Information Component Recognition in Fault Signals for Relay Protection of Electric Grids with HVDC

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***Abstract*—The faults in AC network may cause commutation failure in adjacent inverter station of HVDC, accompanied by injection of DC line discharge current into AC network. In this case a significant number of transient components arises in emergency voltages and currents, which level is comparable with level of main harmonic. Conventional protection relays may miss-operate due to error in non-adaptive orthogonal component filters during processing of such signals. The implementation of adaptive signal processing algorithms for improving relay protection stability is studied. It's shown that improving of signal recognition require proper sampling rate and adaptive signal model order. An adaptive blocking algorithm preventing protection miss-operation in poor measurement conditions is suggested.**

Keywords—adaptive structural analysis of power system signals, protection relays, HVDC transmission

I. Introduction

High Voltage Direct Current (HVDC) transmission systems find increasing implementation due to technical and economic advantages comparing with traditional AC transmission systems. Development of HVDC technologies provided by concept of Energy Strategy of Russia under 2035.

Interconnection of HVDC transmission systems to AC grid causes change of transient electrical characteristics of AC system. Operating experience of combined AC/DC grid has shown that HVDC has sufficient impact on AC system relay protection and may cause it miss-operation [1, 2]. The most dangerous phenomena is commutation failure in HVDC inverter station accompanied by injection of DC line discharge current into AC network. In this case significant number of transient components arises in emergency voltages and currents, which level is comparable with level of main harmonic [1–3]. Non-adaptive filters of orthogonal components [4–6], widely used in conventional AC relay protection, have a significant error when such signals processing.

Maintaining the accuracy of relay protection in such grids needs using algorithms, which have the ability to recognize signals distorted by transient components. One of promising methods is an adaptive structural analysis [7, 8], which origins date back to the Prony method [9–12].

The topic of this research effort is the application of adaptive structural analysis for information component recognition in fault signals of electric grids with HVDC.

II. Adaptive Structural Analysis Of Signals

The key idea of structural analysis is the approximation of electrical grid signal by set of eigenmodes of equivalent linear system (model). The similarity of the model and the fault signal is provided by the inertia of regulatory process in electrical grid, so that the grid behaves as a linear time invariant system at the beginning of the fault. Therefore, the response of the electrical system to fault represents a linear combination of eigenmodes of equivalent system. The size of eigenmodes basis is determined by order of its characteristic equation [8].

The tool for signal structure recognition in the adaptive structural analysis is a digital structural model [13]

$$a_0\hat{x}(k) = -\sum_{m=1}^{M} a_m x(k-\nu m), k \ge M \qquad (1)$$

where $a_0\hat{x}(k)$ is an assessment of the current sample $x(k)$ weighted with a coefficient a_0 (a_0 is voluntary, usually $a_0 = 1$), a_m – desired model coefficients, M is the order of the structural model, , ν – within model decimation coefficient.

Proximity of model (1) to signal is measured by residual

$$e(k) = a_0 x(k) - a_0\hat{x}(k) = \sum_{m=0}^{M} a_m x(k-\nu m). \qquad (2)$$

The characteristic polynomial corresponds to the structural model (1)

$$P_M(\underline{\zeta}) = \sum_{m=1}^{M} a_m \underline{\zeta}^{-m} = 0,$$

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which roots determine the frequency ω_i and damping coefficients α_i of signal components

$$\left(\alpha_i + j\omega_i\right)T_s = \ln \underline{\zeta}_i .$$

Here T_s is a sampling interval.

In terms of matrix algebra the model (1) can be represented as

$$a_0\hat{x}\left(k\right) = -\mathrm{a}^T \mathrm{x}\left(k-\nu\right) \quad (3)$$

where

$$\mathrm{a} = \left[a_M, \quad a_{M-1}, \quad \dots, \quad a_1\right]^T \quad (4)$$

and

$$\mathbf{x}\left(k-\nu\right) = \left[x(k-M), \quad x(k-M+\nu), \quad \dots, \quad x(k-\nu)\right]^T \quad (5)$$

are $\left(\mathrm{M}\times 1\right)$ – vectors of the model parameters and signal samples respectively.

