 Waveform and fractal number of voltage swells

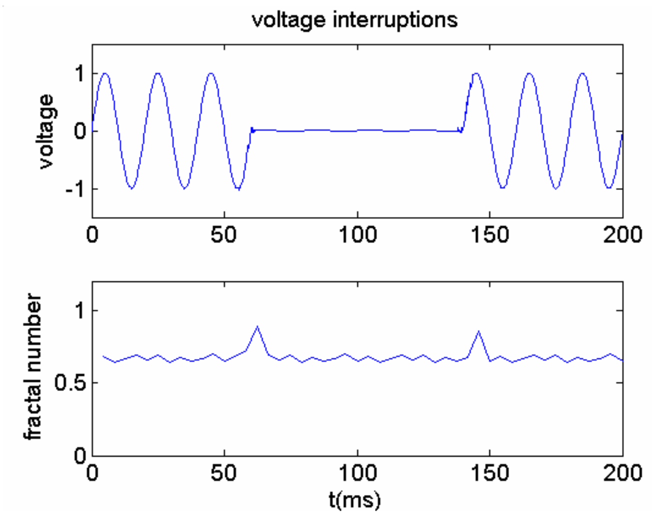

Fig.3 Waveform and fractal number of voltage interruptions

Interharmonics and voltage fluctuations are omitted because these two disturbances are not as abrupt as those concerned here. The simulation time is 200ms, and sampling frequency is 4.8kHz. All data are divided into 48 subsets.

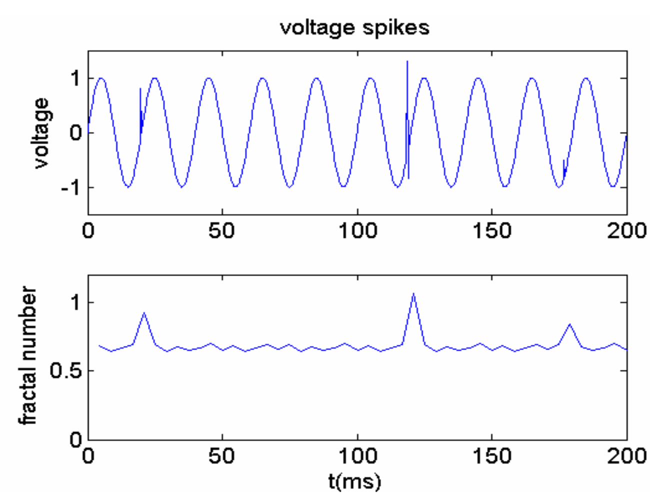

Fig.4 Waveform and fractal number of voltage spikes

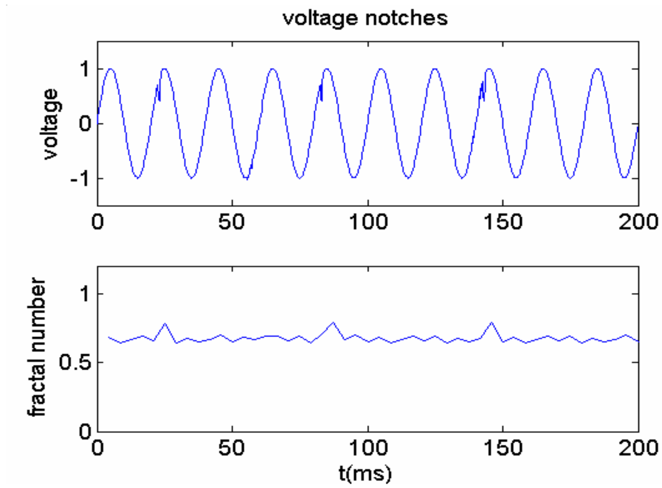

Fig.5 Waveform and fractal number of voltage notches

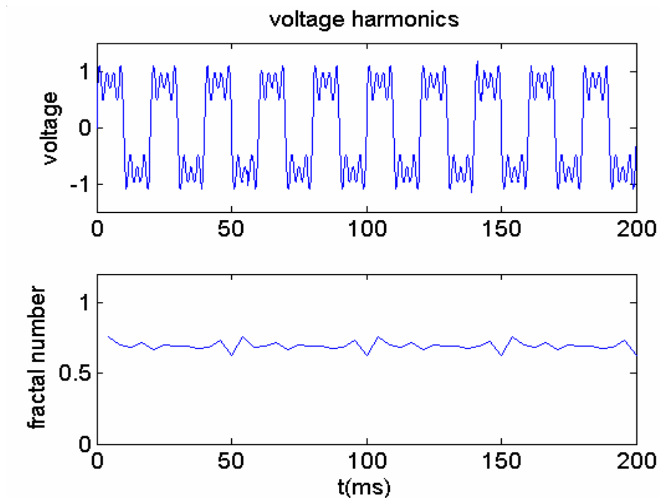

Fig.6 Waveform and fractal number of voltage harmonics

V. Identification Of Power Disturbance Signals Using Phase Space Reconstruction

It is important to choose a proper delay time τ. Although the lag is not the subject of the embedding reconstruction theorems, a good choice of τ in reality facilitates the analysis. If τ is too small, two successive elements $x_{t+i\tau}$ and $x_{t+(i+1)\tau}$ of the delay vectors are strongly correlated. All vectors are then clustered around the diagonal in the $x(t)-x(t+\tau)$ phase plane. If τ is too large, successive elements are already almost independent.