The vector of the coefficients (4) is determined by solving the system of equations

$$\mathbf{Xa} \approx \mathbf{b} ,$$

obtained under the assumption that the model describes the signal well and the samples of the signal and models are close to each other: $e(k) \approx 0,\ k \geq M$. The trajectory matrix **X** [14] and the observation vector **b** is determined with the vector of samples of the signal (5) as follows

$$\mathbf{X} = \begin{bmatrix} \mathbf{x}^T\left(k-\nu\left(L-1\right)\right) \\ \vdots \\ \mathbf{x}^T\left(k-\nu\right) \end{bmatrix} \in \mathbf{R}^{L\times M} ,$$

and

$$\mathbf{b} = \mathbf{x}(k) ,$$

where L is the number of equations.

The main obstacle to achieving a complete agreement between the structural model (3) and the signal is the noise in signal. Therefore ζ_i locate in certain ambiguity area covering the true parameters of signal. To increase the effectiveness of structural analysis it is necessary to reduce the ambiguity area, considering recognition of signals of the electrical system as a task of forming of effective structural models. Under efficiency of structural models is understood their ability to recognize the structure of the signal of any complexity forming effective core in its characteristic polynomial $P_M(\zeta)$, which ideally includes only roots of recognized signal components. During processing of real electric signals effective core includes the roots of significant components of signal.

The noise degrades the resolution of the structural model (3) and leads to the necessity of specifying the order M to be higher than order of the signal M_s. In this regard, the effective structural model of signal can be divided into two parts: the first is aligned with components of input signal and presented in the form of effective core filter with order M_c, and the second is aimed to overcome the noise and presented by noise filter with order [15]

$$M_n = M - M_c \quad (6)$$

Complex amplitudes of the components of a signal $\underline{B}_i$ is determined from the component model of signal

$$x\left(k\right) = \sum\nolimits_{i=1}^{M_c} \underline{B}_i \underline{\zeta}_i^k \quad (7)$$

which include only effective core components of structural model.

Component model setting (7) is realized by solving the matrix system of equations

$$\begin{bmatrix} 1 & \dots & 1 \\ \underline{\zeta}_1 & \dots & \underline{\zeta}_{M_c} \\ \vdots & \ddots & \vdots \\ \underline{\zeta}_1^k & \dots & \underline{\zeta}_{M_c}^k \end{bmatrix} \begin{bmatrix} \underline{B}_1 \\ \underline{B}_2 \\ \vdots \\ \underline{B}_{M_c} \end{bmatrix} = \begin{bmatrix} x\left(0\right) \\ x\left(1\right) \\ \vdots \\ x\left(k\right) \end{bmatrix} .$$

III. Fundamental Properties of Adaptive Structural Models

Adaptive structural model resolution depends on many factors. Analysis showed that main factors affecting the resolution of the structural model are: a) the sampling rate of the input signal; b) the competition of effective core components; c) the order M of the initial structural model.

Consider the influence of these factors on resolution of structural model. Properties of structural models will be illustrated by examples of recognition of the structure of the signal of real emergency process given in Fig. 1. The signal with plain structure is taken to simplify the presentation of the material.

A. Influence of sampling rate

A seemingly obvious way to improve the resolution of structural model by increasing the sample rate leads to the opposite result. Indeed, the reduction of the time interval between adjacent samples makes the signal change slightly distinguishable.

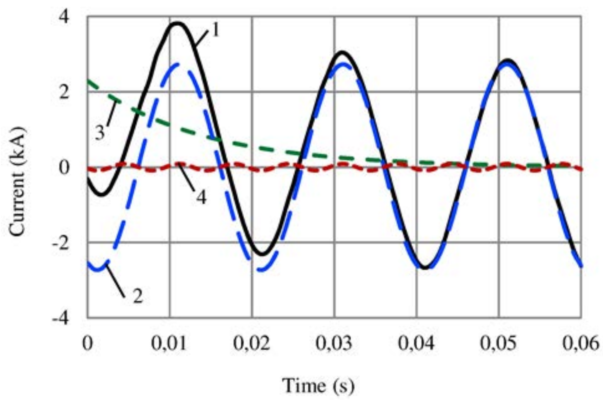

Fig. 1. Fault current oscillogram (1) and its components: fundamental harmonic (2), decaying component (3) and third harmonic (4).

It reduces recognizability of the signal. Therefore, the choice of sampling frequency in digital systems of relay protection and automation should be justified, since this significantly affects the performance and efficiency of signal processing algorithms.

The noise-free continuous signal $x(t)$ can be described by a set of analytical functions, i.e. it can be represented by a Taylor series in neighborhood of the point $t=kT_s$. Therefore, there is a known dependence between the neighboring samples of digital signal obtained by sampling the signal $x(t)$

$$x(kT_s+T_s)=x(kT_s)+\frac{1}{1!}x'(kT_s)T_s+..+\frac{1}{n!}x^{(n)}(kT_s)T_s^{\,n}.$$

It is clear that when Ts→0 sample x(kTs+Ts) will tend to x(kTs), sequentially losing higher order components in decomposition. As result the series representation of complex signal x(t) with small finite values Ts will reshape to the linear component of the decomposition.

Effective improvement of resolution is possible by increasing the distance between samples of signal by virtual change of sampling frequency. The most effective solution is achieved by within model decimation of samples. At the same time, the high-order components grow, and the noise level remains the same. A remarkable feature of this method is that despite the within model decimation the all signal samples with initial sampling frequency participate in signal recognition process, i.e. the within model decimation with reasonable use does not lead to a significant increase in the required length of signal segment.

B. Competition of effective core filter components

When analyzing the properties of the structural model, it is convenient to consider residual signal (2) as output signal of FIR-filter with transfer function

$$H(\zeta)=\sum_{m=0}^{M}a_m\zeta^{-m}.$$

If the structural model is agreed with signal, such a filter will suppress the input signal. Therefore, the filter $H(\zeta)$ can be represented as a cascade of reject filters, each of which suppresses one of component in signal. Filters whose parameters are consistent with the components of pure signal form an effective core filter $H_c(\zeta)$, and the remaining part named a noise filter $H_n(\zeta)$

$$H(\zeta)=\prod_{i=1}^{N}H_i(\zeta)=H_c(\zeta)H_n(\zeta).$$

The effective core filter is fully associated with the components of the signal, and therefore its performance does not depend on order M of initial model.

Consider a frequency response of core filter of example signal (Fig. 2). At initial sampling rate 1200 Hz core filter significantly highlight high-frequency part of spectrum, amplifying noise and thereby worsening structural model resolution. This behavior of efficient core filter will require an increase in the noise filter resources, ultimately resulting in an increase in the order of M of structural model.

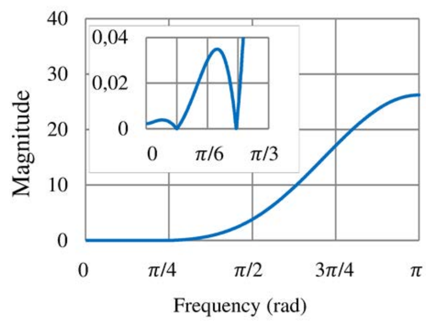

Fig. 2. Frequency response of effective core filter of signal on Fig. 1.