We can apply auto-relativity function or mutual information methods to choose a proper delay time [18]. By computing the auto-relativity function $C_l(\tau)$ or mutual information $I(S,Q)$ of the system $[s,q]=[x(t),x(t+\tau)]$, one can obtain the proper τ in the special case when the function value firstly falls to minimum or a sufficient small value (such as: $1/e$):

$$C_l(\tau)=\frac{\frac{1}{N}\sum_{i=1}^{N}[x(i+\tau)-\overline{x}][x(i)-\overline{x}]}{\frac{1}{N}\sum_{i=1}^{N}[x(i+\tau)-\overline{x}]^2} \tag{8}$$

where $\bar{x}=\frac{1}{N}\sum_{i=1}^{N}x(i)$.

$$I(S,Q)=\sum_{i}\sum_{j}P_{sq}(s_i,q_j)\log_2[\frac{P_{sq}(s_i,q_j)}{P_s(s_i)P_q(q_j)}] \quad (9)$$

where $P_s(s_i)$, $P_q(q_j)$ and $P_{sq}(s_i,q_j)$ are the probabilities of events s_i, q_j and the joint probabilities of s_i and q_j in system $[s,q]$ composed by discrete information series.

The visual effect of τ to the attractor constructed is the expansion degree around the diagonal in phase plane. The trajectory always expands at utmost around the diagonal under the τ chosen based on auto-relativity function or mutual information methods. According to the above metioned property, we choose $\tau=20$ and $\tau=40$ to construct the trajectory after several tests.

All eight disturbance patterns discussed in chapter III are analyzed here. The simulation time and sampling frequency are the same as those in chapter IV. Fig.7(a) shows the trajectory of standard 50Hz sine wave, and Fig.7(b)-(i) show the trajectories of disturbance signals.

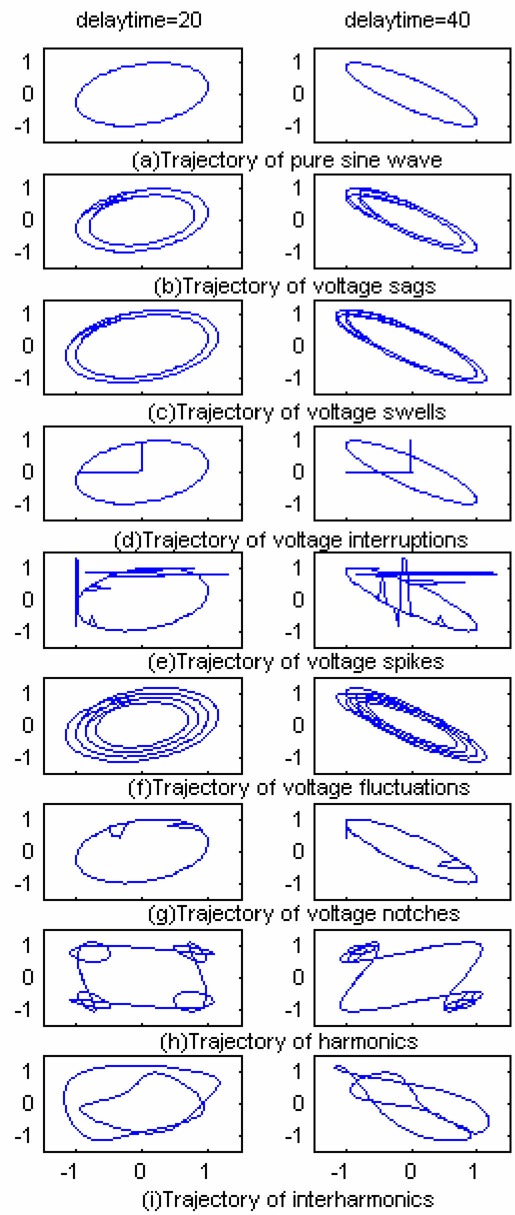

Fig.7 Trajectory of sine wave and power disturbance signals

VI. Conclusion And Prospect

In this work, we attempt to analyze power disturbance signals in time series perspective. This paper applied fractal number measurement and phase space reconstruction to power disturbance analysis and obtained preliminary results. The simulation results show the usefulness of nonlinear time series analyzing tools in power quality field.

1).Fig.1-Fig.6 show that fractal number measurements are effective in disturbance detecting. For abrupt disturbance signals such as voltage spikes, fractal number measurements are useful in time locating. And it is easy to get the duration of disturbance of sags, swells and interruptions taking into account the voltage oscillation at the disturbance starting and finishing time. The index of duration is important when assessing power quality level.

2) Constructing the signal trajectory borrows idea from building strange attractor in nonlinear dynamics. Fig.7 shows a clearly unique characteristic feature for each of the disturbance pattern. This application will be incorporated to an artificial intelligent system such as expert system to be developed for the automatic recognition of disturbance patterns.

3) Along with the development of intelligent measurement instrument, it is convenient to obtain the initial data of field samples, which can be analyzed as nonlinear time series. The methods proposed are therefore practicable, but should be further improved. The appropriate selection of some algorithm parameters such as delay time and sample frequency in different situation, and noise eliminating technology should be pursued in the next step.

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