In addition, the core filter also suffer from mutual influence of its components: filter of fundamental harmonic $H_{c1}(\zeta)$, filter of third harmonic $H_{c3}(\zeta)$ and filter of decaying component $H_{ce}(\zeta)$. It can be clearly seen from frequency response that each core filter suppresses other components (Fig. 3): gains of H_{c3} and H_{ce} filters at fundamental harmonic frequency $\omega_1 T_s \approx \pi/12$ (0,26 and 0,51) and H_{c1} and H_{ce} filters at third harmonic frequency $\omega 3Ts \approx \pi/4$ (0,51 and 0,74) are less than one.

The efficient measure for mitigation of mutual competition between effective core filters is reducing of sampling rate of signal by means of within model decimation. The sampling rate must be changed in such a way that the individual components rejection filters of do not suppress effective core components, providing, if possible, the uniformity of frequency response over the entire frequency band from 0 to the Nyquist frequency. In considered case optimal sampling rate is 400 Hz (within model decimation coefficient ν=3, Fig. 3).

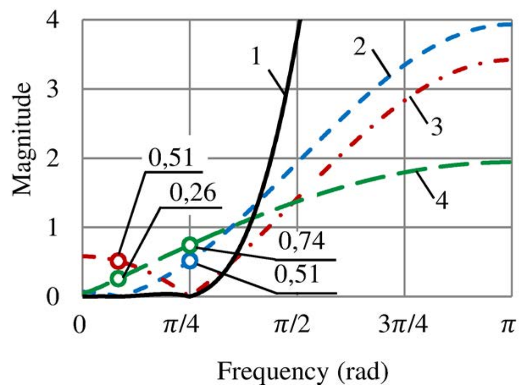

Fig. 3. Frequency response of core filter (1), rejection filter of fundamental harmonic H_{c1} (2), rejection filter of third harmonic H_{c3} (3) and rejection filter of decaying component H_{ce} (4). Sampling rate 1200 Hz.

C. The role of noise filter

Since the efficient core filter is fully associated with signal components, its performance cannot be improved by increasing of its order Mc. Consequently, the full potential of filter associated with structural model order M will be related with noise filter.

Computational experiments show that noise filter does not so much reduce noise, but rather selectively highlight effective core components: first harmonic – in 53.6 times, and third harmonic – in 16.7 times (Fig. 4). Therefore signal structure recognition will be successful if noise filter is able to compensate loss off recognition ability of structural model due to either non-optimal signal sampling rate or weak signal-to-noise ratio. Moreover, it frequency response always provides maximum highlighting of effective core components.

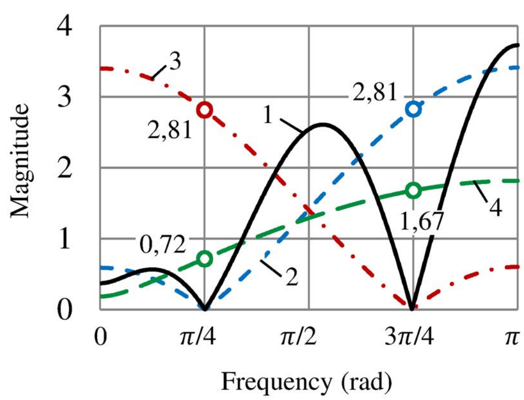

Fig. 4. Frequency response of core filter (1), rejection filter of fundamental harmonic H_{c1} (2), rejection filter of third harmonic H_{c3} (3) and rejection filter of decaying component H_{ce} (4). Sampling rate 400 Hz

IV. Information Component Recognition in Fault Signals with Large Number of Components

Necessary condition for successful signal recognition is a correct choice of the order M of the structural model (3). Thus the order of the signal M_s is a priori unknown the structural model with a known high order is used for recognition. But the order of the structural model determines the length of signal segment therefore the maximum order is always limited by the timing requirements of relay protection algorithm.

As already mentioned, the signals of emergency processes in electric grids with HVDC contain a significant number of transient components. In recognition of such signals for the purpose of relay protection, the maximum order of the structural model M is close to the order of the signal M_s, limiting both noise filter resources (6) and ability of the model to overcome a noise in the signal. If the level of information component is small comparing with the levels of transient components, and the signal is distorted by noise, so the information component may not be recognized in the initial phase of fault.

The transient components in signal are damped with development of process and the effective order of signal M_e is reduced, leading to a redistribution of resources structural models in favor of noise filter. This property of the model ensures a continuous improvement of conditions for signal recognition and higher resolution structural analysis. The transient signal will be recognized as soon as the order of the noise filter will be sufficient to overcome the noise in the signal and to form the effective core of structural model. Therefore, until the signal will be recognized the relay protection algorithm should be blocked.

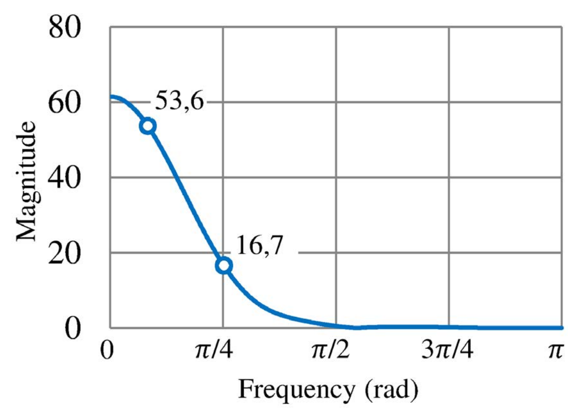

Fig. 5. Frequency response of noise filter

V. Experimental Results

Recognition of basic harmonic in fault currents close to the HVDC station [2] (Fig. 6) by adaptive structural analysis and Fourier filter is illustrated in Fig. 7 and Fig. 8.

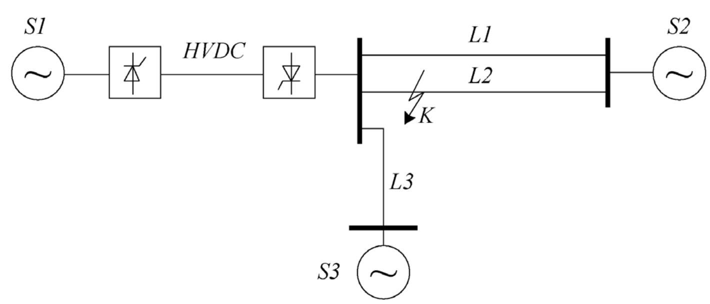

Fig. 6. The scheme of electrical grid with HVDC

The current in health line L1 is strongly distorted by transient components and noise (Fig. 7, a). Fourier filter has an unacceptable high error during first 2.5 periods of the basic harmonic (Fig. 7, b). The relay protection and automation algorithms which used it can have unwanted tripping. Adaptive structural analysis provides detection of the basic harmonic as well after 2.5 periods. However, at the initial phase of fault process the relay protection algorithm will be blocked from unwanted tripping because of absence of the information component in signal model.

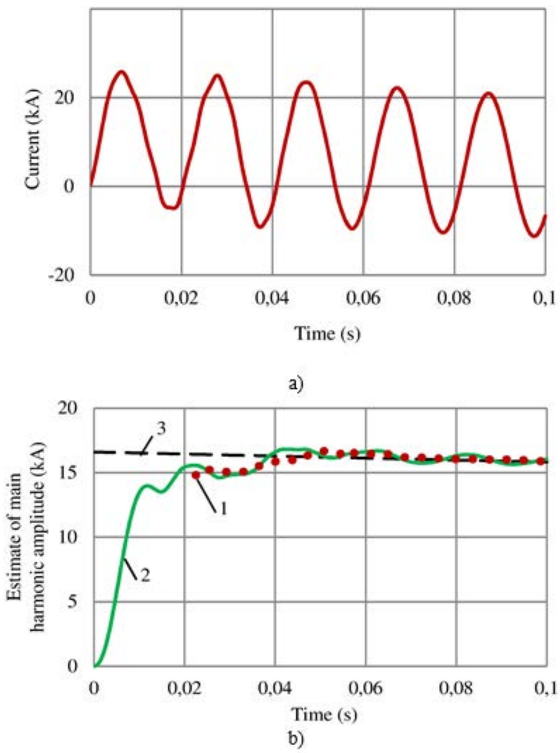

Fig. 7. The curve of phase current in health line L1 during fault in the electric grid, accompanied by commutation failure in HVDC station (a), and the amplitude of the main harmonic (b): curve 1 – an estimate obtained by adaptive structural analysis, the curve 2 – an estimation of the Fourier filter, curve 3 – the actual value. The noise in the input signal is white Gaussian noise with SNR=1000. Maximal order structural model was taken to be 18. Minimum Norm Total Least Square Solution was used to tune the model.

The information component in faulty line L2 is much weaker distorted by transient components (Fig. 8, a). So it is successfully recognized by both methods within one period after the failure (Fig. 8, b).

The selectivity of the relay protection and automation of electric grids with HVDC, that uses a Fourier filter, may be maintained by an operation delay (in this case – a 2.5 period). However, this solution leads to protection speed deterioration located on this faulty line. Signal recognition with application of adaptive structural analysis allows us to provide selectivity of protection for external faults and maintain its operating speed in case of a fault within the protected zone.

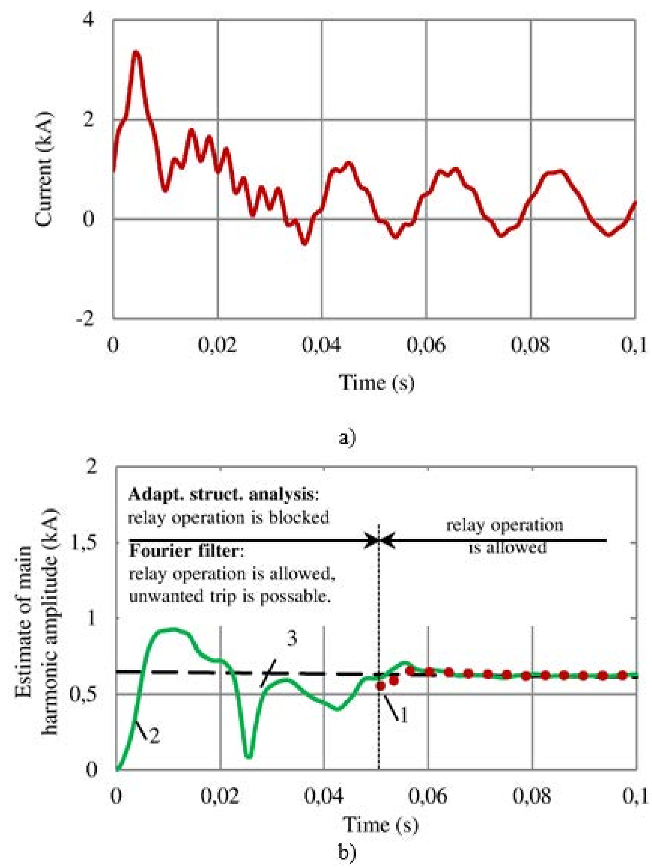

Fig. 8. The curve of phase current in the damaged line L2 during fault in the electric grid, accompanied by commutation failure in HVDC station (a) and the amplitude of the main harmonic (b). Designations of the curves and the characteristics of the noise are same as in Fig. 2.

VI. Conclusions

Application of adaptive structural analysis is one of the promising ways to improve the accuracy and selectivity of relay protection, working in conditions of distortion of the input signal by transient components of the emergency process and noise in the electric grids with HVDC.

The initial interval of the emergency process is characterized by the most difficult conditions for signal recognition. Therefore the selection of weak informational components from signal may become impossible. In this case the relay protection algorithm should be blocked until signal is recognized.

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